ABSTRACT

Title of Dissertation:	THE TROUBLE WITH VOLUNTARY CARBON TRADING FOR BUILDINGS EXPOSED TO HURRICANE RISK
	Xiaoyu Liu, Doctor of Philosophy, 2017
Dissertation directed by:	Professor Qingbin Cui Department of Civil and Environmental Engineering

Increased climate risks pose challenges of combining climate mitigation and adaptation goals into building designs. These two goals are often misaligned, as adaptation measures use additional materials and equipment that are sources of carbon emissions. This phenomenon causes building design to involve tradeoffs between enhancing structural resilience and reducing emissions. This dissertation addresses the need to identify the optimal investment mechanisms for the design of buildings in hurricane-prone regions. Dynamic decision-making models are developed for individual investors to characterize emission trading and risk mitigation behaviors over a building's lifecycle. The models enable the following outcomes: (*i*) evaluation and selection of baseline rules for sectoral emission trading, (*ii*) ability to reflect resilience goals in the building design, construction and maintenance, and to balance between climate mitigation and adaptation goals for a wide range of building examples, and (*iii*) policy

implications for improving emission trading efficiencies and achieving environmental and economic sustainability at community level.

Modeling results indicate that the trouble of voluntary emission trading is mainly attributed to imperfect market information and future climate risks. The uncertainty in predicting emissions and potential baseline manipulation leads to the production of non-additional carbon offsets and an extension of sectoral emission caps. This situation is even bleaker when emission trading is implemented in the areas that have exposure to significant risks of catastrophic events such as hurricanes. The results reveal a trend of a transition from long-advocated low-carbon investment to a risk-oriented portfolio for building retrofits in hurricane-prone regions. The risk mitigation efforts should be pursued with discretion on the accuracy of insurance premium discounts. Meanwhile, subsidies for emission abatements are recommended to accommodate existing emission trading schemes and building property values.

THE TROUBLE WITH VOLUNTARY CARBON TRADING FOR BUILDINGS EXPOSED TO HURRICANE RISK

by

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Dissertation submitted to the Faculty of the Graduate School of the
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Dedication

This dissertation is dedicated to my beloved husband, Zhou Zhou, for all of the support he has given through all of these months of research work. Most of the work occurred on weekends, nights, while on vacation, and other times inconvenient to my family. My daughter, Chelsea, who is unborn at the time of writing, has given me determination to complete this dissertation on time and welcome her into the world in November.

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My appreciation also extends to my dissertation committee, who provided theoretical and technical supports from different perspectives. The discussion with Professor Anand Patwardhan at the proposal stage is especially valuable, and his early insights guided the direction of this study. Professor Roberton C. Williams III's class on Environmental Taxation and Regulation gave me basic skills to develop economic models related to emission trading. His comments on the baseline manipulation model during the class presentation are valuable to develop policy recommendations for sectoral baseline regulation. The publications of Professor Bilal M. Ayyub provided important references for my study on structural resilience. His insights on resilience metrics served as the ground of designing risk-informed portfolios for building retrofits. Thanks also go to Professor Allison Reilly, who discussed with me about major findings before my defense and provided valuable feedbacks on hurricane risk analysis.

Table of Contents

List of Tables

List of Figures

Chapter 1 Overview

While mandated in a few sectors, the actions on global warming are primarily voluntary for many organizations and individuals. The type, quality and quantity of the voluntary actions are affected by the resource use decision of the organizations and individuals. When the benefits of a climate action accrue primarily to those who take decisions, they are more likely to cooperate in achieving the climate targets (Jack et al., 2008). However, climate change is a global public good, which implies that the benefits of a particular climate action flow mainly to others (Nordhaus, 2007). This makes public interests and the interests of the action takers misaligned. The difference in private and social benefits, or the issue of "externalities", results in a classic market failure: the unregulated organizations and individuals may not be willing to take actions on global warming in their own right. This logic explains the failure of meeting climate goals in many countries.

