Modeling technology pathways and retrofit adoption to achieve city-wide building emissions reduction goals

by

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ABSTRACT

Achieving net zero emissions from buildings by 2050 is an unprecedented challenge that will require an all-in effort at local, state, federal, and international levels. The exact path to reach this goal in existing buildings varies widely from one community to another. Thus local planning efforts and a bottom-up approach is needed to attain emissions reduction goals. This dissertation lays out a framework to create technology pathway roadmaps to help cities around the world identify actionable strategies to achieve their building emissions reduction goals. These "technical potential" roadmaps can help policymakers quantify the exact requirements in terms of retrofits, workforce, and material to attain their end goals. The application of these tools in 24 cities around the world are discussed. A sound roadmap is only as good as its implementation, and currently retrofit rates lag what is necessary to achieve 2050 goals on time. One of the oft-cited barriers to retrofit adoption is the high upfront cost. This dissertation documents a survey carried out by the author and the resulting model used to help quantify households' willingness to pay for retrofits. Leveraging the willingness to pay model enables policymakers to analyze the techno-economic pathways to their goals. Finally, one of the greatest challenges to achieve emissions reduction goals is the timeline of retrofit adoption. Under the current business as usual retrofitting rate, less than a fifth of the building stock will be retrofitted by 2050. To help policymakers grasp this temporal challenge, this dissertation introduces a novel application of technology diffusion models that can quantify retrofit adoption over time. The tools developed in this dissertation are aimed at providing communities of all sizes with data-driven insights to meet their ambitious but necessary building-related decarbonization goals in a timely manner.

Thesis supervisor: Christoph F. Reinhart
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Acronyms

AC air conditioning. 17, 41, 43, 98

ACH air changes per hour. 17, 59

AMY annual meteorological year. 17, 53, 58

ASHRAE American Society of Heating, Refrigeration, and Air Conditioning Engineers. 17, 39, 58

BEM Building Energy Models. 17, 25

CV(RMSE) coefficient of variation of root-mean squared error. 17

DOE Department of Energy. 17, 32, 33

E.U. European Union. 17, 21, 56

EE energy efficiency. 15, 17, 69–72, 74, 75, 95, 100, 101, 104

EE+HP energy efficiency and electrification. 15, 17, 95, 100, 101

EE+HP+PV energy efficiency, electrification, and solar. 13, 15, 17, 69–72, 74, 75, 95, 100, 101, 103, 155

EPCs energy performance certificates. 17, 32

EUI energy use intensity. 11, 17, 34, 41, 42, 47, 59, 60, 135

GHG greenhouse gas. 17, 21, 52

GIS Geographic Information System. 11, 13, 17, 24–26, 30, 31, 34, 35, 37, 39, 95, 107, 126, 157

HVAC Heating, Ventilation, and Air Conditioning. 17, 31, 103

IPCC Intergovernmental Panel on Climate Change. 17, 20, 74

kWh kilowatt-hour. 17

LEED Leadership in Energy and Environmental Design. 17, 51

LiDAR Light Detection and Ranging. 17, 26, 52

MAPC Metropolitan Area Planning Commission. 17, 109, 113

MW megawatt. 17

NMBE normalized mean biased error. 17

NREL National Renewable Energy Laboratory. 17, 52, 56, 60

PV photovoltaic. 11, 17, 36, 59–61, 63, 68, 79, 135

TMY typical meteorological year. 17, 31, 37, 39

UBEMs Urban Building Energy Models. 17, 25

UMI Urban Modeling Interface. 17, 39, 53

WAP weatherization assistance program. 17, 67

Chapter 1

Introduction

Climate change is one of the defining challenges of the 21st century. The landmark Paris Agreement codified a limit on global mean warming of 2°C and subsequent Intergovernmental Panel on Climate Change (IPCC) reports have emphasized the need to limit warming to 1.5°C to avoid the most catastrophic impacts of climate change [1]. As seen in Figure 1.1, remaining below 2°C of global warming necessitates limiting total global carbon dioxide emissions to 930 $GtCO_2$ by 2050 [2]. Achieving these targets will require deep decarbonization across all sectors: transportation, agriculture, industry, the power system, and buildings [3]. Buildings

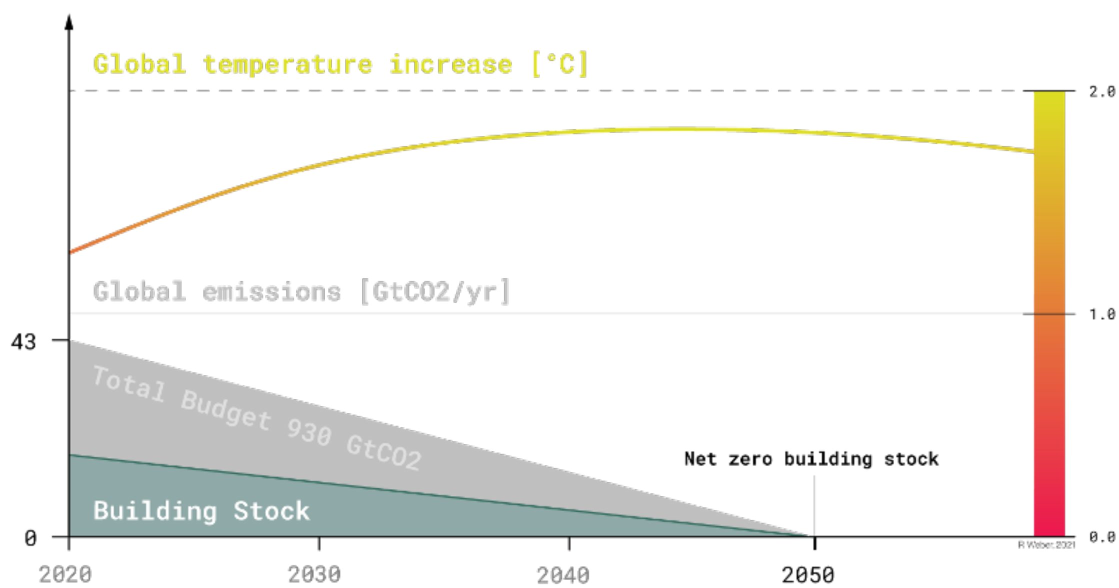


Figure 1.1: Emissions budget to achieve Paris Agreement goals. *Figure from [2], used with permission of the author.*

account for approximately 40% of global carbon emissions so reducing emissions from the built environment is therefore key to combating climate change [3]. Emissions from cities in particular are dominated by buildings. In New York City for example, buildings account for 70% of annual emissions [4].

Recognizing that buildings offer significant emissions reduction opportunities, governments from local to national levels have begun to set greenhouse gas (GHG) emissions reduction goals for their buildings. To date, over 300 cities and governments have set net zero by 2050 or sooner targets [5]. In the European Union (E.U.), the target is 50% below 1990 levels by 2030 with carbon neutrality in 2050 [6]. Achieving these goals means that by 2050 a city's entire building stock, including new construction between now and then, will need to reduce emissions as much as possible and then offset any remaining emissions to achieve carbon neutrality. While usually based on current emissions levels and aligned with the Paris Agreement's net zero by 2050, the targets are often politically-motivated and rarely science-based. Plans for actually achieving these targets are few and far between.

Furthermore, the pace and scale at which changes need to be implemented to meet net zero targets in less than 30 years is daunting. The current building retrofit rate is less than 1% and yet 85% or more of all buildings need to be net zero carbon by 2050 [3]. "The E.U. has thus proposed a 'renovation wave' that will double the rate of retrofit, improve energy standards, and pool these efforts to benefit from economies of scale [7]. However, specific measures and timelines have not been published" [8].[1] The U.S. has likewise announced an effort to retrofit homes to emit 50% less carbon and reduce energy costs by 20% by 2033 [9]. Advances in building technology and decreases in costs over the last two decades have proven that net zero construction is possible across most types of buildings, putting these goals within reach [10]. Net zero buildings are so efficiently designed that they use very little energy and when combined with on-site renewables, they produce as much energy as they consume over the course of the year, which roughly translates into net zero operational carbon emissions [11].

Cost is often a concern when pushing the envelope with any technology. A study in Massachusetts, USA found that net zero designs can actually save on upfront costs when integrated design is used, although sometimes the cost premiums can rise to 7% [12]. Even then, the net zero upgrades had payback times of less than 8 years, which can further be reduced with government subsidies [12]. Given these economics, net zero new construction —especially for residential buildings — is becoming more and more commonplace. Net zero new construction can now technically be adopted anywhere in the U.S. at economic prices [12]. If legislation required it, net zero new construction could become the norm everywhere.

Complicating decarbonization efforts, however, is the decentralized nature of building energy use regulation in the U.S. While federal authority to regulate the energy use of equipment in all buildings already exists, there is no mechanism to require minimum energy efficiency standards for all buildings in the U.S. Instead, building energy code decisions are delegated to individual states. In California, for example, building codes require all new homes must be built to be net zero ready as of 2023 [13]. In New York, legislation was recently passed that will begin to phase out fossil fuel combustion in new construction, a key step towards net zero [14]. Yet this patchwork approach leaves building codes in many states behind the times. 40 states have state-wide residential building energy codes that specify minimum construction standards for new buildings or substantial renovations [15]. Furthermore, only 13% of residential buildings in the U.S. by floor area uses the most current code; with 23 states using codes from 2009 or earlier, as shown in Figure 1.2 [16]. Out-of-date codes leave substantial energy cost and emissions savings on the table for little-

[1] The preceding paragraph is reprinted in its entirety from the author's previous paper [8].

to-no additional upfront cost and furthermore have little impact on the majority of existing residential buildings.

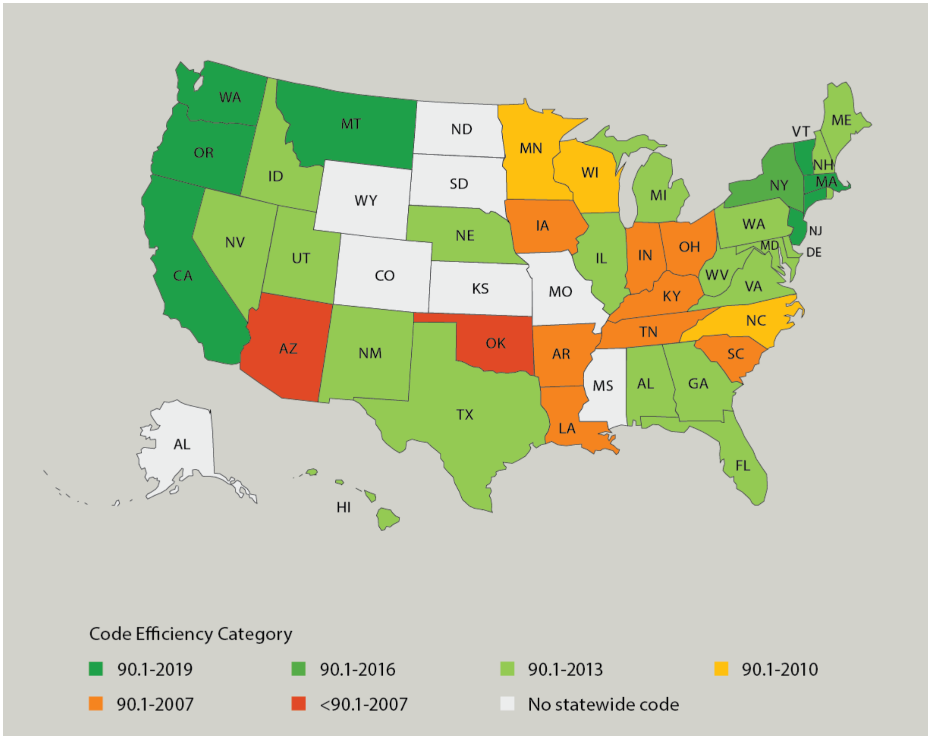


Figure 1.2: U.S. states with residential building codes and their year. Older codes are less efficient. *Figure courtesy of Christoph Reinhart, used with permission.*

Adoption of up-to-date building codes can push the envelope for building energy use but these codes generally only apply to new construction. According to a recent study by McKinsey, over 80% of the building square footage that exists today will still be in use in 2050 [17]. If cities are to meet their 2050 emissions reduction goals, it is therefore critical to decarbonize existing buildings. The U.S. has 105 million individual residential buildings today [18]. Compared to the 5.5 million commercial buildings (everything from offices to warehouses, many of which are owned by only a handful of companies) and 350,000 industrial buildings (i.e. factories), residential buildings are 95% of all buildings in the U.S. [19]. The same concepts for achieving net zero new construction apply to retrofits of existing buildings but the sheer number of individual decisionmakers that need to be convinced to retrofit their buildings by 2050 makes residential decarbonization an extremely challenging and impactful problem.

To achieve retrofitting goals, a handful of cities and states have set caps on building-related emissions using building performance standards, as shown in Figure 1.3 [20]. Building performance standards are enforceable code for existing buildings that require gradual emissions reductions toward net zero by a set date [20]. Buildings that do not comply with the emissions cap in a given year are fined based on their emissions above this cap [20]. The collected fines are then usually used to support additional retrofitting efforts. In this way, these standards are similar to energy efficiency charges that consumers pay to their utility

Figure 1.3: U.S. states with building performance standards. 11 cities and one county also have these standards in place. *Figure created by the author using data from [20].*

per kilowatt-hour they use, but these are only phased in if they use more than a certain amount in a given year. Even then, most building performance standards focus on larger buildings over 25,000 ft^2 or more.

Given the lack of building performance standards in all but a handful of locales, collective local action will be required to physically change the building stock. Thus local governments provide the most viable pathway to reducing energy use and emissions in the built environment.

This dissertation is not the first to suggest a focus on local action to affect change in building decarbonization at the local and national level around the world. The Global Building Performance Network is a group of 300 buildings professionals around the globe working to promote building decarbonization polices and actions. They have outlined a theory of change for their organization with a goal of getting all new buildings to zero emissions by 2030 and all buildings to zero emissions by 2050 [21]. In order to achieve this goal, there are inputs, change levers, intermediate outcomes, and breakthrough outcomes that must be attained, as shown in Figure 1.4. The Global Building Performance Network focuses on

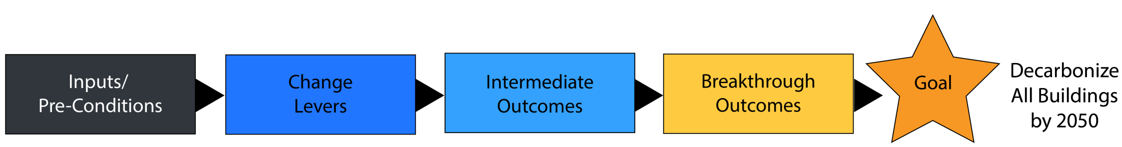


Figure 1.4: Key steps in the Theory of Change. *Figure created by the author from information in [21].*

four key inputs: funding to invest in key areas; people that are committed to the work as a calling; networks to aggregate impact and scale innovation; and trust as a partner for government, community and industry [21]. They have four main change levers: policy reform with bottom-up and evidence-based strategies; market transformation to encourage private sector engagement; providing more universal access to climate-ready and resilient housing; and cultivating an ecosystem of experts and practitioners to scale and sustain decarbonization progress [21]. Taken together, the organization has been able to leverage substantial philanthropic investment to create policy change in India, Indonesia, and China — three countries with greatly increasing energy use and an outsized share of global emissions. The network's focus has been on policy adoption in the "Global South" where emissions from new construction is expected to increase significantly [21].

Drawing on this exemplar, this dissertation focuses on nations that together account for a substantial share of global emissions today and have a large amount of pre-existing buildings that will need to be retrofitted to achieve emissions goals. The main goal of the theory of change is the same: decarbonizing all buildings by 2050. The actual inputs and levers will vary by the geography, but the central belief is that this goal will only be achieved if communities around the world are empowered to make data-driven building decarbonization policy decisions. This bottom-up approach is key to action in the buildings sector given the number of distributed decisionmakers. There are many preconditions for achieving this long-term goal but key inputs identified in this research include:

- Widely available data to inform models
- Accessible tools to leverage the data to inform policymakers
- A knowledgeable workforce to both employ the tools and implement the recommended policies
- Receptive policymakers interested in engaging with the provided information
- Funding to carry out the modeling and ultimately the policies
- Educated constituents and communities that are aware of, engaged with, and supportive of planned actions

Despite national emissions reduction pledges and calls for change, most communities have no concrete plans for how to achieve their emissions reduction goals. This dissertation leverages widely available GIS datasets and puts forward new and more accessible tools and information to help policymakers push forward decarbonization of their respective building stocks. These efforts, when part of larger collective action, can amount to tangible emissions reductions globally. Ultimately, this work aims to inform and catalyze the transformation that must take place in the world's building stock in the next quarter century.

This dissertation focuses on retrofitting opportunities in existing buildings as a foundational first step for city governments to consider before pursuing other carbon emission reduction strategies, including carbon offsets, direct air capture, etc. Parallel analysis is necessary to evaluate emissions impacts from industry, transport, land use, and new construction. For the latter case, unless all new buildings are built to net-zero standards starting today, the challenge cities face in meeting their building-related emissions reduction goals will only be heightened.

1.1 Building Energy Models

Simulation tools, namely Building Energy Models (BEM) are widely used to aid in cost-effective net zero building design. BEMs were created to help architects and engineers design new buildings and retrofit old ones to be more efficient. These models are built around physics-based heat flow equations that are used to calculate building energy consumption and size heating and cooling equipment [22]. EnergyPlus is the most common BEM tool in the U.S. and many countries abroad [22]. First developed in the 1990's by the U.S. DOE, EnergyPlus must have several key inputs:

- Building geometry (i.e., the shape of the building)
- Building construction (e.g., the materials and thickness of walls)
- Equipment specification (e.g., heating and cooling equipment efficiency)
- Schedules (e.g., occupancy, lighting, equipment)
- Weather data [22]

In both new and retrofit net zero projects, building energy modelers create different packages of upgrades and test them using BEMs to determine the most cost-effective ways of achieving a net zero building while also enhancing indoor thermal comfort and health. Common upgrades include using more insulation, specifying more efficient heating, cooling, ventilation, and hot water equipment, conducting extensive air sealing, installing more efficient lighting, buying high-efficiency (e.g. EnergyStar in the U.S.) appliances, and installing rooftop solar. These strategies are lumped together to create technology pathways to net zero: combinations of physics-based interventions in the built environment that achieve net zero energy use in a given year.

While identifying technology pathways towards a single net zero building is a proven field with lots of commercial activity, hiring a building energy modeler to create a BEM for every building in a city, let alone the country or the world, is infeasible. To scale to whole cities and help decisionmakers evaluate the best technology pathways to achieve their emissions reduction goals, a new paradigm is needed: Urban Building Energy Models (UBEMs).

1.2 Urban Building Energy Models

UBEMs apply the same BEM approach of using physics-based heat flow equations to simulate energy use of buildings at the urban scale [23]. Instead of simulating the geometry of a single building, geometries of all the buildings in a city are simulated together. These geometric data are becoming more widely available at the city-scale through the advent of open-data portals and large-scale remote sensing [24]. Common formats such as GIS shapefiles or CityGML files provide building footprint and height data that can be used to generate 2.5D models [25]. In addition to building geometry, the aforementioned weather files used in BEM can also be used in UBEMs. Finally, the non-geometric properties of building construction, equipment specification, and occupancy schedules need to be defined

[26]. Instead of defining these properties for a single building, they are defined for all buildings with a similar program type, age, or category, called an archetype (for example, single-family homes built before 1980) [26]. In order to implement their emissions goals for their building portfolio at urban scales, cities should at a minimum understand what energy savings certain building upgrades would yield at the archetype level. The definition of archetypes will be further discussed in Section 2.2.3

1.2.1 UBEM Key Ingredients

"UBEM is a bottom up approach that has been developed to serve as the analytical backbone for the decision processes laid out above. The field has flourished in recent years, leading to increasingly robust urban data streams that start from Geographic Information System (GIS), Light Detection and Ranging (LiDAR), and tax assessor databases and end in synthetic hourly building energy demand profiles for current and potential future conditions [24]. Depending on the availability of historic building energy use data, a variety of modeling, simulation, and calibration approaches have been developed [27]. The result is a somewhat confusing plethora of UBEM modeling methods for researchers, urban planning teams, energy policy makers, utilities, and building owners to choose from (or rather, get lost in)" [24].[2]

1.2.2 UBEM Simulation Tools

There are a variety of different UBEM simulations tools available today developed by academic groups and national labs, each with its own strengths and weaknesses. The prominent ones include: CityBES, TEASER, CitySim, SimStadt, City Energy Analyst, ResStock/-Comstock, and UMI [23]. Several tools use reduced order models (i.e. resistor-capacitor electrical circuit analogies) to model building energy use [23]. While much faster, these are black-box models with little tying them to the physical geometry. ResStock/Comstock is a hybrid tool. It is solely used in the U.S. and runs actual EnergyPlus simulations for representative buildings seeded with non-geometric properties derived from statistical datasets in that region [28]. ResStock/Comstock is pre-run on a supercomputer, meaning the results are instantly available and useful for state- and country-scale analyses [29]. In smaller communities, the number of representative buildings and the fact it is not tied to actual geometries means it may not be best suited to helping the average mid-sized American town (or any city in another country) get to its emissions goals. Other tools such as CityBES and UMI leverage EnergyPlus and the full geometry of the buildings which ties results to the actual composition of the modeled community [23].

UMI, developed by the MIT Sustainable Design Lab, is a plugin for the Rhinoceros3D computer-aided design (CAD) environment [30]. The energy module in UMI can be used to simulate space conditioning energy use (e.g., heating, ventilation, and air conditioning), hot water energy use, and equipment and lighting loads [30]. UMI uses machine learning techniques, namely k-means clustering, on solar radiation, cardinal direction, and archetype to identify representative clusters [31]. Each cluster is simulated with EnergyPlus using a representative two-zone shoebox that has all the parameters of that clusters' archetype [31].

[2]The preceding paragraph is reprinted in its entirety from the author's previous paper [24].

The results from the shoebox are then multiplied by the floor areas in the cluster, providing city-scale results with a laptop [31]. The shoeboxer method was shown to be accurate at the archetype-level, which is acceptable when providing stock-level analyses for policymakers [31]. For more details see Section 2.4.1.2. While UMI is used in this dissertation because it is scalable and freely available, the workflows and analysis methods contained herein could be carried out with other physics-based UBEM tools that are tied to the geometry of the actual buildings in a community.

1.3 Dissertation Overview

This dissertation aims to address the challenge of providing scalable, actionable, city-scale analysis to policymakers trying to get their community's buildings to net zero on the compressed timelines that the climate crisis requires. Chapter 2 will provide an overview of recent collaborative UBEM development efforts to make the UBEM process more accessible. Chapter 3 will outline the eight steps to streamline the urban modeling process and scale this from neighborhood models to full-scale city models. Chapter 4 is focused on quantifying the impacts of building retrofit adoption under a business as usual scenario. Chapter 5 takes this a step further by conducting a metric survey to quantify homeowners willingness to pay for retrofits. This survey provides more localized information to policymakers trying to understand the levers they can pull to steer their whole jurisdiction towards their emissions reduction goals. Chapter 6 applies the results of this metric survey to the UBEM results obtained in Chapter 3 and introduces a novel application of a diffusion model to understand the possible range of retrofit adoption at the city-scale. Chapter 7 discusses the key takeaways and looks to the future.

1.4 Hypotheses

Achieving net zero global emissions by 2050 is an unprecedented challenge that will require an all-in effort at local, state, federal, and international levels. While the technologies to achieve these goals in every sector are not all available today, most buildings can cost-effectively achieve net zero with today's technology. How to do that varies widely around the world and local planning is required to push this forward. Additionally, the current retrofit rate is paltry compared to the rate needed to meet global goals. Thus jurisdictions will need to implement policies and programs to catalyze the right retrofits at a rapid-enough pace. This dissertation is focused on providing data-driven insights to communities of all sizes to help them plot a path forward to meet their ambitious but necessary decarbonization goals. This dissertation documents the systematic testing of UBEM analyses at the stock level to drive local net zero planning and policy formulation. The key research questions include:

1. How do you make an UBEM analysis accessible to cities anywhere and what concrete value do policymakers gain from them?

2. What factors influence a household's willingness to pay for building retrofits?

3. How does willingness to pay and the realities of retrofit adoption affect a community's ability to meet its emissions reduction goals?

Chapter 2

Streamlining the Urban Building Energy Modeling Process

This chapter presents a review of efforts to streamline the UBEM creation process to make UBEMs available to almost any community in the world. This collaborative foundational work to easily generate UBEMs, define their characteristics, and test the workflow in eight case study cities paves the way for the new contributions in Chapters 3, 4, 5, and 6. In this chapter, the key parameters are defined, data sources for scalable modeling are identified, the key roles involved in the process are discussed, and neighborhood-size case study UBEMs in eight cities around the world are presented. The latter leads to key insights to inform policymakers that justifies the need to build UBEMs for all communities. This chapter is intended as an abridged review to bring the reader up to speed on key developments in UBEMs that the author has contributed to. It is drawn in large part from four papers (cited below) the author has previously co-authored in a journal publication elsewhere and has reprinted here. Some sections (e.g. Section 2.3 and Section 2.4) are taken directly from the corresponding article while others are the result of combinations of sections of these previous articles. For unabridged versions, the readers are directed to the original articles:

- Yu Qian Ang, Zachary Michael Berzolla, and Christoph F. Reinhart. From concept to application: A review of use cases in urban building energy modeling. Applied Energy, 279:115738, December 2020.
- Niall Buckley, Gerald Mills, Christoph Reinhart, and Zachary Michael Berzolla. Using urban building energy modelling (UBEM) to support the new European Union's Green Deal: Case study of Dublin Ireland. Energy and Buildings, 247:111115, September 2021.
- Yu Qian Ang, Zachary Michael Berzolla, Samuel Letellier-Duchesne, Violetta Jusiega, and Christoph Reinhart. UBEM.io: A web-based framework to rapidly generate urban building energy models for carbon reduction technology pathways. Sustainable Cities and Society, 77:103534, February 2022.
- Yu Qian Ang, Zachary Michael Berzolla, Samuel Letellier-Duchesne, and Christoph F. Reinhart. Carbon reduction technology pathways for existing buildings in eight cities. Nature Communications, 14(1):1689, April 2023.

2.1 Introduction

Most previous UBEM studies have focused on the evolving methods used to model multiple buildings at a time. For example, Olkkonen et al. developed optimization methods on top of the iterative "what-if" scenarios in their model of the entire Finnish building stock [32]. Some tools are focused solely on calculating the current emissions from operational and embodied carbon in buildings [33]. There are several excellent papers that provide a thorough review of the different UBEM tools [23], the strengths and weaknesses of different UBEM approaches [34], and the growth of research in this field [35]. Many of these studies evaluate the effectiveness of differing technology pathways, identifying the most cost and carbon savings-effective approach [36], [37]. In select cases, the energy-saving potential from retrofitting existing buildings — for example, in San Francisco, CA and Venice, Italy — was calculated [38], [39]. However, those studies do not report if and how the authors engaged with local governments. The LA100 and Carbon Free Boston studies are notable exceptions where experts from a U.S. National Lab or university collaborated with Los Angeles and Boston, respectively to develop carbon reduction pathways using custom-built, fully integrated cross-sector models [40], [41].

Despite advances in UBEM modeling techniques, several challenges hamper the widespread application of UBEM in practice and policy. Most critically, existing UBEM tools require the individuals building these models to have training in energy policy, Geographic Information System (GIS), and building energy modeling. This selection criterion has limited UBEM's use to a select group of building science researchers and specialist consultants. Another practical concern that drives up the cost of these models is that the collection, consolidation, and pre-processing of existing urban datasets remains tedious and time-consuming. The reason for this can at least partially be attributed to a lack of well-maintained national datasets and common data formats, leaving municipalities to manage their own data with limited — if any — national guidance [25]. Third, defining the physical make-up, properties, characteristics, and systems for buildings in UBEMs to create building simulation templates is laborious and requires expert knowledge of local (historic and current) building practices. These building simulation templates, while commonly deployed for building-level analysis, become arduous to create and assign at the urban scale, especially if the building stock is not homogeneous. Finally, simulation results in their native format can be unintuitive and not directly actionable for policymakers, who either do not have sufficient time or technical understanding to interpret them. This chapter focuses on making these models more accessible and readily available to inform policy design and development.

2.2 Key Components of an UBEM

This section discusses the three main components of an UBEM: weather data, geometry, and non-geometric properties that inform archetypes such as construction practices, schedules, and equipment.

2.2.1 Weather Data

EnergyPlus, the engine that underlies most UBEM tools, uses a standardized weather file format, EnergyPlus Weather (EPW), that is available for 10,000+ locations worldwide [22]. EPW files are usually created from typical meteorological year (TMY) data, which draw on at minimum 12 years of measured weather data [42]. TMYs are intended to represent the average weather during the historical period by picking 12 months, usually from different years, that are the most similar to the mean conditions for that month over the historical period [42].

2.2.2 Geometry

In the context of open-data movements around the world, where public agencies are increasingly amenable to sharing spatial and built environment datasets such as GIS shapefiles, CityGML, and property tax assessment databases, UBEM is meant to lower the barriers to entry for policymakers, urban planning practices, and municipalities working on their first urban or neighborhood analysis, and thus contribute to the proliferation of and access to UBEMs worldwide. Many planning authorities or GIS departments at state, county, or city level provide open data in the form of GIS shapefiles. These shapefiles include building footprints, jurisdiction or municipality boundaries and districts, street centerlines/midlines, and others, which, together with information on building heights or number of storeys/levels, are sufficient to construct an urban geometry model. These geometric models are one key ingredient to creating an UBEM.

2.2.3 Non-Geometric Properties: Archetypes

Once the geometric data is handled, the buildings must be divided into similar groups or archetypes. Typically, national building data is desegregated into archetypes using segmentation and characterization; segmentation filters the building stock into groups based on dimensions, age, and use, while characterization describes the construction materials, thermal properties, usage patterns and heating and cooling systems of these groups [43]. The acquisition process can be greatly simplified by using archetypes that categorize buildings into types based on shared properties that are linked to historic national/cultural construction methods. Construction period and usage type (i.e., residential, commercial, retail, etc.) are the most commonly utilized fields. Although the use of archetypes means that individual building detail is lost, the fundamental differences between types of buildings is captured in the associated data.

For all archetypes, building simulation templates must be developed. These templates contain non-geometric building information that ranges from construction practices to usage schedules, setpoints, and Heating, Ventilation, and Air Conditioning (HVAC) system performance. This is the most challenging part of the analysis, as it usually requires expert knowledge of each city's current and historic construction practices. Although automatic generation of zones using CAD and design environments such as Revit, Rhinoceros 3D, and SketchUp (and their associated plugins) is possible, the process of inputting building properties and characteristics is usually decoupled from geometry creation [26]. This has led to commercial energy modeling software, such as Design-Builder, providing pre-defined templates using default values to facilitate data entry [44]. Some of these templates represent typical constructions while others incorporate considerations for code compliance. Building science practitioners typically assign these templates based on literature, prior knowledge, heuristic/prescriptive rules, procedural methods, and references such as guides published by professional bodies (e.g., ASHRAE Handbook of Fundamentals and International Organization of Standards (ISO) building codes, etc.).

Many different approaches have been studied to segment building stocks and define their simulation templates. In North America, Farahbakhsh et al. and Huang and Brodrick developed archetypes to simulate building energy use under different future scenarios [45], [46]. Heiple and Sailor used Department of Energy (DOE) archetypes run with a BEM software to generate building energy profiles; these archetypes were linked to a geographic building database for a case-study area in Houston, Texas [47]. The estimated aggregated building energy use compared well with observed data at this scale. Davila et al. used a similar process to generate building data suited to running a UBEM for thousands of buildings across Boston [48].

In the European Union, the Energy Performance of Buildings Directive prompted surveys of the building stock within each member state [49]. The data generated have been used to create building archetypes that could be employed to estimate annual energy use for space heating and cooling using a consistent methodology (ISO EN 13790) [50]. The archetypes permit evaluation of energy efficiency measures based on technology and policy interventions applied to the aggregate building stock [51], [52]. Heeren et al. used building archetypes created by the Swiss Federal Office of Energy to simulate different energy saving scenarios based on current and future energy saving plans [51]. Mata et al. also assessed energy efficiency measures across the Swedish national and regional building stock using a BEM and hourly climate data to account for dynamic outdoor conditions [53], [54]. Simulations on 1,400 sample buildings were used to assess 12 efficiency measures applied to the entire Swedish housing stock; the results indicated that these measures could reduce the overall residential energy demand by 53%. Mata et al. extended this work to create building archetypes for Germany, Spain, France, and the UK that were used to estimate the energy use of the residential and commercial building stock [55]. In Ireland, the dwelling energy assessment procedure uses ISO EN 13790 to generate building energy performance certificates (EPCs) that are required for buildings that are sold and/or rented [56]. Famuyibo et al. and Ali et al. used these data to generate archetypes using clustering techniques that were subsequently used to simulate energy use and evaluate energy efficiency measures at a large scale [57], [58].

2.2.3.1 Required Template Characteristics

In the hierarchy shown in Figure 2.1, building templates are constructed from and comprise zone definitions, constructions, and windows. Each zone definition is made up of zone conditioning, ventilation, and internal load parameters, which can be adjusted with schedules of different granularities. Construction assemblies such as walls, roofs, and floors are built using material definitions, which contains specific thermal properties such as solar absorptance, specific heat, etc., as well as other parameters such as cost and embodied energy.

Similarly, glazing units are constructed using glazing and gas material modules, through which thermal and optimal properties such as solar transmittance and reflectance can be defined.

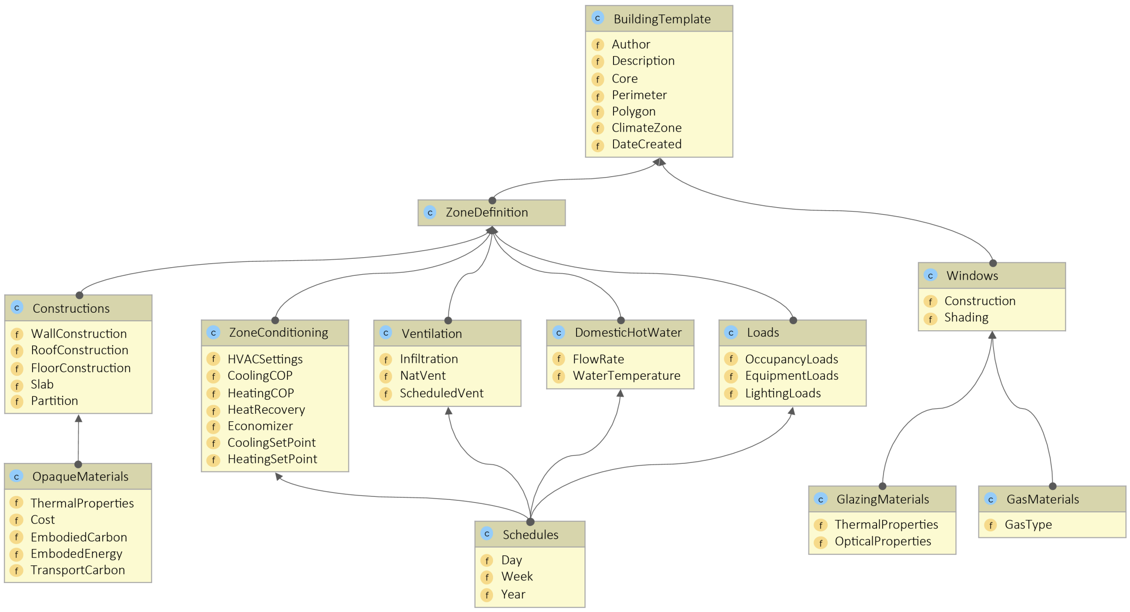


Figure 2.1: Building template structure in the template database library. Figure from [59].

2.2.3.2 Common Template Sources

This section introduces a concept of creating national building archetype libraries that characterize representative buildings in a country. Once these libraries are developed, any city building an UBEM can use the appropriate archetypes for their country and climate zone, without having to build the archetypes from scratch. Having these libraries readily available to any city thus greatly streamlines the modeling process. This work stems largely from a collaboration with Niall Buckley and is documented in [8].

For the U.S., the DOE offers detailed building descriptions for 16 program types and 16 climate zones in the form of Commercial Reference Building EnergyPlus models [60]. The DOE also developed prototype residential buildings representing new construction standards and the ResStock database which provides a statistically-representative model for residential buildings of all ages across the country [61], [62]. These datasets contain all the necessary information (equipment loads, schedules, heating systems, etc.) to build a national template library with all major building types and climate zones. The process of creating templates was automated using Archetypal, a Python-based library that compiles building simulation templates from EnergyPlus model files [63].

For Europe, the Episcope Tabula project was designed to aid the energy retrofit processes in the European housing sector by making the energy needs of buildings and the retrofit options more transparent and effective [64]. Tabula is used to inform property owners, developers, and stakeholders on the best energy saving measures to implement for different types of buildings. The Tabula database contains much of the data required to perform

UBEM energy simulations. This approach can thus be used for any city in Europe where the Tabula archetypes have been mapped to a geographically-referenced and categorized building stock.

The Tabula webtool shows photographs that typify residential building archetypes along with data on construction properties and heating systems [65]. Tabula data includes the information needed to run a thermal model to estimate annual energy demand (kWh/m^2) based on typical weather information. Moreover, the results of different energy efficiency measures, such as wall/roof insulation are also included in the webtool. Tabula building data have been standardized to reduce complexity and enable comparison of building energy performance within Europe [66]. Ballarini et al. and Dascalaki et al. have linked Tabula archetypes with census information on the building stock in Italy and Greece, respectively, to estimate the potential for implementing energy efficiency at the urban scale [67], [68].

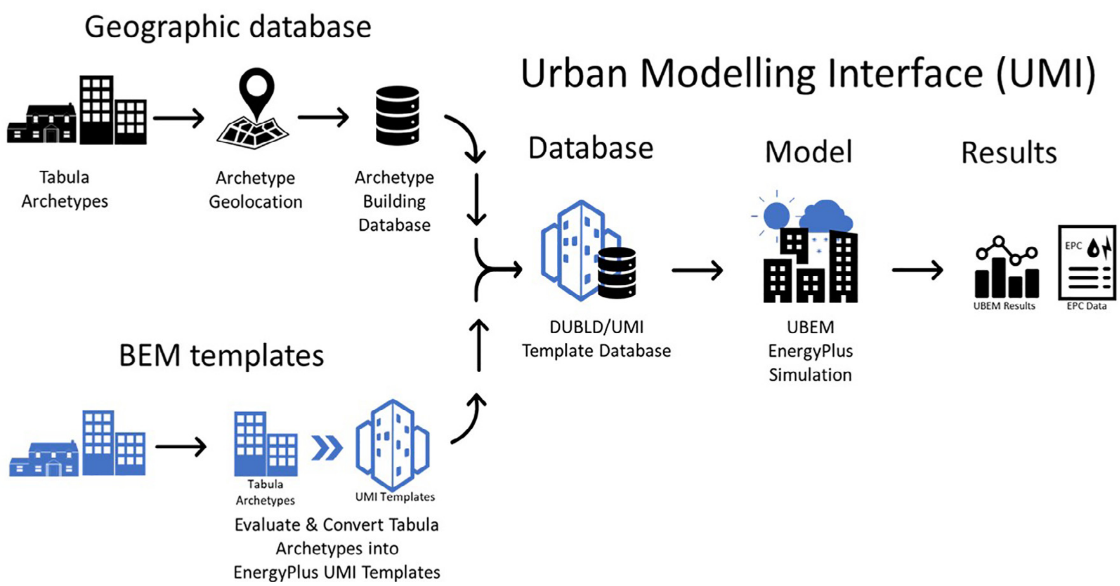


Figure 2.2: The workflow used to create UBEM templates from the Tabula dataset. The geographic database categorizes georeferenced building envelopes into Tabula archetypes and generates a GIS database. The EnergyPlus templates are created from Tabula data and then used to generate UMI template files. The geographic database is integrated with the BEM templates within UMI. Figure from [8]

Figure 2.2 depicts a workflow developed by Buckley et al. for creating UBEM templates from Tabula, which consists of two streams that are merged within the UMI modeling framework [8]. The first stream of work creates a GIS database of buildings each of which is categorized into a Tabula archetype; the details of this work are described in [69]. The second stream describes the conversion of the Tabula database associated with each archetype into templates suited for running UMI. ClimateStudio, a dynamic BEM that uses the EnergyPlus engine, is used to create the UMI templates; this has the advantage of allowing evaluations of BEM simulations against the annual energy use intensity (EUI) data associated with each Tabula archetype. The products of these two streams are merged to create a geographic database of building templates for UMI, which is used to simulate EUI across a neighborhood and test the efficacy of place-based climate change policies.

2.3 Generating an UBEM: UBEM.io

To streamline the UBEM modeling process, UBEM.io, a web framework/tool that largely automates the generation and analysis of UBEMs for stock-level carbon reduction studies was developed. UBEM.io offers several key capabilities. First, the urban model generator module allows users to automatically generate urban building geometries using simple GIS files – a format that urban and city planners are already used to maintaining and manipulating. Second, UBEM.io includes a pre-built building template library for the U.S. and Irish building stocks based on the methodology described in the previous section. These libraries could be expanded further as needed if data is available. Third, UBEM.io adopts an archetype approach to automatically assign simulation templates to buildings belonging to the same categories with similar physical and mechanical representations. This eliminates the need for manual (building-by-building) template assignment, which is time-consuming and difficult to track at the urban scale. UBEM.io also includes an urban model visualizer module that specifically focuses on the effective comparisons of multiple carbon reduction scenarios. Finally, UBEM.io is built in a modular manner that is highly scalable, allowing quick and seamless addition of functionalities and modules from third parties. It should be noted that UBEM.io does not seek to replicate or replace any existing UBEM tools. Instead, it aims to act as an enabler and aggregator for a broader audience to start using any or all the existing UBEM tools. UBEM.io does not implements its own energy simulation or heat transfer equations but rides on the simulation engine of the tool that it is interfacing with.

2.3.1 UBEM.io Template Database

To overcome the laborious process of defining and assigning templates, UBEM.io includes a template library database seeded with the template libraries developed in Section 2.2.3. The system is designed to generate template upgrades and create various custom scenarios for cities and municipalities in real time.[1] For example, for a city looking to enhance wall constructions or lighting fixtures, UBEM.io's backend API can pull wall assembles with lower U-values, as well as assign lower lighting power densities to zones, while keeping other template modules constant. The outcome is a set of automatically generated UBEMs representing various scenarios that the city/municipality might want to explore. Users are also able to customize building templates based on their building stock, and use those template libraries in the UBEMs generated by UBEM.io.

UBEM.io streamlines the entire workflow from technical details to policymaking, saving significant amounts of time and effort. Figure 2.3 compares the time required to build an UBEM using UBEM.io versus the conventional approach. UBEM.io greatly reduces the time required for downstream UBEM processes such as building the urban geometry and assigning building templates. Typically, most energy modelers in consultancy teams are tasked to clean/process GIS files as well as to retrieve building heights — from LiDAR or other channels. Using UBEM.io, is it assumed that the city/municipality already has a set of GIS files as well as building height data. The GIS modeler prepares this data on UBEM.io and hands a .uio file over to the energy modeler, who just has to validate there are no errors

[1]For more technical details, refer to the full paper: Ang et al. [59].

in the file. The time taken to build UBEMs using conventional methods is consistent with academic literature as well as informal validation with consultants [70].

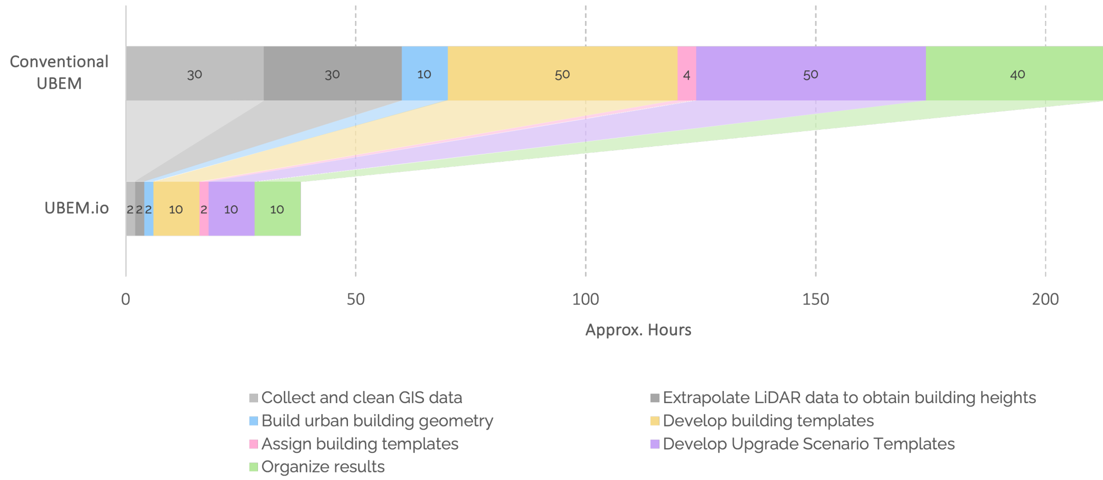


Figure 2.3: Estimated time required using conventional methods of developing UBEMs vs UBEM.io for a medium-sized city. Figure from [59].

2.4 Technology Pathways for Neighborhoods in 8 Cities

This section presents the first study in which a scalable UBEM approach supported by UBEM.io has been tested with multiple, diverse city representatives to understand whether local teams can learn how to use and independently apply the method and provide lasting value for participating jurisdictions [71]. The findings offer insight into what type of building retrofit packages energy policymakers are currently considering for their existing building stock and how resulting carbon emission reductions compare to politically motivated targets.

This section resulted from a collaboration with representatives from eight cities and municipalities around the world to analyze technology pathways to reduce annual carbon emissions in existing buildings based on retrofitting measures and onsite rooftop photovoltaic (PV). These cities participated in a three-day virtual workshop in 2021 led by the author and collaborators from MIT, hereafter referred to as "the workshop." The case study cities were Braga (Portugal), Cairo (Egypt), Dublin (Ireland), Florianopolis (Brazil), Kiel (Germany), Middlebury (Vermont, United States), Montreal (Canada), and Singapore. A requirement for participation was that teams, usually coming from academic research groups, had some expertise in building energy modeling as well as existing relationships with local city representatives. The cities studied are diverse with different climates, socioeconomic demographics, cultures, governing structures, and sizes.