In recently years, voluntary carbon offset programs have emerged as a policy solution for realigning the social and private benefits related to the climate actions. The programs are based on a straightforward proposition: compensate for carbon reduction efforts by allowing the reductions to be traded at a certain price. The program functions outside of the compliance schemes and encourage the carbon reduction on a voluntary basis. With just under $4.5 billion traded over the past decade, voluntary demand for carbon offsets is impactful well beyond the markets' relatively small size (Hamrick & Goldstein, 2015). This demand and resulting finance create new industries and unlock cleaner forms of affordable energy in the unregulated sectors.

Even with promising economic opportunities, the voluntary offset programs have faced substantial criticism in the last few years. There is evidence that a significant number of offsets come from projects that would have been undertaken anyway (Millard-Ball, 2013). These non-additional offsets, when traded to the regulated entities, implicitly expand the emission caps in compliance schemes and result in failing to achieve the desired emission targets. This means that the threshold for determining additionality, a baseline against which emission reductions can be certified as carbon offsets, may be systematically biased. The bias is particularly prominent in evaluating project-based reduction against a counterfactual baseline, that is, a level of emissions that would occur in the absence of the project (Fischer, 2005). As the certifying agency is limited in its ability to propose such a counterfactual baseline, it must consign this task to the individual project proponents. This leaves great uncertainty regarding the integrity of baseline determination.

As an alternative approach, a performance baseline addresses this weakness in that it no longer relies on evaluating individual projects but uses a pre-defined baseline to streamline the process of determining additionality (VCS, 2012). In this way, the performance baseline can establish an emissions threshold for a class of project activities. Individual projects that meet or exceed the threshold automatically qualify as additional projects, obviating the need for each project to determine additionality in its own right. However, the performance baseline is also criticized for producing non-additional offsets (Fischer, 2005). Because it is uniformly applied to a class of project activities, it inevitably over-allocates offsets to some projects and under-allocates offsets to others. The performance baseline is, therefore, also at risk of promoting less cost-effective investment projects and allocating non-additional offsets to those projects.

Chapter 2 is therefore centered on the aforementioned baseline rules, project-based baseline and performance baseline, and compares their effects on sectoral emission mitigation and compliance costs. A dynamic optimization model is created to characterize mitigation decisions of project proponents over a building's life cycle. This chapter contributes to the existing literature on additionality baselines by quantifying the trade-offs between the revenue and incremental costs regarding emission abatement. In contrast to Millard-Ball (2013), Muller and Mendelsohn (2009) and Fischer (2005), who emphasize conceptual design and describe cost and revenue curves in a general sense, this chapter uses the commercial building sector as an example and collects real technology and cost information to characterize a real investment environment. The building sector emits 33% of all global emissions while only accounts for less than 5% of emission reductions in the market (Robert & Kummert, 2012; Kollmuss, 2008). This finding implies that if properly explored, gains from engaging the building sector in voluntary trading would be extremely attractive.

Chapter 2 also contributes to the existing literature by incorporating the co-benefits of emission abatement into the decision model. Thus, the project payback includes not only offset sales but also other possible revenues. In the case of the commercial building sector, the co-benefit of emission abatement is utility savings. Some of the existing literature disregards such co-benefits and exaggerates the non-additionality issue. However, as demonstrated in this chapter, if the co-benefits are properly considered, the optimal baseline can avoid some of the non-additional projects and effectively alleviate global warming.

Chapter 2 assumes that performance baselines are set by regulators who have either perfect or imperfect information about the costs and emissions of projects. In practice, regulators are often less informed than project proponents; therefore, the baselines are more likely to be privately defined even for sectoral crediting. The primary concern with privately defined baselines is that baseline developers may exert their powers to manipulate the baselines, leading to increases in sectoral emission caps (Fischer, 2005). For example, baseline developers may lower the baseline to expel competitors from the offset programs. The decrease in offset supply drives up the offset prices, which creates more surpluses for the developers but risks forgoing the benefits of cost-effective offset projects. It is also possible that the developers increase the baseline above the counterfactual business-as-usual (BAU) emission, allowing themselves to sell non-additional offsets. The non-additional offsets either represent a damage cost due to global warming or an increase in the transaction costs within this sector. Even though such manipulation is reduced to some extent by third-party verifications, it plays a role in the programs that reward offsets based on additionality (Jack, 2008).