The goal for the collaboration was to train city representatives to conduct an urban building energy analysis of a "seed" UBEM — a concept introduced for this project. A seed UBEM is a scaled-down UBEM that covers a limited part of a jurisdiction. Working with seed UBEMs (and fewer buildings) in the workshop is useful for staying nimble and supporting on-the-spot analysis. A seed model should ideally represent the city's overall building stock — i.e., covers building typologies that represent a significant fraction of all buildings—and extend over an area that will soon undergo substantial renovation efforts. If well chosen, the seed model will easily scale up after the workshop and the simulation and analysis results are indicative of the entire stock model since — with more buildings — the difference introduced stems mainly from building geometry.

2.4.1 Methods

A consistent study framework was deployed across the eight cities. Specifically, first the team identified the policy objectives and carbon emissions reduction goals described in Table 2.1. Although the participating cities differ in size, climate, demographics, urban typologies, and building characteristics, most cities in the study had at least economy-wide carbon emissions reduction strategies or climate action plans. These targets are broadly in line with the Paris Climate Agreement, with most plans including a near-term target and a longer-term goal aiming for economy-wide net-zero emissions by 2050. However, only five out of the eight participating cities indicated that they had a detailed carbon inventory, and only four had carbon reduction plans specifically for buildings. Most participating cities originally derived their buildings' carbon reduction goals and targets using a mix of in-house teams, government agencies, and external consultants. Only two cities reported having previously used data-driven methods to inform their targets.

With targets in place, each city identified prototypical regions representing the local building stock (the aforementioned "seed" neighborhoods). Next, the local GIS managers gathered geometric data such as Geographic Information System (GIS)) files containing building footprints and building heights, as well as non-geometrical properties of the building stock, including but not limited to construction properties, window-to-wall ratios, mechanical system types, and occupancy profiles. In addition, TMY weather files were retrieved from freely available public repositories for each of the eight jurisdictions. To study the impact of climate change on the city of Braga, CCWeatherGen tool was used to generate a morphed weather file for 2080 that represents the potential future climate in the region [72].

For each city, two retrofit upgrade scenarios were defined that mostly correspond to shallow (lower cost and/ or easier to implement) and deep (more expensive and/or harder to implement) retrofits. The different high-level scenarios are documented in Table 2.1.

2.4.1.1 Building Templates

Drawing on UBEM.io's template library, a collection of templates was assigned for each city. For the U.S. and Canada, the U.S. DOE Commercial Reference Building were used for Middlebury and Montreal [60]. For Dublin, data from the Tabula Project, as discussed in Section 2.2.3, were used. A similar approach was adopted for Kiel, as Germany had also participated in the Tabula project. For Braga, the UBEM templates were previously developed for the Portuguese building stock by Monteiro et al. [73]. For Cairo, validated building templates from a previous project in Kuwait were used [74]. In Singapore, the team started with the U.S. Department of Energy Reference Buildings for Climate Zone 2A and worked with local building science experts who were part of the city's modeling team to adjust them to the local context [60]. In Florianopolis, templates were provided by building

Table 2.1: Baseline model description and retrofit scenarios for the eight cities

City	Carbon Emissions Reduction Targets	Baseline UBEM Configuration	Shallow Retrofit Scenario	Deep Retrofit Scenario
Singapore	36% reduction by 2030; 50% reduction by 2050 (from Singapore's emissions intensity goals)	65 buildings with two archetypes, primarily residential	Energy-efficient lighting and appliances, improved natural ventilation for commercial buildings	District cooling system, in addition to provisions in shallow retrofit
Cairo (Egypt)	No targets provided or found	38 buildings with one residential archetype	Energy-efficient lighting and appliances	Enhanced HVAC systems, in addition to provisions in shallow retrofit
Florianopolis (Brazil)	43% reduction by 2030; net-zero operational carbon by 2050 (from Brazil's country-wide targets)	93 buildings with four archetypes, mixed	Energy-efficient appliances	Enhanced HVAC systems, in addition to provisions in shallow retrofit
Braga (Portugal)	40% reduction by 2030; net-zero operational carbon by 2050 (targets provided by city representatives)	95 buildings with one residential archetype	Baseline model simulated with future 2080 climate and air conditioning	Improved insulation and shading devices
Kiel (Germany)	95% reduction by 2050	226 buildings with 14 archetypes, mixed	Improved insulation properties for the whole building stock	Heat pumps for space heating, in addition to provisions in shallow retrofit
Dublin (Ireland)	40% reduction by 2030	399 buildings with six archetypes, mixed	Better weatherization properties	Enhanced insulation and glazing, in addition to provisions in shallow retrofit
Middlebury, VT (USA)	40% reduction by 2030; net-zero operational carbon by 2050	93 buildings with three archetypes, mixed	Heat pumps for space heating	Improved envelope, in addition to provisions in shallow retrofit
Montreal (Canada)	55% reduction by 2030; net-zero operational carbon by 2050	113 buildings with nine archetypes, mixed	Baseline model with natural gas furnaces replacing resistance baseboard heating	Heat pumps for space heating

simulation experts from the Federal University of Santa Catarina, who also participated in the workshop. The final simulation settings are described in Table 2.2.

With all the pre-requisite data in place, UBEMs were constructed via UBEM.io using the input GIS, TMY, and template settings described above. Multiple operational energy simulations were then run using UMI to obtain energy use, carbon emissions, and peak demand. Peak demand is the hour in the year when the electricity consumption is maximal across all electricity end-uses in the buildings, setting the yearly peak demand value (in kW). In addition to building retrofits, the maximum onsite electricity generation potential from PV was predicted assuming full rooftop utilization to provide an upper physical limit for onsite carbon emission reductions. To separate the emissions reduction contributions from building upgrades and grid decarbonization, future carbon emissions are shown as a range, assuming current and projected future grid emissions, respectively.

2.4.1.2 Uncalibrated UBEMs

These UBEMs are "uncalibrated," meaning the template values are not systematically adjusted so the energy use of the city aligns with measured data. Instead, tacit knowledge of the building stock is leveraged to ensure that the templates use values that are broadly representative of the given archetype's standard construction practices. Using an uncalibrated UBEM greatly reduces the time required to implement it. Due to the law of large numbers, uncalibrated UBEMs have been shown to yield close results (usually less than 15% error in energy use intensity) compared to actual energy use at the building stock level [27]. A recent review article of over 50 UBEM studies found that aggregate monthly error in uncalibrated models ranged from 10-20% [75]. These levels of accuracy are in line with American Society of Heating, Refrigeration, and Air Conditioning Engineers (ASHRAE) Standard 140 [76]. These findings were confirmed by Bass et al., who developed an uncalibrated UBEM with 51,000 buildings in Chattanooga, Tennessee and compared the accuracy of their model to measured 15-minute electricity data [77]. They found that at the archetype-level, results were consistent with the measured data, but at the individual building level results varied widely [77].

Buffat et al. similarly found that error in an uncalibrated UBEM ranged from 1-18% in mixed use and multifamily buildings in Switzerland [78]. Their error range in single family buildings was higher, ranging from 29-25%, but they found that "buildings with low agreement between modeled and measured demand level themselves out over the study area" [78]. This is a common result — given the high accuracy at aggregate spatial resolutions, more than half of all UBEM studies use uncalibrated models [75]. Figure 2.4 shows similar findings across a wide range of case studies. Further study by the author and collaborators show that only using a handful of archetypes is similarly accurate for the same "law of large numbers" reason [79]. Thus for city-scale policy analyses, uncalibrated UBEMs are thus good enough to provide information to policymakers.

Table 2.2: Descriptions and assumptions for the baseline archetype templates

City	Domestic Hot Water Fuel and System	Heating Fuel and System	2021 Electricity Emissions Factor [kgCO2/kWh]	2050 Projected Electricity Emissions Factor [kgCO2/kWh]	Fuel Emissions Factor [kgCO2/kWh]
Singapore	Electric Resistance Boiler	N/A	0.408	0.08	N/A
Cairo (Egypt)	Electric Resistance Boiler	N/A	0.610	N/A (Egypt has set 2030 interim targets but has no 2050 targets)	N/A
Florianopolis (Brazil)	Electric Resistance Boiler	N/A	0.090	0 (economy-wide including electric grid)	N/A
Braga (Portugal)	Natural Gas Boiler	Fuel-Fired Furnace	0.237	0.369	0.180
Kiel (Germany)	Natural Gas Boiler	Natural-Gas Furnace	0.275	0.180	0.180
Dublin (Ireland)	Electric Resistance Boiler	Natural Gas Furnace	0.325	0.205	0.180
Middlebury, VT (USA)	Natural Gas Boiler	Fuel-Fired Furnace	0.011	0 (by 2035)	0.247
Montreal (Canada)	Natural Gas Boiler	Electric Baseboard	0.0025	0 (by 2035)	0.150

Emissions factors were provided by the city representatives while the projected emissions factors were based on currently published political goals, which may or may not reflect physical reality. The values were based on national or European Union-level targets to reflect the interconnectedness of the grid. Some jurisdictions have earlier zero emissions targets (e.g., the U.S.) but 2050 dates are shown for all. Heating fuel varied by city and therefore the emissions factor for the fuel varies. Finally, Singapore did not have projections for a medium or longer-term emissions factor as verified with staff from the Energy Market Authority of Singapore. The projected emissions is derived by linearly interpolating historical average operating margin emissions factor from 2005 to 2018 for 2050.

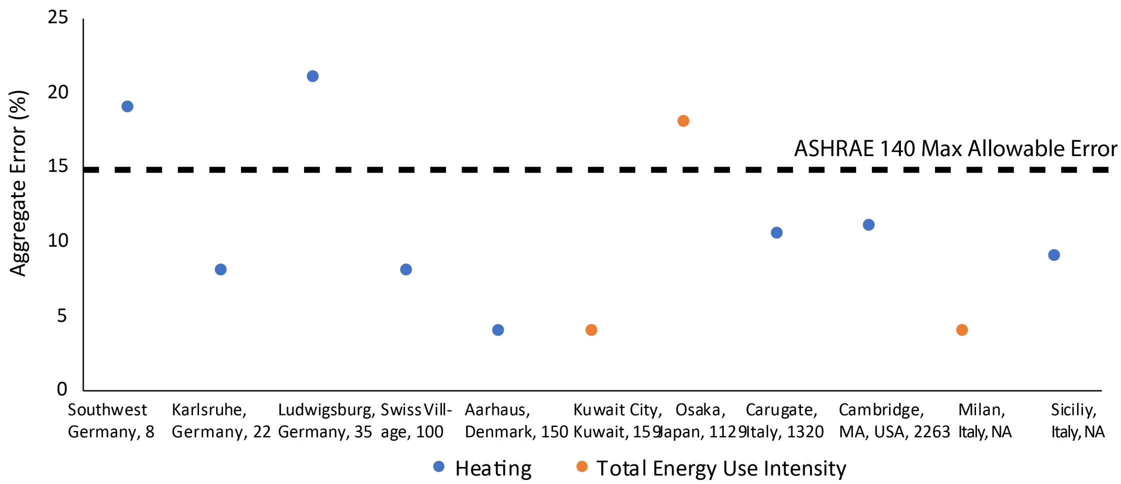


Figure 2.4: Uncalibrated UBEM errors of less than 15% is common across a wide range of case studies. *Figure adapted from results in [27], used with permission of the author.*

2.4.2 Results

2.4.2.1 Energy Use

Onsite baseline EUI predicted by the models range from under 89 kWh/m^2 for Braga to 329 kWh/m^2 for Middlebury, as shown in Figure 2.5. EUIs are mainly influenced by program type, climate, construction standards, mechanical systems, and urban typology. EUI subcategories for heating, cooling, lighting, domestic hot water, and equipment reflect these relationships — i.e., Cairo, Florianopolis, and Singapore are cooling-demand dominated with no heating loads. In contrast, Dublin, Kiel, Middlebury, and Montreal are heating-dominated.

In all cases except for Braga, EUIs fall for both shallow and deep retrofits. In Braga, where residents are expected to widely adopt air conditioning (AC) units in residential construction due to a warming climate, the EUI goes up, driven by an increase in cooling energy use. The overall EUI increases by 24%, although heating demand decreases slightly due to milder winter temperatures. Retrofitting windows and fixed window overhang shading has a small impact in Florianopolis, with a simulated decrease in EUI of only 8%. Given the high cost of these measures, they were not included in the shallow or deep retrofit scenarios. In the other cities, shallow retrofits that address low-hanging fruit like reducing plug and equipment loads lead to decreases in EUI between 13% (Dublin) to 36% (Cairo). Cairo has the largest energy efficiency gains from shallow retrofits since reducing internal loads from lighting and equipment has the dual advantage of also reducing cooling loads.

Deeper retrofits naturally lead to more considerable savings, from 32% in Middlebury to 66% in Kiel. Heat pumps achieve the largest energy efficiency gains in heating-dominated climates even though these savings do not necessarily correspond to the lowest operating costs due to the widespread availability of low-cost natural gas. Kiel, for example, has significant needs for space heating and heat pumps are effective in reducing overall energy use but are historically more expensive to operate than natural gas furnaces. This changed in 2022, with gas prices soaring due to the conflict in Ukraine, underlining the volatility of relying

Figure 2.5: Energy use intensities from each city. Figure from [71].

on fossil fuels. Dublin, like Kiel, has a high proportion of its EUI associated with heating and domestic hot water needs but opted to reduce heating loads through weatherization and insulation. However, additional steps to reduce heating emissions will need to be taken eventually. In Montreal, using natural gas instead of electricity only slightly impacts EUI but raises emissions since the hydro-powered grid is so clean. In contrast, installing heat pumps shaves off 28% from the baseline EUI, primarily from heating and cooling needs.

2.4.2.2 Photovoltaic Modeling and Simulation

To simulate rooftop PV potential, the EnergyPlus PV module is invoked via ClimateStudio [80]. The simulations assume PV module efficiencies of 15%, with modules installed on all rooftop areas in the seed UBEMs. The calculations consider shading from neighboring buildings when estimating potential electricity generation from PV. Figure 2.6 shows the resulting monthly solar energy yield for each municipality.

2.4.2.3 Building-Related Peak Demand

There is widespread consensus that decarbonizing the building sector will require the electrification of all heating systems, while the electric grid will increasingly rely on renewable energy. To realize both strategies simultaneously, it is crucial to minimize the strain that buildings place on the grid. Figure 2.7 accordingly shows each city's hourly annual electricity peak demand from buildings for the three scenarios. This value represents the hour in the year when the combined electricity demand across all existing buildings (minus onsite PV production, if applicable) is highest. Each peak hour's date and time stamp are included in each column. Given that most policy representatives mentioned rooftop PV to reduce onsite carbon emissions, the fourth column in Figure 2.7 shows annual peaks for the deep retrofit scenario combined with PV deployment across all building rooftops.

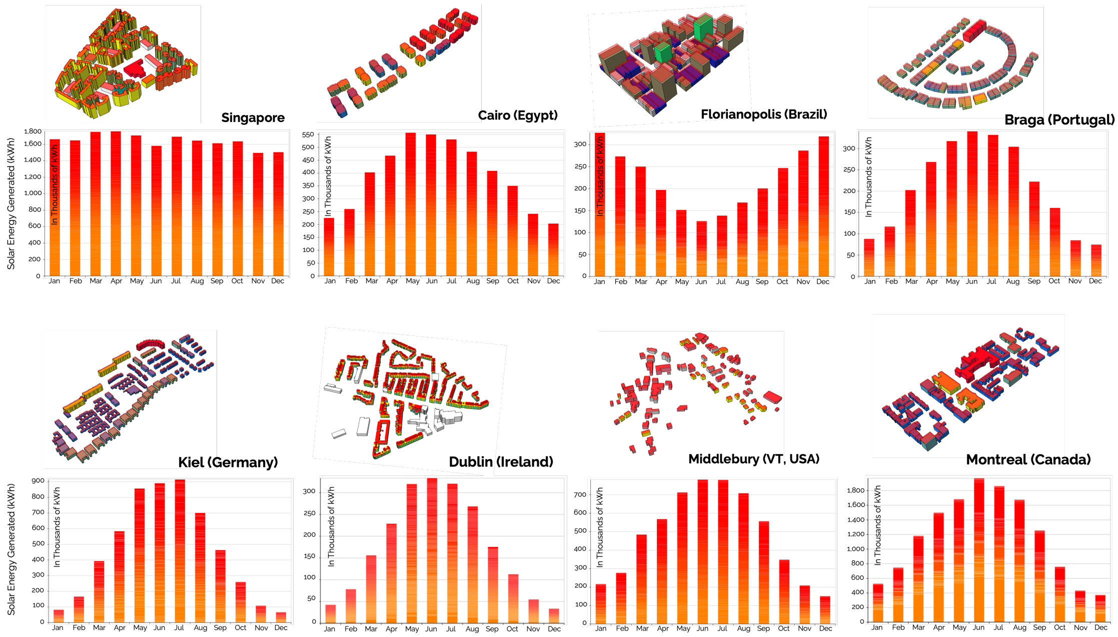


Figure 2.6: Solar results for each city. Figure from [71].

In Cairo, Florianopolis, and Singapore, shallow retrofits reduce the annual peak from 9% to 29%, while deep retrofits reduce the annual peak from 39% to 55%. In Dublin, the heating is provided by natural gas in all scenarios, so the electric peak demand from buildings is driven purely by winter lighting and equipment loads and is only slightly reduced in the shallow scenario. In Cairo, Braga, and Kiel, the peaks remain around the same time of year and occur in the evening/morning for cooling/heating-dominated climates. Given the limited availability of sunlight during those times, the deployment of PV did not affect the peak loads much except in Florianopolis, where the January 23rd 5pm mid-summer peak is delayed to March 23rd at 6pm and reduced by 20%. In Montreal, switching to natural gas or heat pumps for space heating would reduce the peak by a factor of three or more due to the inefficiency of the current baseline electric resistance heat. In Kiel and Middlebury, introducing electric heat pumps more than doubles the peak demand from buildings, suggesting that only electrifying heating would require adding substantial capacity to the power grid in these regions. In Middlebury, the buildings' peak demand hour would further shift from the cooling-driven summer afternoon to winter mornings. However, if further combined with envelope retrofitting measures, the peak in Middlebury could be reduced to even lower levels than the current baseline. Similarly, the widespread adoption of AC units in Braga will put a significant strain on the grid that could be somewhat prevented through deep retrofitting measures. These case studies highlight the importance of an energy efficiency first approach when retrofitting buildings. The findings are consistent with studies underlining the importance of buildings in grid demand management and energy policy planning [81]. Generating units to address these peak loads — especially in the United States — typically rely on fossil fuels and can be costly to operate [82]. Reducing peak demand from buildings thus leads to fewer fossil-fueled generation plants being brought online, decreases total annual power grid emissions, and reduces the need to build new distribution systems

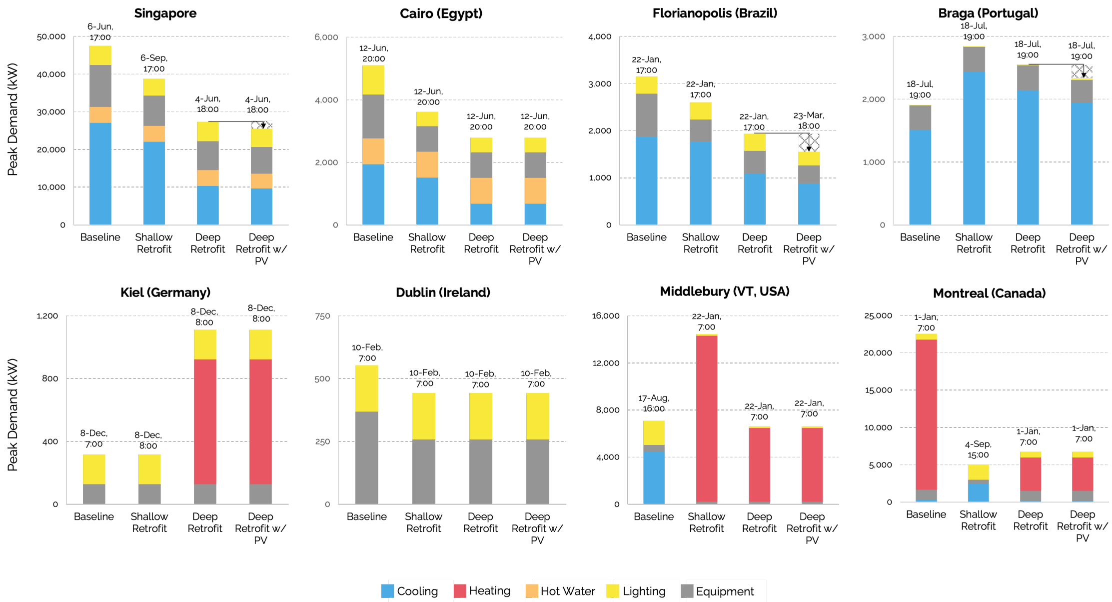


Figure 2.7: Peak demand for each city. Figure from [71].

[83].

Overall, the results show that the widespread use of rooftop PV will not significantly help utilities manage their building-related electricity peaks due to a temporal mismatch in production and demand. However, renewable energy will play a key role in reducing overall building-related carbon emissions as they provide a zero-carbon source of electricity to power electrified buildings.

2.4.2.4 Carbon Emissions

Figure 2.8 shows annual carbon emissions for the baseline, shallow, and deep retrofit scenarios with and without PV deployment across 100% of all rooftops. For the shallow and deep scenarios, results are shown as ranges assuming 2021 and projected 2050 emission factors for electricity and fossil fuels as documented in Table 2.2. The underlying values were provided by city representatives, referenced from reports, and cross-checked where possible. Note that Cairo did not have a grid decarbonization target. The ranges help to separate emissions reductions from buildings and the grid. Where applicable, the city's carbon emissions reduction targets from Table 2.1 are also shown. Without additional grid decarbonization efforts, total carbon emission reductions for buildings range from 13% to 36% for shallow retrofits and 34% to 84% for deep retrofits across all eight municipalities. If projected grid decarbonization plans for 2050 are fully realized, those numbers increase to 100% for shallow and deep retrofits in some municipalities.

Singapore's building energy use is modeled as all-electric, and the projected grid emission reductions would help it surpass its 2050 target for both shallow and deep retrofits. Much of the grid decarbonization will need to come from off-site sources as rooftop solar can only contribute a small part of the investigated residential high-rise buildings that make up much of Singapore's building stock.

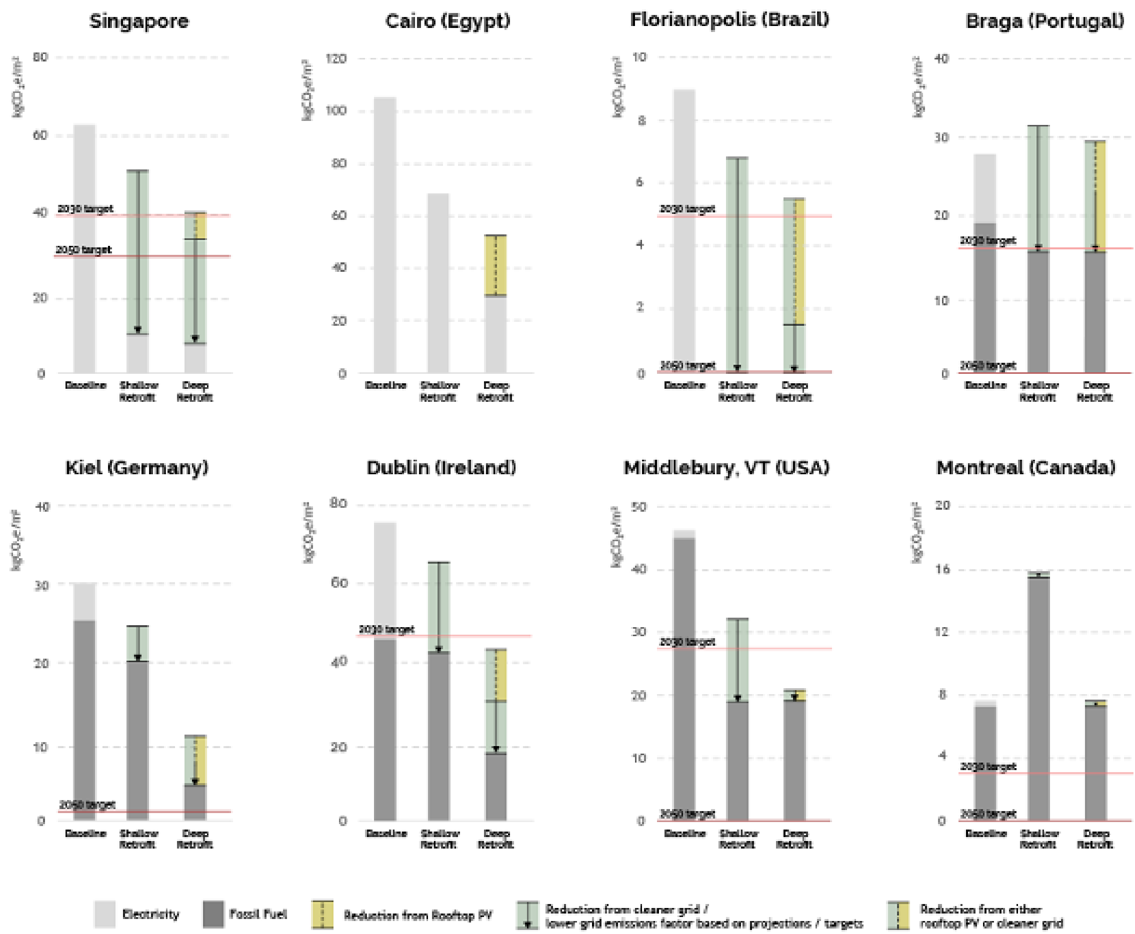


Figure 2.8: Carbon emissions for each city. The range of emissions shown captures current and future predicted emissions from the various jurisdictions. Figure from [71].

Cairo has no publicly available grid emissions reduction plans (nor emissions goals), and the rooftop solar production potential can reduce current emissions by 21% from baseline.

Florianopolis has the potential to meet its 2050 target through Brazil's overall goal of a fully decarbonized grid. Over 80% of those reductions from the baseline can be realized onsite through deep retrofits and rooftop PV.

Braga's rooftop solar potential is substantial and can contribute all the carbon-free electricity needed to meet its electrical needs in the deep retrofit scenario. However, achieving their 2050 targets will require the electrification of all other end uses. The situation is the same in Kiel, Middlebury, and Montreal, where the grid is already largely decarbonized and/or rooftop PV could cover the remaining onsite electricity demand. While traditional net-zero analyses assume that onsite fossil fuel consumption can be offset by rooftop solar, this accounting practice does not work when the local grid is fully decarbonized. Given that domestic hot water contributes substantially to these cities' energy use (as seen in Figure 2.5), it is curious that none of them opted for domestic hot water heat pumps. It is crucial that municipalities embrace a fully decarbonized system, whether fully electrified or through green hydrogen or some other carbon-neutral fuel.

In Dublin, the combination of rooftop PV and the projected decarbonized grid can more than halve the remaining emissions in the deep retrofit scenario. Given this decarbonized grid, electrification of the heating system could help Dublin meet a future net-zero target.

2.4.3 Post-Workshop Follow Up

During the workshop's final day, all teams suggested that the UBEM approach could support their jurisdiction's efforts to reduce building-related carbon emissions. In September 2022 — twenty months after the workshop — all eight city representatives were contacted to understand "what (if any) activity, follow-up modeling efforts, use of the results, discussion, legislation/policymaking, or any other outcome resulted from the workshop." Seven out of eight representatives responded to the request and reported the following activities.

In Braga, to facilitate further use of UBEMs, the local participating partner (Instituto Superior Técnico of Lisbon) developed a building template library for all of Portugal, tested in another workshop led by the author in 2022 involving representatives from three additional Portuguese cities: Porto, Coimbra, and Lisbon.

The Climate Action Coordinator for Dublin shared that the city secured funding from the national government—through the Public Sector Innovation Fund—to "further utilize UBEMs to model retrofit options."

In Florianopolis, the study became part of a guiding principles report for public policies. This report was developed through the Efficient Cities Project of the Brazilian Council for Sustainable Construction to advise the Municipality of Florianopolis in setting up its energy efficiency program.

The University of Kiel, in collaboration with Shell Germany, built an UBEM of the whole city that contains around 36,000 buildings. The city is interested in using the data to inform the management of its district heating network and future incentive programs.

Following the workshop, the author mentored a team from Middlebury College in expanding the seed UBEM to the entire town of Middlebury. The model has grown further and now covers all of Addison County's 23 towns, with approximately 12,000 buildings. A representative survey to better characterize the building stock was carried out in the summers of 2022 and 2023. This information is being used to better characterize heating sources for the UBEM and plot a path to county-wide goals.

The Université de Montréal, in collaboration with the municipal government, has developed a "virtual island" model of the whole metropolitan area. The project is funded by the Institut Trottier de l'Énergie, and efforts are underway to calibrate the model using select measured data and develop plans for a heat-sharing network in neighborhoods undergoing major redevelopment.

In Singapore, students from the National University of Singapore expanded the seed model, focusing on solar energy potential for high-rise buildings.

2.4.4 Discussion

The three-day workshop experiment and post-workshop survey confirm the widely reported political momentum among city governments to reduce carbon emissions. While many cities recognize the urgency to reduce carbon emissions of their existing building stock and have established ambitious targets, municipal representatives struggled to define clear technology pathways that they can communicate to their constituents. These representatives thus appreciate data-driven methods to guide their policy development. While leveraging UBEMs to provide this information to policymakers has typically been costly and time-intensive, this chapter lays out various improvements that streamline the UBEM creation process for many cites around the world. These methods were tested through the three day workshop and clearly shown to fill this need.

These UBEM analyses also revealed a harsh reality for many cities. For many cites aspiring to reach net-zero carbon emissions — such as Braga, Florianopolis, Kiel, and Montreal — a full-scale implementation of what their representatives consider a deep retrofit along with deployment of PV on all rooftops can only reach this goal for existing buildings if their grid is decarbonized at the same time and heating and hot water end uses are fully electrified [84]–[86]. This need extends to cold climates where heat pump manufacturers now also offer viable solutions [87]. However, in cities like Montreal, owners thinking of adopting heat pumps now face two barriers: it is currently cheaper to heat a building with natural gas, and there is still widespread (if disproven) skepticism as to whether the latest generation of air-source heat pumps can reliably heat a building in such a cold climate [88]. As a transitional solution, existing electric resistance heating systems in Montreal could remain in place and back up newly installed heat pumps if needed. Otherwise, owners who decide today to switch to natural gas-based heating will likely remain with that technology for decades [89]. Most participating municipalities in the study also disregarded the remaining fuel use from domestic hot water, which faces the same dilemma as the electrification of space heating but (at least for the study participants) currently seems to receive less attention. A reason for this may be that domestic hot water heat pump installations in cold climates remain somewhat rare.

The study also revealed that policymakers must contend with certain factors that are outside their jurisdiction. Figure 2.8 highlights the tight relationship between buildings and the electric grid, showing they must be decarbonized together. While municipalities are probably in a better position to help their constituents to renovate their buildings, only utilities understand the impact of such changes on the grid along with other trends, such as the widespread adoption of electric vehicles. It therefore seems that rather than working with a single cross-sector carbon reduction target, cities need specific guidance on how much savings their building stock needs to accomplish and at what time. This workshop shows that UBEM-based approaches can help implement those building-specific targets.

A major workshop finding is that each city's specific technology measures significantly vary due to climate, political, and economic boundary conditions, and the state of existing buildings. There is no one-size-fits-all approach for the built environment. It should be stressed that while the technology measures modeled and explored in this study consider local building stock characteristics, they would not necessarily deliver the most cost-effective decarbonization or EUI reductions nor move the city/municipality most expediently towards its stated carbon goal. This is not surprising. Decades ago, individual building energy models were developed to help design teams identify the most suitable combination of energy conservation measures for a particular building project.

While the seed UBEMs used in this workshop provide a first benchmark result, cities with non-homogenous building stocks will need to model their entire building stock. The required effort mainly consists of additional simulation time and data storage, i.e., cost, rather than human resources or additional expertise. Fortunately, four out of eight participating municipalities of varying size (Dublin, Kiel, Middlebury, and Montreal) did manage to secure public or private funding to make UBEMs an integral part of their decarbonization planning, whether managing local energy infrastructure, such as district heating systems, establishing retrofit incentive programs, or communicating their goals to their residents. Therefore this approach is scalable and municipalities worldwide should conduct similar data-driven studies to establish baselines and predict the saving potential for various technologies. The resulting policy plans, which describe what upgrades need to happen in which type of buildings, can be effective for political consensus building as individual homeowners, who ultimately have to pay for implementing those changes, can understand how their contributions fit within a larger context. Such an analysis also ensures that cities do not overlook energy use from, for example, domestic hot water.

2.5 Summary

Politically driven carbon reduction goals for existing buildings are currently somewhat disconnected from technical realities in terms of both the extent of considered upgrades and the speed of implementation. Urban building energy models offer actionable information for municipal decision-makers to identify technology pathways to retrofit their existing buildings. They also ensure that no emissions-reducing interventions are left on the table in the quest to achieve ambitious but necessary emissions-reduction goals. This chapter discusses how previous work developing an easy to use web app, UBEM.io, and a solid workflow to create template libraries in North America and Europe can be used to build UBEMs anywhere in the world. This workflow was clearly tested with case studies in eight cities in a wide variety of climates. The next step, discussed in Chapter 3, is to define who is involved in this workflow and what the tasks are to simplify the modeling process and make it accessible to any community without requiring a university or national lab led research team.

Chapter 3

An eight-step simulation based framework to help cities reach building-related emissions reduction goals

This chapter presents a novel eight-step framework for applying UBEMs to whole cities. The framework integrates three key personas developed in Ang et. al (2022) and draws on experiences from the eight cities workshop and additional follow-on workshops around the world [59]. In total, this framework has been used in 18 cities in 12 countries. In addition to the technical pathway to achieve the jurisdiction's goals, key implementation challenges such as workforce and material shortage are quantified. This chapter is an edited version of the author's journal paper published in a standalone format:

Zachary Berzolla, Yu Qian Ang, Samuel Letellier-Duchesne, and Christoph Reinhart. An eight-step simulation-based framework to help cities reach building-related emissions reduction goals. Environmental Research: Infrastructure and Sustainability. October 2023.

3.1 Introduction

One of the first city-wide UBEMs was built for the City of Boston by the MIT Sustainable Design Lab using publicly available GIS datasets in 2016 [48]. This model provided actionable information to policymakers on how Boston could achieve its net zero energy goals through efficiency retrofits and also was used to identify the energy use requirements for developing critical load microgrids [90]. This UBEM, however, took over a year of development work, required highly specialized experience in GIS data, energy models, and energy policy, and lots of manual labor to build. In short, the approach was not widely scalable outside of academia or a highly-experienced modeling team with former academics. Even then, because of the specialized expertise required, the costs to do this kind of study puts it out of reach for all but the largest of cities. Yet mitigating GHG emissions to prevent the worst of global warming and adapting to the impacts of climate change requires action in every community. This chapter lays out an eight-step framework aimed at overcoming these challenges.

A key development to simplify the UBEM modeling process in collaboration with Yu Qian Ang was identifying the concept of three key personas critical to creating any UBEM: a GIS manager, a sustainability champion, and an energy modeler [59]. This chapter builds on the three key personas and experience gained developing UBEMs in eight cities around the world that illustrated the needs and challenges policymakers face when trying to achieve their stated emissions reduction goals, as described in Section 2.4. Leveraging these experiences, this chapter prescribe an innovative framework for communities around the world to create and use uncalibrated UBEMs at the city-scale to develop retrofitting programs to meet their emissions reduction goals. The framework reduces the cost and complexity of a whole-city UBEM putting the models at the disposal of communities of all sizes, not just the largest cities. Through a case study of Oshkosh, Wisconsin, a small American city with 13,100 residential buildings and 66,000 residents, this chapter details how the eight-step process works and its scalability and accessibility to any community with the requisite data. In the U.S. alone, the approach used for Oshkosh opens the door to addressing emissions reductions in the 78 million housing units outside of major cities [91].

This chapter is organized as follows: Section 3.2 presents the framework for communities to use an UBEM for emissions reduction planning, Section 3.3 discusses how this framework was applied to Oshkosh, and Section 3.4 focuses on challenges with implementing the technology pathways and takeaways for future studies in other communities.

3.2 Methods

The emissions reduction goals, local climate, building construction, and requirements of communities around the world vary widely [71]. Yet despite their differences, every community, from a small farming town to a big metropolis, can follow the eight-step framework outlined in Figure 3.1 to create an UBEM that covers their entire building stock. The key innovation of the eight-step framework is defining the roles each of the three personas — GIS manager, sustainability champion, and energy modeler — plays in each step based on experience with case studies around the world. These steps are specifically chosen so that each persona works on tasks that are already under their purview and they are thus already

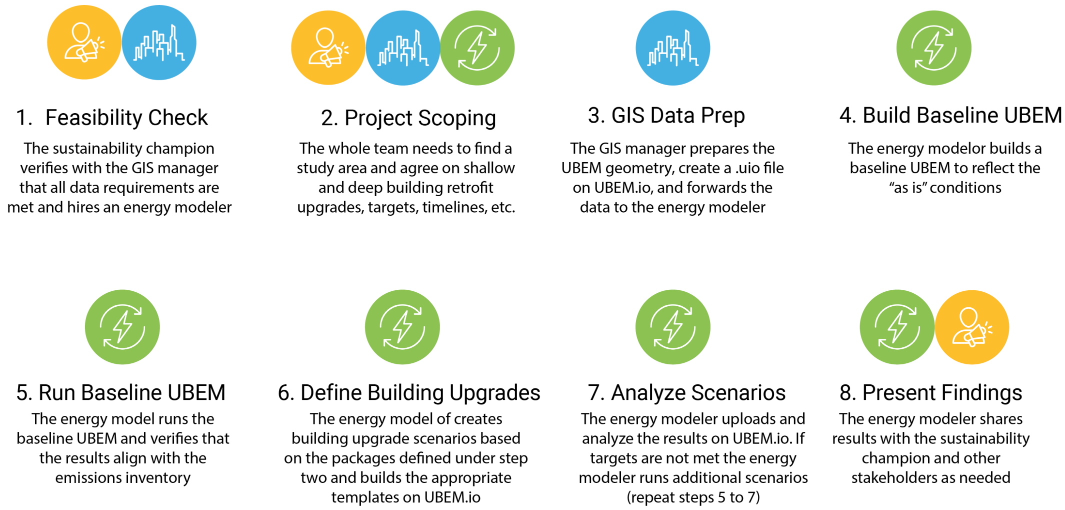


Figure 3.1: Eight steps to meeting a community's emissions reduction goals. The key personas for each step are defined. A sustainability champion (in yellow), a GIS manager (in blue), and an energy modeler (in green).

familiar with. In this way, the framework streamlines the modeling process so communities save time, money, and resources.

The GIS manager is in charge of the community's GIS dataset, usually a shapefile, geojson, or a CityGML file [92]. These positions exist because GIS data is used for everything from property taxes to life safety. GIS datasets contain accurate footprints of buildings so that the digital depiction of a property is accurate and thus property taxes are not over or under charged [93].

The sustainability champion can take many forms but they are also commonplace. In many mid-to-large cities, this is a salaried position whose job is to support the city and its residents in being more sustainable. In smaller communities this could be a volunteer, volunteer group, a function of the city council, or a secondary responsibility of a city staff member. In most jurisdictions, the sustainability champion is a generalist, dealing with everything from recycling and compost to buildings and transportation. The sustainability champions are a convener, they know the right people within the city government and within the broader community that need to be involved in any given project. They write grants to get funding for projects and are usually a respected voice in the broader community when it comes time to implementation. They are not usually, however, technical experts. Building emissions are just one part of their portfolio and they rely on others to inform them of best practices for building decarbonization.

The energy modeler is deeply familiar with individual building energy models. The field of building energy modeling has proliferated in the last decades with the growth of Leadership in Energy and Environmental Design (LEED) and other similar building-rating systems. Modelers are familiar with building technologies and the construction practices of the local building stock. Either through their collaborations with local engineers or intrinsic knowledge from previous projects, they understand what can and cannot be physically implemented in their local communities. Through the eight-step process, they apply their individual building energy modeling skills to whole communities at one time.

3.2.1 Step 1: Feasibility Check

The first step for any community looking to meet their emissions reduction goals is to ensure they have the people and data that will be integral to their study. The sustainability champion initiates this step. Do they have baseline energy and emissions data for their building stock from a recent greenhouse gas (GHG) emissions inventory? If not, they will need to conduct a GHG study using city-wide energy use data (e.g. natural gas and electricity) and current emissions factors for these sources. These energy consumption data can usually be provided by the local utility in an aggregated form without causing data privacy issues. With a baseline established, does the community have specific emissions reduction targets defined? With this key background information in hand, they engage the GIS manager to ensure they have all the necessary GIS data. At this point, the community is well-situated to put out a bid for an energy modeler to join the team.

3.2.2 Step 2: Define Project Scope

The scoping consultation is where the energy modeler, GIS manager, and sustainability champion formulate a series of questions they want to explore. Once the key building-retrofit related questions have been agreed upon, the sustainability champion can work with the energy modeler to transform these questions into strategies that can be studied with an UBEM. At this stage, the team is ready to define the scope of the study - e.g. what building types to include and which power grid decarbonization projections to use. This information should ideally come from a reputable source such as a local utility's goals or the National Renewable Energy Laboratory (NREL)'s Cambium dataset [94].

3.2.3 Step 3: GIS Data Preparation

In Step 3, the GIS manager is tasked with preparing the city's GIS dataset to be used for the UBEM. While they have never built an UBEM before, all the requisite data, detailed in Table 3.1, fall within their domain expertise. Leveraging the GIS manager's expertise in

Table 3.1: Required data for building simulation.

Property	Source	Common Approach	More Detailed Approach
Footprint	Shapefile/Geojson	OpenStreetMap [95]	Aerial imagery
Height	Tax assessor	Extrapolate from floors	Use LiDAR data
Use Type	Tax assessor	Zoning data	Detailed description
Age	Tax assessor	Year of construction	Year of last renovation

preparing the GIS file means that the energy modeler can focus solely on modeling building physics. This keeps costs on the project low since the GIS manager and sustainability champion are usually salaried positions in the city (or are volunteers).

3.2.4 Step 4: Build the Baseline UBEM

In Table 3.1 the GIS manager already identified the common parameters used to segment building stocks [55]. The energy modeler's job is now focused on defining the simulation inputs (the equipment specification, construction properties, heating and cooling systems, and schedules that are part of any energy model) based on the previously defined segmentation. These data have typically been a chokepoint in creating UBEMs, oftentimes requiring hundreds of hours of pre-processing [96]. The use of standardized archetypes describing representative building construction and use properties has helped streamline this process [26]. Creating archetypes previously required expert knowledge of the local building stock and a substantial amount of time, limiting the ability for small towns to afford UBEMs. Leveraging UBEM.io's library of building templates removes this barrier. Templates are currently available for anywhere in the U.S. based on U.S. Department of Energy prototypes and creating template libraries for other countries from national databases such as TABULA has been proven out in Buckley et al., as described in Section 2.2.3 [8]. Crucially, these templates only need to be created once for each region and then they can be accessed and used by all communities on UBEM.io or other repositories.

With templates defining the building's simulation properties defined, selected, and assigned to the various geometries in the GIS file, the UBEM model can be created. The GIS footprints are extruded to the given height and assigned a template based on their segmentation characteristics.

3.2.5 Step 5: Run the Baseline UBEM

With these data in place, the model is run using urban building energy modeling software. For stock-level analysis, physics-based models such as EnergyPlus are most common and are more accurate than other model types such as regression-based statistical or reduced order models [92]. UBEM.io is built to export to the Urban Modeling Interface (UMI) although the eight-step framework outlined in this chapter can be used with any other physics-based urban modeling software such as CityBES or TEASER [92]. No matter the tool being used for analysis, when the model is run, it should be compared to measured baseline energy use data such as electricity and natural gas consumption to test for accuracy. To properly make this comparison, the model must be run with measured weather data for the same time period as the measured energy data (i.e. an annual meteorological year (AMY)) [97].

The resulting model is uncalibrated; the results will be based off the geometries and simulation parameters. As part of defining the templates, the energy modeler can use their tacit knowledge of the building stock to tweak the templates to better reflect the local context. While the parameters can be manually tweaked as the modeler sees fit, this is not meant to be a building-by-building level of effort. Using an uncalibrated model does not mean that the results will be inaccurate. As mentioned in Chapter 2 Section 2.3, uncalibrated

UBEMs are usually within 15% of the measured data the archetype-level. These results are in part due to well-defined templates from national building stock surveys and in-part due to energy modelers' expertise and tacit knowledge of the local building stock. If the UBEM results are more than 15% off from the baseline inventory, then the emissions factor assumptions and templates need to be revisited. While previous studies have stressed the need to use calibrated models, the focus has usually been on providing detailed data at the archetype-level [98]. An uncalibrated model provides sufficient information to answer policymaker questions at the stock-level [43]. Calibration efforts and the data privacy issues that arise when using building-level measured energy data would unnecessarily increase the time, cost, and complexity of the UBEM study, limiting its scalability.

3.2.6 Step 6: Create Building Upgrades

With a plausible baseline model established, the energy modeler turns their efforts to defining different building upgrade scenarios. These upgrades should represent feasible solutions that can be carried out in the majority of buildings in that category. Upgrades should be tailored to the building typology and region. Once several different upgrade strategies are identified, they can be simulated and the process moves to Step 7 to identify the best-performing options. Rapid iteration at this stage is critical.

This is usually the most labor-intensive step for the energy modeler, yet most upgrades follow similar patterns for different regions and building types. UBEM.io has pre-defined common upgrade packages to help modelers speed up the process. Additionally, standardized upgrades could be developed at the state or national level, as has been done in the TABULA project [64]. Once a few "off the shelf" scenarios have been tested, the energy modeler can identify further improvements that are specific to the community. Using the standard scenarios as a starting point greatly reduces study costs and opens UBEMs to every community.

3.2.7 Step 7: Analyze Scenarios

From the options studied in Section 3.2.6, the energy modeler narrows down the recommended upgrades to a handful of strategies that enable the city to achieve its emissions reduction goals. Computational tools such as optimization can play a role in helping the team identify the most impactful and cost-effective options. This is a crucial step as too many options can overwhelm decisionmakers. Before the energy modeler presents these strategies to the sustainability champion and/or other local government representatives, they must be translated from technical terms into easy to understand concepts. Furthermore, the energy modeler should conduct some basic cost/benefit and payback analyses as part of this step to ensure that all recommendations presented are reasonable economically for all involved.