Therefore, Chapter 3 focuses on the motivation for manipulating baselines and its impact on the reduction of global emissions. The hypothesis is that baseline developers can always gain more by deviating from the unbiased baseline, which is an emission threshold that surpasses the 80^{th} percentile of comparable peers (UNFCCC, 2006). The analysis is performed in three steps: (*i*) emission abatement decision is modeled as a response to the sectoral performance baseline. Observing the baseline, self-informed project proponents decide whether to participate and how much to reduce their emissions. Each project proponent's emission reduction is a function of the baseline. (*ii*) One of the project proponents in the program is chosen to be the baseline developer who solves an optimization problem in the context of adverse selection. The developer takes others' response functions as given and uses them to set the baseline that maximizes its expected payoffs. (*iii*) The functional forms are specified in the context of the U.S. commercial building sector. Closed-form solutions for the optimal baseline are derived, which are compared against the unbiased baseline to demonstrate that the baseline manipulation has a high chance of occurring.

Chapter 3 highlights the significance of answering a question, namely, who should be the baseline developer. My theoretical results show that the extent to which the baseline is manipulated highly depends on who is assigned to be the baseline developer. The more the baseline developer emits, the more likely the developer exerts its power to manipulate the baseline. A case study of the U.S. building sector reveals that, because of the notably low price elasticity of the offset supply, the privately defined baseline is often positively deviated and produces more non-additional carbon offsets.

While Chapters 2 and 3 have emphasized on carbon mitigation, Chapter 4 steps beyond it and discuss the necessity of climate adaptation for commercial buildings in disaster-prone regions. Carbon mitigation policies, such as the voluntary offset programs, are economically efficient in an environment where the projects can gain stable revenues in the presence of carbon price signal; however, they are suspected to be less attractive in areas at substantial risks from catastrophic events such as hurricanes and floods (Guikema, 2009). These events cause damage to the local buildings and result in significant direct costs such as restoration costs and indirect costs such as loss of business revenue and economic growth in impacted areas. To balance against the future costs of structure failure, project proponents have been advised to pay extra up-front costs to enhance structural resilience, and to prepare, absorb, recover from and adapt to natural disasters (Linkov, 2014).

The way to address climate risks depends on the investment decision that trades off, at least implicitly, emission abatement (slowing down the global warming) for resilience management (adapting to the global warming). As a traditional solution, adopting emission abatement measures can save energy cost and generate revenues from carbon offset sales. Kneifel (2010) showed that these measures can be used to save energy use in new commercial buildings by 20-30% on average. The life-cycle cost can be reduced by 3% on average and up to over 6% for some building types and locations. However, these revenue sources may be interrupted due to structure failures in disasters, making the abatement investment less attractive than ever. As global temperature continues increasing and more areas are subjected to severe natural disasters, a vast majority of property and wealth is under the risk of significant damages. UNISDR (2012) reported that the annual loss induced by infrastructure failure amounted to about $55 billion in the United States. This number is expected to increase because of a combined effect of climate change and increased coastal inventory of assets (Ayyub et al., 2012). The expected damages emphasize the need to enhance resilience to sustain building's operation and accelerate post-disaster recovery. According to the studies of ULI (2015) on South Florida Resort, the use of hurricane resilience measures can lower annual expected damages by an estimated $500,000, offering a significant reduction in annual operating expenses. This makes resilience management an important addition to traditional low-carbon development paths, and if it is cooperates properly with emission abatements, will lead to a more sustainable and resilient community.