3.2.8 Step 8: Present Findings and Develop Implementation Plans

With a simple message and a small number of potential retrofit options, the energy modeler presents their results to the sustainability champion. They must lay out the different technology pathways to achieve the city's emissions goals and the costs and savings associated with implementing these pathways. At this point, the energy modeler hands the project and data back to the sustainability champion for implementation. The sustainability champion can leverage the data from the modeler to draw conclusions about the size of the workforce needed to implement these technology pathways. The champion might involve the GIS manager for data visualization but in general they have now been given all the information they need to design programs and policies to implement the technology pathways.

The outputs of an UBEM are designed to communicate the need for collective building retrofits to meet a community's emissions reduction goal. Nolan et al. showed that messages about neighbors' energy conservation behavior spurred people to conserve more energy [99]. Jachimowicz et al. showed that people will save energy if they think other people in their area care about saving energy [100]. Furthermore, Alcott and Rogers showed that long-term reductions in energy consumption require repeated communication efforts in order to create lasting change [101]. Thus to catalyze homeowner action, the sustainability champion will likely need to create a well-publicized demonstration project of the proposed retrofits while also streamlining the implementation for all residents. Furthermore, by educating the population that upgrading a home to be more energy efficient is both desirable and necessary to reach community goals, the uptake of the retrofit program should increase [102].

Finally, implementation needs to be accessible to all. This is where straightforward financing options through local banks or on-bill financing in collaboration with the local utility can make a big difference. If homeowners have easy access to capital and quick payback periods, they will be more inclined to carry out retrofits [103], [104]. Ultimately, successfully encouraging widespread program adoption will require a multi-pronged approach that makes building upgrades a simple and financially attractive process.

3.3 Results

The above described emissions reduction framework is demonstrated in the town of Oshkosh, Wisconsin, USA. Oshkosh is a midwestern city with 66,000 residents in ASHRAE climate zone 5A - cool humid. In many respects it is typical of any small American city, with an actively-engaged volunteer sustainability advisory board that sets goals and runs sustainability programs and a small paid planning department that manages the GIS data. For this analysis, the GIS manager was a town employee from the planning department and the sustainability champion was the town's volunteer sustainability committee. Like most communities of its size, Oshkosh does not have the resources to commission an energy modeler to build a traditional UBEM model from the ground up. Yet using the previously outlined eight-step framework, the Oshkosh UBEM was built in a matter of tens of hours instead of hundreds of hours for a traditional UBEM [59]. In conversations with practicing energy modelers who were introduced to the eight-step framework presented here, the cost estimate for such a study is approximately $15,000. While substantial for the operating budget of a small community, this cost is on-par with grants provided by non-profits and utility energy programs.

3.3.1 Step 1: Oshkosh Feasibility Check

After a quick check, Oshkosh has access to all the necessary data to build an UBEM. Their planning department has a GIS shapefile with building footprints for the entire city and tax assessor data with building use type and age. Through ICLEI – Local Governments for Sustainability (a coalition of over 1,700 city and state governments around the world), Oshkosh conducted a baseline greenhouse gas emissions inventory using measured gas and electricity consumption data for residential buildings from the local utility [105]. Oshkosh and ICLEI used the emissions inventory to inform a series of emissions reduction targets: 25% by 2025, 40% by 2035, and 80% by 2050 [106]. In terms of residential building emissions, this translates to city-wide residential building targets of 178,000 metric tons of CO_2e in 2025, 143,000 metric tons in 2035, and 47,500 metric tons in 2050.

3.3.2 Step 2: Defining Project Scope

With the baseline data in place, the author, acting as an energy modeler, met with the Oshkosh sustainability champions. The team discussed the capabilities of UBEM tools and the questions that they wanted to explore. Ultimately, the questions focused on identifying cost-effective retrofits and renewable energy to meet their emissions reduction goal. These questions are aligned with that of most other sustainability-minded communities around the world.

The team agreed to use NREL's 2021 Cambium data for grid emissions to provide consistency between today's emissions and projected future emissions. Cambium contains state-by-state projections for the cost and emissions of electricity in the U.S. out to 2050. Cambium's 2022 (the first year in the database) long-run marginal emissions (0.59 kg CO_2/kWh) are roughly in line with the 0.54 kg CO_2/kWh emissions factor provided by the local utility, Wisconsin Public Service [107]. This is higher than the U.S. average of 0.40 kg CO_2/kWh and the E.U. average of 0.23 kg CO_2/kWh but lower than other areas of the world [108], [109]. The other main source of emissions in the study area is from natural gas furnaces for heating and hot water. The emissions factor for natural gas was assumed to be 0.18 kg CO_2/kWh.

In consultation with the sustainability champion, it was assumed that all new buildings built in Oshkosh will be efficient enough to not significantly impact emissions – i.e. all new buildings from 2022 onward were ignored. This assumption could be revisited at a later date as the progress of retrofits is reviewed, but it was a low priority because of the limited building stock growth rate of Oshkosh over the past ten years. The sustainability champion also narrowed the scope of the study down to only residential buildings. The reason for this decision was two-fold. First of all, residential buildings are the predominant building type in Oshkosh and their distributed ownership makes them a much more challenging sector to retrofit compared to the handful of owners of the commercial buildings in Oshkosh. Second, the narrowed scope provides a learning opportunity for the city that they can apply to other building types.

3.3.3 Step 3: Preparing the GIS Data

With the study scope defined, UBEM.io was used to import all the GIS data provided by the GIS manager. Some key pre-processing was involved in this step, mainly assigning all sheds and similar auxiliary structures to the shading layer and determining building ownership. Owner-occupancy was identified by the sustainability champion as a key factor in whether a building will be eligible for retrofit given current incentive programs. Since the city's GIS file did not have a category denoting whether a structure is owner-occupied, the mailing address for the tax bill and the building's physical address were compared. If the two were the same, then the building was assumed to be owner-occupied. Across Oshkosh, 74% of residential buildings were calculated to be owner-occupied. Additional checks were carried out to ensure that building geometries did not overlap and there were unique ids for each geometry.

3.3.4 Step 4: Build the Baseline UBEM

The final UBEM included 13,100 residential buildings. Nearly all the residential buildings in Oshkosh are single family attached or detached homes, with a few multi-family buildings. Due to Oshkosh's low-density housing, the construction practices do not differ much between the single and multi-family low-rise residential buildings of the same vintage. Thus the residential archetypes are segmented only by age of construction. The three categories are: pre-1980 residential, post-1980 residential, and new residential (anything built after 2004). 1980 in particular reflects the post-oil crisis implementation of building energy codes across the U.S. that led to standard energy-efficient construction practices. Each building in the city was assigned non-geometric properties along the divisions of these archetypes using the DOE's age-appropriate residential building data and some tacit knowledge of the building stock with salient characteristics documented in Table 3.2 [61], [110]. In this study, due to the lack of additional data, all on-site combustion of fossil fuels is assumed to be natural gas.

Table 3.2: Oshkosh baseline building archetype characteristics. These values are based on the U.S. DOE residential prototype buildings and ResStock data.

Archetype	Annual Fuel Utilization Efficiency	Equipment Power Density	Lighting Power Density	Infiltration	Wall Insulation Thermal Resistance	Attic Insulation Thermal Resistance	Floor Insulation Thermal Resistance	Window Thermal Transmittance
		(W/m^2)		(ACH)	(m^{2}K/W)			(W/m^{2}K)
Pre-1980	80%	15	7.5	0.75	0.53	6.3	None	2.0
Post-1980	80%	10	5.0	0.75	2.3	6.3	0.70	2.0
New	95%	3.0	1.5	0.20	4.4	8.6	0.70	2.0

3.3.5 Step 5: Run the Baseline UBEM

UMI was used to simulate the full model of Oshkosh in about five hours on a standard Windows desktop with 8 cores and 32 GB of RAM. With prodding from the Oshkosh officials, the local utility provided 2019 electricity and natural gas consumption data for residential buildings in Oshkosh. Thus, the model was run using a 2019 AMY weather file created from measured data at the local airport using *diyepw* [111].

The model results were compared to the emissions from the carbon inventory and found to be within 9% of the measured data. The 9% error meets the ASHRAE 140 Standard and falls within the range of expected values (5% to 15%) for an archetype-level study [43], [77]. While not absolutely conclusive, the alignment between measured and modeled data showed that using DOE templates to create archetypes predicts the energy use and emissions of Oshkosh's buildings well.

3.3.6 Step 6: Create Building Upgrades

With a thus "plausible" baseline model, the focused turned to different technology pathways that could be combined to meet Oshkosh's emissions reduction goals. It is key to note in Figure 3.3 that natural gas is the predominant source of residential emissions. Consequently, even if the electric grid decarbonizes significantly as the Cambium dataset suggests, Oshkosh will not be able to meet its emissions goals without transitioning away from fossil fuels for heating, hot water, and other end uses. The baseline model also showed that pre-1980 and post-1980 residences account for nearly all of Oshkosh's emissions. Consequently, in consultation with the sustainability champion, post-2004 residences were not considered for retrofits. Three retrofit strategies were defined. The first is focused on energy efficiency, the second takes the efficiency and electrifies equipment and heating, and the third includes all of the energy efficiency and electrification retrofits and adds photovoltaics.

The energy efficiency upgrade strategies investigated are based on the DOE's ENERGY STAR Certified Home program [112]. This nationwide program defines prescriptive insulation and airtightness goals by climate zone for new construction that greatly decrease a building's energy consumption but do not rise to passive house standards. This means homes could be further upgraded if desired, but the goal is to use strategies that are low-cost and scalable. While meant for new construction, the prescriptive requirements work well in retrofits as well. The insulation upgrades (listed in Table 3.3) generally require a layer of continuous external insulation that would coincide with siding replacement and adding insulation in wall cavities if they are un-insulated (e.g. in pre-1980 residences). The standards further specify air sealing all cracks, adding further insulation in the roof, and installing some underfloor insulation between the basement and first floor. The program also requires all lighting to be LEDs and all appliances to be ENERGY STAR certified. Finally, the furnace needs to be upgraded to an ENERGY STAR certified 95%+ efficient unit.

The second stage retrofit consists of electrifying the heating system using a cold climate heat pump for heating/cooling and a heat pump water heater for hot water in addition to the energy efficiency upgrade package. This retrofit enables Oshkosh to eliminate the buildings' natural gas consumption.

While the electrification upgrades provide the potential that a decarbonized electricity

Table 3.3: Oshkosh upgrade requirements by archetype. Note the windows were not upgraded because their payback period is over 20 years.

Archetype	Annual Fuel Utilization Efficiency	Equipment Power Density	Lighting Power Density	Infiltration	Wall Insulation Thermal Resistance	Attic Insulation Thermal Resistance	Floor Insulation Thermal Resistance	Window Thermal Transmittance
		(W/m^2)		(ACH)	(m^2K/W)			(W/m^2K)
Pre- & Post-1980	95%	3.0	1.5	0.15	4.4	8.6	5.3	2.0

Note: air changes per hour (ACH) is unitless.

grid will help Oshkosh meet it's goals, the city and its residents can be actively involved in this work by deploying distributed energy resources such as rooftop PV. This has the further added benefit of being a good financial choice for most buildings. To this end, the final upgrade analyzed differing amounts of rooftop PV. Using the EnergyPlus PV module with a conservative 15% efficient PV panel and a 90% efficient inverter, the team simulated the electricity production potential of all the rooftop area in Oshkosh. The validated EnergyPlus PV module uses a full solar radiation analysis that accounts for shading, reflections, and temperature-dependence [113]. Based on the simulated average yearly electricity production potential from this PV across all of Oshkosh, the required cumulative PV array size was scaled to the remaining emissions reduction needs after the electrification retrofit.

3.3.7 Step 7: Analyze Scenarios

The three technology pathways developed in Step 6 require increasing amounts of effort but also lead to decreasing energy use intensity. As seen in Figure 3.2, the efficiency upgrade leads to a 61% decrease in energy use, mostly from heating, and the efficiency and electrification upgrade leads to an 84% energy use reduction.

The PV retrofit includes approximately 78 MW of installed PV. This requires approximately 30% of the rooftop area in Oshkosh, although it could be installed on a mixture of rooftops and the ground or procured through a power purchase agreement. An array this size produces 30 kWh/m^2 of electricity across Oshkosh annually, resulting in a nearly net zero EUI and Oshkosh achieving its 2050 target.

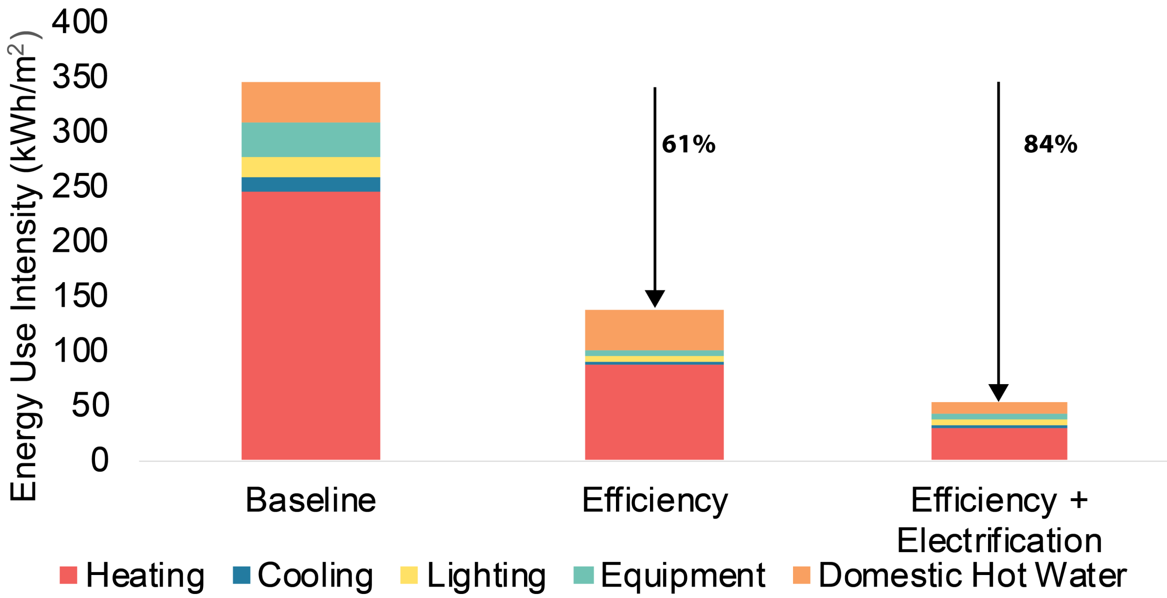


Figure 3.2: The energy use intensities by end use of the baseline model for the two technology pathways in Oshkosh. The PV pathway is excluded as the consumption EUI does not change from the electrification upgrade.

3.3.8 Step 8: Present Findings and Implementation

While the energy use reductions presented in Step 7 are laudable, the city is ultimately concerned with the emissions reduction potential of the technology pathways that are feasible and economical for residents. Persuading homeowners to upgrade their homes will require a combination of economic and social capital. On the economic side, costs for each upgrade are tabulated based on RSMeans and NREL Electrification Futures Study data using the approximately 220 m^2 DOE prototype single family home for area-dependent costs [61], [114], [115]. Using the energy savings based on simulations and utility costs the savings and payback periods for the different upgrade packages that each homeowner can choose from are calculated. This analysis is required to ensure that technically feasible pathways are economically feasible for homeowners.

In carrying out a payback period analysis, the energy modelers would find that although heat pumps lead to substantial emissions reductions, the efficiency and electrification upgrade has a payback period of 43 years for pre-1980 residences. This is longer than the lifetimes of heat pumps so the electrification upgrade does not make economical sense in Oshkosh at the moment. This currently occurs because the cost of natural gas is so low compared to the cost of electricity. These economics are community-specific and may change as the cost of electricity and natural gas shift in the coming years. Consequently, the best course of action for homeowners in Oshkosh is either the efficiency or efficiency + electrification + solar retrofit (where the low-cost solar electricity negates the economic issues with electrification). The final combinations of the strategies presented to Oshkosh are shown in Figure 3.3. These strategies empower Oshkosh to take charge of achieving its emissions reduction goals through local retrofits but also place them in the context of emissions reduction efforts on the power grid. Given 2050 projected grid emissions, the third retrofit actually enables Oshkosh to meet nearly net-zero emissions goals.

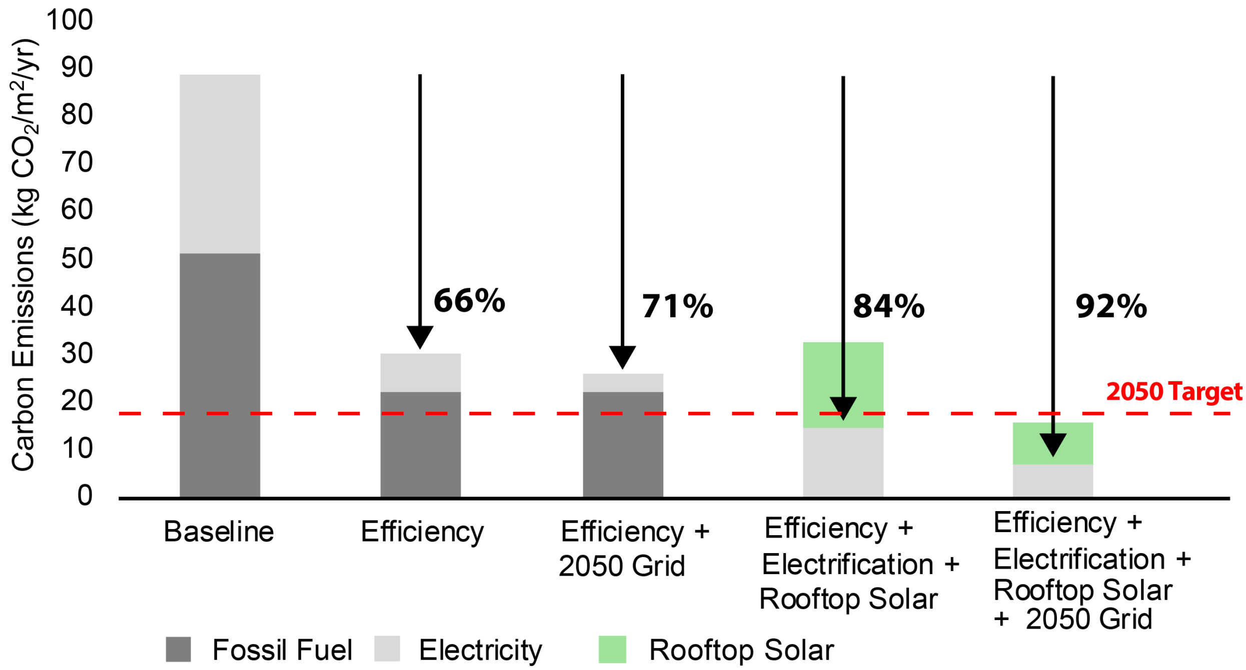


Figure 3.3: The strategies for Oshkosh to meet its emissions reduction goals. It is only through a combination of all three strategies (energy efficiency, electrification, and photovoltaics) that Oshkosh can meet its 2050 goal. The addition of grid decarbonization lets Oshkosh achieve nearly net zero by 2050.

A clear takeaway from these results is that Oshkosh cannot meet its emissions reduction goals through efficiency and grid decarbonization alone. They must electrify their end uses in order to achieve their 2050 goals. Additionally, while this goal is technically feasible, current retrofitting rates hover around 1% a year, making achieving them by 2050 unlikely [7]. The key for Oshkosh will thus be motivating homeowners to partake in these upgrades. An example "back of the envelope" calculation to present the technology pathways to owners of pre-1980 residences is shown in Table 3.4. This information could be turned into graphics and provided as part of the implementation process. It is meant to show homeowners that their individual contributions matter and make economic sense. They also urge action and would be distributed via local channels such as town meetings and the planning office.

The additional savings for post-1980 residences versus the pre-1980 residences detailed in Table 3.4 come from the 10% increase in the average floor area of these newer homes across Oshkosh. This trend toward bigger houses is common across the country, and while it raises retrofit costs a little bit, the resulting savings are more pronounced. The costs factor in federal tax credits available in 2022 and assume aggregation of PV installations to attain a commercial-scale installation price of $1,720/kW [116].

Table 3.4: Back of envelope calculations for pre- and post 1980 homes to undergo retrofits.

	Energy Efficiency Retrofit		Energy Efficiency, Heat Pumps, Solar	
	Pre-1980	Post-1980	Pre-1980	Post-1980
Save Each Year	$1,000	$1,500	$1,600	$2,000
Pay Now	$10,000	$8,700	$23,000	$22,000
Break Even Year	10	5.5	15	10
Emissions Reductions	30%		85%	

3.4 Discussion

The eight-step framework outlined in this paper has been successfully applied in Oshkosh, WI, at cost and effort levels that are scalable across the U.S. wherever GIS data sets are available. The Oshkosh case study highlights a few key takeaways for applying the eight-step process in other municipalities. First, the goals need to be clearly set to guide all decision making. Second, the boundary conditions must be agreed upon at the outset of the study. This includes what types of buildings to include, what emissions are counted, what baseline data set is used, and how the power grid emissions are expected to evolve. The grid emissions, in particular, have an outsized impact on the results. Another key takeaway from the Oshkosh case study is that although end use electrification is not always economical today, its emissions reduction potential as the grid decarbonizes will be critical to meeting emissions reduction goals. These facts are not unique to Oshkosh and will be a challenge for communities around the world that will need to be accounted for in any emissions reduction planning.

There is an opportunity to use this framework to engage whole regions at a time. For example, the suburbs of Boston are all similar in composition and one energy modeler could build an UBEM for the entire area and engage with communities' respective sustainability champions to tweak results presentations as needed. This efficiency in modeling is enabled by breaking down the modeling process into the discrete tasks listed in this chapter. To further demonstrate the validity of this approach, models were developed in collaboration with eleven communities in North America and four in Europe: Petaluma, CA, USA; Bristol, VT, USA; Sandy Springs, GA, USA; Codman Square, Boston, MA, USA; Everett, MA, USA; Framingham, MA, USA; Natick, MA, USA; Somerville, MA, USA; Reading, MA, USA; San Pedro Garza Garcia, Mexico; Calgary, Canada; Zagreb, Croatia; Porto, Portugal; Lisbon, Portugal; and Rotterdam, The Netherlands. The development of these UBEMs and their respective findings are discussed in Chapter 7 with additional information available at www.ubem.io/case-studies.

3.4.1 Putting the retrofits in perspective

The author calculated the job creation potential of similar efficiency and electrification retrofit packages in Oshkosh and four other cities around the U.S. [117]. The energy efficiency package was estimated to require 91 hours per home and the efficiency, electrification, and

PV package 157 hours per home based on RSMeans data [114], [117]. Using these numbers, an assumption of 25 years of retrofits and 1,560 on-the-job hours per year per full-time equivalent worker, at least 31 and 53 workers respectively will be needed in Oshkosh alone each year to implement these packages. According to utility rebate data from 2015 through May 2021, less than 1,500 heat pumps were installed in Wisconsin in total, with only 136 contractors across the whole state performing these installations [118]. Even then, nearly 25% of these systems were installed by the same five contractors [118]. Oshkosh accounts for just half a percent of the state's housing stock, so even if equally distributed, statistically there is only one contractor in the city that can perform the requisite retrofits [119]. On the other hand, Vermont, with 1/8th of the population of Wisconsin, installed over 10,300 heat pumps in 2020 [118], [120]. Based on a twenty-five year retrofitting program, 525 retrofits would be needed each year, which is nearly equal to the number of heat pumps installed across the whole state in 2020 [118]. Clearly, the workforce required to implement retrofits in Wisconsin will need to grow exponentially in the coming years. Yet current efforts across the state are lagging behind — a recent press release lauded the funding of 42 trainees for clean energy and water efforts in 2023, not even enough to meet the needs of Oshkosh, let alone the rest of the state [121]. This issue goes beyond Wisconsin, with the U.S. and Europe already constrained on heat pump installations by the lack of skilled craftspeople to install them [122].

Furthermore, with so few heat pumps currently being installed the supply chains to support this scale of retrofitting will need to be ramped up. One specific challenge is the raw materials required. Heat pumps require supply-constrained components such as Copper, Nickel, Aluminum, steel, and several microprocessors for the control panels, pumps, and fans [122], [123]. The semiconductor challenge is more systemic, with heat pumps often being deprioritized when supply is short [122]. Even with the raw material, the International Energy Agency has found that current manufacturing capacity for heat pumps is 60% below what it needs to be to achieve 2050 goals [122]. While some of the systemic supply chain issues might affect long-term retrofitting, the U.S. installed 4.3 million heat pumps in 2022. This pace, which, if kept up, puts retrofitting at least 75% of the U.S. building stock with a heat pump in 25 years in the realm of possibilities [124]. While these numbers are specifically focused on heat pumps, similar issues in energy efficiency measure installation (e.g. insulation) will also need to be addressed.

Finally, there is the issue of adoption (or lack thereof) of building retrofits in rental units. Due to the Landlord-Tenant problem, renters are unlikely to invest in any efficiency upgrades and the landlords have little incentive to invest either [125]. Consequently, rental units are unlikely to be retrofitted and significant emissions reduction potential is missed. As shown in Figure 3.4, when rental units are not retrofitted, renter-dominated neighbors in Oshkosh have substantially higher emissions in 2050. This leads to a significant decrease in emissions reduction from the full technical potential. Whether by regulation or through creative on-bill financing tied to the address not the renter, there are pathways to overcome this challenge but they have yet to be addressed in Oshkosh [126].

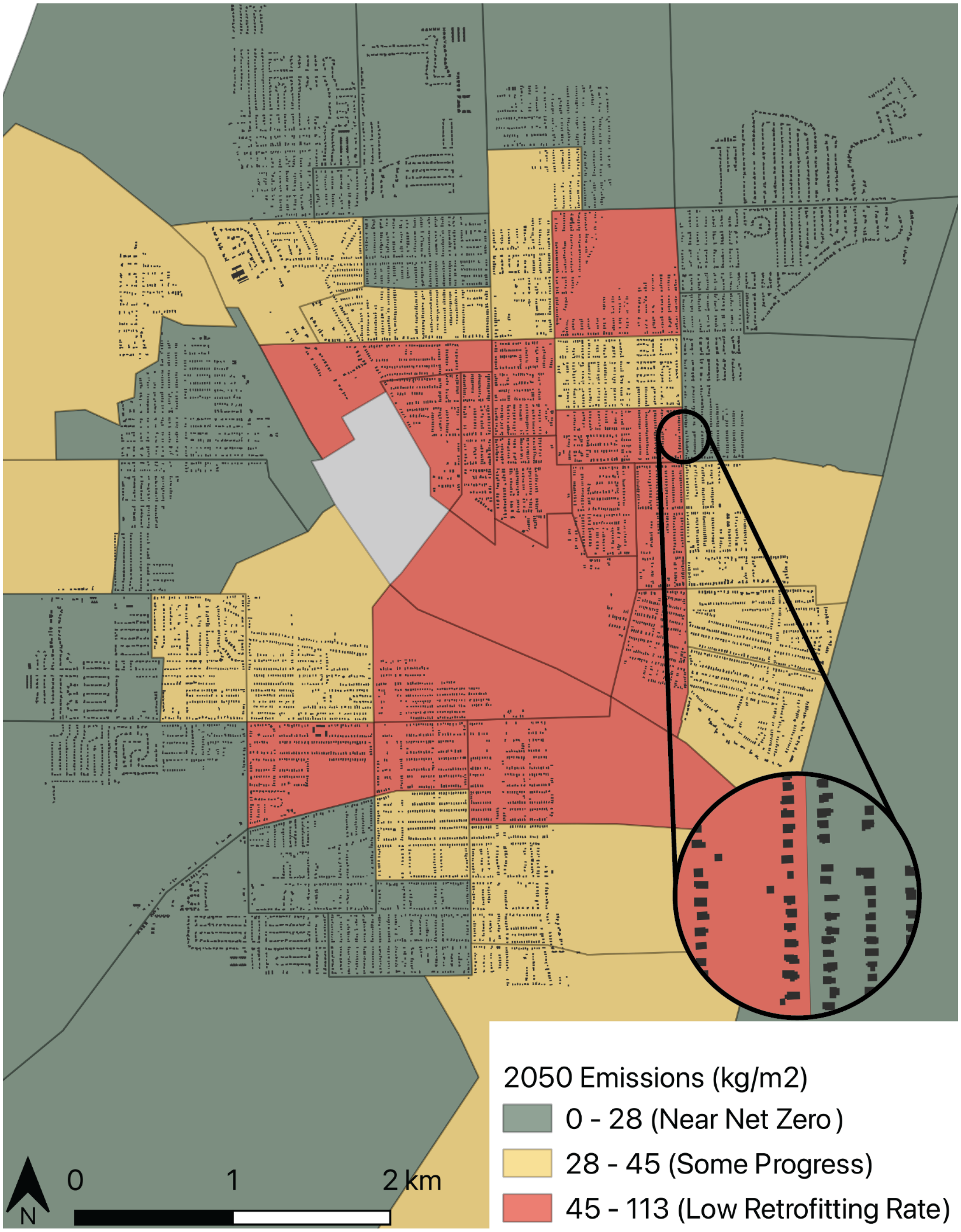


Figure 3.4: Area-normalized emissions from residential buildings at the census block level in Oshkosh. Red areas will need to be focus areas for new programs and policies that engage rental units in retrofits.

3.5 Summary

This chapter presented an eight-step UBEM-based framework for communities to identify technology pathways for their building stock to reach previously defined carbon reduction targets. The eight steps were developed and refined through previous case studies at the neighborhood level in cities around the world. Its application at the city-scale is illustrated in this chapter through a case study of 13,100 buildings in Oshkosh, WI, USA. By clearly defining the role for the GIS manager, sustainability champion, and energy modeler in each step, these powerful models can be built at the city-scale for approximately $\$15,000$, less than a tenth the cost of bespoke UBEMs built by consultants for large cities. This cost level makes them accessible to diverse communities, no matter the size. The Oshkosh UBEM was used to identify economically-feasible retrofit strategies that can be rolled out across the building stock to achieve their emissions reduction goals. UBEMs can also quantify the lost emissions reductions potential across a city when systemic barriers such as the lack of retrofits in renter-occupied units are accounted for. They can also identify the most cost-effective and coordinated way to approach retrofits in a specific city. Finally, as shown in this chapter, UBEMs can also be used to quantify additional impediments to retrofit adoption such as a lack of a trained workforce or adequate supply chains. The ultimate goal of these quantification efforts is to motivate policymakers to find creative solutions to longstanding issues to drive building retrofit adoption to the levels required to reach communities' 2050 goals.

Chapter 4

Developing a Building Retrofit Adoption Model

In this chapter, the adoption of the retrofit packages for Oshkosh, WI proposed in Chapter 3 are evaluated. The best available model quantifying the ultimate market penetration of an energy efficient technology is used to evaluate adoption rates under increasingly realistic scenarios. The UBEM model is leveraged to provide spatially-resolved emissions reduction results that helps inform policymakers of the consequences of business-as-usual adoption. This chapter is an edited version of the standalone publication:

Zachary Berzolla, Yu Qian Ang and Christoph Reinhart, "Combining Urban Building Energy Models with Retrofit Adoption Models for Time-Dependent Carbon Emissions Projections," in Proceedings of the 2022 ACEEE Summer Study on Energy Efficiency in Buildings. August 2022.

4.1 Introduction

The preceding chapters document improvements in the technical ability to model technology pathways to a communities' greenhouse gas emissions reduction goals. These analyses, however, ignore the socioeconomic realities of the residents of the investigated buildings as well as how fast these various technologies may be implemented. Additionally, the current 1% adoption rate of building retrofits is far too low to achieve anything near the technically feasible technology pathways that would get a city to its emissions reduction goals in 30 years [3]. Furthermore, communities are diverse with differing socioeconomic and demographic statuses – such as income, education, and home ownership levels. These factors, among others, will affect the actual adoption of retrofits in the built environment, crucial to meeting the city's emissions reduction goals. For example, the U.S.'s weatherization assistance program (WAP), which is aimed at low-income homeowners, only leads to an average energy savings of 25%, far below levels needed to achieve emissions reduction goals [127].

Different technology upgrades also compete. For example, an owner who purchases a new, high efficiency gas furnace today effectively locks in this technology and the underlying infrastructure for the coming decades. To help cities better gauge the speed and type of upgrades residents will consider, this chapter introduces a framework that connects UBEM-based emissions reduction predictions with a census block level technology adoption model. Both modeling approaches are bottom-up, based on individual buildings and thus complement each other. This approach supports micro-scale predictions of when and where retrofits of various types are likely to occur. This information is crucial for policymakers aiming to speed up the progress to meet looming carbon reduction deadlines while ensuring that no neighborhood is left behind. Following a review of technology adoption research, this chapter presents an initial building retrofit adoption model for buildings and apply it to the city of Oshkosh, WI.

4.2 Background

Just because a technology exists and is economically sensible, i.e. the person paying for the technology will eventually get their investment back, does not mean that it will ever be widely implemented. Economic feasibility is of course a necessary requirement for most investments which is why literature on building retrofits has thus far focused on this metric at the individual building, city, and country scale [89]. For example, Wilson et al. studied economically-feasible retrofits in terms of eliminating retrofit packages that did not achieve a simple payback period of less than five years, and suggested that homeowners typically consider only retrofits with a quick payback period [28]. To further understand technology adoption over time, another key factor has been identified: market potential [128]. Whereas economic potential depends on the cost of the upgrade and the income of the potential homeowners, market potential tries to understand what percentage of all economically feasible retrofits will ultimately be implemented and/or adopted [128]. Transferring these concepts to the building retrofit market, an adoption analysis needs to account for the actual pool of eligible residences and the relative cost of various retrofit options vis-à-vis inhabitants' household income.

Interestingly, while there is extensive literature on the adoption of products such as Roger's "Diffusion of Innovation," there is very little documented data on adoption of building retrofits [129]. To the best of the author's knowledge, the only in-depth study of building retrofit adoption was carried out for the U.S. Department of Energy by the Arthur D. Little company as part of a broader energy technology potential model in the 1970s [130]. In this chapter, total market potential for building retrofits such as insulation and equipment upgrades are predicted based on two key factors: upfront cost and payback period. Yet no additional modeling or analysis for the built environment along similar lenses has been done since. There is, however, expansive literature on the adoption of solar photovoltaic (PV) arrays [131], [132]. While an analogy to PV is useful, the deep building energy retrofits required to meet emissions goals are a lot more disruptive to residents' life and the economics are more uncertain, especially considering the potential rebound effect of somewhat increased energy consumption post-retrofit [133]. Consequently, more research must be done to better understand the potential for the adoption of building retrofits. To develop a sense for the required order of magnitude of different adoption rates, the initial adoption model is based on the oft-cited baseline building retrofit rate of 1% [3]. This figure is an upper estimate as it includes non-energy renovations of buildings and additions. While some of these renovations may be driven by thermal performance goals, many are driven by owners' desires to remodel their homes for various reasons. These renovations may or may not include more efficient construction practices. An old home that is remodeled may get new, higher-performance windows simply because that is what is available on the market today. These non-energy driven retrofits are important because the cost of certain upgrades such as new windows may be cost prohibitive on their own. However, these energy efficiency co-benefits are likely limited and are encompassed by the 1% retrofit rate assumption. For example, in Massachusetts, while 9% of owner-occupied single family homes are renovated each year, only 5% of these include adding insulation, for a less than 0.5% overall adoption rate [134]. In the U.S. as a whole, the American Housing Survey estimates that the rate for retrofits that included insulation in 2020 was a paltry 0.07% [18].

Another confounding factor for building upgrades is ownership: It is nearly impossible for tenants to initiate the installation of photovoltaics or other building retrofits and they are not incentivized to do so [135]. There have been proposed approaches to overcome the landlord/tenant barrier in Europe, but barring major policy shifts that require landlords to meet energy efficiency standards in rental units and/or substantially expanded budgets to adequately incentivize landlords to take action, few if any rental units will be voluntarily retrofitted [136]. Therefore, in this analysis the pool of eligible homes is limited to only those that are owned to reflect current political realities in the U.S. Scenarios where home ownership is not accounted for show the potential emissions reductions if new policies or incentives are implemented to break down this ownership barrier.

4.3 Methods

For this study, the state of the art in urban building energy modeling is combined with existing adoption models to predict the adoption of technology pathways defined and tested with the UBEM. Three levels of refinement to the 1% retrofitting rate are presented to illustrate how adoption occurs in the city. This model draws on the UBEM developed in Chapter 3. In the previous chapter, two main pathways to Oshkosh's emissions reduction goals are outlined: energy efficiency (EE) and energy efficiency, electrification, and solar (EE+HP+PV). These same upgrades are considered in this chapter.

4.3.1 Adoption Model

For the initial adoption model, it is assumed that 1% of the building stock will be renovated each year. As explained above, this assumption is probably optimistic and does not yet consider the effect of more targeted incentive structures. For the baseline scenario, called "1% all buildings," the adoption rate for all buildings is assumed to be the same. For each year in the projection, a dice is thrown for all buildings in the UBEM model deciding whether the building is retrofitted, with a 1% total likelihood that each building is upgraded to either EE or EE+HP+PV, equating to 0.5% for each upgrade. Given the 20+ year lifespan of a gas furnace, packages EE and EE+HP+PV are mutually exclusive. Accordingly, it is assumed that only one package or the other will ever be adopted per building between now and 2050. Once the building has been retrofitted, it is ignored in future years. Given that ownership and household income affect the adoption of retrofits, a further, more realistic scenario with varying adoption rates between buildings and upgrade packages is also introduced.

4.3.2 Ownership

One of the major limitations in predicting adoption is that retrofits occur at the individual building level but key metrics such as ownership and income are only readily available from census data that is reported at the block level. While ownership data was available in Oshkosh, for broader applicability this chapter proposes a stochastic modeling approach to assign census data to individual buildings. These characteristics are assigned to buildings before each model simulation based on its likelihood from the census data. E.g., if a building falls in a block group with 25% ownership according to the census, the refined model scenario, called "1% with ownership," throws the dice for each building to determine owner occupancy before beginning the thirty-year retrofit adoption simulation. For the example building, this will stochastically happen once every four iterations. Buildings that are not owner-occupied are not considered for retrofit. To maintain an overall annual retrofit adoption rate of 1%, an adjusted adoption rate for the initial pool of owned eligible buildings is calculated. For Oshkosh, where approximately 70% of residences are owned across the city, the effective adoption rate for owner occupied buildings is 1.6%. This rate is evenly split between packages, leading to 0.8% for each.

4.3.3 Upfront Cost and Payback Period

Building retrofits, especially the "deep" retrofits required to meet emissions reduction goals, are expensive. It is thus expected that EE will have a higher adoption rate than EE+HP+PV. To attempt to quantify this split, a third model scenario, "1% with ownership and costs" uses a market penetration analysis inspired by the Arthur D. Little model [130]. The Little model predicts the total market penetration of a building technology based on the

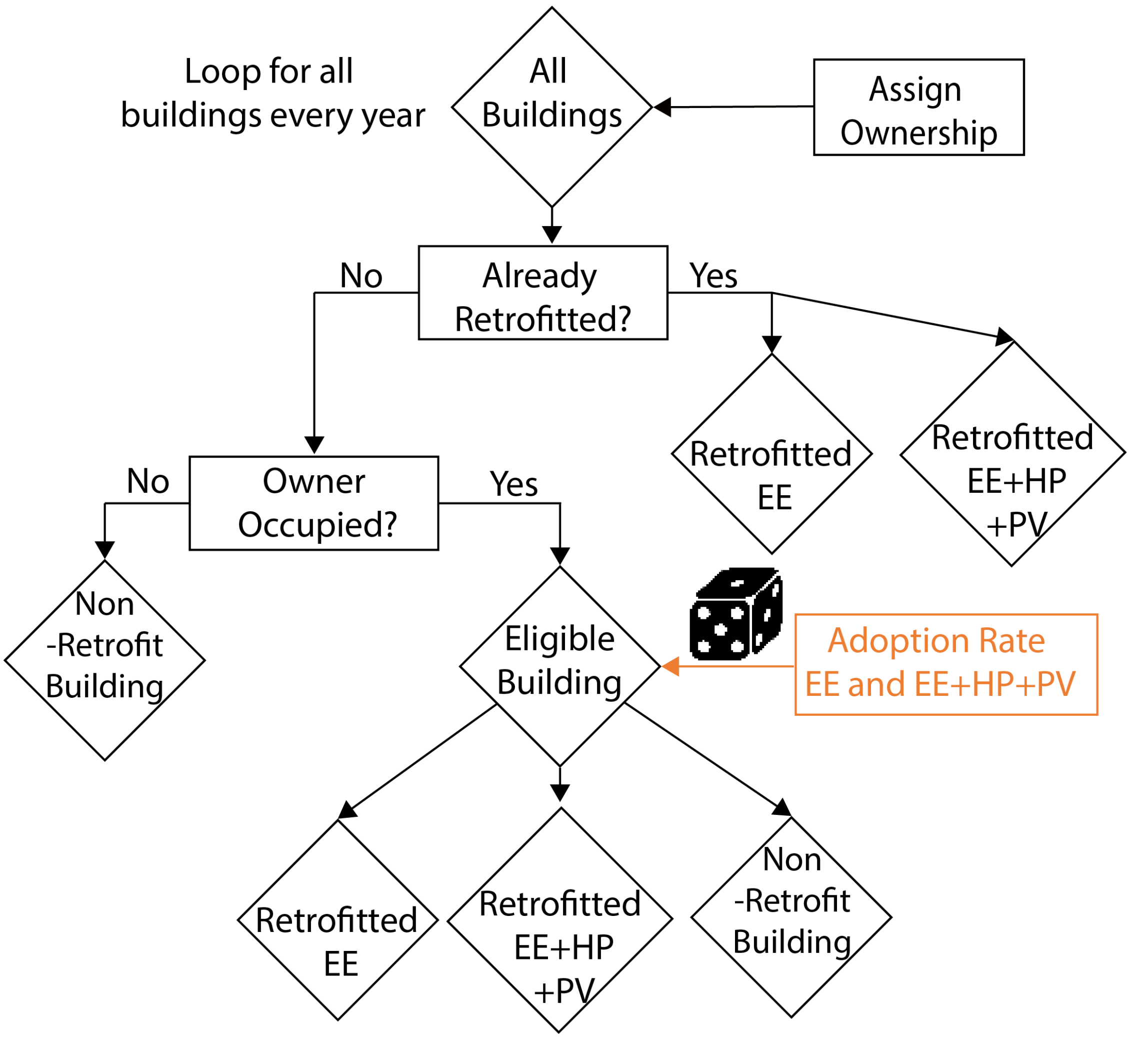


Figure 4.1: Outline of adoption model. This full model is used for the upfront cost and payback period with the adoption rate varied based on the Little Model. The ownership model instead considers these adoption rates as equal between the two packages. Ownership is not accounted for in the baseline model.

upfront cost and the undiscounted simple payback period [130]. The Little model is from 1979 so the first cost is normalized based on the $16,841 national median household income in 1979 [137]. The resulting first cost as a percent of median household-income is shown in Figure 4.2. For the upgrades considered in Oshkosh, costs from Chapter 3 and the 2020 median household income from Wisconsin ($61,747) are used [119].

The predicted market penetration percentages from the graphs in Figure 4.2 are multiplied together to give a total market penetration for each upgrade, as shown in Table 4.1. Leveraging the Little model market penetration provides insight into the split in adoption between the two measures, assuming the 1.6% (1% effective) adoption rate for all upgrades to owned residence. For example, in pre-1980 residences, EE is five times as likely as EE+HP+PV and thus the adoption rate is 1.33% for EE and 0.267% for EE+HP+PV. The average adoption rates for all building types and ownership combinations are given in

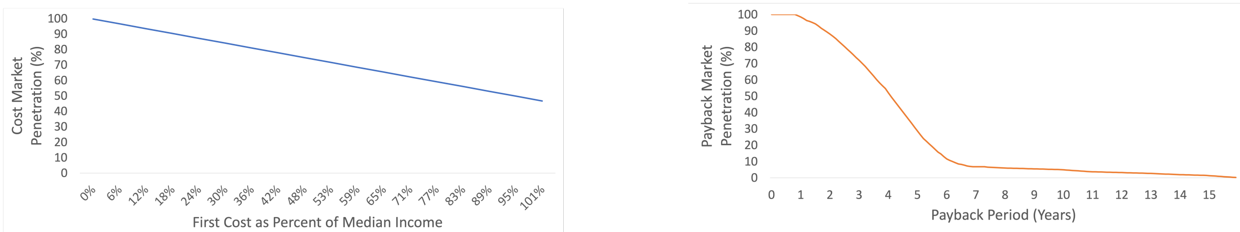


Figure 4.2: Arthur D. Little market penetration by first cost normalized by median household income (left) and payback period (right). Total penetration is determined by multiplying the two factors together. Adapted from [130]

Table 4.1: Market penetration predicted by the Little model for the upgrade packages.

Archetype	EE	EE+HP+PV
Pre-1980	5%	1%
Post-1980	19%	4%

Table 4.2.

Table 4.2: Adoption rates in the various scenarios tested.

Condition	Archetype	Upgrade	Adoption Rate
1% all buildings	Pre-1980 & Post-1980	EE	0.50%
		EE+HP+PV	0.50%
1% all owned	Pre-1980 & Post-1980	EE	0.80%
		EE+HP+PV	0.80%
1% with ownership and costs	Pre-1980	EE	1.33%
		EE+HP+PV	0.27%
1% with ownership and costs	Post-1980	EE	1.32%
		EE+HP+PV	0.28%

For the "1% all owned" scenario, for an effective adoption rate of 1%, the adoption rate is 1.6%. For the "1% with ownership and costs," the 1.6% adoption rate is split up based on the ratio of the predicted final market penetrations given in Table 4.1

4.4 Results

The adoption model was run for 30 years to simulate the adoption of building retrofits through 2050, the year Oshkosh has set for its 80% emissions reduction goal. The refinements for predicting adoption in the methods section are run and the results presented in Figure 4.3. In order to test model stability, the simulations were run through 100 iterations leading to mean emissions results with standard deviations to define the uncertainty in the results. In all scenarios for all years, the standard deviation never exceeded 0.31%. This means there is very little uncertainty in the model and it is stable across different stochastic runs. A profound but expected result is the 1% with ownership and costs scenario leads to the smallest emissions reductions of all scenarios. This occurs because homeowners are a lot more likely to pick EE than EE+HP+PV and EE only leads to an average 30% emissions reduction per home compared to an average 85% emissions reduction per home for EE+HP+PV. This is seen in Figure 4.4, where the total number of residences retrofitted to each package diverges. The fossil fuel lock-in that results is made clear by the 1% with ownership result in Figure 4.3. Ultimately, the analysis shows that the predicted emissions reductions in 2050 do not come close to approaching Oshkosh's 2050 emissions target or the theoretical maximum for each pathway investigated. It is especially clear from Figure 4.3 that higher adoption rates will be necessary if Oshkosh is to meet its emissions reduction goals.

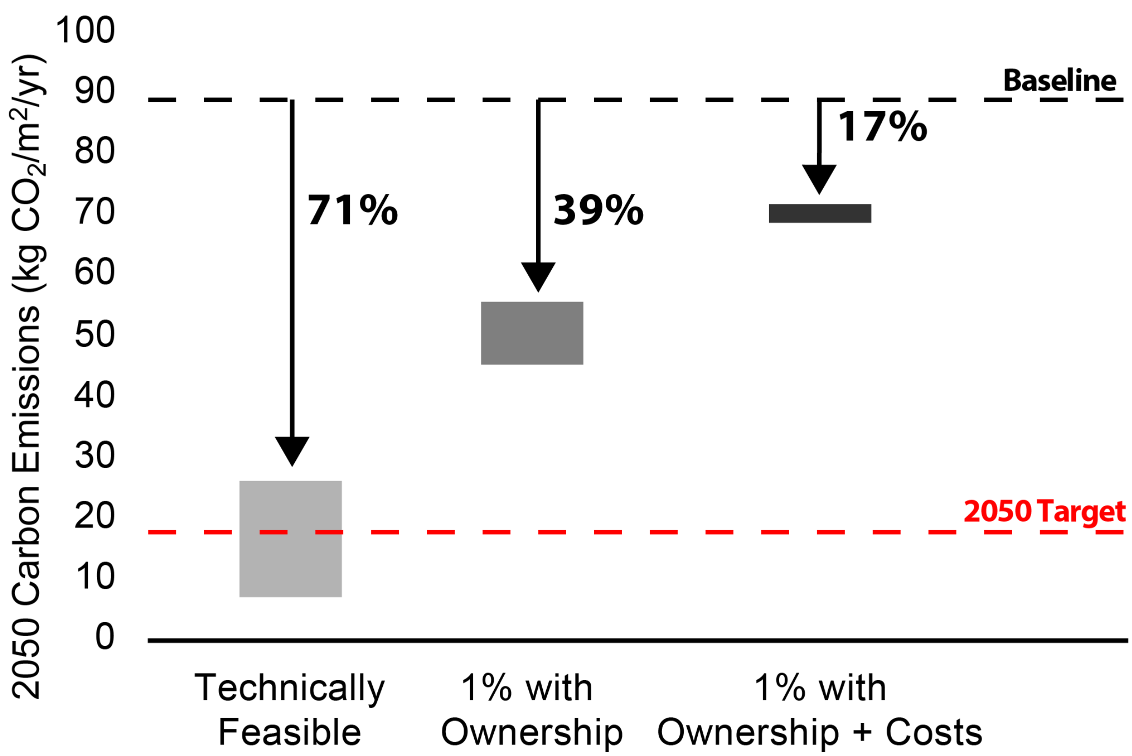


Figure 4.3: Range of 2050 emissions results for the Oshkosh case study with different adoption model refinements. The high and low bounds are set by the mean of 2050 results for each the two upgrade scenarios over 100 stochastic runs.

The other glaring issue is that even 100% EE+HP+PV adoption in owned residences leaves almost a third of the buildings (and emissions) in the baseline (non-retrofit) state. If this gap is addressed, the theoretical maximum of 100% adoption of EE+HP+PV shown in Figure 4.3 can be reached.

Looking only at overall emissions reduction will not lead to an equitable decarbonization future. The three scenarios examined in this study paint disparate pictures when it comes to the spatial distribution of upgrades and which upgrades occur. By assigning the predicted retrofit status in 2050 to the original buildings in an UBEM, the fraction of buildings upgraded in each census block becomes apparent. In Figure 4.5a, the 1% all buildings scenario,

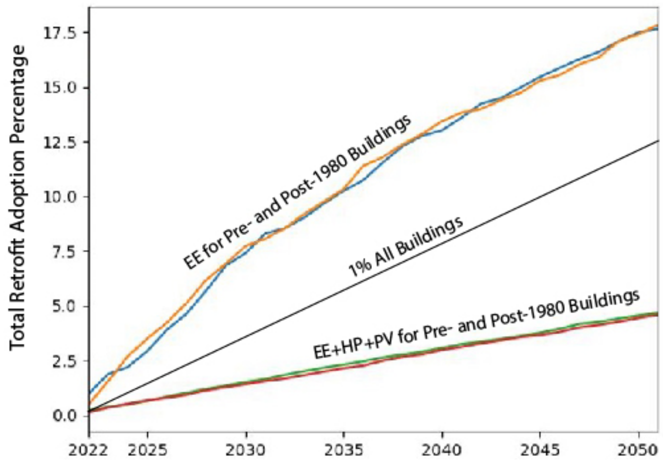
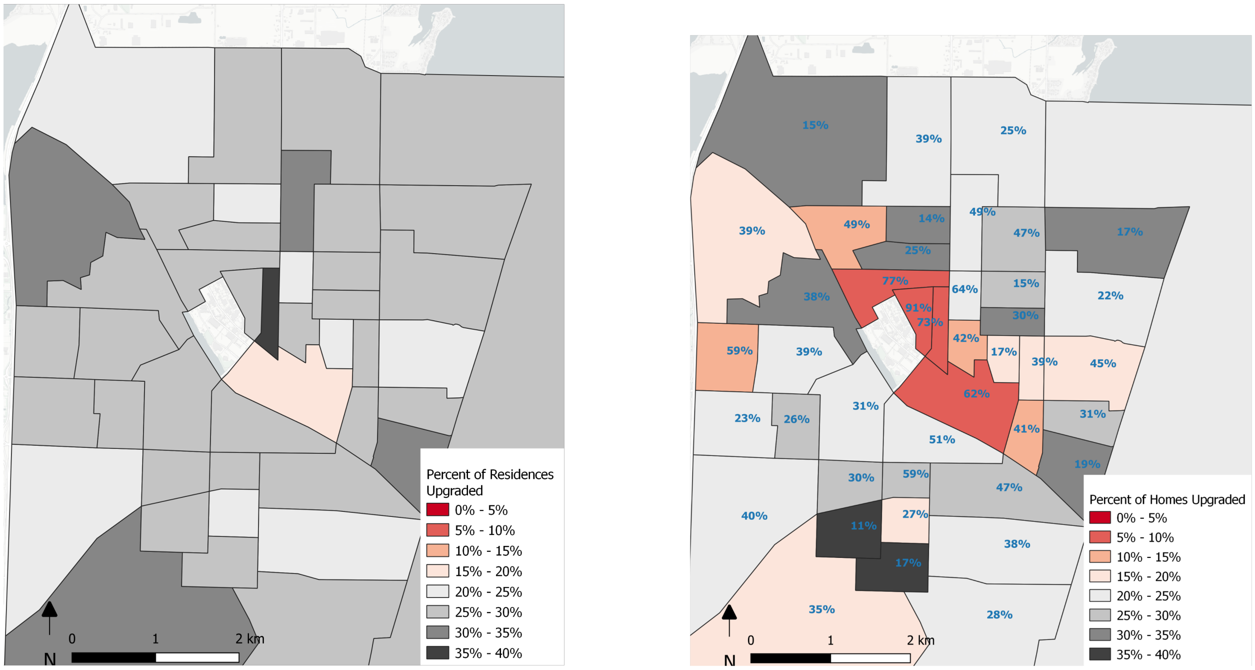


Figure 4.4: Building retrofits per year for the 1% with Ownership and Costs scenario. In both the baseline and ownership scenarios the retrofits per year are all roughly the same.

the retrofits are evenly split between the two packages. The mean percent of residences upgraded per census block is 27% and upgraded buildings are fairly evenly distributed between blocks, as seen by most blocks falling into the 25-30% category. The minimum percent retrofitted in any block is 18%, while the max is 35%.

In Figure 4.5b the 1% all owned scenario, the inequity in terms of which buildings are upgraded becomes apparent. WAP-eligibility is used as a proxy for income in this analysis. The lowest percent of residences upgraded per block (0% to 5%) occur in blocks with the highest WAP-eligibility (62% - 91%). Meanwhile, the highest percent of retrofits (35% - 40%) occurs in blocks with the lowest WAP-eligibility (11% and 17%). Furthermore, the minimum retrofitting rate falls to 5% and the maximum is 37%. The equity impacts mirror but enhance the 1% all owned scenario, with the lowest percentage of retrofits in the lowest income blocks. Consequently, the more realistic 1% all owned and 1% with ownership and cost scenarios show that residences in lower-income census blocks are left behind compared to other parts of the city.



(a) 1% all buildings scenario

(b) 1% all owned scenario

Figure 4.5: Spatial adoption prediction in 2050. Each census block in Figure 4.5b is labeled in blue text with the percent of WAP-eligible residences per census block.

4.5 Discussion

The Intergovernmental Panel on Climate Change (IPCC) states that buildings will play a pivotal role in meeting global emissions reduction targets, estimating that the emissions of existing residential buildings can be reduced by 50% to 75% in many geographical regions [138]. The analysis in this paper confirms that current adoption of building retrofits is far too low to achieve anything near the technically feasible technology pathways identified in Chapter 3 that would get a city to its emissions reduction goals. The retrofits that do occur, especially when costs and ownership are considered, are EE-like packages that are inadequate to meet ambitious emissions reduction goals. Furthermore, the mutually exclusive nature of EE and EE+HP+PV leads to disparate future outcomes. Homeowners who continue to install the natural gas furnaces in EE lock in natural gas infrastructure for the foreseeable future. Additionally, the cost of maintaining the aging natural gas distribution infrastructure to supply the furnaces will fall on these homeowners who cannot afford to install EE+HP+PV (or do not own the residence) and must remain connected to the gas utility. Beyond the financial and climatic harms represented by this pathway, these homes will continue to be affected by the adverse health effects of gas appliances, further exacerbating health issues amongst lower-income populations [139].

It is well documented that low-income – as well as Black, Hispanic, and Native American households – have household energy costs that are a greater proportion of their income (approximately 8% to 10% compared with 2% for the average household), with studies suggesting that low-income households face three times higher energy burdens than other households

[140], [141]. Many of these households are eligible for the U.S. Department of Energy's WAP program, which in theory provides a low-to-no cost home retrofit to homeowners. Unfortunately, the 25% average energy savings from a WAP project is far lower than the 38% energy savings from EE or the 62% energy savings of EE+HP+PV in this analysis [1] [127]. When you further consider that Blacks, Hispanics, and Native Americans own homes at 25% to 30% lower rates than non-Hispanic white homeowners, the discriminatory nature of energy burdens becomes clear [142]. It is therefore crucial from both an equity and an emissions reduction standpoint that cities have a strategy to ensure their rental buildings are also retrofitted to the necessary standards. By presenting data on the loss in emissions reduction potential when rented residences are excluded, policymakers can justify new ordinances that target rental efficiency measures specifically, such as the one passed in Burlington, VT in 2021 [143]. There are only a handful of municipalities that have enacted such legislation and this framework is meant to help address this glaring issue most cities face in meeting their emissions reduction goals in the built environment [144].

The mapping of adoption by block group with key demographic data such as WAP-eligibility used in Figures 4.4, 4.5a and 4.5b is a crucial tool for city decisionmakers trying to pursue equitable decarbonization of the built environment. These maps — which can be created at different levels of granularity — will be helpful for city decisionmakers trying to roll out programs that change the way building retrofits are adopted, by targeting specific areas of a city. For example, decisionmakers can focus on areas that have high WAP-eligibility and low predicted upgrade percentages. This kind of targeted outreach will likely be necessary to raise adoption rates.

4.6 Conclusion

Information about building retrofit adoption is crucial to communities trying to achieve their emissions reduction goals in the built environment. Most analyses today assume buildings will automatically be retrofitted as technology improves. The framework presented in this paper provides key decisionmakers with an understanding of where buildings retrofits will naturally occur and under what financial parameters, so they can target programs to support adoption towards buildings that would otherwise not participate. This framework not only provides decisionmakers with the temporal accompaniment to their emissions reduction goals, but it also provides them with the ability to target programs that support higher rates of building retrofit adoption and address the longstanding inequality in the built environment. While net zero emissions reduction goals in most municipalities are physically feasible if deep energy retrofits are implemented and the grid decarbonizes, the current retrofitting rate of 1% is not nearly enough to achieve the full technical potential by 2050, when most communities' net zero targets are set. Furthermore, when accounting for more realistic adoption based on building ownership and retrofit cost, the actual adoption rate and therefore emissions reduction drops even further. When accounting for these crucial factors, the distribution of retrofits is clearly unjust, disproportionately occurring in high-income, high-ownership areas of a city. While it is not surprising that retrofits are currently limited

[1] *Note: to compare to the WAP findings, these are energy savings not carbon savings from the Oshkosh retrofits.*

to wealthy homeowners, the disparity laid bare in this analysis should be a call to action for policymakers. Cities around the world need to address the inequity in the adoption of building retrofits while also greatly expanding support to all retrofit projects to drive higher adoption rates of more comprehensive retrofit packages that will put communities on target to meet their emissions reduction goals. Ultimately, the results presented in this chapter are a more realistic baseline for how emissions reductions in the built environment will play out in most communities. The framework presented here can and should be used by communities around the world looking to equitably achieve their GHG emissions reduction goals.

4.7 Summary

The adoption model presented in this chapter shows that homeowners are not going to implement technology pathways fast enough to achieve their emissions reduction goals. Furthermore, the current paradigm in adoption will lead to inequity in emissions reductions and lock in fossil fuel equipment in many households due to lower-cost fossil fuel retrofits.

Chapter 5

Deal or No Deal: Homeowners' Willingness to Pay for Residential Building Retrofits

This chapter presents the methods and results of a willingness to pay study carried out via internet survey of 2,000 households in Massachusetts and New York. The resulting model predicts homeowners' willingness to pay for retrofits of differing upfront costs based on their socioeconomic and household energy data. This chapter is an edited version of a journal article the author has co-authored that is currently under review and is also published as a preprint available at SSRN:
Berzolla, Zachary M., Ting Meng, and Christoph Reinhart. "Homeowners' Willingness to Pay for Residential Building Retrofits." *Under Review*
Berzolla, Zachary and Meng, Ting and Reinhart, Christoph, Homeowners' Willingness to Pay for Residential Building Retrofits (August 10, 2023). Available at SSRN: https://ssrn.com/abstract=453673
or http://dx.doi.org/10.2139/ssrn.4536734

5.1 Introduction

In the U.S., 80% of the buildings that will be in use in 2050 already exist today [17]. Yet currently less than 1% of the building stock is retrofitted annually, well below the rate needed to achieve net zero global emissions by 2050 [3]. One complicating factor in the residential building sector is the sheer number of distributed owners that will need to be convinced to retrofit their buildings. There are many systemic barriers to achieving a higher retrofitting rate, but the high upfront cost of building retrofits is one major hurdle. The deep building retrofits necessary to achieve emissions reduction goals can easily cost $50,000 or more, which seems unrealistic for most households in the U.S. where the median household income is $70,784 [145], [146]. Consequently, low-income households are less likely to adopt energy saving measures even if they would be economically beneficial for them in the long-run [147].

If homeowners are going to be convinced to retrofit en masse to meet 2050 goals, significant financial subsidies will be needed to make building retrofits economically attractive. The U.S. and other governments have recently made enormous sums of money available for supporting building retrofitting activities. In the U.S., the 2022 Inflation Reduction Act includes $8.8 billion in rebates and an unlimited amount of tax credits worth over $3,200 per home per year for building retrofits [148], [149]. Given the daunting costs of retrofitting almost all existing buildings, retrofitting programs cannot afford to over-subsidize inframarginal purchases. In other words, policymakers should design programs to give individual households the minimum amount of subsidies necessary to convince them to take action. Current programs fall short, with 60% of the tax credits for solar panels and 90% of the tax credits for electric vehicles going to households in the top 20% of household income in the U.S. [150]. To find this balance, the author explored the use of willingness to pay studies, which is commonly used to price various consumer goods. To the authors knowledge, no other studies have focused on homeowners' willingness to pay for deep building efficiency retrofits for their homes.

This study fills that gap by identifying homeowners' willingness to pay for deep building efficiency retrofits costing up to $50,000 based on novel survey data from the Northeastern U.S. With this information in hand, policymakers can more readily determine adequate levels to stimulate building retrofit adoption for different household types without overly subsidizing inframarginal purchases.

Section 5.2 presents prior willingness to pay literature for energy and energy efficiency technologies. Section 5.3 outlines the survey used to capture homeowners willingness to pay for energy efficiency retrofits in Massachusetts and New York and discuss the data collected and its analysis. Section 5.4 presents the results of the survey data and its use to predict whether or not homeowners are likely to pay for the upgrades at varying upfront cost and payback periods. Section 5.5 discusses the implications of the willingness to pay data. Finally, Section 5.6 outlines how this survey can be used to support policy decisions to subsidize the adoption of efficiency technologies in the built environment.

5.2 Background

The first (and only) study the author is aware of relating the cost of building technologies to their total market penetration was carried out by the Arthur D. Little company in the 1970s, as discussed in Chapter 4 [130]. However, these data are now out of date and do not capture any socio-economic factors that might influence an individuals' propensity to pay for an upgrade. More recently, Dong and Sigrin used surveys in four states to determine homeowners willingness to pay for photovoltaic (PV) panels [131]. They required a minimum of 100 respondents per state to seed their models and looked specifically at owner-occupied single family homes [131]. They asked respondents about their required net monthly bill savings or required simple payback time [131]. The survey instrument used in this chapter draws from Dong and Sigrin and applies some of the methods to energy efficiency retrofits of buildings.

In terms of energy efficiency retrofits in particular, there is very little existing literature at the scale of a deep retrofit. The only study of willingness to pay for energy efficiency in residential buildings that the author is aware of focused on consumers' willingness to pay for a \$1,000 water heater [151]. This study elicited discount rates for individuals and tied them back to socio-economic factors, with higher education levels leading to lower discount rates (and thus greater willingness to pay for energy efficiency) [151]. However, willingness to pay \$1,000 for an appliance purchase is very different from willingness to pay for a \$50,000 deep energy retrofit that this chapter explores.

On the deeper retrofit side, Lai et. al. studied past retrofits in New York City multifamily properties and found that an internal rate of return of 21% was required for most retrofits – corresponding roughly to a five year simple payback. This agrees with the commonly-cited five-year simple payback period advanced by [28]. Schleich, Faure, and Meissner conducted a demographically representative survey of 6,600 homes in Europe looking at past energy efficiency adoption decisions. They found that residents' propensity to have adopted at least one retrofit measure in the past ten years increased 3.6% when they had easier assess to capital [103]. With \$100,000 in low-to-no interest funding for efficiency retrofits available in many European states, this should mean access to capital is not an issue. However, Zhao et. al surveyed approximately 500 households in Florida to understand whether tax credits or interest-free loans were more effective at promoting adoption of efficiency retrofits [147]. They found that tax credits were much more effective than interest-free loans at increasing adoption [147]. As one would expect, they also found that retrofit adoption decreased as the upfront cost increased [147]. This is likely driven in part because debt-averse households, approximately 22% of all households in the European survey, are less likely to adopt [103].

Drawing on the rebate-focused approach, Shen et al. conducted a study on heat pump adoption and found that a rebate program led to an approximately 5% increase in the adoption rate of heat pumps, which was a 26% increase over the baseline [152]. While rebates were the best tool to spur adoption, they were less effective for lower income households [152]. Other studies have looked at the impact of rebates on the uptake of EnergyStar appliances. Datta and Gulati found that for every additional rebate dollar provided for EnergyStar clothes washers, the total market share increased by 0.4% [153]. They did not find statistically significant results for the two other appliances they studied — dishwashers and fridges — but this was most likely due to exogenous factors such as the high percentage of EnergyStar-rated dishwashers on the market, for example [153]. The most closely related study was carried out in Germany using a revealed choice method from a standard residential energy consumption survey [154]. They found up to 50% of those partaking in subsidy programs are free-riders, meaning they would have adopted the retrofit without the subsidy. The German model specifically looked at energy costs, income, and information access as the key factors predicting consumers' willingness to pay for retrofits [154]. It is clear from Dong and Sigrin that additional socioeconomic factors need to be taken into account when predicting willingness to pay for retrofits in the U.S. [131].

One common concern with willingness to pay surveys is their reliability. Respondents often overstate their actual preferences by about 21% since they do not have to spend actual money in the moment [155]. This limitation is acknowledged by framing most of the model around a decision of whether a respondent would or would not pay for an upfront cost no matter the specifics. This binary decision is called the retrofit "deal or no deal." Assuming that most people have a clear sense of the maximum amount that they would, in the best of circumstances, spend on a certain amenity, "no deal" votes have the highest certainty. The goal for this chapter is thus to show how this kind of metric survey can provide a floor on the minimum public funding required to stimulate building efficiency retrofits independent of any other systemic issues that need to be resolved. Furthermore, these data can later be used to help identify how to best distribute the funding.

5.3 Methodology

The data for this study was collected via internet survey. The survey was distributed to 2,000 customers of a large investor-owned utility in Massachusetts and New York State. The utility serves several million residential customers, providing both natural gas and electricity services, although in some regions they only provide one or the other. The customers are part of a focus group for the utility designed to be representative of their broader residential customer base. The respondents received a small financial reward for completing the survey but the reward was independent of their responses.

5.3.1 Survey Design

The survey included 16 questions. Respondents were asked to estimate their average monthly electricity and oil, natural gas, wood, or propane bill. Key demographic data was collected such as their household income bracket, zip code, and highest level of education. Information about their residence was also collected: the year it was built, the number of bedrooms (a proxy for square footage), whether or not they own it, and the number of people residing there. They were asked questions about their energy knowledge: how they thought their energy bills compared to their neighbor (higher, same, lower), how concerned they were about carbon emissions (in a five-point likert scale), and to rank the top three factors affecting their decision when thinking about home efficiency upgrades (environment, energy costs, value of residence, ease of selling their residence, comfort, and health). Respondents were also asked four questions about their willingness to pay for energy efficiency retrofits to their residences based around five levels of upfront cost: $500, $5,000, $10,000, $25,000, and $50,000. The first question asked respondents the longest payback time they would accept up to "more than 10 years," including "too expensive" and "I'd do it anyway." The second question asked respondents the minimum savings on their monthly energy bill they would be willing to accept for the different upfront costs. The question was populated based on respondents' earlier reported monthly energy bill amounts and presented absolute monthly savings amounts in increments of 10%. For example, a household that reported monthly energy bills of $250 would have been offered monthly savings from the retrofit amounting to $25, $50, etc., up to $250. Respondents could again choose "too expensive" or 0% (corresponding to "I'd do it anyway"). While the answers to the latter two questions are technically redundant, since payback time determines monthly savings, the questions were asked given that previous surveys found that many respondents have a hard time conceptualizing these numbers [131]. The key summary statistics describing the responses can be found in Table 5.1.

5.3.2 Data Overview

The survey yielded 1,136 responses for a 57% response rate. Of those responses, 167 were ultimately dropped from the final analysis. 110 of these were dropped because the respondents were not homeowners. Renters are generally constrained in their ability to carry out a deep energy retrofit of their residence and, even if they were able to convince the building owner to do so, they do not necessarily benefit from the upgrade economically. This is born out empirically in Massachusetts, where 93% of participants in the utility-funded efficiency program are homeowners [156]. Three responses were dropped because they stated that their energy bills were greater than $9,500 a month ($114,000 a year), which is three standard deviations above the mean. These responses are either typos, their yearly energy use, or they were running a commercial business with a residential rate. Three were dropped because their zip code was not a valid US zip code, 18 were dropped because they preferred not to answer about their highest level of education, and 33 were dropped because they did not know their building's approximate age.

5.3.3 Data Pre-Processing

Income has been known to be a key factor in willingness to pay for efficiency measures for decades [130]. 152 respondents chose "prefer not to answer" for the household income question. This represented a significant number of responses and since income is key to the analysis, several methods were tested for providing replacement income data for these respondents. The first method assigned income based on the respondent's zip code. This analysis relied on the IPUMS dataset which provided median household income at the census tract level based on the 2020 American Community Survey 5-year estimates [157]. These median incomes were then mapped to zip codes based on the U.S. Department of Housing and Urban Development's 2020 ZIP Crosswalk data [158]. The second approach utilized an ordered probit regression based on respondents education and number of bedrooms to predict respondents income. The coefficients for these factors were all of similar magnitudes and were all significant. The regression methodology placed more respondents in the highest income category (34% vs. 23%) at the expense of a more uniform distribution throughout the rest of the income categories versus the ZIP methodology. When applied to the main dataset, however, the significant factors and their signs did not change, so the income by ZIP code method was chosen to be used for all future analyses since it is the simplest and most repeatable.

The income categories used in the survey were large, with a substantial number of responses in the “greater than $150,000 income” bin. To better estimate the median income and the responses in this high-income bin, the author used von Hippel et al.’s bin smoothing approach [159]. This method applies a distribution on top of the income bins gathered in the survey to provide more accurate income estimates. Using this approach, the median income in the dataset is $94,827. This is substantially higher than the national median household income of $70,784 or the median household income of New York of $75,157, but aligns well with the median household income in Massachusetts of $89,026 [146], [160].

5.3.4 Analysis Approach

Multiple regressions were carried out on the two main willingness to pay response questions asking about maximum payback time and minimum percent savings on monthly energy bills. The first regression for each is based on the principle that the most important question is whether the respondent will even consider the upfront cost no matter the duration of the payback time or percent savings. Thus a logit regression is used to identify the attributes that influence a respondents’ willingness to pay for a deal at all. The explanatory variables include the year the residence was built, the number of bedrooms in the residence, the number of residents in the residence, the yearly energy cost for the residence, the respondents education, the respondents income, the respondents concern about emissions from their residence, the upfront cost, and how much energy respondents think they use versus their neighbor. Further differentiation in required payback time for only those that are willing to pay is analyzed using an ordered probit regression. The same explanatory variables are used for this model as with the logit model. Differentiation in the minimum percent savings for only those that are willing to pay is analyzed using an ordinary least squares regression. Since the payback period is calculated based on respondents’ energy cost, this variable is removed from the explanatory variables but all the rest remain. The explanatory variables were checked for multicollinearity with all having a variance inflation factor less than 10, as detailed in Appendix A.1.

5.4 Results

5.4.1 Survey Results

Some key high-level trends in the data include that 33% of respondents were not at all concerned about their carbon emissions while only 8% were extremely concerned about them. 88% of respondents own their residence, with 64% living somewhere built before 1980, when energy codes first started to be implemented. These homes are the most likely to need substantial energy efficiency retrofits. Respondents care a lot about energy costs, with 91%

ranking it as their number one or two concern. Comfort, which is harder to quantify, was next highest, with 67% of respondents ranking it as their number one or two concern. 81% of respondents have completed a post-secondary degree, nearly double the national average of 48% [161]. Additional summary statistics can be found in Table 5.1.

Table 5.1: Summary statistics of survey questions.

Question	Mean	S.D.	Unit	Description
Year built	2.8	0.95	1 - 4	1= 2006-2022, 2= 1981-2005, 3= 1946-1980, 4= before 1945
Highest education level	3.9	1.20	0-5	0= some H.S. or less, 1= H.S. diploma or GED 2= some college, 3= associates degree, 4= bachelors degrees, 5= graduate or professional degree
# of bedrooms	3.2	0.94	bedrooms	1 bedroom= 0, 2= 1, 3= 2, 4= 3, 5= 4, 6+= 5
# of residents	2.6	1.34	residents	Raw number
Annual household income	3.2	1.49	0 - 5	0= < $25k, 1= $25k-$50k, 2= $50k-$75k, 3= $75k-$100k, 4= $100k-$150k, 5= > $150k
Concern about emissions	1.4	1.29	0 - 4	0= not at all, 1= slightly, 2= somewhat, 3= moderately, 4= extremely
Energy use vs. neighbor	1.0	0.77	0 - 2	2= higher, 1= same, 0= lower
Energy cost	3.4	2.02	Thousand $	Reported annual energy use
Upfront cost	N/A	N/A	Thousand $	The survey asked about five different upfront costs: $0.5, $5, $10, $25, $50

Note: Year built is the only variable that does not start at zero because the zero response corresponds to unknown date.

5.4.2 Retrofit: Deal or No Deal

The decision of whether the consumer is willing to pay for a given upfront cost provides a powerful deal or no deal framework to this analysis. It can be assumed that not even the best payback terms or additional non-monetary benefits such as comfort or reducing emissions will convince a consumer to invest in the retrofit. While differentiating between specific levels of payback might be harder in the abstract, the ability to say that an upfront cost is just too much gives a no deal decision high credibility. The significant factors for a logit regression on whether a respondent is willing to pay at all are detailed in Table 5.2.

Upfront cost is the largest factor (as seen by the standardized coefficient in Table 5.2) in willingness to pay for a deal by far. This leads to a deal or no deal framework driven

Table 5.2: Results for logit model on deal or no deal for the payback question.

Variable	Coef. (est. err.)	Std. Coef. (est. err.)	P-value
Year built	-0.051 (0.031)	-0.066 (0.033)	
Education	0.110 (0.026)	0.093 (0.034)	***
# bedrooms	0.272 (0.043)	0.194 (0.037)	***
# residents	0.087 (0.030)	0.085 (0.036)	**
Income	0.046 (0.005)	0.322 (0.036)	***
Concern	0.271 (0.030)	0.274 (0.034)	***
Upfront cost	-0.058 (0.002)	-1.000 (0.037)	***
Neighbor	-0.029 (0.051)	-0.023 (0.037)	
Energy cost	-0.012 (0.021)	-0.025 (0.038)	

*Note: P-values: *= 0.05, **= 0.01, ***= 0.001. In the standardized model all explained variables are standardized by their mean and standard deviation.*

largely by upfront cost. The author illustrates this in Figure 5.1 with data populated from a post-estimation prediction using mean responses for all factors and varying the upfront cost. While on average 86% of all households are willing to pay for a retrofit costing $500, only 26% are willing to pay for a retrofit costing $50,000. The high and low bounds on this willingness to pay are detailed in Table 5.3. It is interesting to note that only 13% of respondents are willing to pay for a $50,000 retrofit when this is put in terms of their monthly energy bill savings. There was general agreement, however, at the low-end of the upfront cost spectrum (86% vs. 88% willing to pay $500). The differentiation at $50,000 can likely be attributed to the fact that someone with the median monthly energy cost of $287 would have a payback time of 14.5 years for this upgrade if their energy savings were 100% of their monthly bill. This is much longer than the ten-plus years asked in the payback question. To further show that this is the case, the median required percent savings for the $50,000 upfront cost is 90%, which corresponds to a 16.1 year payback with respondents energy costs. The rest of the chapter focuses on using the payback-period derived willingness to pay because this is the most optimistic case.

Unsurprisingly, income is also a large determiner in homeowners' willingness to pay for retrofits. As seen in Table 5.4, for every thousand dollars in additional income a household makes, they are 1% more likely to be willing to pay for a given upfront cost. Consequently, income will be a driving factor deciding whether or not a household will pay for a given retrofit package cost. Furthermore, homeowners with bigger houses are more likely to be willing to pay, with the odds of a deal increasing 4% for every additional bedroom beyond two they have in the house. Similarly, each increase in a five-point scale of residents' concern about CO_2 emissions beyond "slightly concerned" increased their willingness to pay by 4%.

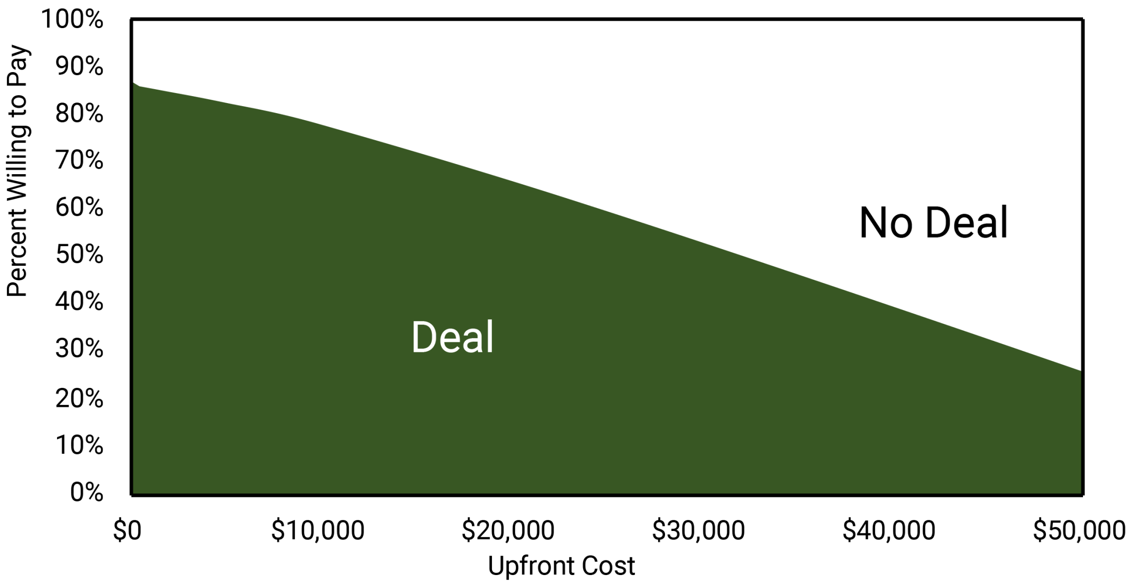


Figure 5.1: Retrofit deal or no deal prediction based on upfront cost.
Note: The green area is the percent of respondents willing to pay for an efficiency retrofit at that upfront cost. Those in the white "no deal" area will not pay for a retrofit of that upfront cost no matter the payback period.

Table 5.3: Willingness to pay for building retrofits (as percent of all households).

Upfront Cost	Willingness to Pay	Lower Bound	Upper Bound
$500	86%	73%	93%
$5,000	82%	67%	91%
$10,000	78%	61%	89%
$25,000	60%	31%	77%
$50,000	26%	13%	44%

Note: Median values are used for all post-estimation predictions for willingness to pay. Upper and lower bounds are one standard deviation away from the mean value.

Table 5.4: Marginal effects, odds ratio, and confidence intervals (CI) for respondents willingness to pay for a retrofit.

Variable	Odds Ratio	95% CI	Marginal Effects
Year built	0.95	0.89 - 1.91	-1%
Education	1.12	1.06 - 1.17	2%
# bedrooms	1.31	1.21 - 1.43	4%
# residents	1.09	1.03 - 1.16	1%
Income	1.05	1.04 - 1.06	1%
Concern	1.31	1.24 - 1.39	4%
Upfront cost	0.94	0.94 - 0.95	1%
Neighbor	0.97	0.88 - 1.07	0%
Energy cost	0.99	0.95 - 1.03	0%

5.4.3 Payback Period

Even if a homeowner is willing to pay for a given upfront cost, they may have additional provisions on the deal, specifically a maximum acceptable payback time. The results of the ordered probit regression on the payback period data for those willing to pay for at least one of the upfront costs is detailed in Table 5.5. The homeowner's income, education level, energy cost, and their concern about emissions are all significant factors affecting the required payback time for a given upfront cost.

Table 5.5: Results for the ordered probit model on payback period.

Variable	Coef. (est. err.)	Std. Coef. (est. err.)	P-value
Year built	0.008 (0.019)	−0.015 (0.018)	
Education	−0.099 (0.017)	−0.132 (0.019)	**
# bedrooms	0.008 (0.022)	0.049 (0.020)	
# residents	−0.041 (0.015)	−0.125 (0.020)	
Income	0.007 (0.002)	0.053 (0.020)	**
Concern	0.067 (0.014)	0.149 (0.018)	***
Upfront cost	0.023 (0.001)	0.255 (0.019)	***
Neighbor	−0.025 (0.026)	−0.033 (0.021)	
Energy cost	−0.049 (0.010)	−0.093 (0.021)	***

*Note: P-values: *= 0.05, **= 0.01, ***= 0.001. In the standardized model all explained variables are standardized by their mean and standard deviation.*

Table 5.6: Odds ratio and confidence interval for the ordered probit regression on payback period.

Variable	Odds Ratio	95% CI
Year built	0.98	0.95 - 1.02
Education	0.95	0.92 - 0.99
# bedrooms	0.97	0.93 - 1.01
# residents	1.02	0.99 - 1.05
Income	1.01	1.00 - 1.01
Concern	1.08	1.05 - 1.11
Upfront cost	1.02	0.94 - 0.95
Neighbor	1.03	0.98 - 1.09
Energy cost	0.95	0.93 - 0.97

The increasing required payback time as upfront cost rises can be seen in the orange line in Figure 5.2. While the increase in acceptable payback time with increased cost is counter-intuitive for those used to working in finance, it bodes well for building retrofits. More comprehensive retrofitting packages tend to bundle lower cost and quick payback measures — such as efficient appliances, solid state lighting, and weatherization — with more costly and longer payback upgrades such as added wall insulation, heat pumps, and photovoltaics. As a consequence, deep retrofit packages have higher payback times than low retrofit packages.

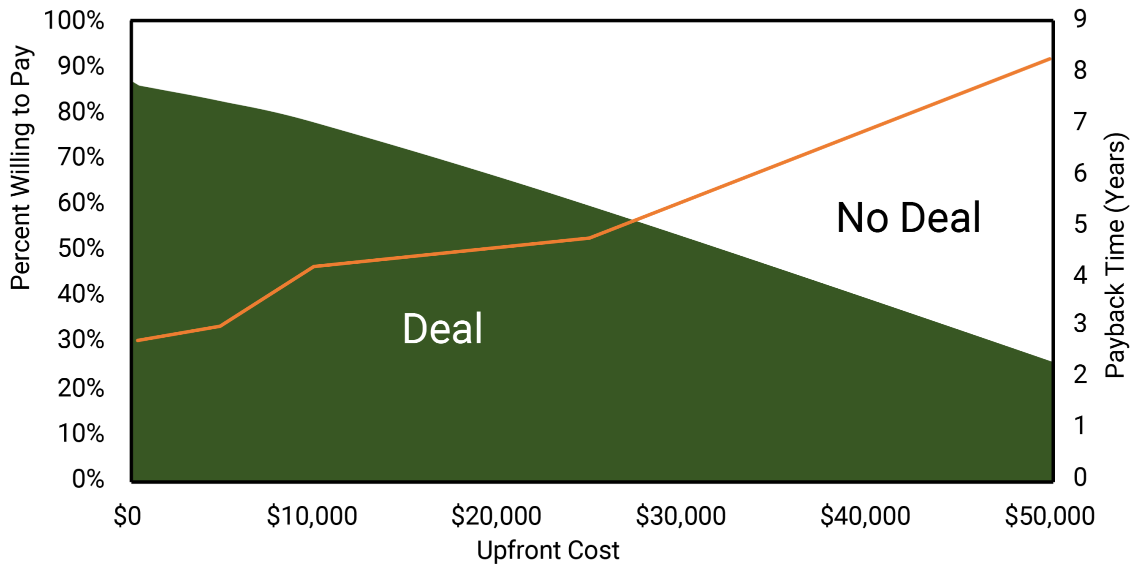


Figure 5.2: Retrofit deal or no deal with orange payback curve showing the predicted median required payback time.

There are a few salient takeaways from the payback period analysis in Table 5.6. First, as homeowners' education increases by one level, the odds that they will accept a longer payback period decreases by 5%. On the contrary, those that are "moderately concerned" about emissions from their homes are 1.31 times more likely to accept a two-year longer payback than those only somewhat concerned. For the "greater than 10 years" payback period, this translates into 10% more acceptance of this long payback period for those extremely concerned vs. those not at all concerned.

The percent savings on a monthly energy bill regression led to similar significant factors and results. Overall, however, respondents were more optimistic in their willingness to pay for a more expensive deal when it is put in terms of payback period instead of required percent savings. This is in agreement with [131]. For those that were willing to pay for the deal, there was good correspondence between the median payback times for the raw question and the derived payback from the percent savings question, as seen in Figure 5.3. While the medians agree for each payback period, there is a lot of variation in the percent savings responses which shows that the "average person" is logical in their decision-making, even if not every respondent was.

5.4.4 Robustness Checks

Several analyses were carried out to test for the regressions' robustness. As in [147], the responses were split into low-and high-income groups by the median-income. This leads to a roughly even split in the dataset. While there are slight changes in the subsamples reflecting heterogeneity in the results, all the significant variables used in the full dataset retain the

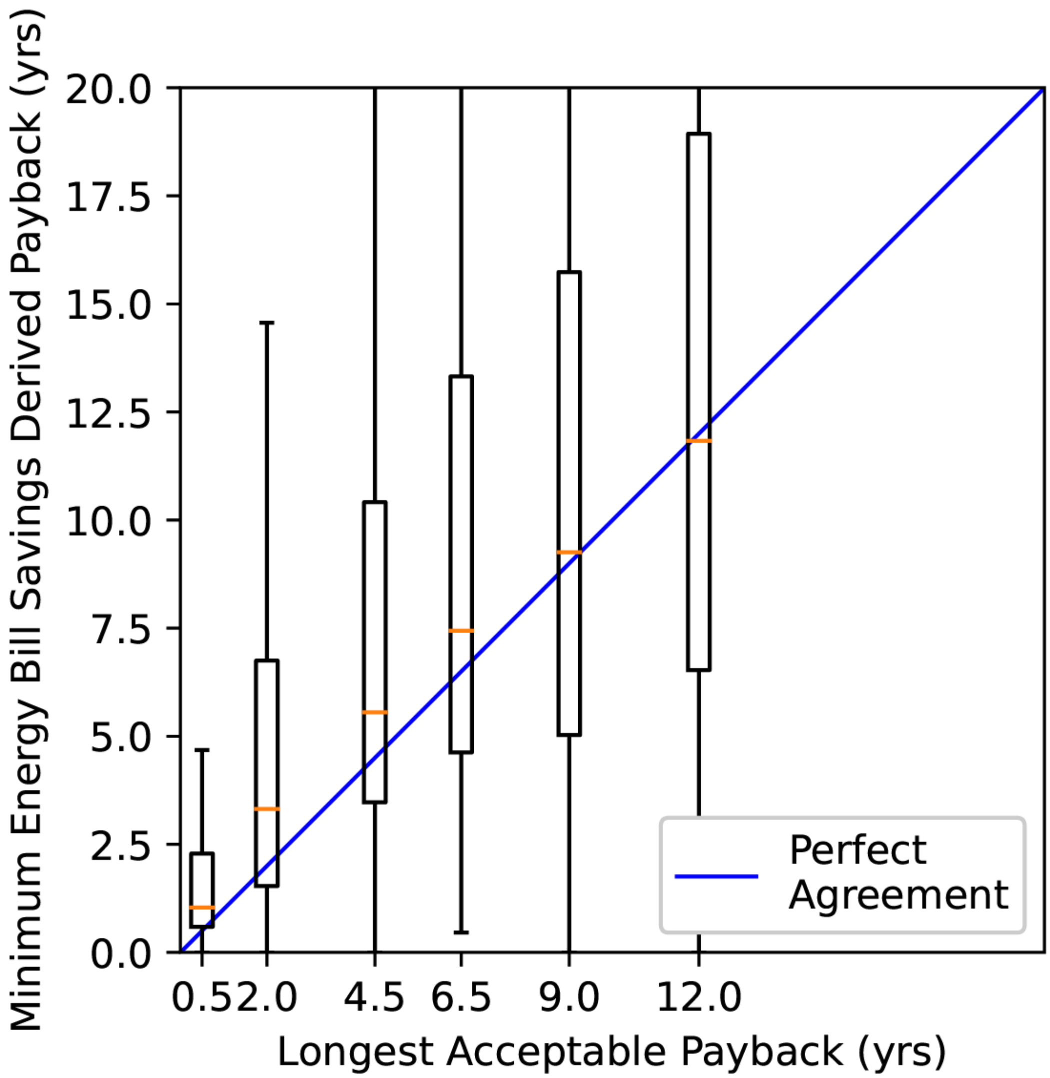


Figure 5.3: Respondents' longest acceptable payback period versus the payback period derived from respondents' minimum required energy bill savings.

same direction and magnitudes. To further test for robustness of the regression, insignificant factors were dropped from the regression. As each variable is dropped from the deal/no deal regression, the remaining variables all remain significant and their coefficients do not change sign. Tables with the robustness test results can be found in Appendix A.

5.5 Discussion

Ultimately, the deal or no deal model developed based on 969 included survey respondents across the Northeastern U.S. is a robust approach for identifying the maximum upfront cost for a retrofit package that homeowners would be willing to pay for. Most people intrinsically understand if a specific upfront cost is out of their reach economically. Thus a "no deal" prediction means that person will absolutely not pursue a retrofit at that upfront cost. Additional subsidies will be needed to convince them to retrofit. When a household falls into the "deal" prediction, the result is more nuanced. Households might have specific requirements (such as a payback period) or impediments to them carrying out the retrofit. These factors will all have to be dealt with to realize full adoption.

Concern about emissions from residences was a particularly strong indicator of a homeowner's willingness to pay for a deal and a longer payback time. This agrees with Nolan et al. who concluded that showing messages about neighbors' energy conservation behavior spurred people to conserve more energy [99]. While as of 2022 more than 70% of Americans believe in climate change, only half believe their individual actions (e.g. changing the emissions from their residences) have an effect on climate change [162]. This disparity leaves the door open for significant improvements through education campaigns.

The model developed in this chapter can be used to estimate the required incentives needed to retrofit all residential, owner-occupied buildings in a given city, utility service territory, state, or country. For example, using post-estimation analysis the subsides required for the surveyed owner-occupied households to be willing to pay for a "deep" $50,000 retrofit can be predicted. The initial subsidy offered is $0 and then subsides are increased in $1,000 increments until the cost to the homeowner is $0. The deal or no deal model is run each time the subsidy is increased. Because households' willingness to pay is probabilistic, the model is run one hundred times and the median results are taken. The standard deviations are not shown as they are minimal. Of the 969 households, 32% are willing to pay for the upgrade with no subsidies and zero households are fully subsidized. The cost to the government to subsidize all the houses requiring subsidy is $2.5 million. The homeowners spend $46 million of their own money on the retrofits, meaning every dollar of subsidy activates $18 of private investment. This is the absolute lowest amount that the government will spend because the incentives are tuned to the exact upfront cost owners are willing to pay (in thousand dollar increments). While this level of customization is not feasible in the real world, it shows that at least some additional gradation in subsidies can still activate homeowners investment in retrofits.