Therefore, Chapter 4 builds on the investment decision model in Chapter 2 and characterizes the decision problem in the context of disaster-prone regions where the buildings are exposed to the risk of hurricane events. Different from Chapter 2 in which the project proponents only decide the amount of GHGs to reduce, in Chapter 4 they are offered with an option of enhancing structural resilience for adapting to hurricane events in the future. A dynamic decision-making model is developed for individual investors to maximize their expected payoffs over a building's lifecycle. The model is built upon the evaluation of non-stationarity hurricane damages and building's emission performances under different mitigation scenarios. The optimal investment allocation is determined by characterizing individual investment behaviors on emission abatements, hurricane mitigation, and the interaction between those two actions. This chapter enables the following outcomes: (*i*) development of a hybridized decision model that allows the balance between resilience and sustainability objectives, (*ii*) ability to reflect resilience goals in the building design, construction and maintenance, and (*iii*) application of the model to a selected county to demonstrate its ability to handle a wide range of building examples, and provide policy implications for a county's environmental and economic sustainability.

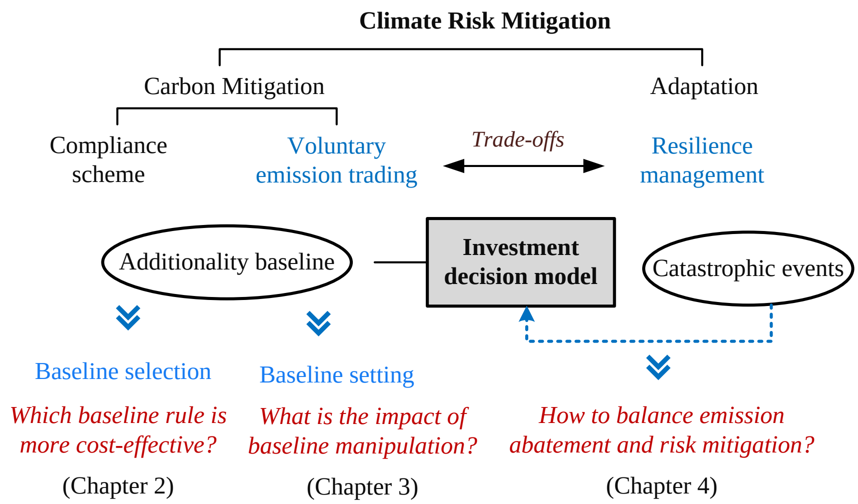


Figure 1.1 Dissertation framework and key scientific questions

The roadmap of this dissertation is displayed in Figure 1.1. Key contributions are summarized as follows.

- This dissertation evaluates the environmental and cost effects of different baseline approaches for voluntary emission trading. The results will be valuable for policy makers to understand which baseline approach is more cost-effective in which circumstances, and guide the selection of baselines for a particular sector. While this dissertation only demonstrates the results for the commercial building sector, similar policy implications can be applied the issue of baseline feasibility for other sectors.

- This dissertation is the first attempt of studying baseline manipulation in voluntary offset programs. Past studies almost exclusively assume performance baselines are set by regulators who have either perfect or imperfect information about the costs and emissions of projects. In practice, the baselines are more likely to be privately defined and have a risk of being manipulated. This dissertation models baseline manipulation behaviors in the context of adverse selection, where participants can self-select into the market. The results will shed light on the motivation and consequences of baseline manipulation, and provide policy suggestions on the regulation of baseline integrity.
- To realign the conflicts between climate mitigation and adaptation goals, this dissertation develops a framework to find the optimal investment allocation between mitigation and adaptation measures for the design of buildings in hurricane-prone regions. The optimal portfolio reflects low-carbon and resilience goals in the building design, construction and maintenance. The framework is applied at county level to demonstrate its ability to handle a wide range of building examples, and provide policy implications for a county's environmental and economic sustainability.