A limitation of this work is that it focuses on owner-occupied buildings because renters are rarely incentivized to invest in energy efficiency. Landlords traditionally have not been incentivized to invest in efficiency either. However, Collins and Curtis found that most renters are willing to pay an average of $450 a year more in rent for energy efficient apartments [104]. While this opens up a retrofit costing landlords about $5,000 with a (longer-than usually accepted) 10-year payback time, the deep energy retrofits required in the Northeastern U.S. are an order of magnitude more costly at approximately $50,000. Thus, additionally incentives and/or regulations such as New York's Local Law 97 or Burlington, Vermont's minimum housing code weatherization ordinance for rental units will need to be implemented.

This survey was limited to the Northeastern U.S., specifically Massachusetts and New York. While the median income of respondents was higher than the national average, it is more in line with the median incomes of the surveyed states. Massachusetts and New York also have higher costs of living, 148% and 125% of the national average, respectively [163]. With Massachusetts and New York comprising roughly half of the Northeastern U.S.'s population, the author believes this survey is representative for the region. In the absence of a broader survey, since respondents' median incomes aligned with the respective state's median incomes, the willingness to pay model developed in this chapter could be used across the U.S. At the same time, further distribution of surveys across the country (using the survey instrument available in the original paper) to better characterize U.S.-wide willingness to pay for retrofits would benefit policymakers. Using this model outside the U.S. would likely require administering the survey in additional countries first.

5.6 Conclusion and Policy Implications

If cities and countries globally are to achieve their stated Paris Agreement emissions reduction goals, "deep" energy retrofits to achieve net zero in 80% of today's building stock are needed in the next 26 years. The actual upgrades will vary by geography and climate, but are generally costly, on the order of tens of thousands of dollars or more per residence. Many households globally lack the upfront capital and/or income to finance these retrofits. If jurisdictions are to meet their stated emissions reduction goals, governments will need to supply generous subsidies to many households.

The model presented in this chapter enables policymakers to quantify the amount of required subsidies to make building retrofits acceptable to any owner-occupied household. For example, for a median household in the dataset, the model predicts that households are only likely to pay for a \$50,000 retrofit 29% of the time. The same household is likely to pay for a \$25,000 retrofit 64% of the time, so a \$25,000 subsidy would lead to a 32% increase in retrofit adoption. The model can help policymakers reduce retrofitting subsidy costs by decreasing inframarginal subsidies, focusing on those most in need and stretching limited government funding further. However, the model does not yet address questions of equity that policymakers must ponder along with budget constraints. For example, should policymakers try to limit rebates for high-income households willing to pay for a \$50,000 upfront cost so that incentive money is available only for those that are only willing to pay lower amounts?

Given the hassle factor typically encountered when pursuing a deep building retrofit, U.S. policymakers have thus far often chosen to make the financial benefits so attractive that those who would have been willing to pay an even higher upfront adopt without hesitation. This approach — used previously for solar, electric vehicles, and other energy technologies — relies on technology cost learning curves, where more installations, no matter who installs them socio-economically, will bring down the cost for everyone in the medium term. How to prioritize limited funding is ultimately up to policymakers to decide, but the willingness to pay model developed in this chapter can provide quantification of the necessary subsidy costs for a given jurisdiction.

Beyond providing a baseline assessment of the subsidies required to convince households to retrofit, the model can help policymakers identify levers they can pull to stimulate retrofit adoption. By changing the input assumptions, policymakers can evaluate the impact of non-economic levers such as homeowners concern about emissions from the their residence. By doing this, they can thus evaluate the impact of an outreach and education campaign to raise households' concern about emissions and thereby reduce the required subsides. For example, if communities are able to move the majority of their residents from "slightly concerned" to "extremely concerned," homeowners will be 12% more likely to be willing to pay for a $50,000 retrofit. In the aforementioned post estimation analysis of nearly 1,000 households in Massachusetts and New York, if all households are "extremely concerned", the subsidies required to convince homeowners to be willing to pay for the $50,000 retrofit are reduced from $2.5 million to $1.2 million. The education and outreach program leads 44% of households to be willing to pay for the $50,000 upfront cost without any subsidies versus the 32% before. In this sample of 1,000 representative homes, this program could probably be implemented for less than $200,0000 and the million dollar savings spent on other pressing priorities.

5.7 Summary

The model presented in this chapter provides policymakers with a powerful tool to evaluate different policy levers and subsidy amounts for building retrofits. The deal or no deal model evaluates levers such as direct subsides to reduce upfront cost, targeting subsidies at specific income brackets, or educating households about the impact of their emissions, and quantifies their impacts on homeowners willingness to retrofit. Ultimately, households' concern about emissions from their residences ranks next to upfront cost and income as the top driving factors in households willingness to pay for a retrofit. The model further found that for a payback period of five years, the commonly cited maximum payback period acceptable to most of the public, homeowners are willing to pay around $25,000 for a retrofit. At this upfront cost, the median household has a 64% likelihood of adoption, a significant improvement over the 29% likelihood at $50,000. Tacking on the educational program's 12% increase in adoption likelihood, nearly 80% of all households would adopt. This information is meant to guide policymakers in ensuring that building retrofit adoption rates rise commensurate with the need to retrofit most of the world's existing buildings in the next 26 years.

Chapter 6

Modeling techno-economic adoption of building energy retrofits at the city-scale

This chapter applies the willingness to pay model developed in Chapter 5 to the UBEM of Oshkosh, WI as a follow-on to the adoption model of Chapter 4. Census data are assigned to each household and a building-by-building geometry-based cost model is used to better quantify retrofitting cost. The model is then run for the same three retrofit packages across all of Oshkosh. Finally, a novel application of a diffusion model is used to set retrofitting rates based on historic adoption patterns for building-related components. This chapter can help policymakers understand the challenges to achieving high adoption rates for retrofits and how to best direct their limited funding. This chapter is an edited version of a journal article that the author has submitted for review:

Zachary Berzolla*, Zoe De Simone*, and Christoph Reinhart. "Modeling techno-economic adoption of building energy retrofits at the city-scale." *in preparation* * equal contributions

6.1 Introduction

As described in previous chapters, cities around the world are striving to meet aggressive emissions reduction goals in the built environment. In much of the U.S., common retrofit packages usually include deep energy retrofits coupled with heat electrification and a clean electricity supply [164]. These retrofits can be expensive, often costing $30,000 or more [164]. To date, literature has cited the high upfront cost of retrofits as the key impediment to retrofit adoption [165], [166]. This lack of adoption threatens to derail communities' plans to achieve emissions reduction targets. This chapter strives to understand whether households in a U.S. city — Oshkosh, WI — are willing to pay for retrofits and what their rate of adoption means for achieving the city's emissions reduction goals. Understanding this key piece of information at the city-scale can help policymakers understand whether the technology pathways (retrofit packages) they defined to meet their city's emissions reduction goals are actually financially feasible for their residents. Furthermore, understanding the timing of this feasibility can inform whether retrofits will be adopted quickly enough to achieve the city's 80% emissions reduction target by 2050.

Chapter 4 combined UBEMs and adoption models to show how they can help policymakers understand how retrofits will be adopted in their jurisdiction. It further showed how adoption of these retrofits would affect achieving emissions reduction goals and how current policies would exacerbate inequitable adoption of building retrofits, namely that higher income neighborhoods would have higher adoption rates than lower income neighborhoods. This model was based on Department of Energy data from the 1970s and lacked any connection to socio-economic data, leaving an opening for further study of retrofit adoption today. To fill in this gap, the author carried out the willingness to pay study detailed in Chapter 5. In this chapter, the model of homeowners' willingness to pay is applied to an UBEM of the city of Oshkosh, Wisconsin to determine households' willingness to pay for three different retrofit packages. Households that are willing to pay for a retrofit package are then put into a "potential adopters" pool and randomly chosen to implement the retrofit based on a spread of common adoption rates from the literature (discussed in Section 6.2) that determines *when* the household will actually implement the retrofit. Combining these data with yearly emissions data per building provides annual building-related emissions in the city each year to 2050.

6.2 Methods

The willingness to pay model developed in Chapter 5 requires nine inputs: year built, highest education level, the number of bedrooms in the residence, the number of residents, annual household income, households' concern about emissions, household energy use versus their neighbors, the household's annual energy cost, and the retrofit's upfront cost [167]. The energy cost and emissions for the region are also needed. These data are not all available from one source for Oshkosh so five different sources are combined — UBEM data from Chapter 3 [167], American Community Survey 5-year estimate census data [168], NREL's Cambium grid emissions data [169], Yale's Project on Climate Change Communication environmental attitudes model [170], and a retrofit cost model based on NREL's REMDB [171] (discussed in Section 6.2.4) — to create a dataset for all of Oshkosh, as shown in Figure 6.1. Where values are not available on a building-level, they are stochastically assigned. Certain factors such as the energy costs, emissions from grid electricity, and the retrofit cost vary with time.

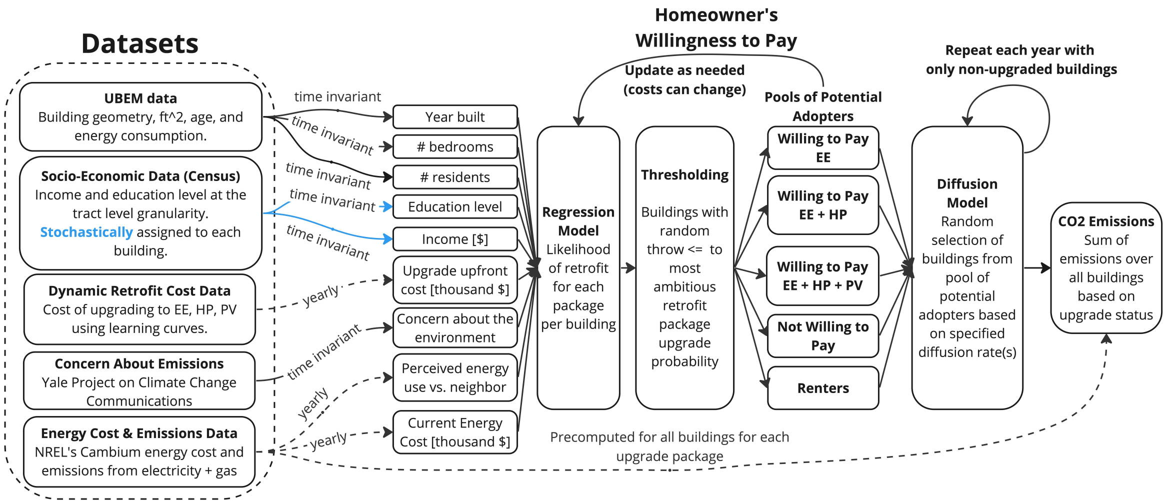


Figure 6.1: Workflow used to integrate data.

6.2.1 UBEM Data

The GIS file from Oshkosh contains the year built and the number of bedrooms in the residence. The file does not specify the number of occupants, but this is inferred from the number of bedrooms. Households are assumed to think they use the same amount of energy as their neighbor, the finding in Chapter 5. Once the UBEM is run, the model has energy consumption data for electricity and delivered fuels for every building in baseline and retrofitted status. These values do not change from year to year. There are three scenarios studied in this analysis taken from previous work and described in Table 6.1: energy efficiency (EE), energy efficiency and electrification (EE+HP), and energy efficiency, electrification, and solar (EE+HP+PV) [164].

Table 6.1: Retrofit package requirements for EE and EE+HP. EE+HP+PV adds approximately 6kW of rooftop solar to each residence.

Package	COP	Equipment Power Density	Lighting Power Density	Infiltration	Wall Insulation	Attic Insulation	Floor Insulation	Window U -Value
		(W/m^2)		(ACH)		(m^{2}K/W)		(W/m^{2}K)
EE	0.95	3.0	1.5	0.15	4.4	8.6	5.3	2.0
EE + HP	3.0	3.0	1.5	0.15	4.4	8.6	5.3	2.0

6.2.2 Energy Costs and Emissions

The annual energy costs in the baseline state are calculated using the UBEM's energy consumption data and the appropriate years' retail rate projections from NREL's Cambium data. The mid-case Cambium scenario is used for these analyses. This dataset also provides emissions values for the electricity use in that year which will be used to calculate city-wide emissions at every time step.

6.2.3 Socio-Economic Data

The education level and household income data are not available at a household level due to privacy concerns. To assign these characteristics, the U.S. Census's American Community Survey five year estimates for the respective census tracts in Oshkosh is queried [119]. Buildings are assigned a given census tract based on their geographic location from the UBEM. A value for education and income is assigned to each individual building using a stochastic process based on distributions of these characteristics centered on the mean value reported by the census.

Residents concern about the environment is not a factor that is captured in the U.S. Census but it is a key factor in the willingness to pay analysis. The Yale Program on Climate Communication's climate opinions maps are utilized to inform this variable [170]. This national study characterizes Americans feelings about the environment and climate change. Specifically this dataset estimates the percentage of all residents who think that global warming is caused mostly by humans at the county level for the whole U.S. [170]. For Winnebago County, WI, where Oshkosh is located, the study estimates that 54.9% of the county's residents are concerned [170]. To implement this information in the model, a stochastic assignment based on a distribution centered on the given value are assigned to the households in Oshkosh.

6.2.4 Retrofit Cost

To identify the total retrofit cost for all of Oshkosh, the author and collaborators developed a cost estimating model for UBEMs. This model calculates the areas for all the relevant building characteristics such as the wall area, ground floor area, window area, roof area, and total square footage all based on the geometry in the UBEM. Each retrofit is then categorized into its volumetric cost and/or its unit cost. These cost data are drawn from RSMeans as well as data from the National Renewable Energy Laboratory's REMDB [114], [171]. Heat pump costs are based on the moderate scenario in the NREL Electrification Future Study, including its technology learning curve [115]. These heat pump costs are likely not representative of actual installed costs but are the best estimates available today. Similarly, there are open questions about how reliable RSMeans is for estimating specific project costs in different parts of the country. However, until better cost estimating information is developed, these are the best available sources to inform policymakers today. Retrofit packages are assembled by combining different retrofits. The costs of certain retrofits, namely solar and heat pumps, are assumed to get cheaper over time due to learning curves, as shown in Figure 6.2. Using this model, the retrofit cost for each household is calculated. Together,

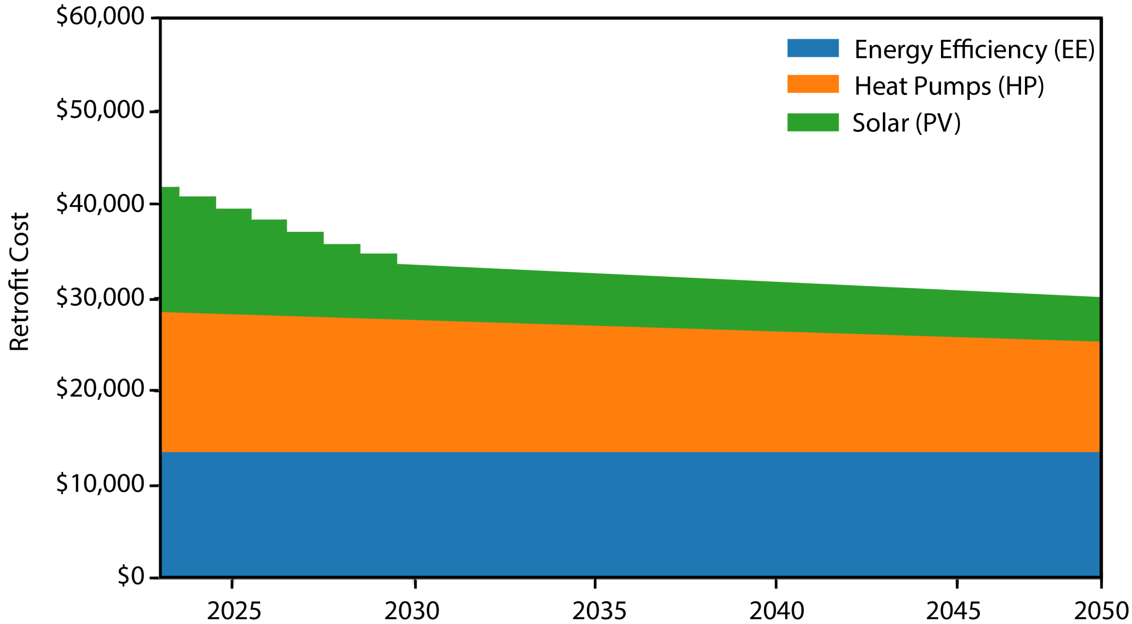


Figure 6.2: Mean retrofit costs per household each year. The energy efficiency costs are assumed to be time-invariant. The costs of heat pumps decline over time, but solar declines the fastest.

these data provide costs for each building to be retrofit based on its respective geometric characteristics. While not perfect, this method provides a good estimate of costs for any building at a level of detail required for the willingness to pay model.

6.2.5 Willingness to Pay

With all these data in place, the willingness to pay model is run. The model provides a likelihood that each household is willing to pay for a given retrofit. This serves as a cost-test determining how financially feasible a given retrofit is for a household (and also accounts for non-economic factors such as environmental concern). A proverbial dice is then thrown and if the households' willingness to pay likelihood exceeds the resulting random probability from the dice roll, they are designated as willing to retrofit. The highest-cost package that the household is willing to pay for given their dice roll is chosen. This household is then placed in the pool of all households that are willing to retrofit. Once a household is in the pool, it is assumed to stay there until it is retrofitted. This pool will grow over time as the technology becomes cheaper (as seen in Figure 6.2) and more households are willing to pay for the upfront cost of a retrofit. Not every household that is willing to pay, however, will retrofit in the first year they are in the pool of adopters. To capture the pace of adoption over time, a Bass diffusion model is implemented.

6.2.6 Bass Diffusion Model

The Bass diffusion model was first proposed in 1969 by Bass [172]. This model relates the purchase of a consumer good to the number of previous buyers. The model captures how quickly a technology is adopted over time. This model was adapted by Rogers (1976) and can help define what is now referred to as an early adopter, as shown in Figure 6.3 [129]. The biggest unknown in Figure 6.3 is the actual dates of the x-axis. For some technologies, 50% or more market share is achieved in just a few years, where for others it takes decades. Identifying this timeline is the crux of the challenge for predicting building retrofit adoption.

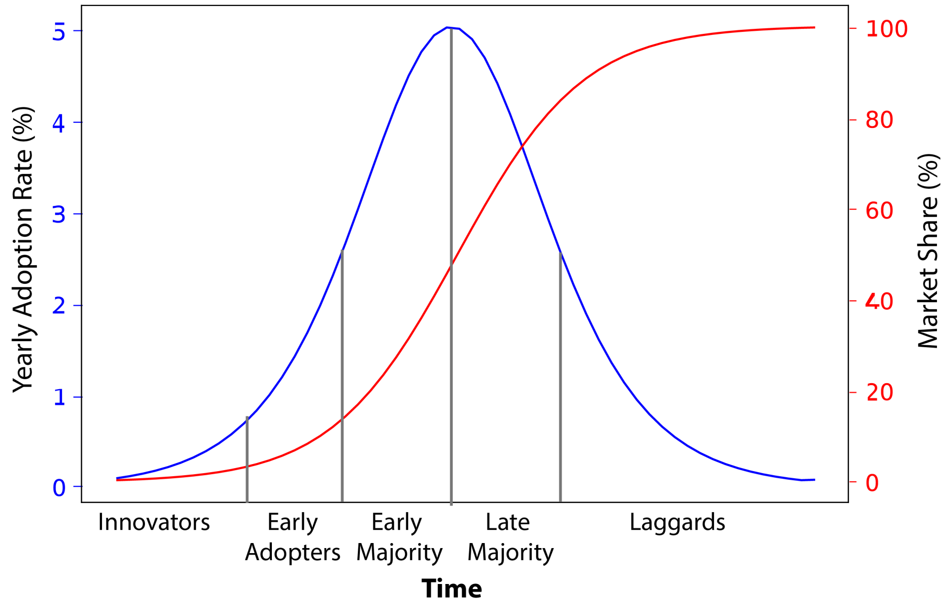


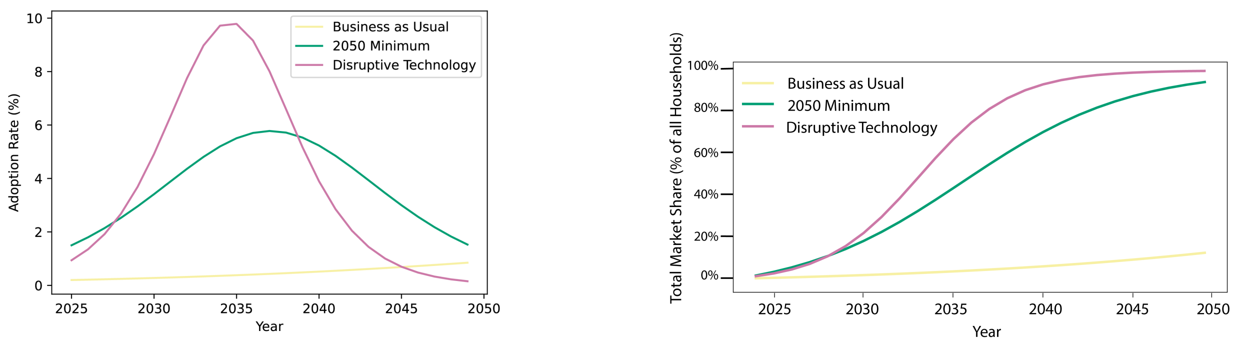
Figure 6.3: Early-adopters S-curve showing the yearly adoption rate (blue) and total market share (red). Figure created by the author based on information in [129].

This model is used because once households are identified as willing to pay and put into the appropriate "pool of potential adopters," they will not all retrofit at once. The model captures all the non-technical aspects of adoption that affect the rate of uptake: social parameters, technology-specific growth challenges, scalability of the technology, etc. The model is parameterized by two key components: the imitation (q) and innovation (p) parameter [172]. The basic model is formulated according to Equation (6.1).

$$f(t) = \frac{1 - \mathrm{e}^{-(p+q)t}}{1 + \frac{q}{p}\mathrm{e}^{-(p+q)t}} \tag{6.1}$$

The imitation and innovation parameters vary by the product. The most commonly used values of p and q, $p = 0.03$ and $q = 0.38$, are from a meta-study covering a broad range of technologies [173]. One specific technology studied in this timeframe was room air conditioning (AC) diffusion in the U.S. over a 12 year period with a total potential market size of 50 million households [174]. Shrinivasan et al. used nonlinear estimation techniques based on the historic adoption of room AC and found $p = 0.0094$ and $q = 0.3748$ [174]. This is an aggressive diffusion rate that reflects what happens when there is no other technology available to meet consumers' needs. In the early days of AC adoption, households that did not adopt them had no easily accessible alternative mechanical cooling technology. On the other end of the spectrum, Hlavinka et al. conducted an analysis of ductless heat pump adoption in single-family homes in the U.S. Pacific Northwest [175]. They found $p = 0.002$ and $q = 0.068$, reflecting early adoption of these units in a market with existing alternatives, leading to adoption rates of less than 1% per year predicted over the next 30 years [175]. While a pessimistic scenario, this likely reflects a business as usual case for most retrofits, given that current retrofitting rates are around 1% per year. More recently, Uidhir et al. found that there is no literature on whole-home retrofit diffusion rates available [176]. They set $p = 0.015$ and $q = 0.2$ by backcasting from the 100% retrofit adoption required to meet Ireland's emissions reduction goals [176]. Although not grounded in actual data, this approach lays out the theoretical path to a 2050 full adoption scenario.

This chapter uses the three aforementioned Bass diffusion curves to bracket potential adoption. The window air conditioners represent a fast adoption rate when a disruptive technology comes onto the market and outperforms all other technologies on the market, hereafter referred to as a "disruptive technology" option. The heat pumps in the Pacific Northwest represent a business as usual slow adoption rate, hereafter called "business as usual." Finally, the Irish backcasting curve represents the requisite adoption to meet policy goals, hereafter called the "2050 minimum." The resulting adoption and total market share for the different Bass diffusion adoption rate curves are shown in Figure 6.4a.



(a) The three Bass diffusion curves for the adoption rates used in these analyses.

(b) Cumulative adoption or market share for the given adoption rates out to 2050.

Figure 6.4: Bass Diffusion model implementation

As seen in Figure 6.4b, business as usual does not lead to enough adoption by 2050 for even 20% of all households to be retrofitted. The "disruptive technology" diffusion rate leads to a 95% market share by 2041, almost 10 years ahead of the goal. As one would expect for a solution designed via backcasting, the 2050 minimum, achieves the 95% market share target in 2050.

6.3 Results and Discussion

6.3.1 Technical Potential

The technical potential for emissions reduction assumes all buildings in Oshkosh are retrofit to a given package. The resulting city-wide emissions from full adoption, taken from

Chapter 3, can be seen in Figure 6.5. This figure shows that grid decarbonization leads to a substantial improvement in baseline emissions but full adoption of any of the three packages leads to much greater emissions reductions. It is crucial to note in Figure 6.5 that the EE+HP retrofit leads to more carbon emissions today compared to just EE, reflecting the relatively dirty grid in Wisconsin for the coming few years. This only lasts for less than two years, with a crossover predicted in 2025. This shows how important looking at future grid emissions projections are for making policy decisions in such a dynamic system. Ultimately, the figure shows how the full deep retrofit, heat electrification, and rooftop solar EE+HP+PV is necessary to achieve nearly-net zero emissions in Oshkosh by 2050.

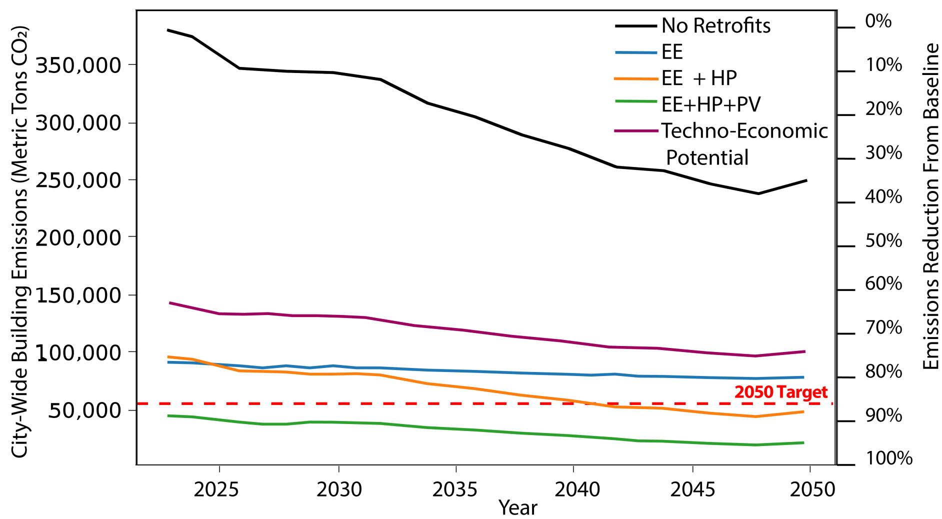


Figure 6.5: Emissions reduction potential for each retrofit package adopted to 100% in Oshkosh. Techno-economic potential assumes adoption of only the packages that households are willing to pay for.

6.3.2 Willingness To Pay Results

To evaluate whether retrofit adoption will achieve this full technical potential, it is critical to understand which households are in the pool of potential adopters in the first place. This is where the willingness to pay analysis comes into play. By running the analysis for Oshkosh with the relevant census-derived socio-economic data, households can be put into five different pools: renter-occupied, potential adopters for EE, potential adopters for EE+HP, potential adopters for EE+HP+PV, and not willing to pay for any package (they would need additional incentives or factors to adopt). Renters are assumed to never adopt, given the split incentive and historical lack of adoption among rental units. Within this framework, where only 26% of households in Oshkosh are renters, the pool of potential adopters is fairly large. The breakdown between these pools can be seen in Figure 6.6. Ultimately, 9,153 of the 13,100 households in this study of Oshkosh are willing to pay for one of the three packages. If all those households adopt, the emissions reduction potential in Oshkosh can attain the "techno-economic potential line in Figure 6.5. One reason most households are willing to pay for retrofits is that the EE package had a median cost across

Oshkosh of only \$11,000, which, according to the the willingness to pay model, should be acceptable to most households. High income census tracts where the median income is over \$100,000 leads to high willingness to pay for the EE+HP+PV retrofit which had a median cost of \$40,000.

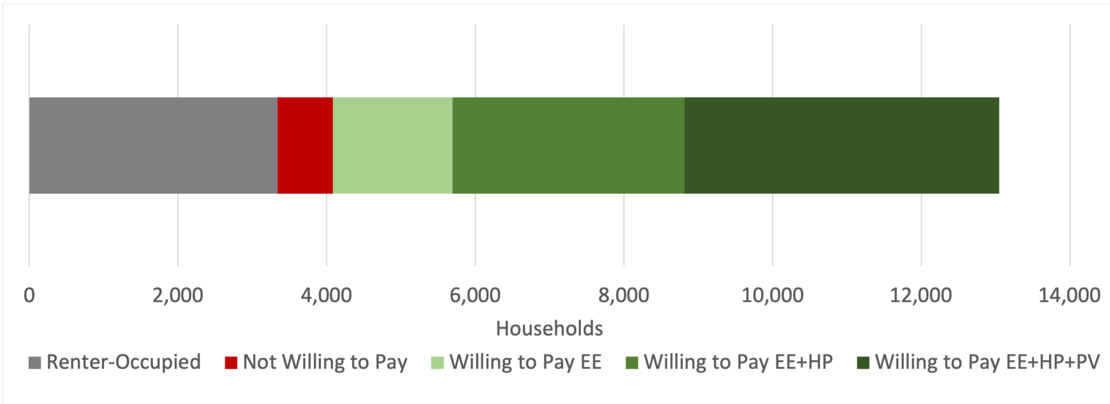
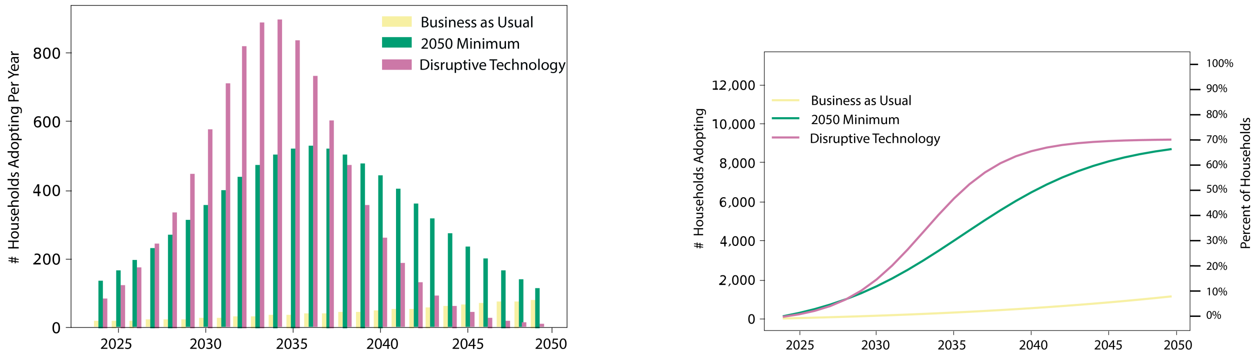


Figure 6.6: Willingness to pay breakdown across Oshkosh. Only the households in green are willing to pay for the retrofits.

A key finding of the willingness to pay model shown in Figure 6.6 is that only 8% of all owner-occupied households are **not willing to pay for a retrofit**. This means incentives are not the main limiting factor to retrofit adoption. Therefore, additional money will not help much to increase retrofit adoption in Oshkosh among owner-occupied houses. In this analysis, the answer to Oshkosh's adoption challenges is not necessarily more money to households. Instead, limited resources should be funneled toward overcoming two major burdens to realizing full potential: renter-occupied housing and implementation programs that foster a knowledgeable and available workforce, makes it easy to for homeowners to retrofit, and educates households about the benefits of retrofitting. Addressing renter-occupied housing is outside the scope of this chapter, although a good example of retrofitting rented affordable housing is documented in [177]. Additionally, a small amount of money could be spent on top-up payments to the 12% of households that adopt the EE package to get them to adopt the EE+HP package. This will help avoid the lock-in of fossil fuel infrastructure that comes if households install a fossil fuel heating system today instead of a heat pump.

6.3.3 Diffusion Results

With the willingness to pay data in place, the diffusion model is run from 2024 to 2050. Each year, the number of households that are willing to pay for a retrofit are identified as the pool of potential adopters. Each year, this pool is randomly sampled to pick households that will adopt based on the diffusion model's predicted adoption rate for that year. The progression of this model in Oshkosh is shown in Figure 6.7.



(a) Yearly adoption for Oshkosh with three different Bass diffusion curves.

(b) Cumulative adoption prediction numbers for Oshkosh.

Figure 6.7: Diffusion of retrofits in Oshkosh.

6.3.4 Emissions Results

With only those willing to pay identified and the diffusion model run for these households, the resulting energy use and emissions across Oshkosh in each year can then be tabulated. There are two salient takeaways from Figure 6.8. First, the business as usual diffusion scenario and the no retrofits scenarios are nearly identical. This aligns with the results found for a flat 1% adoption rate in Berzolla et al. (2022) [178]. In short, many households are willing to pay for a retrofit but few actually choose to do so because of natural inertia or other exogenous factors, leading to minuscule emissions reductions. Yet achieving high adoption rates that would translate to greater emissions reductions has been shown to be possible in the past in the "disruptive technology" example. Bridging the gap between "business as usual" and "disruptive technology" diffusion is thus the core challenge.

For a community looking to achieve this level of adoption, there are two likely pathways to attain it: make the retrofits highly desirable or make regulations such that there is no alternative to adopting at the disruptive technology rate. On the desirability front, Tesla has shown that electric vehicles can be a desirable status symbol and drive rapid adoption. If communities can show that net zero homes are the "Teslas" of houses, then this level of adoption might be possible. On the regulation-driven front, two non-mutually exclusive options are building performance standards and building codes that make energy efficient buildings and heat pumps the de-facto choice. For example, Washington State recently introduced new building codes that will require high efficiency heating equipment — so efficient that only heat pumps can meet the requirements [179]. The U.S. states of Maryland, Colorado, Washington, and Oregon have implemented building performance standards that require large commercial buildings to lower their emissions each year toward net zero by 2050 or sooner or else faces fines for every ton they are over the cap [20]. This approach could be applied to smaller households too, although it has not yet at the state-level. No single policy will likely be the silver bullet to achieve the "disruptive technology" rate of adoption for building retrofits. Communities will need to track retrofit adoption and adjust programs to meet their goals.

Second, Oshkosh faces a challenge of rental units not being renovated since the landlord rarely has the incentive to do so. 26% of all households in Oshkosh are renters so the only

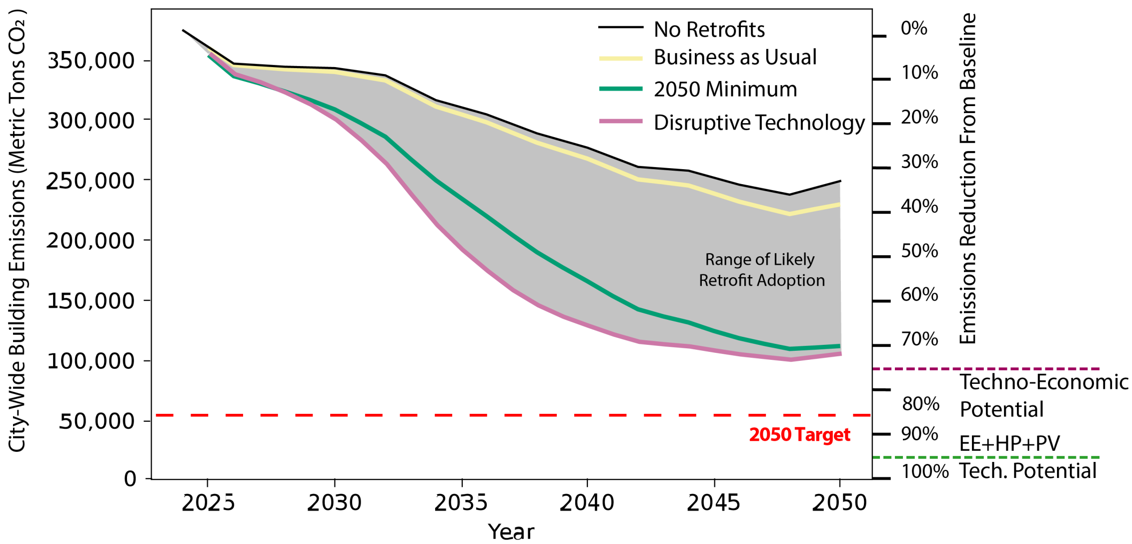


Figure 6.8: Oshkosh-wide results for the three different diffusion scenarios compared to the baseline of no retrofits and the technical potential, 100% adoption of the EE+HP+PV retrofit package. They grey area is the range of likely outcomes depending on the actual diffusion rate.

emissions reductions from these buildings comes from the decarbonization of the electricity supply. Even if the former issue is solved and adoption looks like the 2050 minimum or "disruptive technology" pathways, there is a gap of over 100,000 tons of CO_2 emissions in Figure 6.8 between the technical potential if all buildings are retrofitted and if only those that are willing to pay are retrofitted. Leveraging the finding that most owner-occupied households do not need subsidies frees up money that can be used to target the remaining households and make retrofits feasible for landlords.

There is one additional aspect that cannot be captured in the analysis of Oshkosh-wide emissions alone. As shown in Berzolla et al. (2023), there are areas in Oshkosh that have lower emissions reductions because they are predominantly renter-occupied neighborhoods. It is critical to address and prioritize emissions reductions in these neighborhoods. However, this must be a both-and approach. Otherwise, Oshkosh risks a "tale of two cities" where certain neighborhoods adopt and others are left to shoulder the burden of the remaining natural gas grid and all the negative impacts of burning fossil fuels in homes [178]. These disparities will be less apparent in the high adoption scenarios but will nevertheless be a concern for equitable adoption of retrofits.

One of the challenges with achieving the same growth as disruptive technology in the Heating, Ventilation, and Air Conditioning (HVAC) industry is that by and large the industry is not yet ready to put its full force behind heat electrification. If a households' furnace dies, the household will call their HVAC company who can usually replace it with a new furnace within a day or two. Retrofitting in a heat pump can often take much more time if the unit is even available — they often have to be special ordered or are on back order. Plus, there is an acute lack of workforce trained to install heat pumps and so finding a contractor to install a heat pump when you need it can be difficult. If there is no alternative other than a heat pump and adequate workforce training to ease the transition, these challenges could be alleviated. Furthermore, the energy efficiency measures, especially the air sealing and insulation in the EE package used in this chapter, are key to cost-effectively and comfortably using a heat pump in many regions of the country (especially in Oshkosh with its cold winters). But these EE measures cannot be done overnight, so they must be staged before the current heating system wears out. This could be done — buildings with old heating systems could be first priority for energy efficiency retrofits and funding — but this is not current practice. This efficiency first approach will have the further benefits of reducing the demands of electrification on the power grid and reducing the upfront cost for implementation since a smaller heat pump will be needed once the building is weatherized.

6.3.5 Applicability Elsewhere

This analysis identified non-monetary factors as the key challenge to achieving the retrofit adoption necessary to achieve Oshkosh's emissions reduction goal. A lack of trained workforce and misinformation about the economics of heat pumps are endemic issues in the U.S. so money spent to counter these challenges will help raise the retrofitting rate in all cases. Additionally, money spent on policy to create a "disruptive technology" landscape for households will also help drive up the retrofitting rate. However, there will be areas in the country where households are not willing to pay for most retrofits and thus spending money on subsidizing retrofits will be crucial to seeing substantial adoption. For example, willingness to pay for retrofits is highly tied to income and so low-income areas will have much smaller pools of potential adopters. Willingness to pay is high in Oshkosh because the EE package is cheap enough and lower-income areas tend to be smaller and thus have lower retrofitting costs, making their likelihood of being willing to pay higher. This is one of the biggest benefits of calculating the retrofit cost based on the actual building geometry. In the real world, there will likely be additional costs that this model does not account for, such as remediating mold or lead that are pre-existing.

6.4 Conclusion

The model developed in this chapter is designed to help identify programs and policies necessary to achieve full technical potential emissions reductions given the socio-economic realities of a city. It leverages a previously developed willingness to pay model that provides a likelihood a household will adopt a retrofit based on the upfront cost of the retrofit and their socio-economic indicators. By defining this information based on census data for every building in Oshkosh, the model can decide whether or not a household will retrofit and to which package. Encouragingly, only 8% of owner-occupied households are not willing to pay for any retrofit. This shows there is an economically-captive market for retrofit in Oshkosh. Achieving Oshkosh's emissions goals is thus not an issue of having enough money to give to households to encourage them to retrofit as it is a follow-through challenge of getting households to actually implement retrofits. To this end, this chapter introduces a novel application of a diffusion model to analyze how adoption will play out based on a range of diffusion rates from the literature. As expected, a "business as usual" adoption rate of 1% is incompatible with achieving 2050 emissions reduction goals. However, adoption that mimics the rise of "disruptive technology" can lead to 92% retrofit adoption in owner-occupied homes by 2050. If the latter adoption rate is attained, the only thing keeping Oshkosh from achieving it's emissions goals is addressing the emissions from renter-occupied housing.

Thus this chapter shows that one of the most crucial policies to achieve Oshkosh's emissions reduction goals is to either implement programs that make deep retrofits highly desirable so that adoption rates mimic the "disruptive technology" or to implement policies that require a high adoption rate of energy efficiency, heat electrification, and solar retrofits such as building performance standards. If well-implemented, these policies will ultimately reach every household and help Oshkosh achieve its goals. While this analysis has been demonstrated in Oshkosh, WI, it can be carried out in other cities in the U.S. where a UBEM has been built and census data is available. Given that 66% of all households nationally are owner-occupied and in Oshkosh this was only a little higher at 74%, this result will likely hold in most communities in the U.S. The biggest difference will likely arise in communities with higher retrofitting costs, more renters, and lower household incomes, as fewer households will be willing to pay for the retrofit's cost. Either way, this approach can be used to quantify emissions reduction gap cites face with current policies and motivate further policymaking to address these challenges.

6.5 Summary

By combining the willingness to pay model and building-based cost and energy savings, this chapter enables bottom-up modeling of retrofit adoption in a city. For the first time, households that are identified as willing to pay for a retrofit are placed into a "pool of potential adopters." These households are then sampled from for yearly adoption based on a diffusion model, with likely diffusion rates sampled and a range of outcomes shown. The results show that Oshkosh retrofitting is diffusion-limited, not upfront cost-limited. In a business-as-usual diffusion scenario of a 1% adoption rate, emissions reductions are minimal and mimic the results found in Chapter 4. In a higher diffusion rate scenario with adoption following that of window air conditioners when they were first introduced (a "disruptive technology" scenario), emissions reductions can achieve their techno-economic potential in owned homes. This chapter thus shows that in Oshkosh (although not necessarily in every community) funding is best spent on building out programs and policies to support retrofit adoption rather than solely on subsidizing the retrofits themselves.

Chapter 7

Conclusion

This dissertation has outlined the systematic use of UBEMs and accompanying techno-economic analyses to drive net zero planning and policy formulation for any community in the world. This dissertation is the first time to the author's knowledge that UBEMs have been leveraged in a highly repeatable manner specifically to inform policymakers. This work is driven by a theory of change that data-driven local collective action is a key avenue to achieving global emissions reduction goals. By empowering data-driven decision-making in the built environment through the techno-economic and adoption model development, this dissertation hopes to help policymakers incentivize the right programs and implement the best policies to achieve emissions reduction pledges in line with the Paris Agreement. In addition to the in-depth case study of Oshkosh, WI, these tools have been proven through successful case studies in 24 cities globally which is discussed in Section 7.1 of this Chapter.

This chapter revisits the hypothesis from Chapter 1 and discusses them given the findings of the proceeding chapters. Finally, Section 7.7 will evaluate the impact the tools developed in this dissertation can have in the world and some broader challenges that will need to be addressed.

7.1 Applying the 8 Step Framework Globally

One of the core research focuses for this dissertation has been streamlining the process to build an UBEM to support data-driven decision-making for any community trying to achieve their emissions reduction goals in the built environment. One of the key methods used to advance this goal has been iterative development of the UBEM tools, namely UBEM.io, through workshops run by the author. To date, these workshops have touched 24 communities on five continents (see Figure 7.1 for a complete list). Each successive workshop has

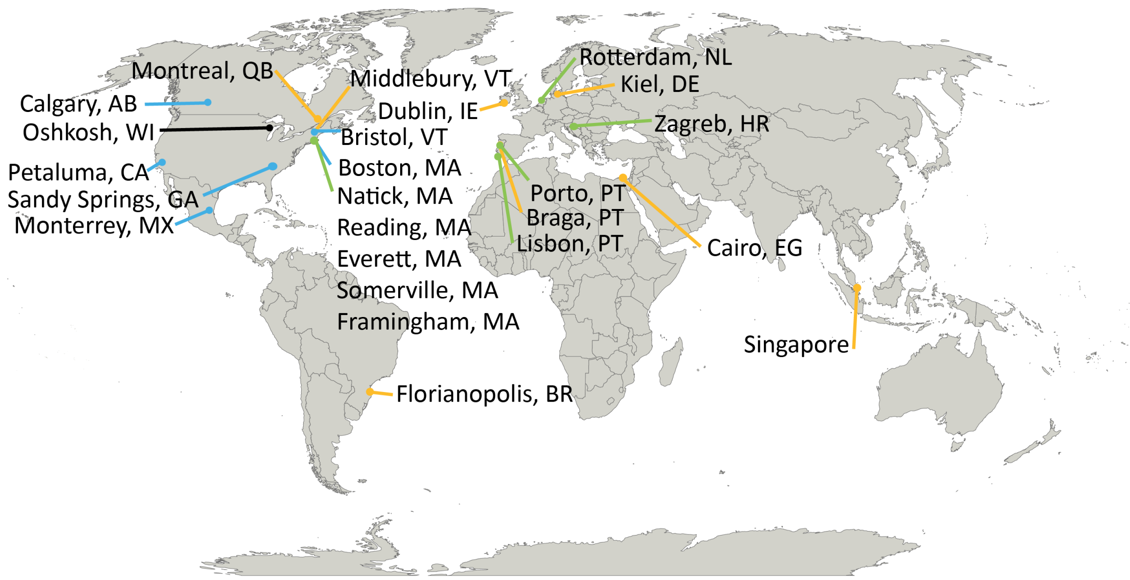


Figure 7.1: Cities modeled in workshops the author has led. Cities in green introduced the sustainability champions as a key component of the work, cities in blue leveraged a local GIS manager, and cities in orange partnered with local energy modelers as well.

helped refine the tool and helped simplify the modeling process to reduce the time, cost, and effort for building an UBEM. The workshops have further created a wealth of knowledge around opportunities to better engage and provide additional value to policymakers by layering analyses on top of UBEMs and creating opportunities to partner with community-based organizations to ensure these models and their findings have staying power and go on to inform policy changes.