Chapter 2 Value of Performance Baseline in Voluntary Carbon Trading under Uncertainty

Abstract

Voluntary carbon trading has long been criticized for producing a large number of non-additional offsets. The reason for this production lies primarily in the use of a project-based baseline that due to information asymmetries, misrepresents the business-as-usual (BAU) emissions of individual projects. The performance baseline was recently introduced as an alternative to the project-based baseline. The performance baseline does not rely on evaluating individual BAU emissions, but rather, it uses a pre-defined threshold to streamline the process of determining additionality. This chapter compares the effects of the two baseline approaches on sectoral emission mitigation and compliance costs. In the context of the U.S. commercial building sector, a dynamic optimization model is created to characterize mitigation decisions of project proponents over a building's life cycle. The results indicate that while both baseline approaches are capable of reducing sectoral emissions when information is perfect, a performance baseline is especially advantageous in cases of imperfect information and uncertain price environments, as it is expected to reduce non-additional offsets by 19% and increase private profits by 2%. Nevertheless, special attention should be given to the potential inequity in offset allocation with performance baselines in sectors that are highly diversified in emission magnitudes.

2.1 Introduction

To address the threat of climate change, high polluting sectors in the United States are regulated through compliance schemes and assigned legally binding emission caps. These caps constitute a finite supply of emission allowances that can be traded among the regulated entities. In contrast to the compliance schemes, voluntary offset programs provide a market that can encourage unregulated entities to participate. The voluntary programs certify carbon offsets that can be traded in the compliance schemes and counted toward compliance goals in the regulated entities. Therefore, this program contributes to internalizing emissions cost and provides incentives for seeking cost-effective means to control carbon emissions (Kollmuss et al., 2008).

The voluntary offset program, however, has faced substantial criticism in the last few years, and there is evidence that a significant number of offsets come from projects that would have been undertaken anyway (Millard-Ball, 2013). These non-additional offsets, when traded to the regulated entities, implicitly expand the emission caps in compliance schemes and result in failing to achieve the desired emission targets. This means that the threshold for determining additionality, a baseline against which emission reductions can be certified as carbon offsets, may be systematically biased. The bias is particularly prominent in evaluating project-based reduction against a counterfactual baseline, that is, a level of emissions that would occur in the absence of the project (Fischer, 2005). As the certifying agency is limited in its ability to propose such a counterfactual baseline, it must consign this task to the individual project proponents. This leaves great uncertainty regarding the integrity of baseline determination.

As an alternative approach, a performance baseline addresses this weakness in that it no longer relies on evaluating individual projects but uses a pre-defined baseline to streamline the process of determining additionality (VCS, 2012). In this way, the performance baseline can establish an emissions threshold for a class of project activities. Individual projects that meet or exceed the threshold automatically qualify as additional projects, obviating the need for each project to determine additionality in its own right. However, the performance baseline is also criticized for producing non-additional offsets (Fischer, 2005). Because it is uniformly applied to a class of project activities, it inevitably over-allocates offsets to some projects and under-allocates offsets to others. The performance baseline is, therefore, also at risk of promoting less cost-effective investment projects and allocating non-additional offsets to those projects.

The impact of an additionality baseline, either a project-based baseline or aperformance baseline, has been extensively studied under the Clean Development Mechanism, where the baseline is applied to developing countries for generating certified emissions reductions that relieve the reduction obligation of developed countries (Bento et al., 2015; Strand & Rosendahl, 2012; Kallbekken, 2007). The impact analysis centered on alternative baseline rules, such as the rules of historical emissions, expected emissions, and industry-average emissions. Different baseline rules represent different trade-offs between the concerns of information accuracy, participation incentives and investment cost-effectiveness. Because project performance is often context dependent, there has not been a consensus on the most effective baseline rule for a universal case, indicating that additional research is needed to evaluate which baseline rule is the most appropriate in which circumstance. In addition, previous studies raise a concern regarding the co-benefit of carbon mitigation, e.g., production efficiency improvement. The co-benefit sometimes enables a project to be self-profitable, which is, by definition, one type of non-additional project. This issue, however, has yet to be incorporated into a quantitative analysis. Thus, there is a need to advance the understanding of the cost-effectiveness of mitigation projects, taking into account the potential co-benefits of such projects as well as the nature of the price and technology uncertainties.

This chapter offers three main contributions. First, it contributes to the existing literature on additionality baseline by quantifying the trade-offs between the revenue and incremental costs regarding emission abatement. In contrast to Millard-Ball (2013), Muller and Mendelsohn (2009) and Fischer (2005), who emphasize conceptual design and describe cost and revenue curves in a general sense, this study uses the commercial building sector as an example and collects real technology and cost information to characterize a real investment environment. The building sector emits 33% of all global emissions while only accounts for less than 5% of emission reductions in the market (Robert & Kummert, 2012; Kollmuss, 2008). This finding implies that if properly explored, gains from engaging the building sector in voluntary trading would be extremely attractive.

Second, the study builds on the previous static analysis of abatement decisions and extends it to a dynamic decision process. Dynamic decision analysis is important because emission abatement in different periods is not always independent. For example, installing exterior wall insulation in a particular year can contribute to emission reductions for the next 40 years. Some of the existing literature assumes that abatement decisions are independent and that a project proponent chooses to opt in only if its one-time revenue exceeds the one-time cost (Millard-Ball, 2013; Kallbekken, 2007; Fischer, 2005). This chapter, however, takes the project proponent as a forward-looking decision maker who discounts all future expected revenues.

Third, this study incorporates the co-benefit of emission abatement into the decision model. Thus, the project payback includes not only offset sales but also other possible revenues. In the case of the commercial building sector, the co-benefit of emission abatement is utility savings. Some of the existing literature disregards such co-benefits and exaggerates the non-additionality issue. However, as demonstrated in this chapter, if the co-benefits are properly considered, the optimal baseline can avoid some of the non-additional projects and effectively alleviate global warming.

2.2 Optimization Model of Dynamic Emissions Abatement

This section characterizes a decision framework for investing in building carbon mitigation. A two-stage dynamic optimization problem is formulated to model the selection of energy standards and emission abatement technologies over a building's life cycle. Two baseline approaches are defined and incorporated into the model to study the baseline effects on carbon mitigation and offset allocation.

2.2.1 Two-Stage decision problem

Project proponents, designated an $i = 1,\ldots, N$, design, construct and operate buildings. The building designs meet, at a minimum, the energy standard ASHRAE (American Society of Heating, Refrigerating, and Air-Conditioning Engineers) 90.1-2007. Complying with higher energy standards is voluntary and requires extra up-front investments. However, investments in energy conservation are compensated with annual utility savings and carbon offsets. Only when the compensation exceeds the up-front investments, the project proponents are willing to reduce energy consumption beyond ASHRAE 90.1-2007. The project proponents are referred to as firms throughout the remainder of this chapter.