The first workshop, held in January 2021 and documented in detail in Section 2.4, showed how the models and results varied widely and justified the need to carry out UBEM modeling around the world. This first workshop was characterized by engagement with city representatives who brought their city's goals and retrofit ideas. Each team had several MIT students working over three days acting in the then-unnamed roles of energy modelers and GIS managers to provide results. The participating cities were recruited through collaborations with local universities. A lot of effort and hand-holding was required to gather all the necessary data and ensure it would work for the modeling efforts.

The second workshop was held virtually in January 2022. The focus was instead regional, on North America, to try and tease out common challenges among communities. In this workshop, drawing on lessons learned from the 2021 workshop, the focus was on identifying GIS managers and sustainability champions in each community that would support the modeling effort and shepherd its use after the workshop. The city of Sandy Springs, Georgia, was a perfect example. The team from the town included the "sustainability manager" and their GIS specialist. Working with them, getting the appropriate data was easy and it worked on the first attempt. They also provided helpful links to their broader policy goals. In Monterrey, Mexico, the author worked with a whole team of consultants who were helping the city in its energy transition. They again were very knowledgeable about energy modeling and had access to all the right data. These two examples showed how their is no one size fits all approach to UBEM modeling, but the UBEM.io pipeline was flexible to handle them all.

Leaving this workshop, the author and his advisor spent substantial time documenting the entire UBEM process on a companion website to UBEM.io. This website acts as a step-by-step guide for any community looking to build an UBEM and addresses frequently asked questions along the way. In collaboration with other researchers, key data checks were also integrated into UBEM.io so that data issues could be rapidly identified and addressed in GIS software by the respective GIS managers. The result is that on-boarding for future modeling exercises can be done in a 30 minute group call where key information about the UBEM process is shared and city representatives asked to fill out online forms and test their own data to ensure it works before the workshop even starts. This greatly reduces the workload during the workshop and helps to keep the focus on technical retrofit pathways. Ultimately, the broad range in climate zones across North America (2A in Mexico and 7 in parts of Canada) meant that these retrofit pathways varied widely from city to city. The main benefit of the regional approach was the ease of scheduling that came from working across only three time zones instead of 12.

The next workshop, held in September 2022 in Lisbon, Portugal, was the first held in person. The workshop brought together stakeholders from several communities across Europe from Portugal, the Netherlands, and Croatia. Once again, the GIS managers and sustainability champions were a key first point of contact. The vice-mayor of Zagreb, Croatia acted as one sustainability champion, as he was tasked by the mayor with making the city more sustainable. Furthermore, every GIS manager the team interacted with knew exactly what to do when asked for the GIS data and produced it in a matter of hours. One was even somewhat offended when asked if the data "was clean" and passed the UBEM.io checks. The level of sophistication for using GIS data in Europe led in part to this success. For the first time, the energy modelers also came from local communities as well. Some modelers were employed by energy programs for their respective cities and others came from research institutions that partnered with the cities for their decarbonization planning. This was a key step in separating the UBEM process from an academic institution-led process.

The key improvement for this workshop was a total redesign of UBEM.io that added in the ability to hand over files between the GIS manager and energy modeler easily, specify retrofit packages on the website and update the model, and a visualizer to work with the results online once the model was run. With these improvements, the energy modelers only needed a background in individual building energy modeling to participate. The focus of the workshop was thus teaching them how to transition their thinking to the urban-scale and was greatly enhanced by the familiar setup of defining retrofits as "measures" that could be applied through the web app. After an hour touching on key concepts, these modelers knew exactly what to do and were quick to push the envelope of modeling possibilities. By bringing the energy modelers all together in one room and zooming in the sustainability champions, teams could learn quickly from each other. The synergies of all being in one room helped enhance the overall product.

One of the other outcomes of this workshop was the need for city governments to engage in a series of follow-up exercises after building the initial UBEM. These analyses include carefully considering the costs to homeowners of the desired upgrades, raising awareness of existing incentive programs among eligible citizens, and potentially lobbying for new subsidy programs that ensure retrofit measures are implemented across the demographic spectrum. Training a local workforce to implement those changes at fair costs is also vital. These issues thus became a central focus for this dissertation.

The culmination of these efforts was a workshop held in person at MIT in January 2024. This workshop engaged communities across Massachusetts in collaboration with the Metropolitan Area Planning Commission (MAPC). MAPC is a state government organization tasked with helping 101 communities in the metro Boston area with all their planning needs. They have been engaging on emissions reduction planning for several years but had not provided energy model-driven results to date. This workshop was a test case to see how they could leverage an UBEM to provide a value-added service to their communities. By leveraging MAPC's existing relationships with cities and their status as a trusted go between with community based organizations, recruiting interested cities was easy. 12 communities expressed their interest in participating during a week-long call for interested parties. From this list, five communities were chosen based on their socio-economic, geographic, and building type diversity. Each community leveraged their GIS departments to provide the requisite GIS data and had a sustainability champion join the introductory and concluding sessions via zoom. The energy modelers came from both MAPC and several local firms that are traditionally focused on building energy modeling.

Half a day of the workshop was focused on implementation challenges ranging from costs to workforce development and equity impacts. A nationally-renowned workforce development expert, Dr. Girard Melancon, joined to lead the conversation and learn from the challenges each community faces. Dr. Melancon sits on the U.S. DOE's 21st Century Workforce Advisory Board and shared numerous key takeaways for each community attempting to address their workforce shortage to implement retrofits.

January 2024 was the first workshop where non-academic partners were the sole participants. The success of this arrangement showed that UBEM modeling can be scaled to any community in the world, regardless of whether an academic institution or consulting firm plays an anchoring role. This was confirmed by MAPC expressing its desire at the end of the workshop to continue these efforts and grow the UBEMs to be a service they can offer as part of their broader decarbonization planning efforts for communities. Having a governmental organization excited to take the lead for UBEM planning is a monumental outcome of these efforts.

In summary, through four years of development UBEM.io can now be used by non-experts in the field to successfully build an UBEM, evaluate techno-economic pathways to emissions reduction goals, and identify key implementation tasks to achieve these goals. By breaking down the UBEM process into core focus areas and tapping into existing expertise in communities, the modeling process can happen quickly and cheaply, therefore making it scalable to any community with the requisite data.

7.2 UBEM Accessibility

In Chapter 3, a scalable eight-step process to make UBEMs accessible to any community is tested with a case study of Oshkosh, Wisconsin. Drawing on several previous advances in the literature, this process leverages already existing expertise in the GIS manager, Sustainability Champion, and Building Energy Modeler to open UBEM analyses to communities at relatively low time and thus cost. It is estimated that a small American city like Oshkosh would only need about $15,000 to implement a stock-level UBEM using UBEM.io. This framework is applied to a total of 24 cities on five continents through the workshops described in Section 7.1. The broad application and its success in these diverse case studies have demonstrated the approach's efficacy in aiding policymakers with their decision-making. Thus **the eight-step framework makes community-scale UBEMs achievable for any community in the U.S. with the proper data and a small grant from the utility, a nonprofit, or the federal government, making them readily scalable**. Furthermore, leveraging the geometry-based approach of a bottom-up UBEM, these analyses showed that **UBEMs can readily quantify material and labor requirements to implement the requisite technology pathways. This information enables policymakers to develop policies and programs to overcome any technical, material, and labor-related roadblocks to achieving their goals.** These key takeaways can inform next steps for a community to take as they strive to reach net zero by 2050 or sooner.

7.3 Willingness to Pay for Retrofits

In Chapter 5, the author conducted a survey of households across two Northeastern U.S. states and leveraged regression analyses to model how likely homeowners of varying socioeconomic background are to pay for a retrofit. This chapter showed that **homeowners income, concern about emissions, and upfront cost drive their willingness to pay for retrofits.** The research also found that for the median of a five-year payback period, the average homeowner would be willing to pay for a roughly $25,000 retrofit. This novel finding adds a cost threshold to the oft-cited five-year payback time threshold commonly used in the literature. It also found that for the average household, a $25,000 subsidy on a $50,000 deep energy retrofit would more than double (from 27% to 61%) a household's likelihood of adopting this retrofit. Additionally, an education campaign that raises concern about emissions from a household from an average of "slightly concerned" to "extremely concerned" would increase the likelihood of adoption by 12%. Thus a key outcome of this work is that **a combination of an educational campaign about the impact of household emissions and $25,000 in rebates to lower upfront costs for the average household in the study could increase the likelihood they pursue a $50,000 deep energy retrofit from 27% to 78%.** This chapter greatly improves policymakers' understanding of a homeowner's financial decision-making when it comes to pricey deep energy retrofits.

The ability to use this model to identify the techno-economic retrofit potential, as discussed in the first section of Chapter 6, has wide-ranging impacts for implementing policies and programs to support communities' emissions reduction goals.

7.4 Modeling Adoption

Techno-economic modeling using UBEMs and willingness to pay is a necessary but not sufficient step to achieving communities' emissions reduction goals. Even with the material, workforce, and technology to retrofit entire communities quantified, retrofits will not happen overnight. The planning process for complex retrofits can take months or years and households will take time to come to the decision on their own. Incorporating a realistic retrofitting rate into UBEM techno-economic pathways can thus help policymakers understand how their emissions reductions will proceed over time. Chapter 4's review of building retrofit adoption literature leads to iterative improvements in adoption modeling from most optimistic to most realistic. It clearly shows that the emissions from rented buildings can significantly decrease emissions reduction potential across a city. Furthermore, because of longstanding redlining practices and other realities, most rental housing and low-income housing are co-located in geographic areas within individual communities. When viewed spatially, this leads to areas of the city with little-to-no retrofit adoption and thus a **tale of two cities, with some neighborhoods adopting retrofits and others left behind. The economic realities of retrofit adoption today lead to inequity at the city-level that will need to be addressed in order to ensure a just transition.** Chapter 6 refines this model by implementing a willingness to pay criteria and a diffusion model to better estimate actual adoption rates in Oshkosh and thus yearly emissions. The key finding is that **in owner-occupied housing in Oshkosh, households' willingness to pay for a retrofit is not a significant barrier to emissions reduction, with 92% of all owner-occupied households willing to pay for one of the retrofit packages. Instead, the key barrier is the rate of adoption of these retrofits, governed by the non-financial challenges such as availability of a trained workforce, ease of implementation, and whether desirability or policy requirements are in place that could create a "disruptive technology" adoption scenario.** Subsidies could thus be better spent to prevent the lock-in of business as usual fossil fuel equipment, addressing the aforementioned renter adoption challenge, and dealing with the non-financial implementation challenges. Without increasing implementation rates beyond a "business as usual" 1%, any chance of achieving net zero by 2050 is lost.

7.5 Future Work

This dissertation has been focused on rapidly and cheaply developing UBEM models for communities around the world and using these models to help inform policymakers. Specifically, the focus has been on identifying technology pathways to reduce operational energy-related emissions, quantifying the subsidies required to get a household to pay for a retrofit, and identifying the impacts of non-monetary programs that can support retrofits.

This dissertation was focused on operational energy use for buildings and did not delve into embodied energy. As buildings become more efficient, their embodied energy becomes a larger portion of their overall emissions. For example, one case study found that the embodied energy of super-efficient Passive House buildings account for 77% of their lifetime emissions [180]. This does not have to be the case, as more cognizant choices of low-embodied energy materials can reduce this figure substantially. UBEMs are well-positioned to answer embodied energy questions as well. Sory (2023) introduced a method for doing this using the same UBEM tools used in this dissertation, albeit not yet in a way that is repeatable at the same scale [181]. Future efforts in this area could provide policymakers with complementary embodied energy information.

7.6 Addressing the Theory of Change Pre-Conditions

Cities today face structural issues in deployment and roll out beyond the techno-economic ones captured in the previous chapters. If policymakers go through the aforementioned process of building an UBEM, designing technology pathways, and identifying the required resources to make retrofits financially acceptable to all residents, their work will only be starting. The policymakers will need to leverage this information to set clear direction for their city and everyone working on the issue from local non-profit housing owners to individual homeowners. Their cooperation will be necessary to braid together the city, state, utility, and federally-funded incentives that will make retrofits financially feasible for all residents to overcome the financial barriers to retrofit adoption.

Chapter 1 identified six key pre-conditions to the theory of change required to achieve widespread building decarbonization by 2050 put forth in this dissertation. These pre-conditions are: widely available data to inform models, accessible tools to leverage the data to inform policymakers, a knowledgeable workforce to both employ the tools and implement the recommended policies, receptive policymakers interested in engaging with the provided information, funding to carry out the modeling and ultimately the policies, and educated constituents and communities that are aware of, engaged with, and supportive of planned actions. This dissertation's contributions to each of these pre-conditions are addressed below.

7.6.1 Widely Available Data

As seen by modeling efforts in 24 cities around the world, the necessary GIS data to build an UBEM can be found in a wide array of countries on six continents. By engaging a local GIS manager, this data is usually easy to access and manipulate as needed.

7.6.2 Accessible Tools

While initial UBEM tools required a PhDs' worth of knowledge to use, UBEM.io has overcome this by breaking down the modeling process into discrete steps for the energy modeler, GIS manager, and sustainability champion that draws on their existing expertise. The workshops have again shown that these tools are accessible. Furthermore, by partnering with MAPC and essentially handing the tool over to them for further use, the UBEM tools can have a greater impact beyond academia. This ultimately is a great arbiter of accessibility.

7.6.3 Knowledgeable Workforce

This is a two-fold problem and this dissertation focuses on the first part. The author has undertaken extensive efforts to foster a knowledgeable workforce that can use UBEM tools to help make data-driven building decarbonization policy a reality around the world. The author has delivered talks to:

- 150 participants from across India, including the Minister of Power, in a U.S. Agency for International Development webinar
- 100+ stakeholders across the 22 communities that have participated in UBEM modeling workshops
- 30+ building simulation experts through an International Building Performance Simulation Association webinar on UBEM.io
- 200+ total scientists, engineers, and policymakers through conference presentations at the American Physical Society New England Spring 2023 Section meeting, American Geophysical Union Fall 2023 meeting, Getting to Zero Forum Fall 2021 meeting, and the Fall 2021 ASHRAE Building Performance Analysis Conference

These talks have educated scientists and engineers about the possibilities for using UBEM tools to effect change in their own communities.

As for developing the workforce to implement the modeled retrofits, this is a whole different issue. This dissertation has shown in Chapter 3 that UBEM can be used to quantify the required workforce and engage policymakers on the need to address the current workforce gap in the energy efficiency sector. Additional efforts to actually train a workforce are beyond the scope of this dissertation.

7.6.4 Receptive Policymakers

In general, most communities that engage in building an UBEM have receptive policymakers that want to leverage the information provided to benefit their community. In fact, recent funding from the federal government under the Inflation Reduction Act to support emissions reduction planning has been accepted in all but four U.S. states [182]. This shows that policymakers across the political spectrum are interested in understanding the emissions reduction potential (and the usually accompanying energy savings and job creation) that building retrofits can bring. Thus overall, policymakers in the U.S. are receptive to engaging on emissions reduction planning. In the four states that have not accepted the funding, it has instead been sent to the largest cities in those states to support their own city-level work [182]. This shows that real progress has been made towards policymaker acceptance of the need to conduct decarbonization planning across the country.

7.6.5 Funding

The willingness to pay model developed in this dissertation was designed to help identify the funding requirements necessary to support high rates of retrofit adoption. Thankfully, during the course of this research, the U.S. passed the Inflation Reduction Act which has provided substantial federal funding to support many of the retrofits included in common UBEM packages. This additional funding for both modeling efforts (as described above) and implementing retrofits is crucial to achieving the long-term decarbonization goal.

7.6.6 Educated Residents

Educating households across the U.S. and the world about the benefits of decarbonization retrofits is challenging. One way to succeed in the grassroots-level action needed to convince thousands of individual owners to take action is to engage people through their communities and trusted organizations will be key to achieving this goal. Chapter 5 showed how much an education campaign can increase a household's willingness to pay for a retrofit. This information can be used to support the need to fund programs that engage community members in a wide variety of ways. Ultimately, one approach that has been shown to be incredibly useful in reaching low-income, non-native English speaking, and/or minority populations in a healthcare setting is the use of a "patient navigator" [183]. These navigators "foster trust and empowerment within the communities they serve" and work with patients to help them deal with the healthcare system, picking the right insurance plans, choosing the right doctors, etc. so they can get the best outcomes [183]. A similar approach was used to help households navigate signing up for insurance plans when the U.S. Affordable Care Act healthcare mandate went into effect in 2014 [184]. Healthcare navigators provided free, unbiased advice to households and business trying to choose plans and submit documents.

Training and supporting "retrofit navigators" could therefore be a key way to build support and increase adoption of building retrofits in any community. These retrofit navigators will promote retrofits, coordinate subsidies, aggregate retrofits to crate bulk purchasing programs, set up resident support programs, and organize block-level coordinated retrofit projects to drive adoption even among low-income communities. Even if ultimately some households do not pursue a retrofit that year, their unbiased knowledge about the potential benefits of retrofitting will be greatly improved. For example, when it comes to installing heat pumps, too often households only know what their HVAC contractors tell them — which today is often outdated or biased information about how heat pumps are not cost-effective or will not work in cold climates. Despite being disproven for most areas in academic literature and field studies, these rumors persist and hinder heat pump adoption. An unbiased navigator could help households wade through the confusing array of information and prepare to decarbonize their home. This approach has, in fact, been implemented in Framingham, MA, a Boston-area community that joined the January 2024 workshop. The leveraged federal funding to support one position starting in 2023 to help community members prepare for retrofits.

This section has ultimately shown that between policy shifts at the national scale such as the Inflation Reduction Act and experiences working with communities around the world documented in this dissertation, all of the necessary pre-conditions to achieve the goal of decarbonizing all buildings by 2050 have been met. Thus, the hard work now comes in implementing change levers and achieving intermediate outcomes on the path to attaining the ultimate goal.

7.7 Looking Forward

For a city, state, or other jurisdiction to be successful in convincing the majority of its residents to retrofit their buildings, the implementation program will need to be of a scale and scope that is unrivaled anytime in recent history. The challenges are numerous but salient issues will need to be addressed such as: how to train the required workforce, secure the necessary materials, provide financial mechanisms to fund retrofits for those without the upfront capital, and engage individual residents to carry out the retrofits. While the challenges are numerous, the frameworks and analyses presented herein are intended to make the first parts of the problem tractable for a large number of communities. Through unwavering commitment to reaching emissions reduction goals in the necessary timeframe and collective action by millions of communities around the globe, a more sustainable, climate change resilient future is possible for the world's citizens.

Appendix A

Chapter 5 Appendix Tables

This appendix is taken directly from the Appendix of the journal paper behind Chapter 5. It can be found here: Berzolla, Zachary and Meng, Ting and Reinhart, Christoph, Homeowners' Willingness to Pay for Residential Building Retrofits (August 10, 2023). Available at SSRN: https://ssrn.com/abstract=4536734 or http://dx.doi.org/10.2139/ssrn.4536734

A.1 Robustness Tables

Table A.1: Variance inflation factor (VIF) for each variable in the logit and ordered probit models.

Variable	Logit VIF	Probit VIF
Year built	3.9	6.9
Education	7.0	9.3
# bedrooms	9.7	8.0
# residents	8.1	5.7
Income	3.8	3.8
Concern	2.2	2.3
Upfront cost	2.3	2.0
Neighbor	3.2	3.2
Energy cost	5.2	5.1

Table A.2: Results for the deal/no deal regression when dropping insignificant factors.

Variable	Coef. (est. err.)	P-Value
Education	-0.088 (0.023)	***
# bedrooms	0.243 (0.040)	***
# residents	0.066 (0.028)	*
Income	0.047 (0.005)	***
Concern	0.263 (0.029)	***
Upfront cost	0.023 (0.002)	***

Table A.3: Robustness results for a deal/no deal logit regression with households split by the median income.

Variable	Low-Income Coef. (est. err.)	P-Value	High-Income Coef. (est. err.)	P-Value
Year built	-0.101 (0.042)	*	0.059 (0.052)	
Education	0.104 (0.034)	**	0.068 (0.046)	
# bedrooms	0.239 (0.056)	***	0.327 (0.069)	***
# residents	0.050 (0.043)		0.093 (0.044)	*
Income	0.112 (0.002)	***	0.027 (0.007)	***
Concern	0.298 (0.041)	***	0.249 (0.044)	***
Upfront cost	-0.063 (0.003)	***	-0.053 (0.003)	***
Neighbor	-0.012 (0.068)		-0.006 (0.081)	
Energy cost	-0.035 (0.028)		0.017 (0.032)	

*P-values: *= 0.05, **= 0.01, ***= 0.001. In the standardized model all explained variables are standardized by their mean and standard deviation.*

Table A.4: Robustness results for a payback ordered probit regression regression with households split by the median income.

Variable	Low-Income Coef. (est. err.)	P-Value	High-Income Coef. (est. err.)	P-Value
Year built	-0.030 (0.028)		0.018 (0.026)	
Education	-0.082 (0.021)	***	-0.013 (0.027)	
# bedrooms	0.034 (0.031)		-0.069 (0.030)	*
# residents	-0.042 (0.025)		-0.006 (0.018)	
Income	0.041 (0.013)	***	0.004 (0.003)	
Concern	0.092 (0.022)	***	0.086 (0.019)	***
Upfront cost	0.026 (0.002)	***	0.020 (0.002)	***
Neighbor	-0.038 (0.039)		0.124 (0.036)	***
Energy cost	0.003 (0.016)		-0.037 (0.014)	**

*P-values: *= 0.05, **= 0.01, ***= 0.001. In the standardized model all explained variables are standardized by their mean and standard deviation.*

Appendix B

Chapter 1 Figures

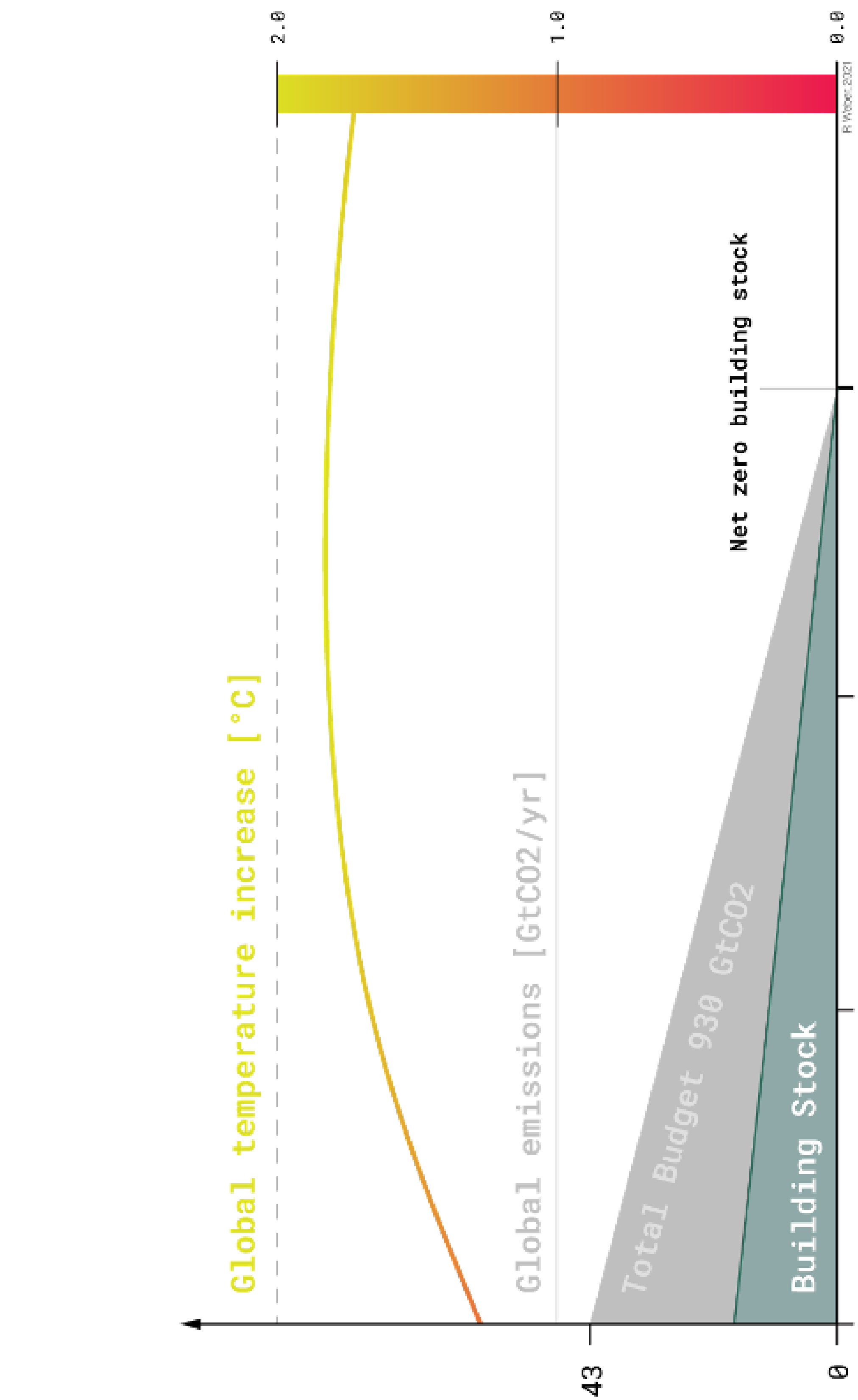


Figure B.1: Emissions budget to achieve Paris Agreement goals. *Figure from [2], used with permission of the author.*

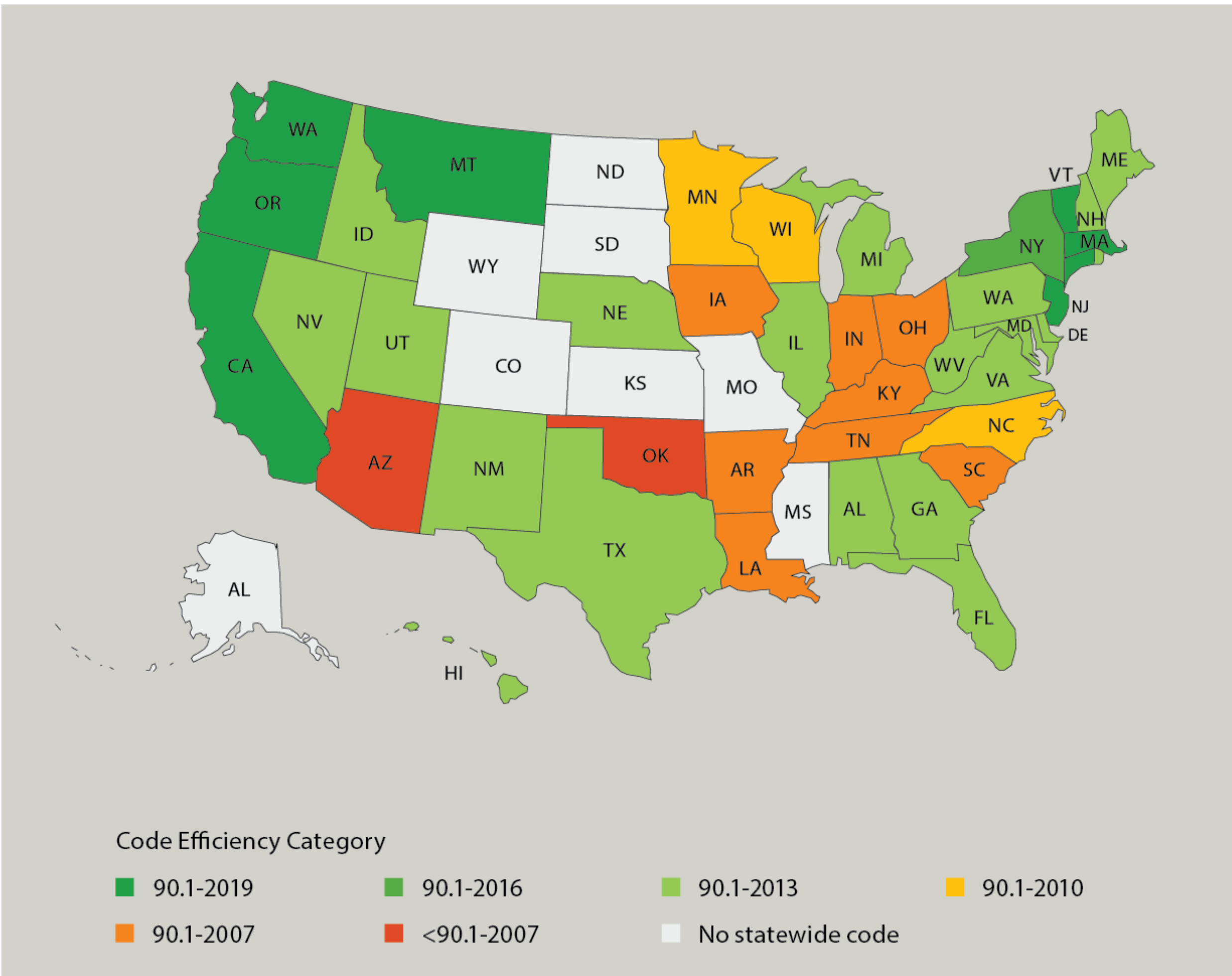


Figure B.2: U.S. states with residential building codes and their year. Older codes are less efficient. *Figure courtesy of Christoph Reinhart, used with permission.*

Figure B.3: U.S. states with building performance standards. 11 cities and one county also have these standards in place. *Figure created by the author using data from [20].*

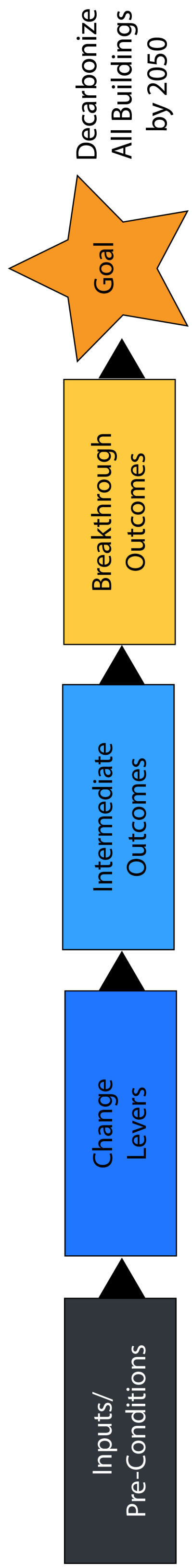


Figure B.4: Key steps in the Theory of Change. *Figure created by the author from information in [21].*

Appendix C

Chapter 2 Figures

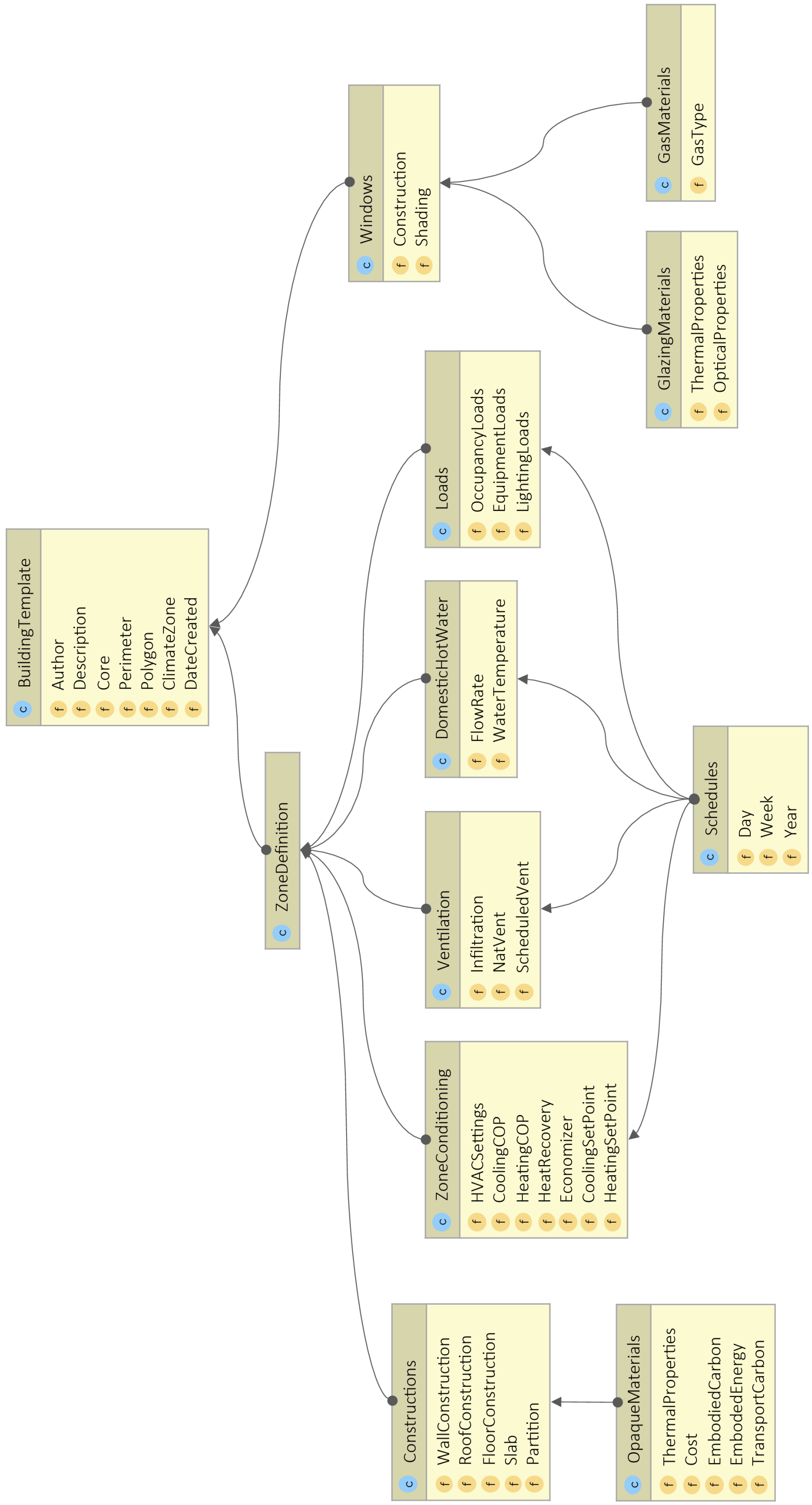


Figure C.1: Building template structure in the template database library. Figure from [59].

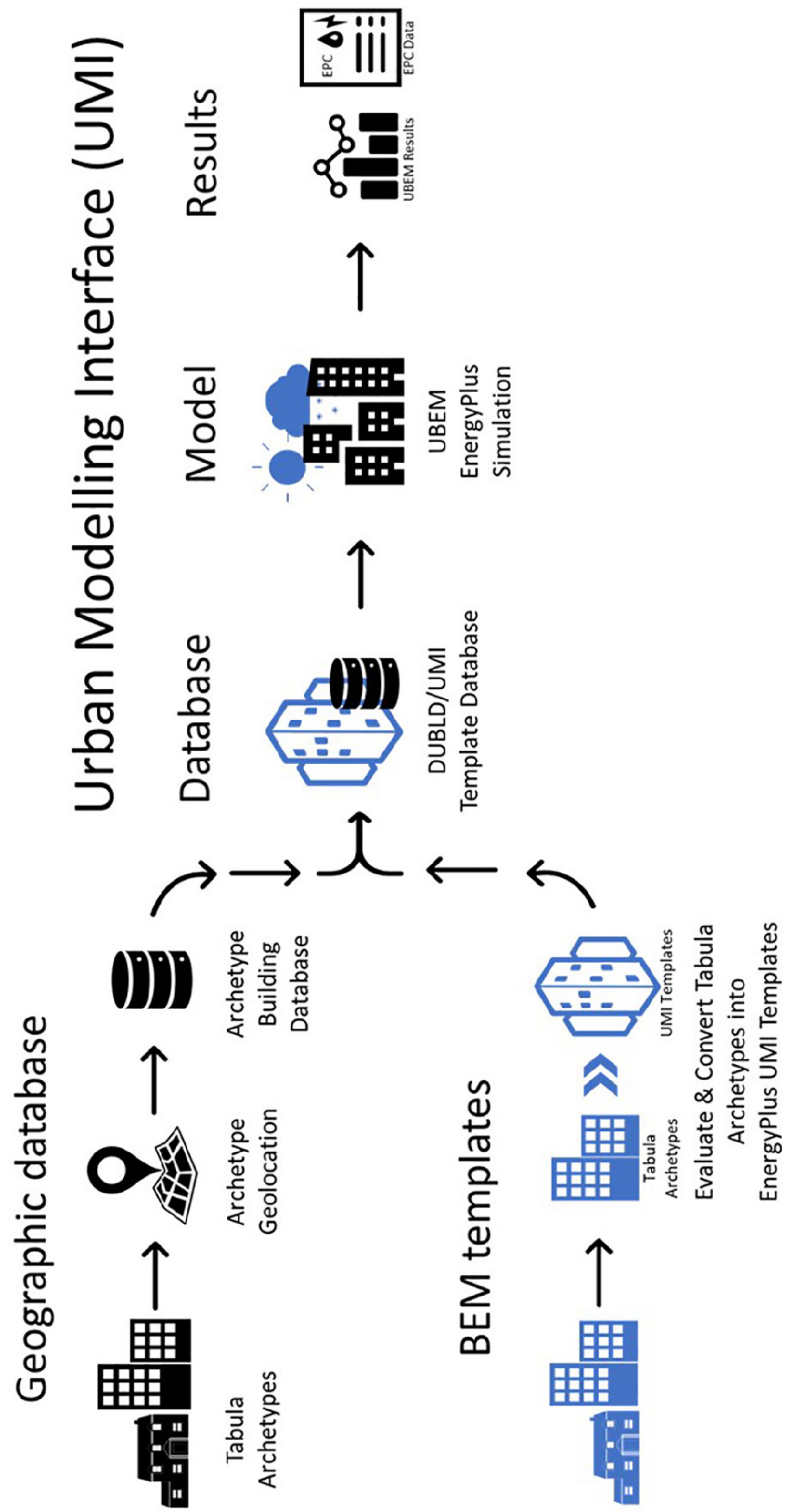


Figure C.2: The workflow used to create UBEM templates from the Tabula dataset. The geographic database categorizes georeferenced building envelopes into Tabula archetypes and generates a GIS database. The EnergyPlus templates are created from Tabula data and then used to generate UMI template files. The geographic database is integrated with the BEM templates within UMI. Figure from [8]

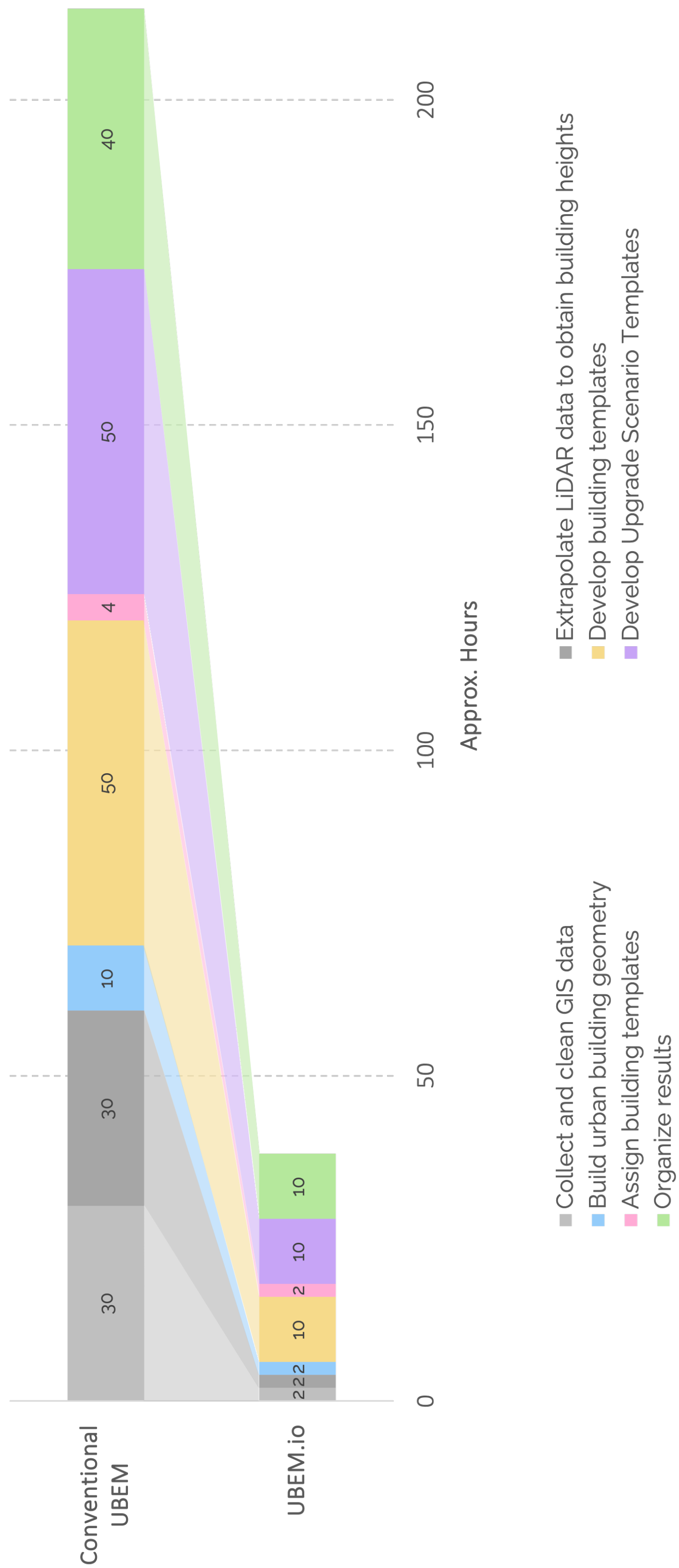


Figure C.3: Estimated time required using conventional methods of developing UBEMs vs. UBEM.io for a medium-sized city. Figure from [59].

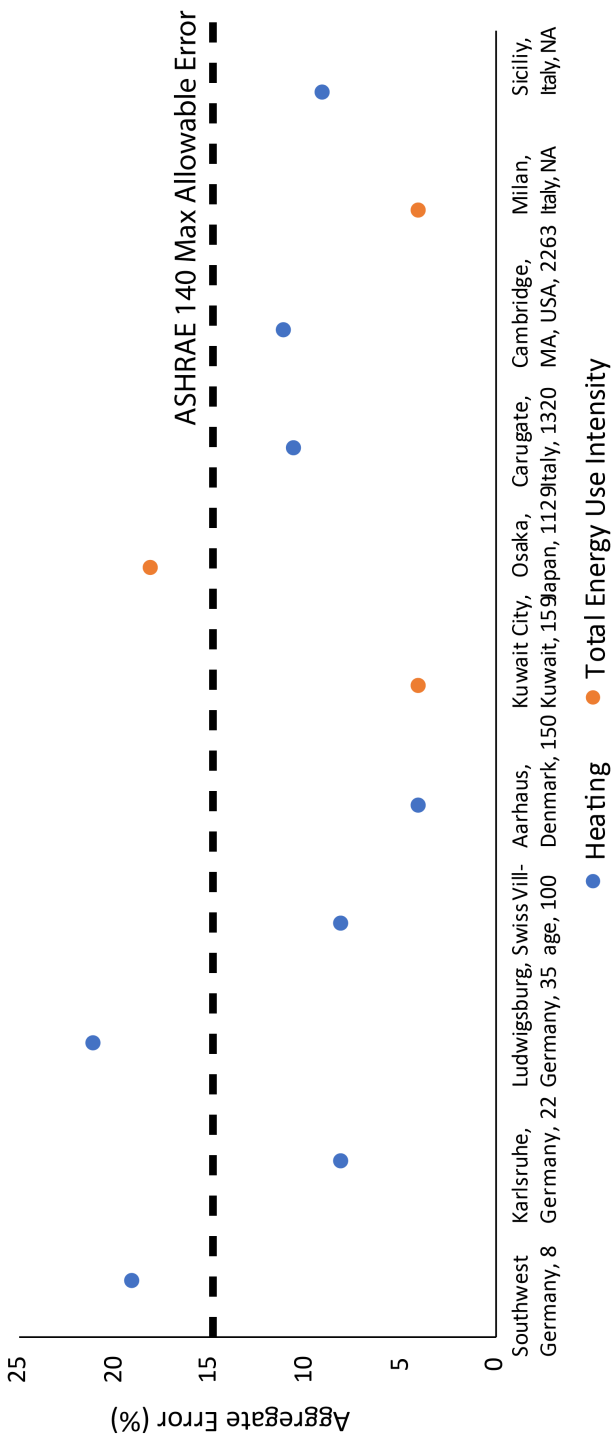


Figure C.4: Uncalibrated UBEM errors of less than 15% is common across a wide range of case studies. *Figure adapted from results in [27], used with permission of the author.*

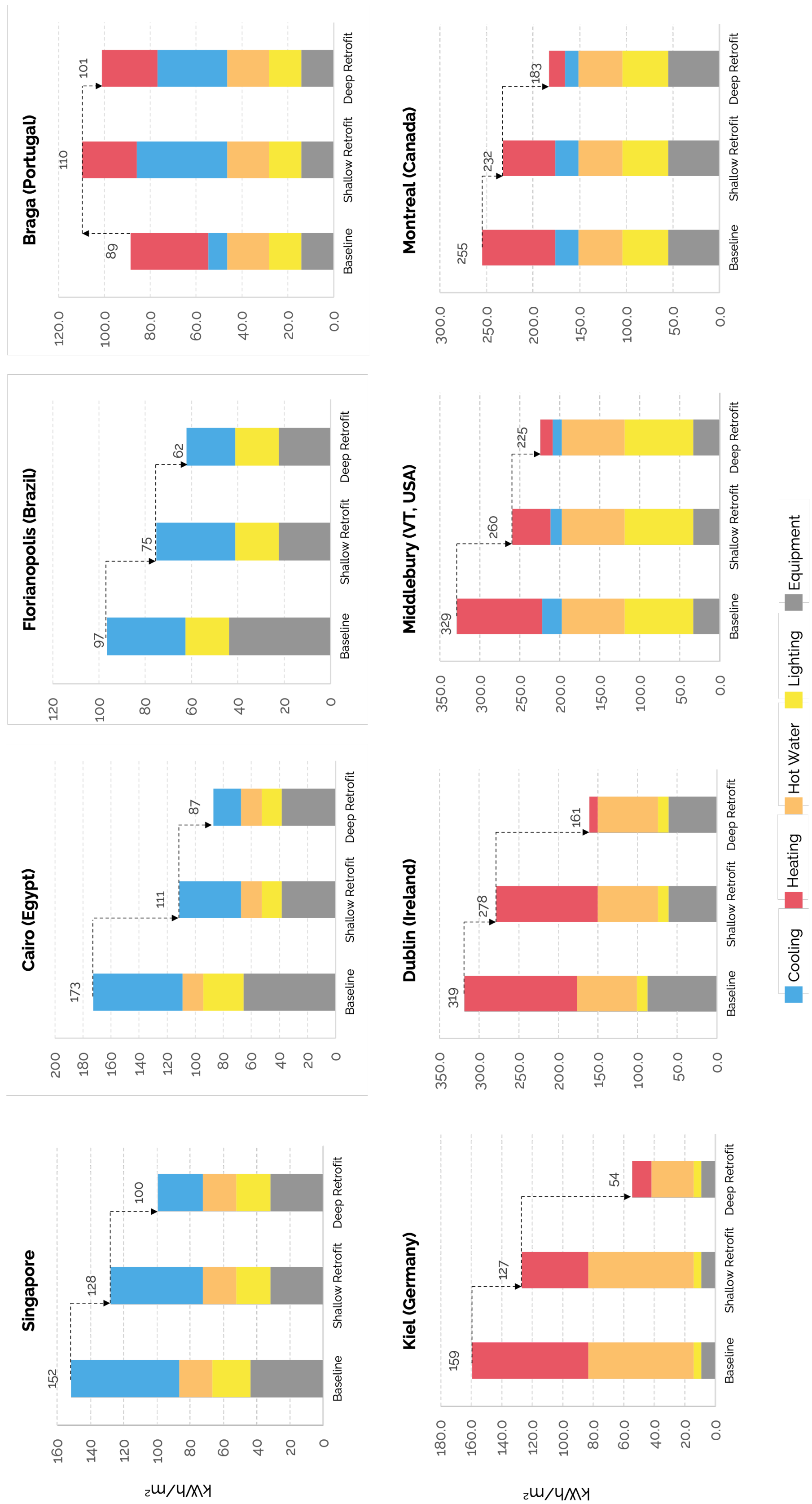


Figure C.5: Energy use intensities from each city. Figure from [71].