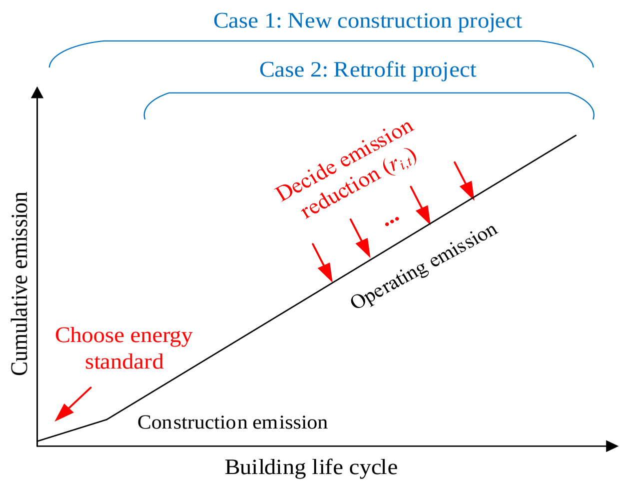


Figure 2.1 Framework of the Firm Decision Problem

Each firm makes a two-step decision to reduce energy consumption and associated carbon emissions, as depicted in Figure 2.1. In the first step, the firm designs a building by choosing one of the ASHRAE energy standards, namely, ASHRAE 90.1-2007 (standard *A*), ASHRAE 90.1-2010 (standard *B*) or ASHRAE 90.1-2013 (standard *C*). Later versions of the energy standard represents more stringent energy efficiency requirements. Each firm has a BAU emission $z^0(A)$ based on the minimum requirement of ASHRAE 90.1-2007. If it does not increase energy efficiency, its emission remains as $z^0(A)$ and its incremental cost is zero. If the firm chooses a higher energy standard, for example, ASHRAE 90.1-2010, the annual emission is reduced to $z^0(B) = z^0(A) - \Delta z$ and the incremental cost is $ic(B)$. Assuming every unit of emission corresponds to γ utility bill, the annual utility saving is $\gamma[z^0(B) - z^0(A)]$. The use of ASHRAE 90.1-2013 is associated with the annual emission $z^0(C)$, and the incremental cost is $ic(C)$. Each firm is assigned an additionality baseline $b_{i,t}$ by the regulator. Reductions below $b_{i,t}$ can be sold as offsets at an exogenous price *p* if the firm opts in. Assuming risk neutrality, the firm will choose a standard *x* that satisfies

$$x = argmax\{\mathbb{N}\left(p\left[b_{i,t} - z^0(x)\right] + \gamma[z^0(x) - z^0(A)]\right)\} - ic(x), x = A, B, C \qquad (2.1)$$

where $p\left[b_{i,t} - z^0(x)\right]$and $\gamma[z^0(x) - z^0(A)]$ represent the annual carbon offset sales and utility savings, respectively. $\mathbb{N}(\cdot)$ represents the net present value of the annual paybacks, a linear function that converts future annual uniform cash flow to the present value.

Once the firm has chosen an energy standard for its initial construction, in the second step, it makes decisions about the retrofit plan over the building's life cycle. Each firm has its initial emission $z_{i,0}$. If the firm does not retrofit, its abatement cost is zero, and its emission is $z_{i,1} = z_{i,0} + \epsilon_{i,1}$, where $\epsilon_{i,1}$ reflects the BAU emission adjustment due to an external environment change from $t = 0$ to $t = 1$. Otherwise, it chooses abatement $r_{i,1} > 0$, incurs an abatement cost $c_{i,1} = \mathbb{C}(r_{i,1})$ and reduces emissions to $z_{i,1} = z_{i,0} - r_{i,1} + \epsilon_{i,1}$. At $t = 1$, the firm is faced with an additionality baseline $b_{i,1}$, and only the emissions below $b_{i,1}$ can be sold as offsets at an exogenous price p_1. At $t = 2$, the firm observes a new price p_2 and decides whether to further reduce emissions. If the firm does not further reduce emissions, its abatement cost remains at $c_{i,1}$ and its emission is $z_{i,2} = z_{i,1} + \epsilon_{i,2}$. Otherwise, it chooses abatement $r_{i,2} > 0$ and has a cumulative abatement such that $q_{i,2} = r_{i,1} + r_{i,2}$. The associated abatement cost is $c_{i,2} = \mathbb{C}(q_{i,2})$, and the emission is reduced to $z_{i,2} = z_{i,1} - q_{i,2} + \epsilon_{i,2}$. In this context, a risk-neutral firm will maximize its life cycle profit by Equation 2.2. Accordingly, the firm will participate in the program if and only if $\pi_{i,t} \geq 0$.

$$\max_{r_{i,t}} \pi_{i,t} = p_t\left(b_{i,t} - z_{i,t}\right) + \gamma_t q_{i,t} - \mathbb{C}\left(q_{i,t}\right) + \mathbb{C}\left(q_{i,t-1}\right) + \beta\pi_{i,t+1} \quad (2.2)$$

$$\text{s.t.} \quad q_{i,t} = q_{i,t-1} + r_{i,t}$$

$$z_{i,t} = z_{i,0} - q_{i,t} + \sum \epsilon_{i,t}$$

2.2.2 Additionality baseline

The additionality baseline is still in its infant stage of development, and there is no consensus on establishing an effective baseline in the voluntary offset program. The baseline is normally defined in two ways, specifically, project-based baseline and performance baseline. The project-based baseline is the counterfactual BAU emission level of the building, which represents an emission level without the adoption of any energy efficiency technologies. In this case, the project-based baseline for firm *i* is its

BAU emission $z_i^0(x^*)$ adjusted for external environment change $\epsilon_{i,t}$. Accordingly, the baseline varies from building to building and changes over time.