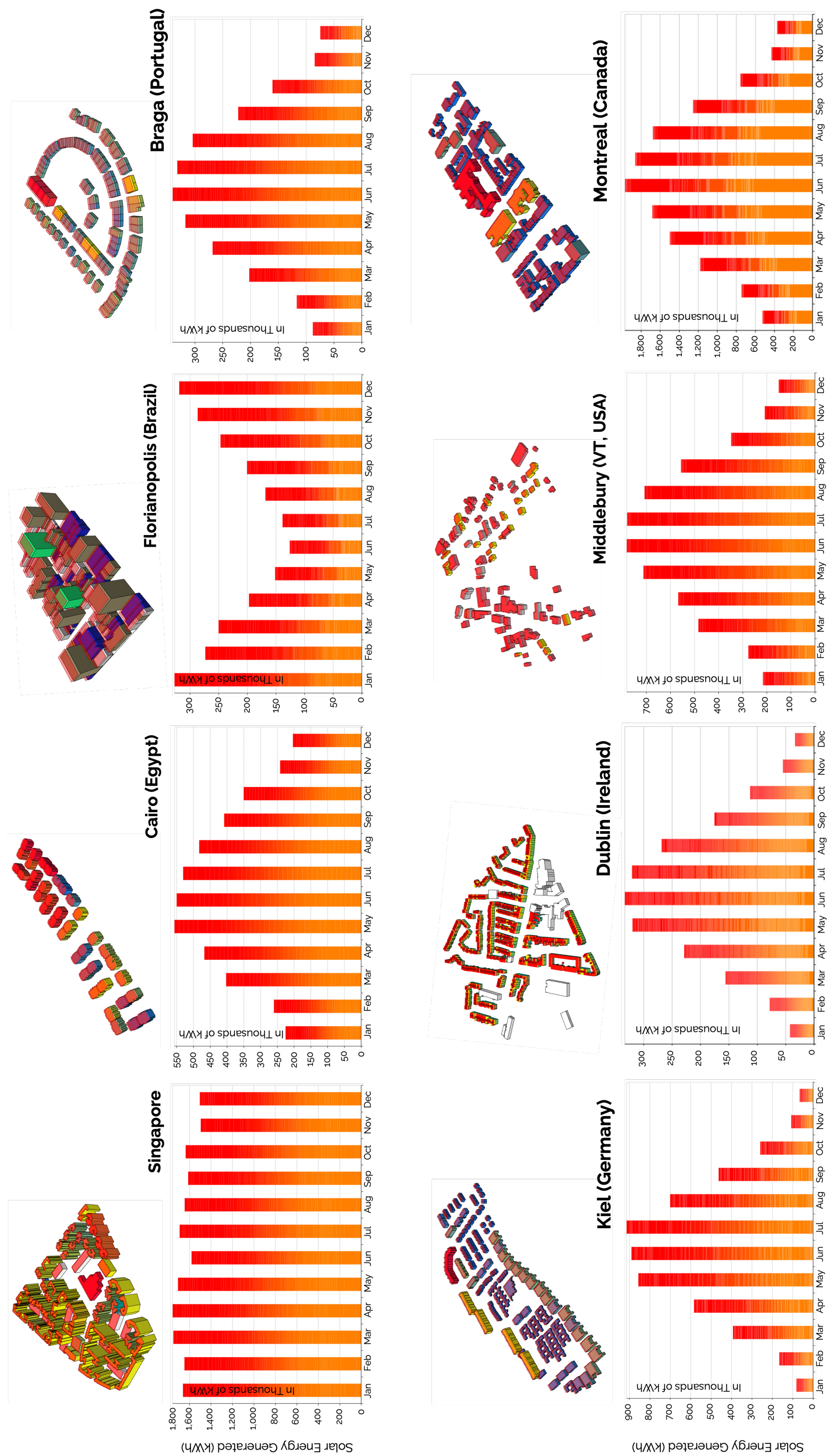


Figure C.6: Solar results for each city. Figure from [71].

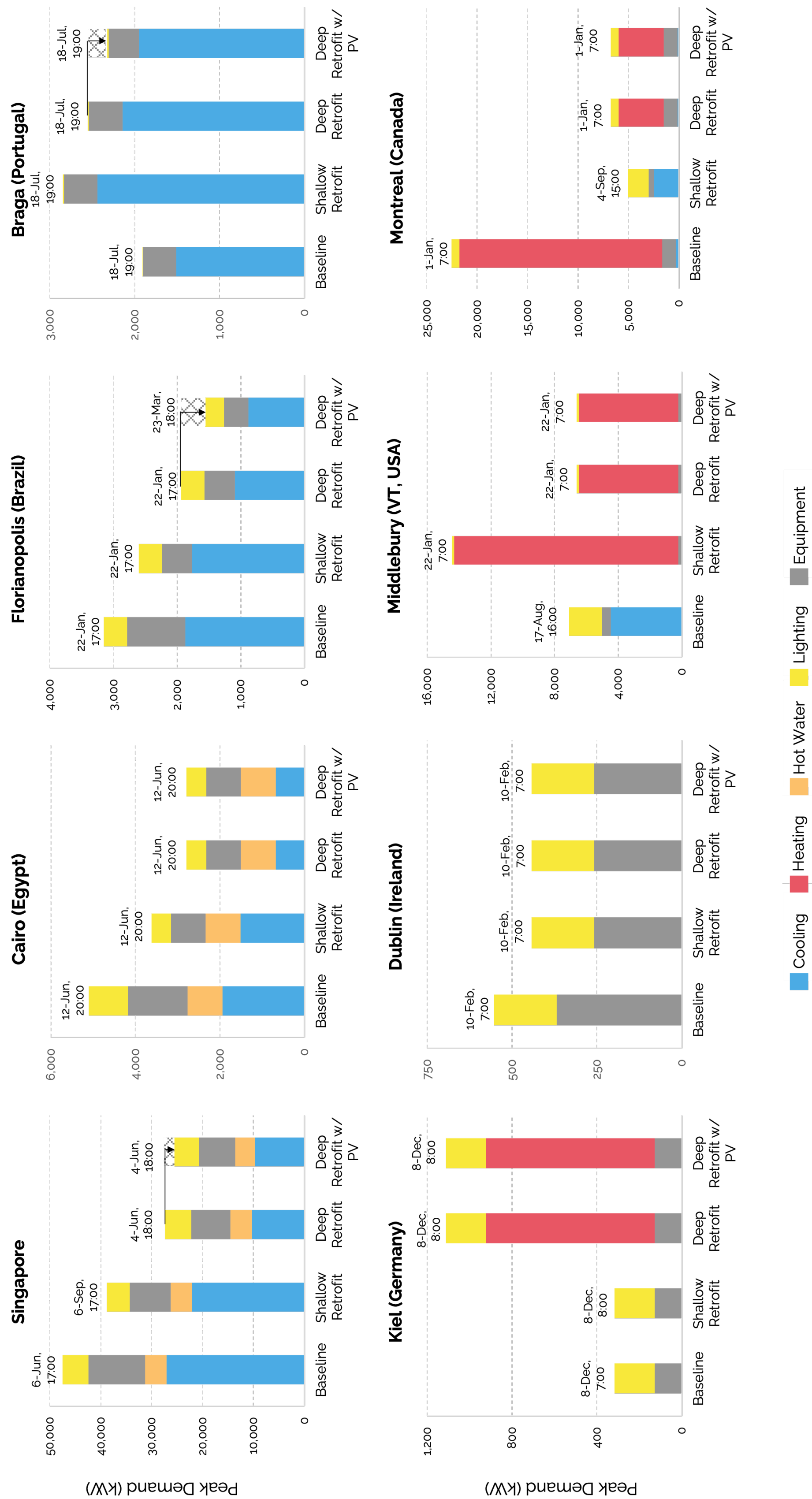


Figure C.7: Peak demand for each city. Figure from [71].

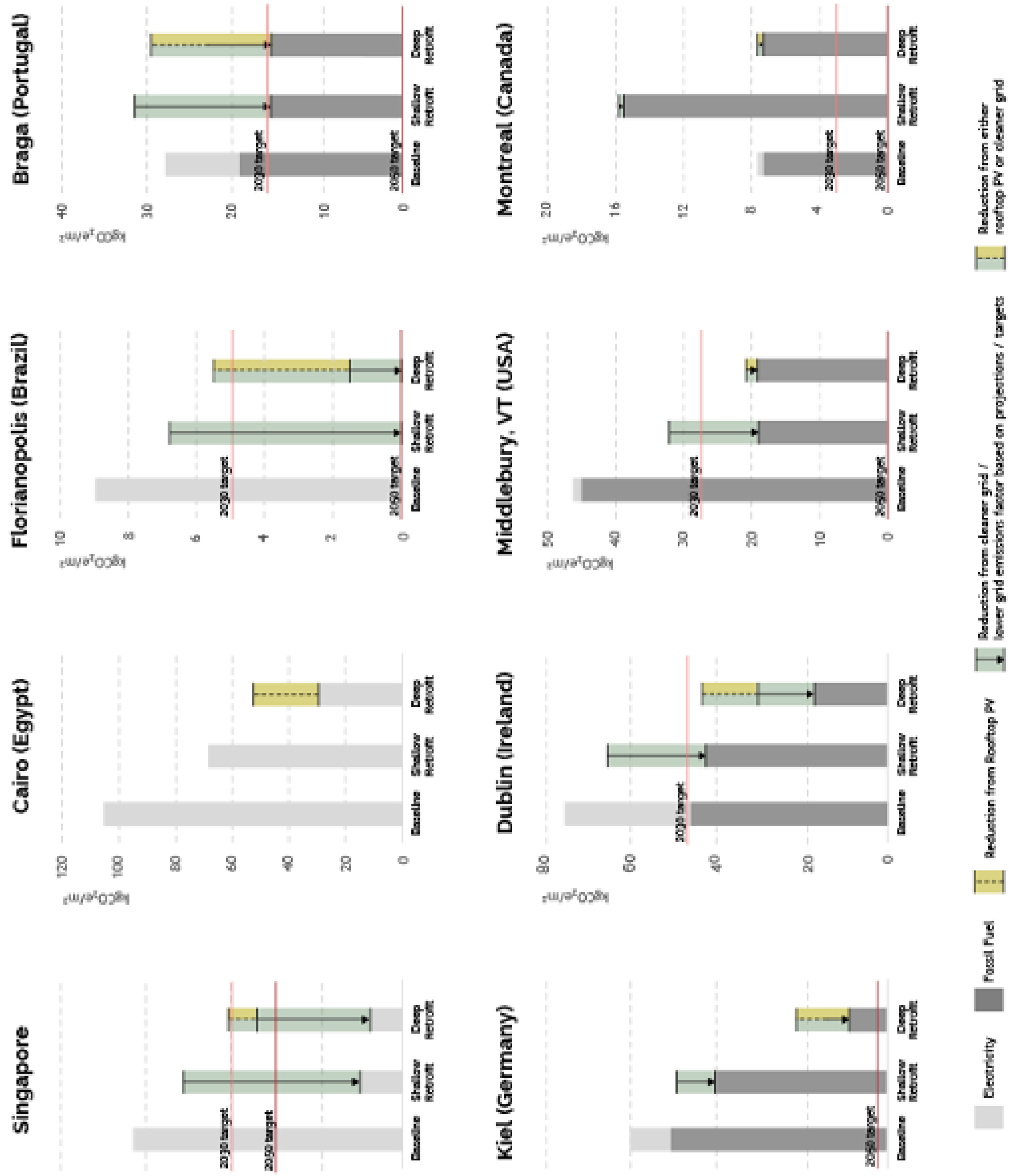


Figure C.8: Carbon emissions for each city. The range of emissions shown captures current and future predicted emissions from the various jurisdictions. Figure from [71].

Appendix D

Chapter 3 Figures

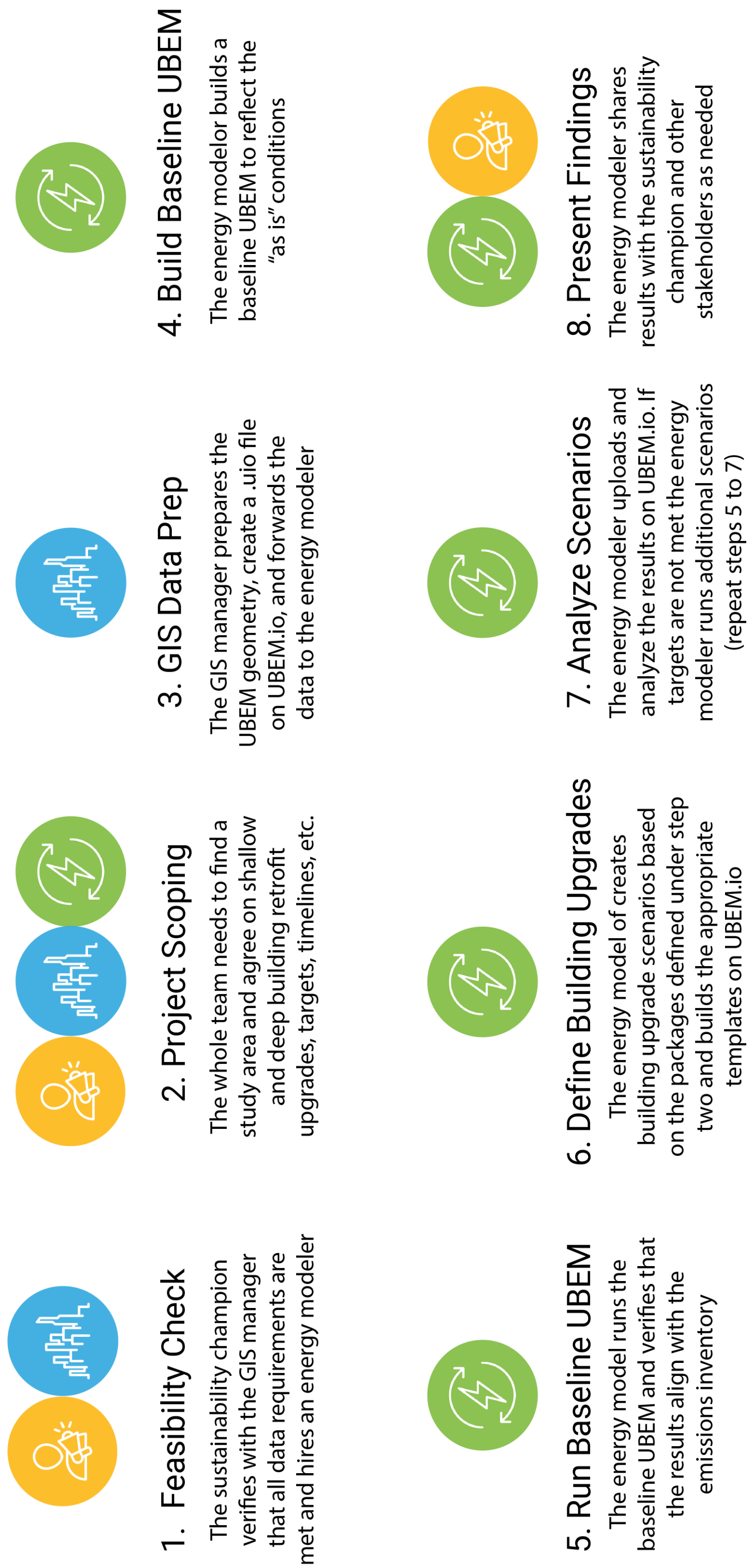


Figure D.1: Eight steps to meeting a community's emissions reduction goals. The key personas for each step are defined. A sustainability champion (in yellow), a GIS manager (in blue), and an energy modeler (in green).

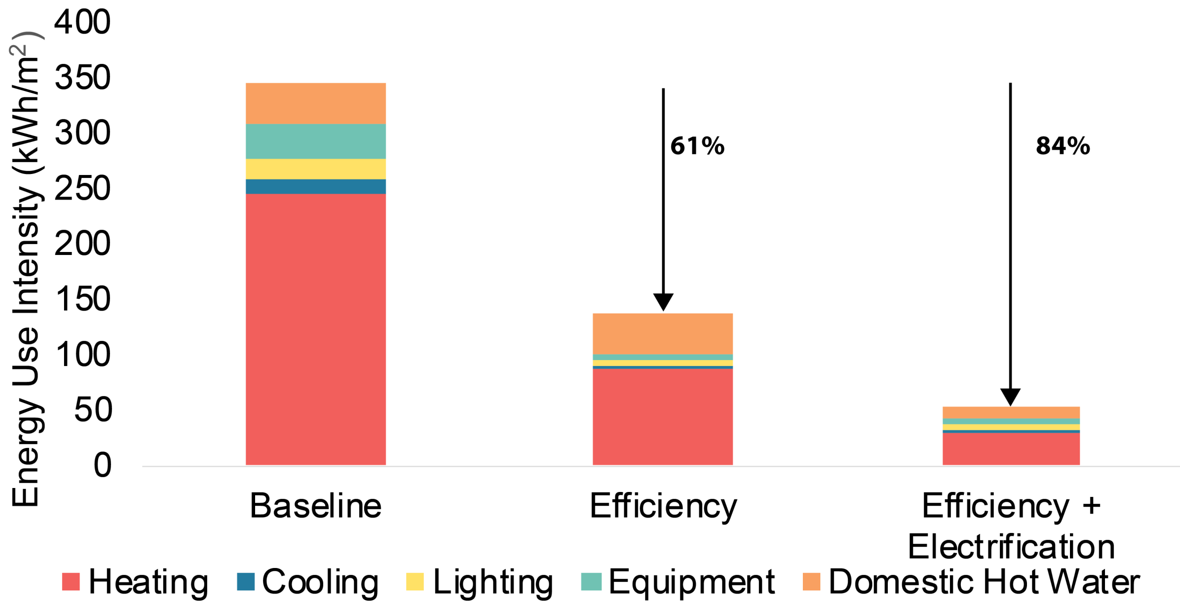


Figure D.2: The energy use intensities by end use of the baseline model for the two technology pathways in Oshkosh. The PV pathway is excluded as the consumption EUI does not change from the electrification upgrade.

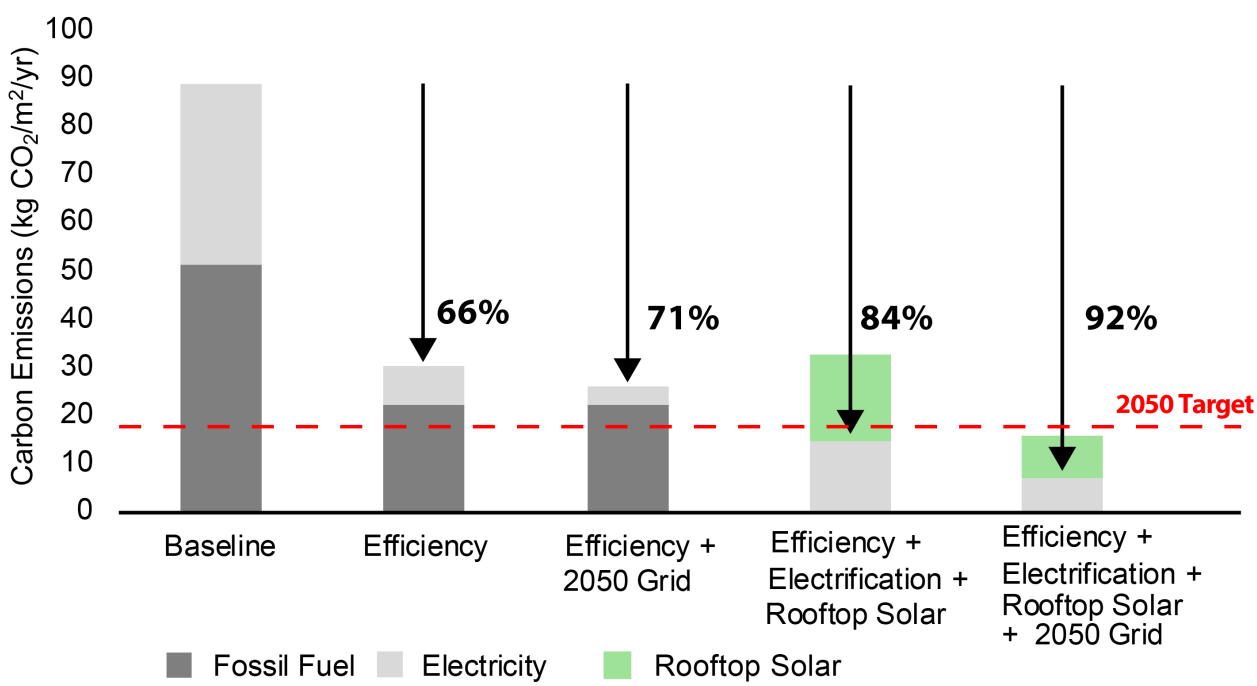


Figure D.3: The strategies for Oshkosh to meet its emissions reduction goals. It is only through a combination of all three strategies (energy efficiency, electrification, and photovoltaics) that Oshkosh can meet its 2050 goal. The addition of grid decarbonization lets Oshkosh achieve nearly net zero by 2050.

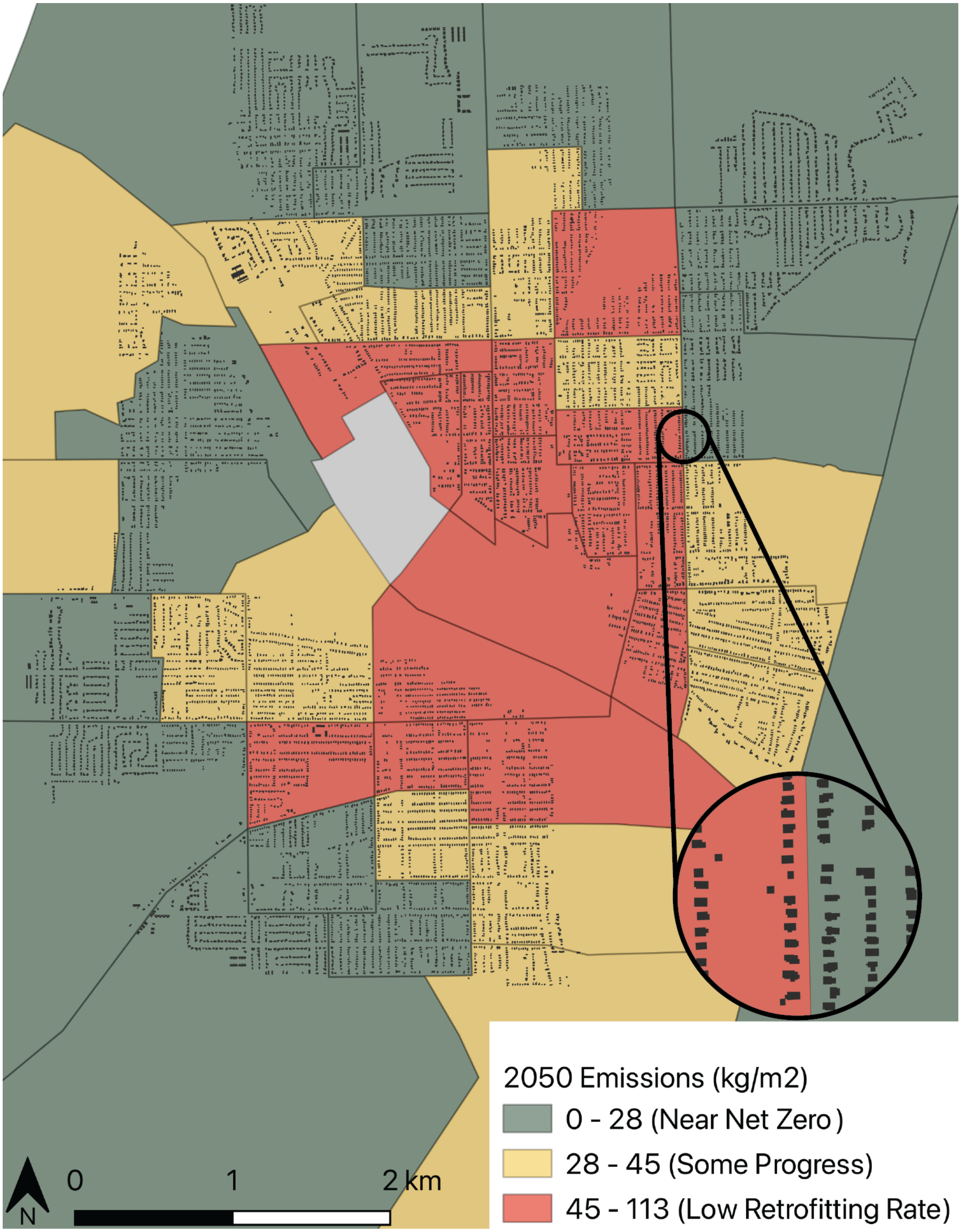


Figure D.4: Area-normalized emissions from residential buildings at the census block level in Oshkosh. Red areas will need to be focus areas for new programs and policies that engage rental units in retrofits.

Appendix E

Chapter 4 Figures

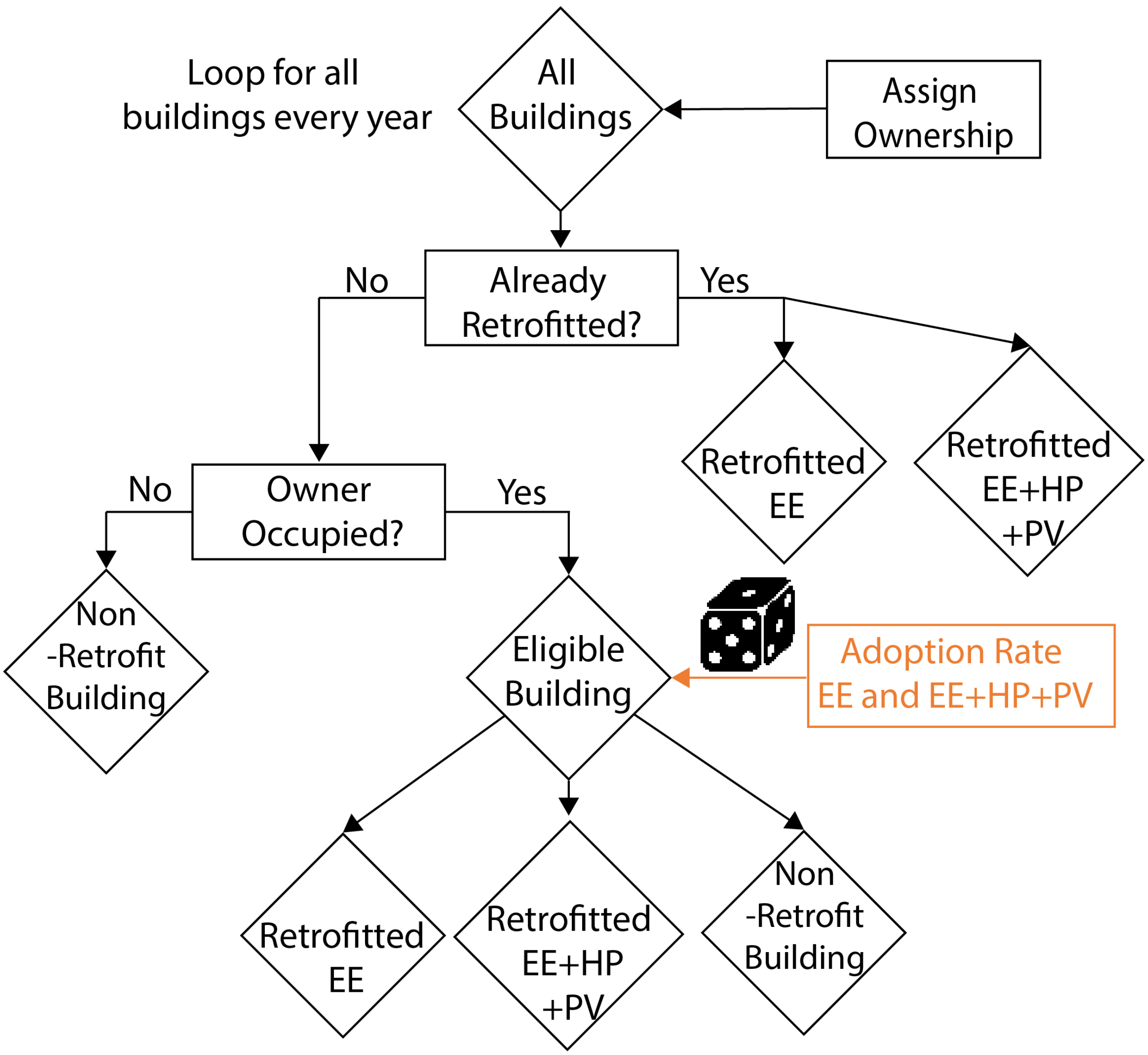


Figure E.1: Outline of adoption model. This full model is used for the upfront cost and payback period with the adoption rate varied based on the Little Model. The ownership model instead considers these adoption rates as equal between the two packages. Ownership is not accounted for in the baseline model.

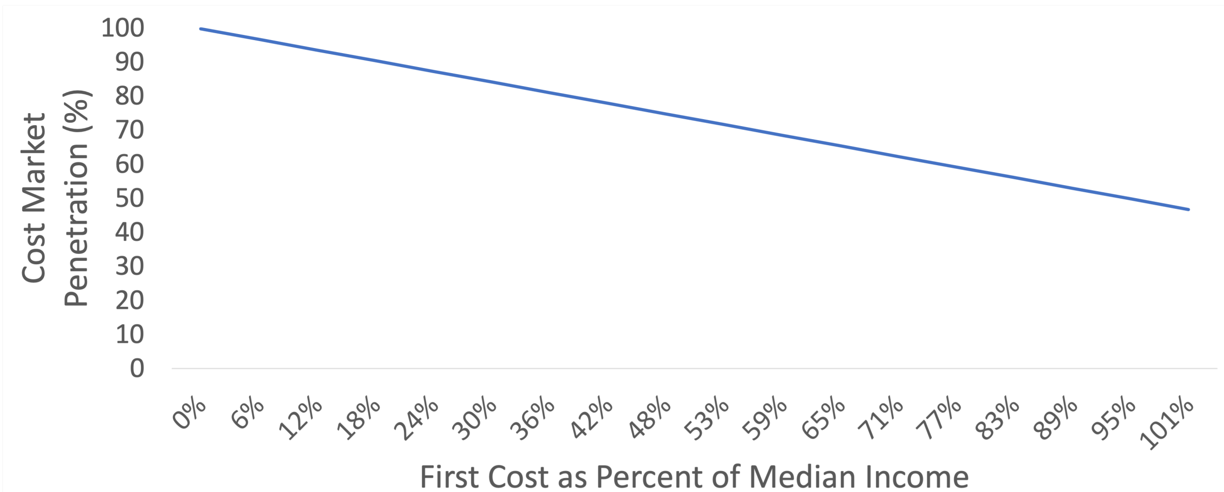


Figure E.2: Arthur D. Little market penetration by first cost normalized by median household income (left) and payback period (right). Total penetration is determined by multiplying the two factors together. Adapted from [130]

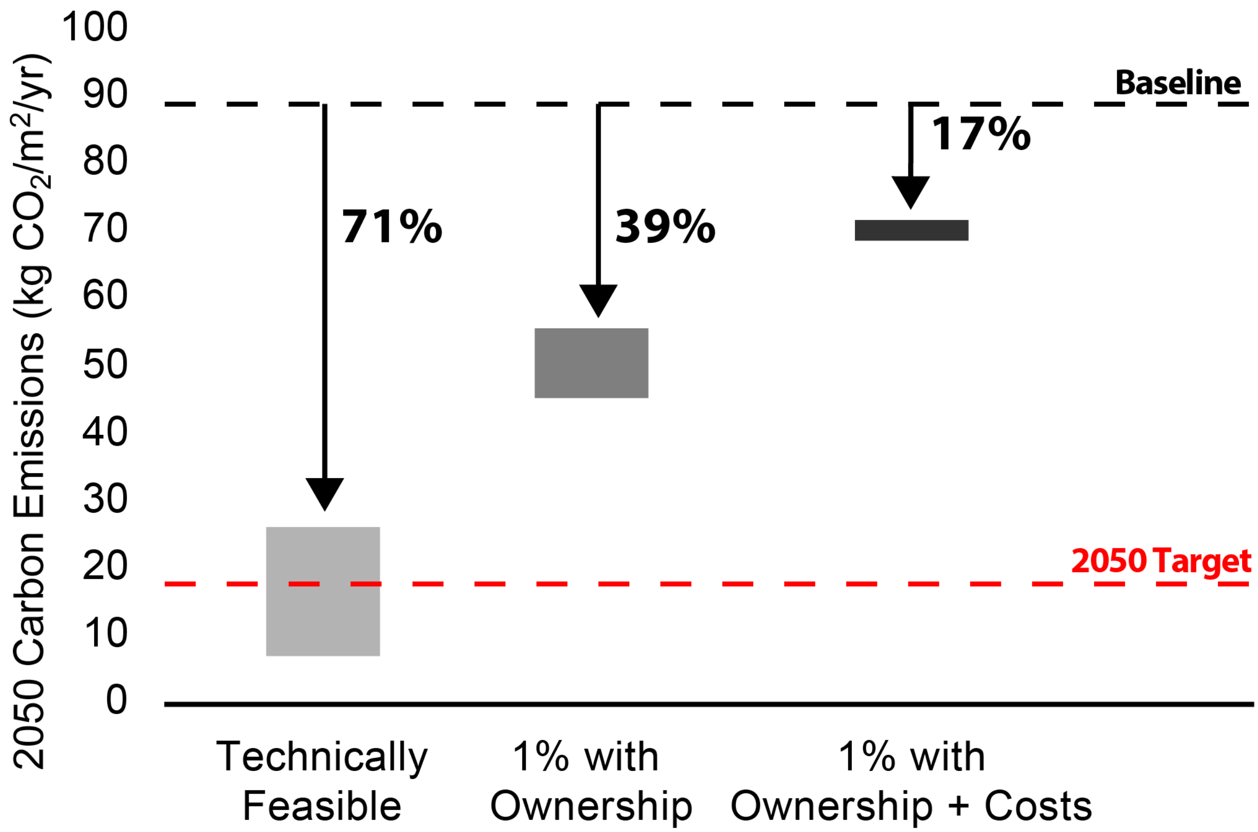


Figure E.3: Range of 2050 emissions results for the Oshkosh case study with different adoption model refinements. The high and low bounds are set by the mean of 2050 results for each the two upgrade scenarios over 100 stochastic runs.

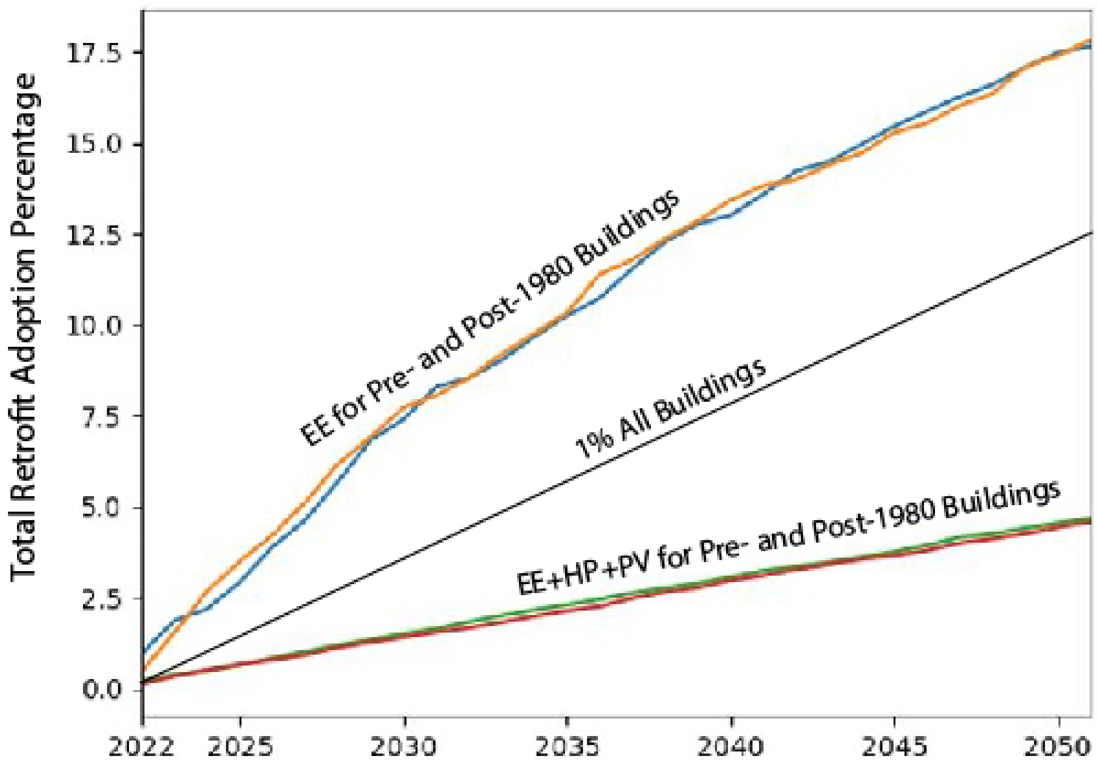


Figure E.4: Building retrofits per year for the 1% with Ownership and Costs scenario. In both the baseline and ownership scenarios the retrofits per year are all roughly the same.

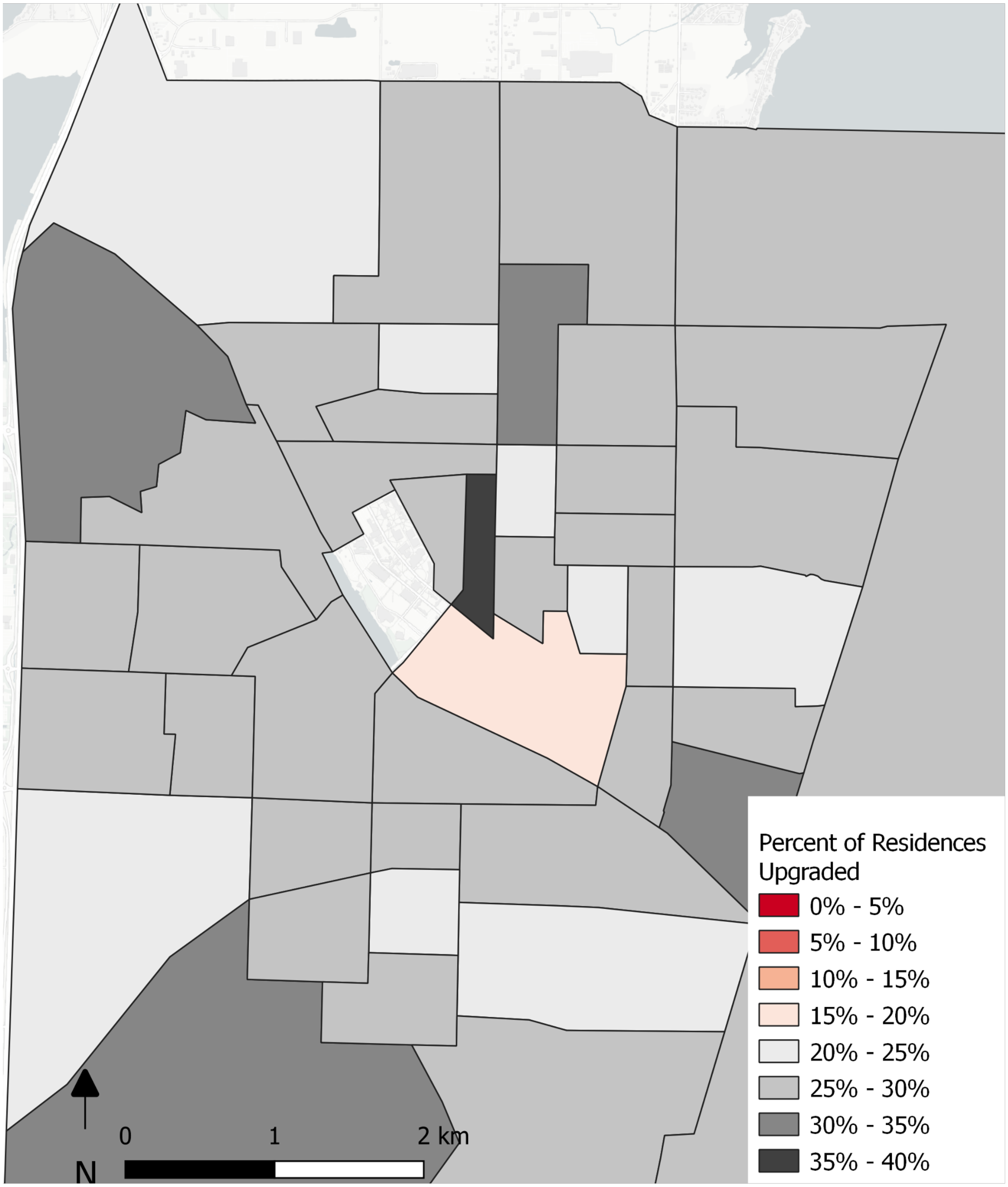


Figure E.5: Spatial adoption prediction in 2050 in the 1% all buildings scenario

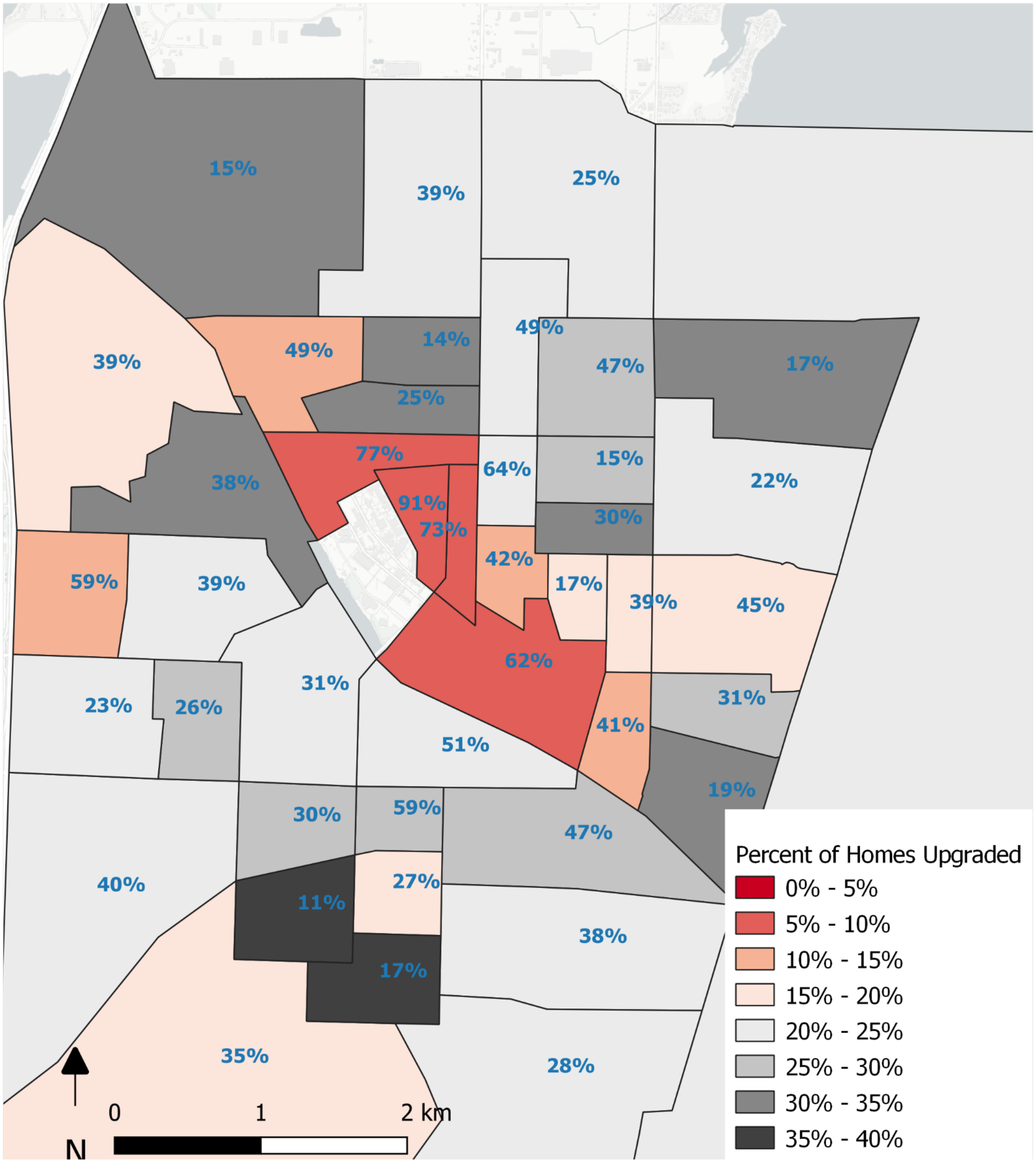


Figure E.6: Spatial adoption prediction in 2050 in the 1% all owned scenario. The blue text is the percent of WAP-eligible residences per census block.

Appendix F

Chapter 5 Figures

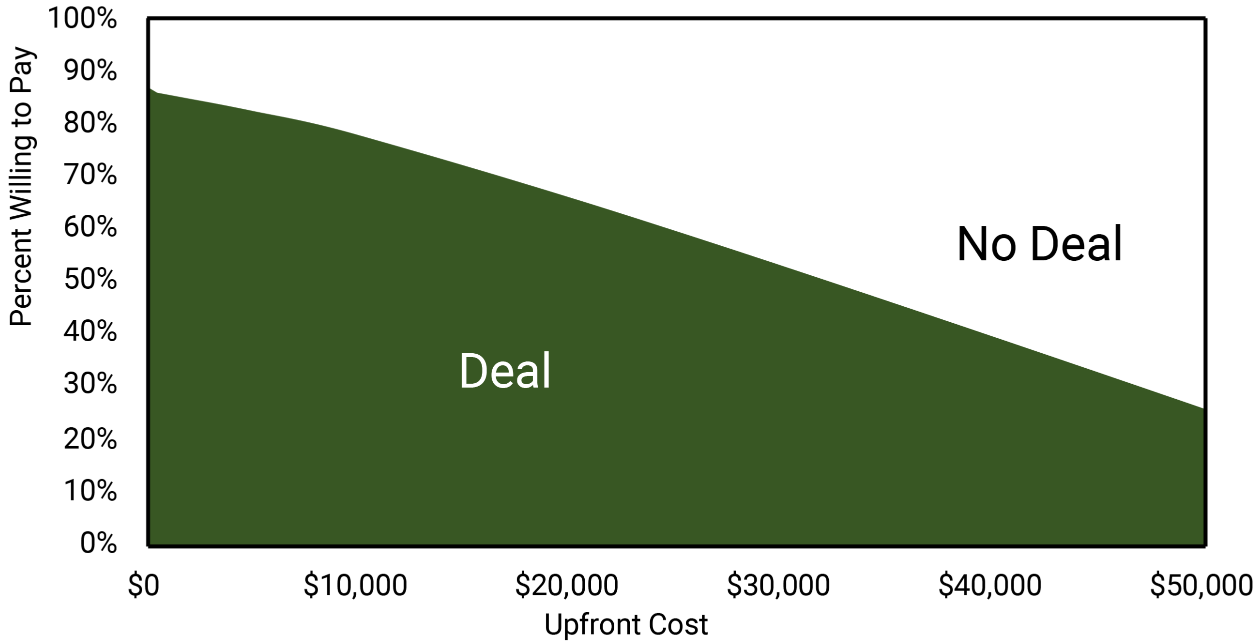


Figure F.1: Retrofit deal or no deal prediction based on upfront cost.
Note: The green area is the percent of respondents willing to pay for an efficiency retrofit at that upfront cost. Those in the white "no deal" area will not pay for a retrofit of that upfront cost no matter the payback period.

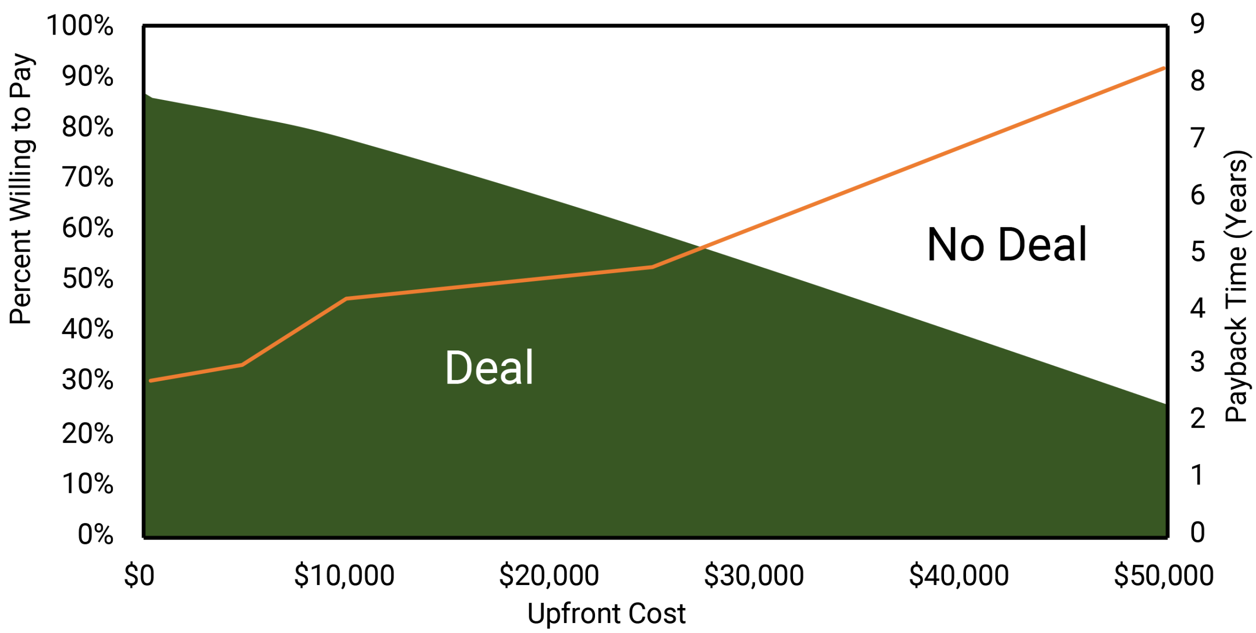


Figure F.2: Retrofit deal or no deal with orange payback curve showing the predicted median required payback time.

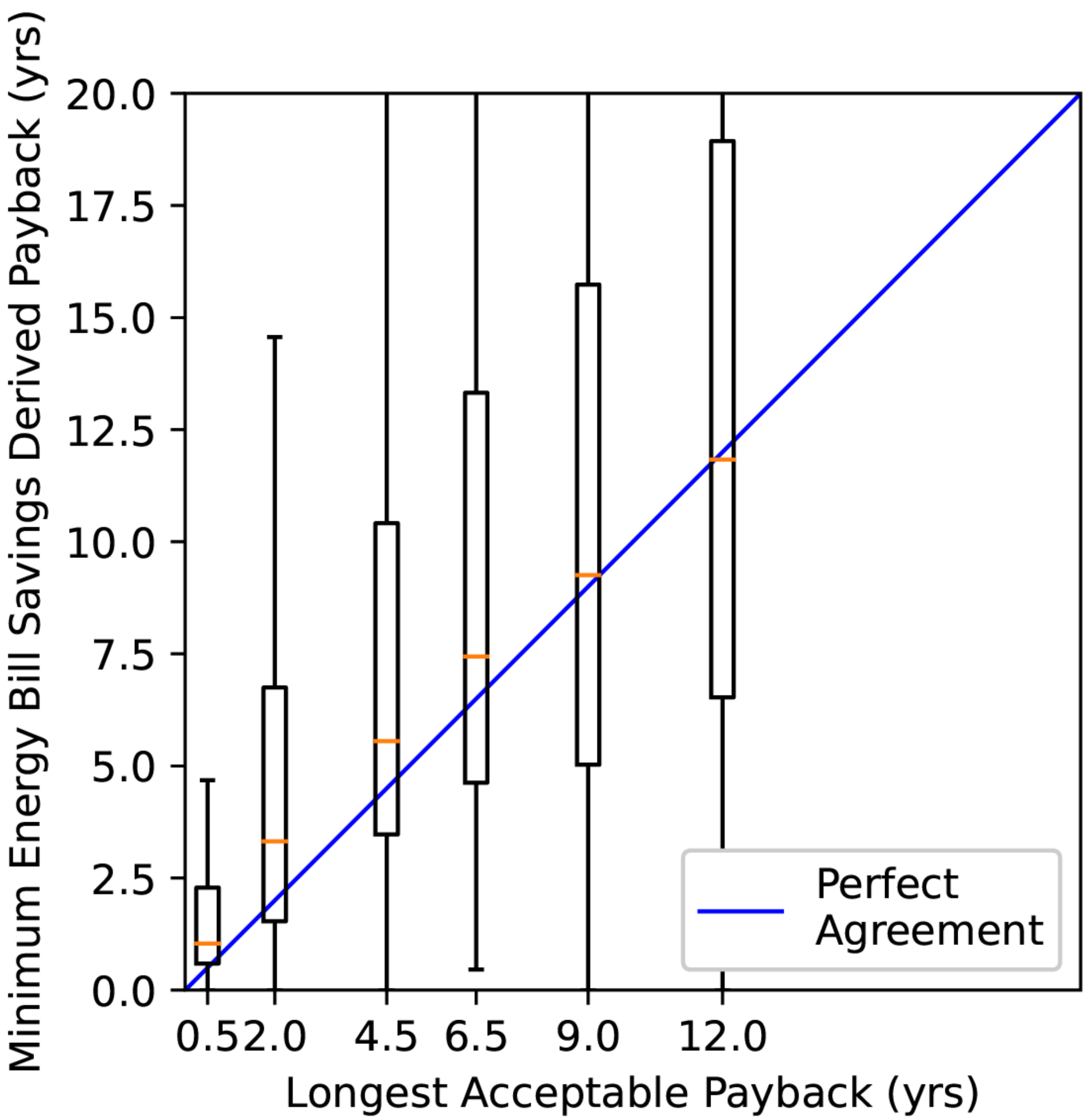


Figure F.3: Respondents' longest acceptable payback period versus the payback period derived from respondents' minimum required energy bill savings.

Appendix G

Chapter 6 Figures

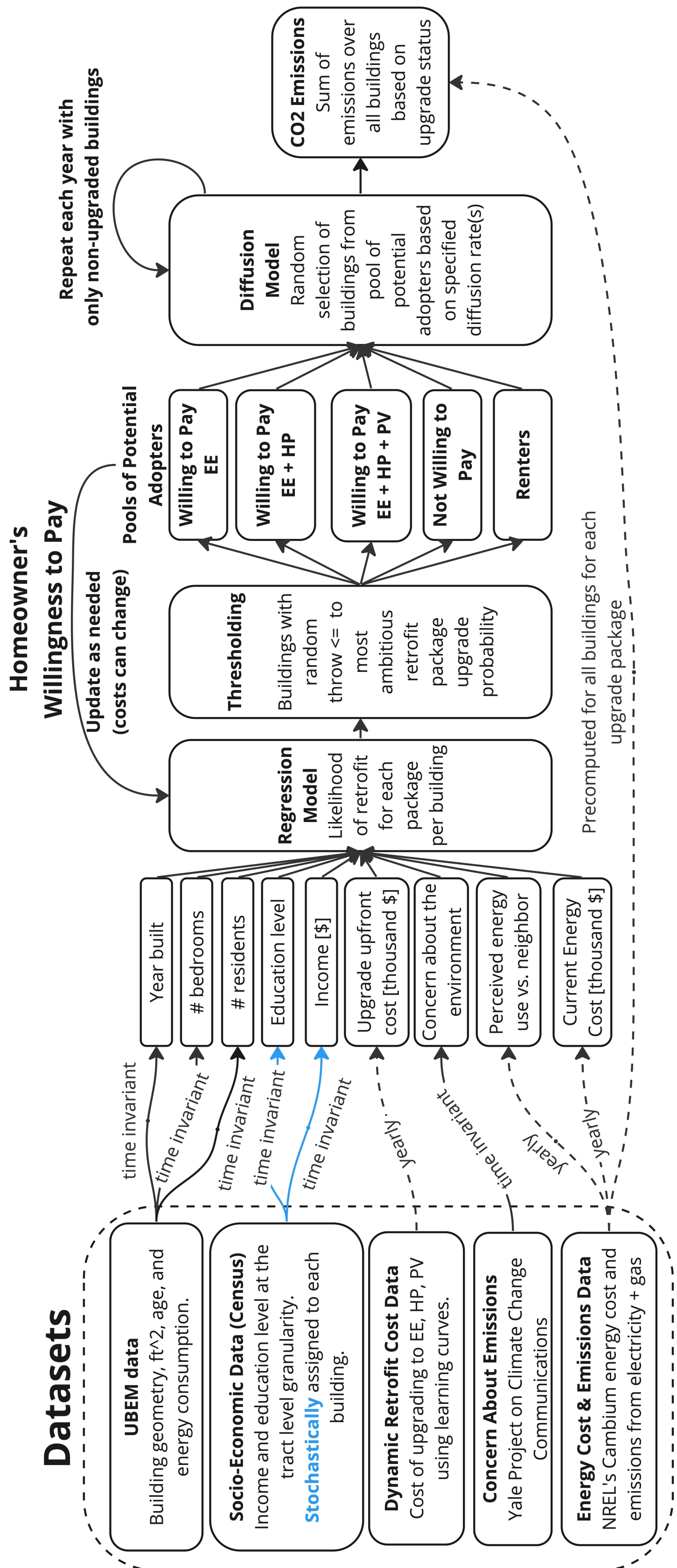


Figure G.1: Workflow used to integrate data for the willingness to pay adoption model.

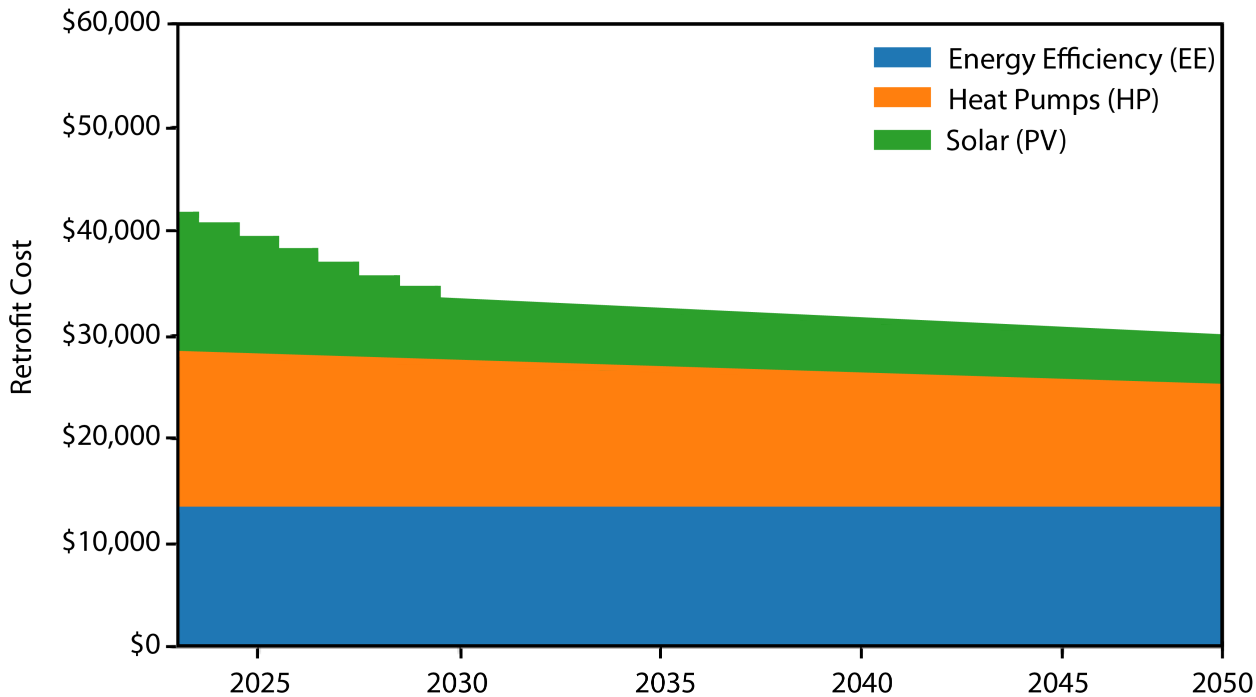


Figure G.2: Mean retrofit costs per household each year. The energy efficiency costs are assumed to be time-invariant. The costs of heat pumps decline over time, but solar declines the fastest.

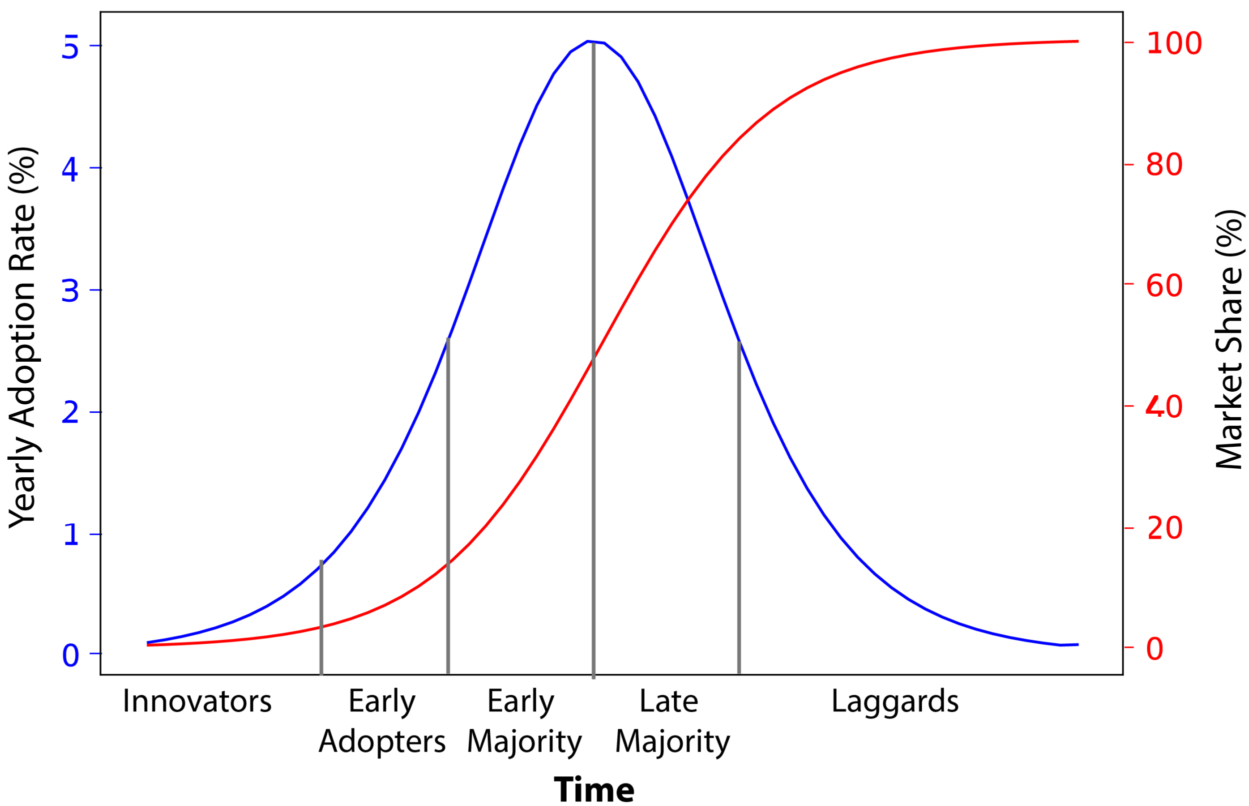
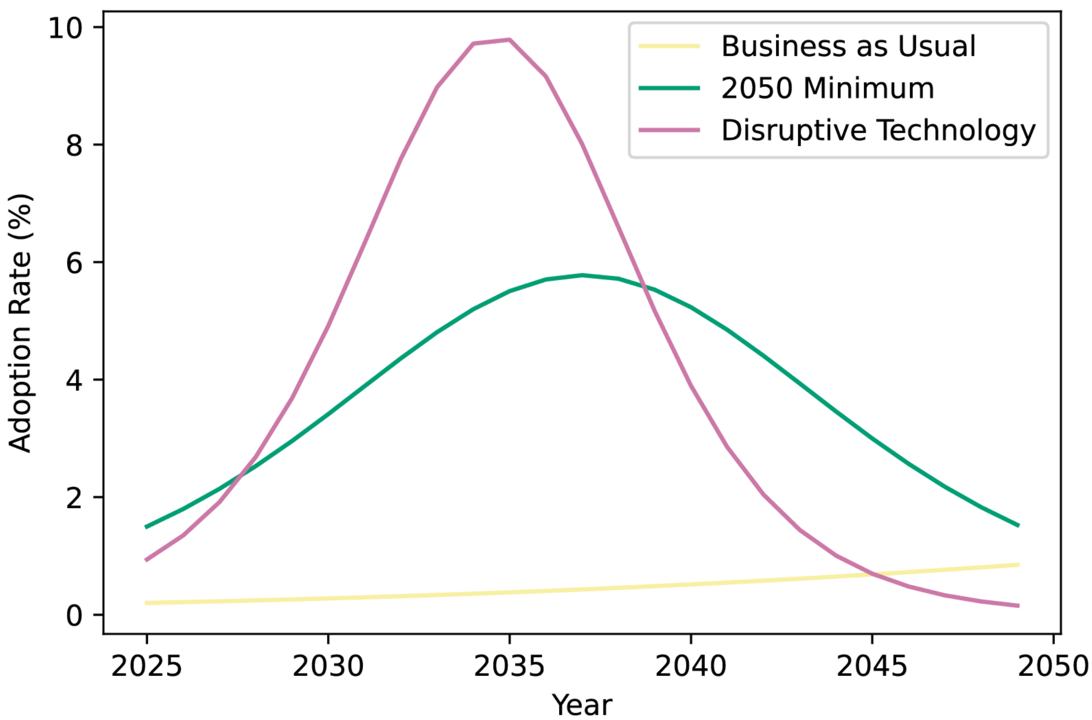
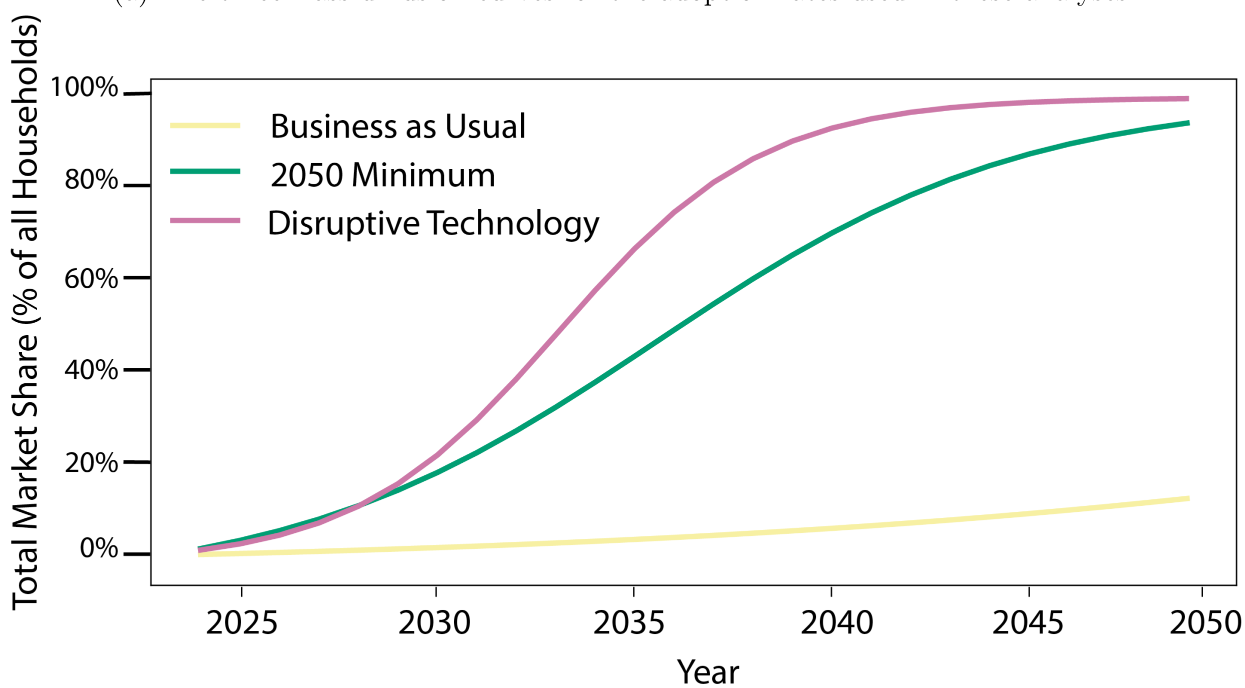


Figure G.3: Early-adopters S-curve showing the yearly adoption rate (blue) and total market share (red). Figure created by the author based on information in [129].



(a) The three Bass diffusion curves for the adoption rates used in these analyses.



(b) Cumulative adoption or market share for the given adoption rates out to 2050.

Figure G.4: Bass Diffusion model implementation

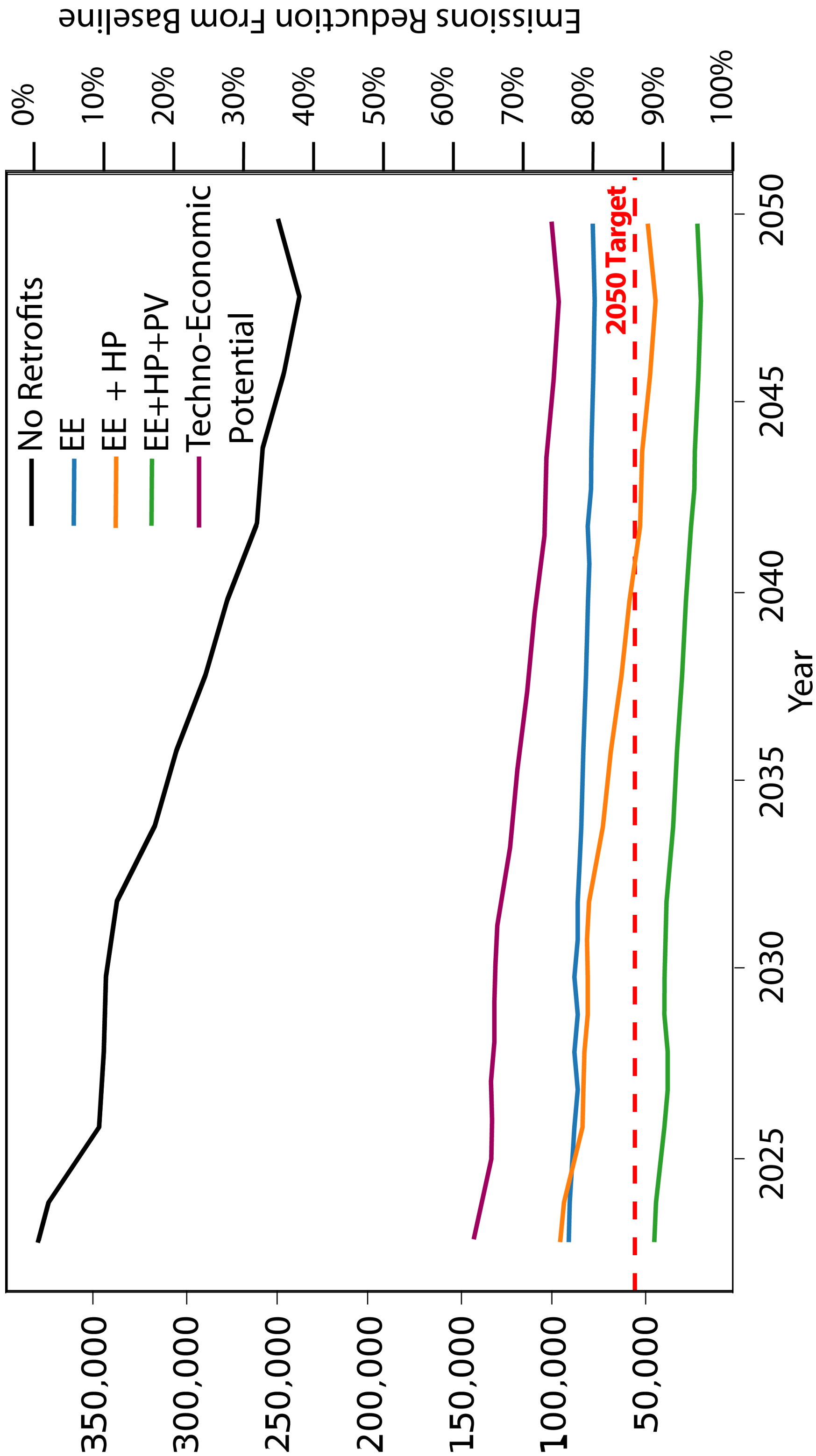


Figure G.5: Emissions reduction potential for each retrofit package adopted to 100% in Oshkosh. Techno-economic potential assumes adoption of only the packages that households are willing to pay for.

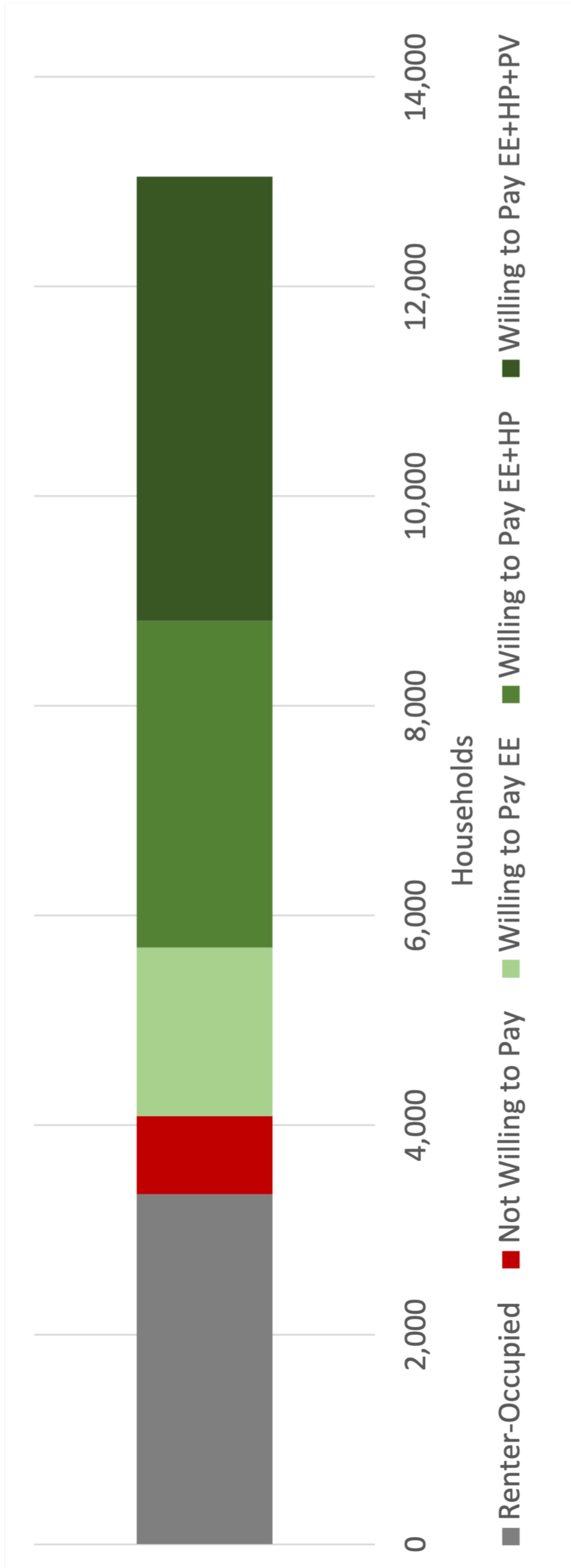
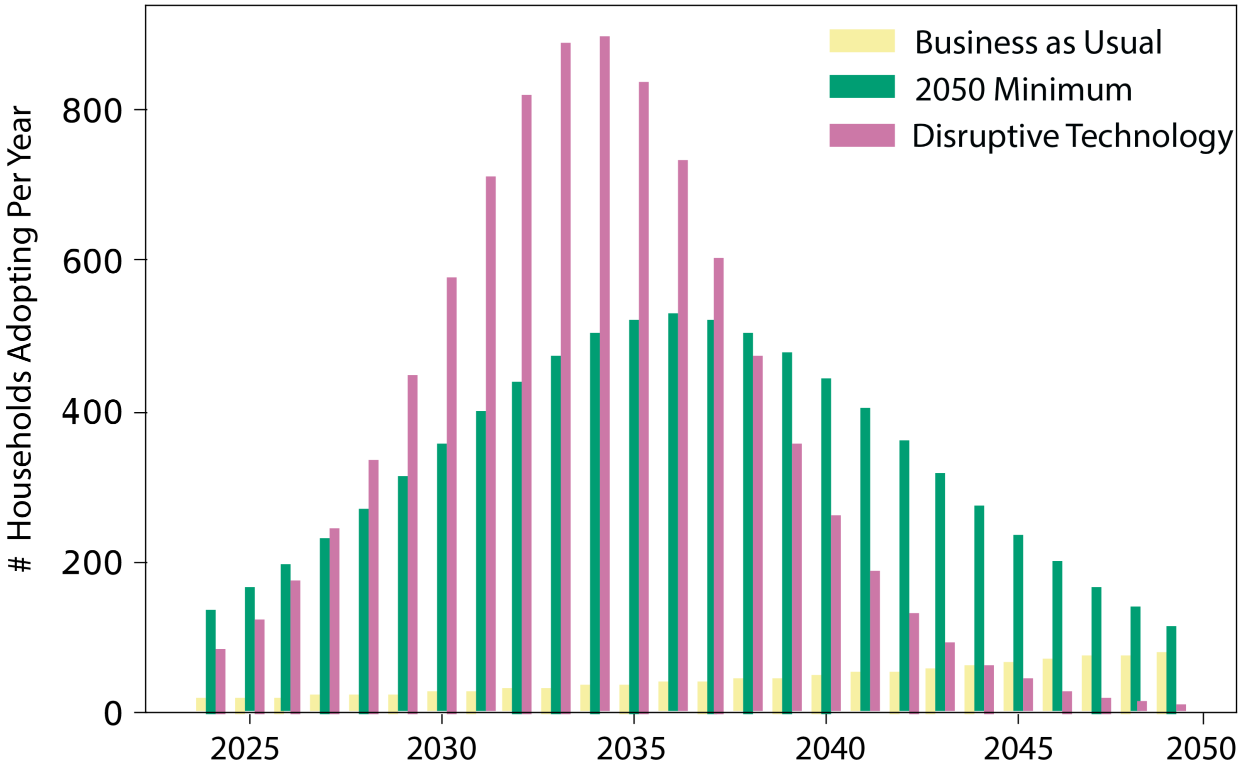
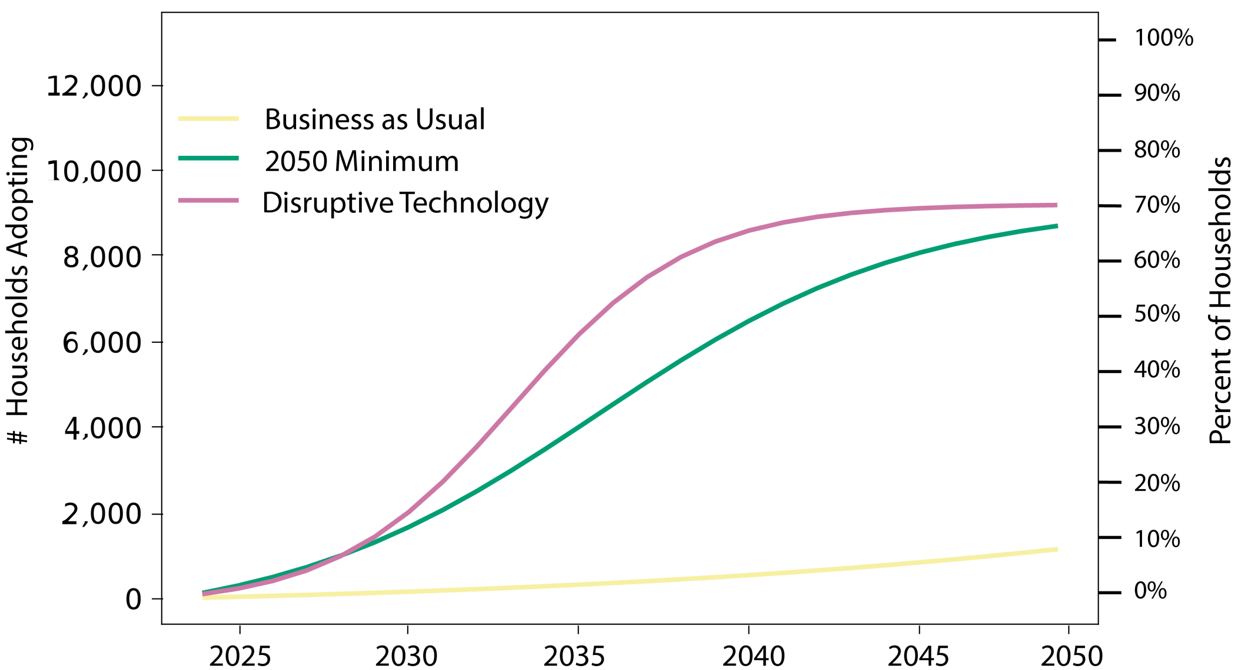


Figure G.6: Willingness to pay breakdown across Oshkosh. Only the households in green are willing to pay for the retrofits.



(a) Yearly adoption for Oshkosh with three different Bass diffusion curves.



(b) Cumulative adoption prediction numbers for Oshkosh.

Figure G.7: Diffusion of retrofits in Oshkosh.

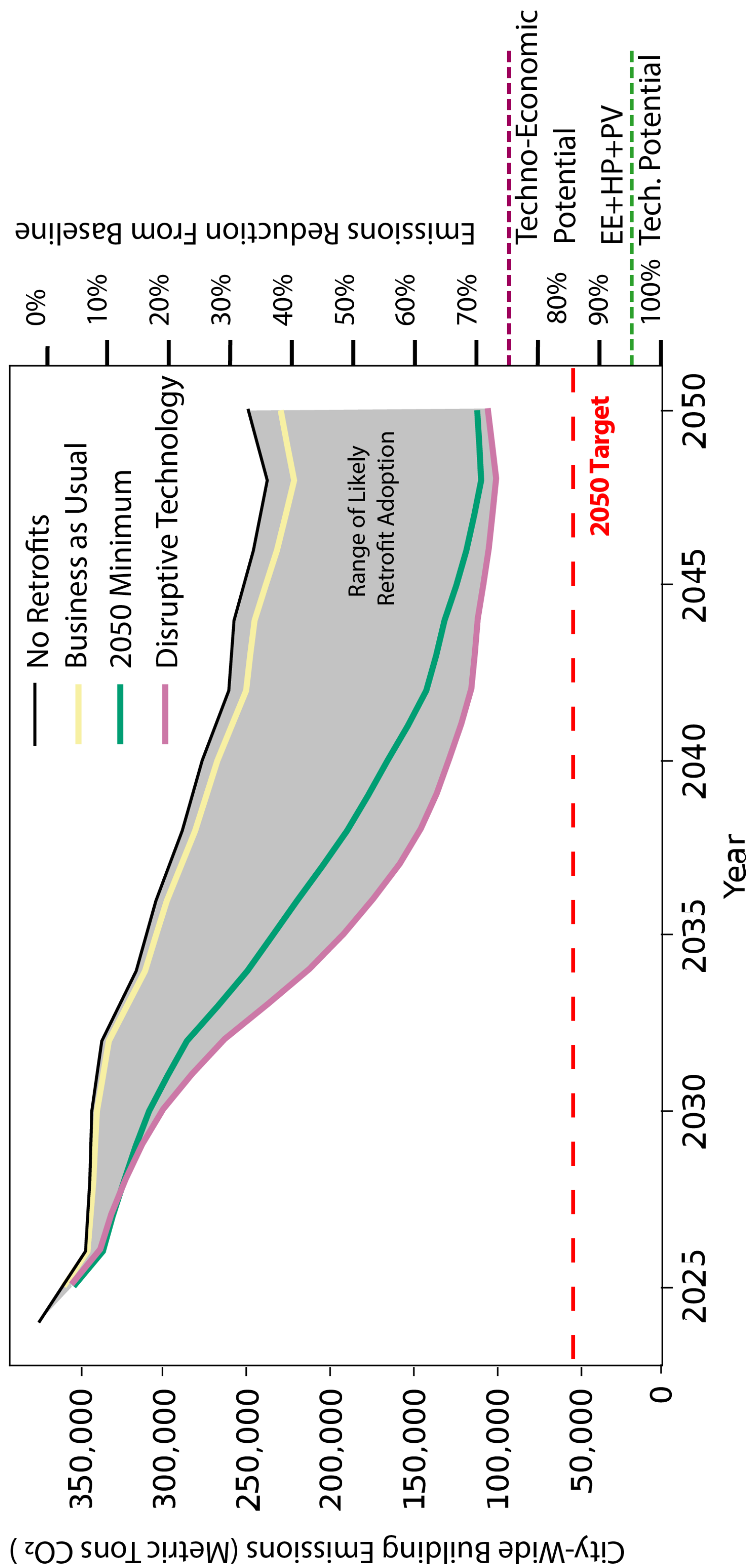


Figure G.8: Oshkosh-wide results for the three different diffusion scenarios compared to the baseline of no retrofits and the technical potential, 100% adoption of the EE+HP+PV retrofit package. They grey area is the range of likely outcomes depending on the actual diffusion rate.

Appendix H

Chapter 7 Figures

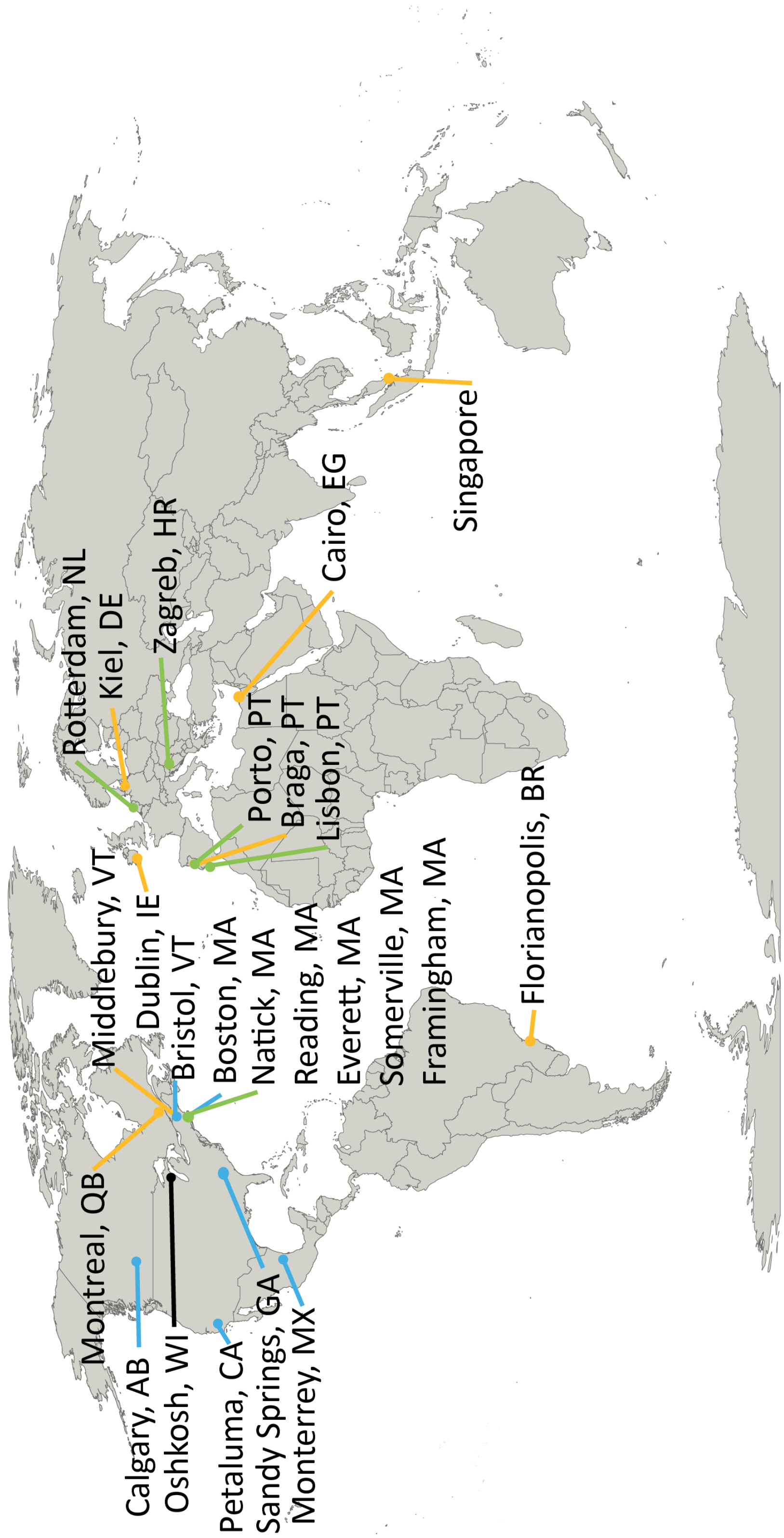


Figure H.1: Cities modeled in workshops the author has led. Cities in green introduced the sustainability champions as a key component of the work, cities in blue leveraged a local GIS manager, and cities in orange partnered with local energy modelers as well.

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