The performance baseline, in contrast, is often a sector-wide threshold that is uniformly applied to all buildings without considering individual differences. The United Nations Framework Convention on Climate Change (UNFCCC) established in its Marrakech Accords that an additionality baseline is sufficient if the baseline surpasses the 80th percentile of comparable peers (UNFCCC, 2006). The comparable peers include the project activities undertaken in the previous five years in similar social, economic, environmental and technological contexts. For simplicity, it is assumed herein that all firms in this study are comparable peers and therefore comprise the bundle for the performance baseline. It is also assumed that the BAU emission $z_i^0(x^*)$ follows a normal distribution with mean $\bar{z}_i^0$ and standard deviation $\sigma(z_i^0)$. Given this, the performance baseline is $\bar{z}_i^0 - 0.84\sigma(z_i^0)$ and is adjusted for external environment change $\epsilon_{i,t}$. This represents the 80th percentile threshold of all building BAU emissions.

As previously stated, two alternative baseline approaches are offered that the regulator may adopt in the voluntary offset program. The approaches are expressed as follows.

$$\text{Project-based baseline: } b_{i,t} = \begin{cases} z_i^0(A), & \mathrm{t} = 0 \\ z_i^0(x^*) + \epsilon_{i,t}, & \mathrm{t} \geq 1 \end{cases}$$
$$\text{Performance baseline: } b_{i,t} = \begin{cases} \bar{z}_i^0(A) - 0.84\sigma(z_i^0), & \mathrm{t} = 0 \\ z_i^0(x^*) - 0.84\sigma(z_i^0) + \epsilon_{i,t}, & \mathrm{t} \geq 1 \end{cases} \tag{2.3}$$

2.3 Estimation of Building Emissions

Linear regression models are created to estimate building emission $z_{i,t}$ and identify available techniques to reduce emissions $r_{i,t}$ and $q_{i,t}$. From a life cycle perspective, building emissions consist of initial construction emissions, described in Section 2.3.1, and operation emissions, described in Section 2.3.2.

2.3.1 Building construction emissions

Building construction emissions consist of the emissions from construction material production, transportation, and installation. These processes consume energy, such as coal, diesel and natural gas, all of which emit carbon dioxide during combustion. Emission from electricity consumption is traced back to the upstream electricity generation station, where carbon dioxide is emitted as a byproduct of fuel combustion. In addition to the energy-related activities, carbon dioxide is also emitted from certain non-energy chemical reaction processes, e.g., the process of converting limestone to lime.

The above emission sources are estimated using the Athena Impact Estimator for Commercial Buildings. This estimator accounts for the emissions of major building assemblies that include columns and beams, floors, roofs, foundations and walls. The design of the prototype buildings is referred to as the medium office sample project provided by the Athena Institute. The prototype buildings are medium-sized office buildings that have three floors and a total of 53,660 ft^2. They are designed to meet the ASHRAE 90.1-2007, 90.1-2010, and 90.1-2013, respectively. The standard increases the requirements for envelope insulation (R-value increase) from 2007 to 2013, thus the thickness of the insulation for roofs and walls are increased to meet different ASHRAE energy standards in different climatic zones. All of the buildings use the same insulation materials, specifically, polystyrene expanded for roofs and blown cellulose for exterior walls. On average, the insulation materials for the ASHRAE 90.1-2010 are 3 mm and 6 mm thicker for roofs and walls compared to the ASHRAE 90.1-2007.

Estimation results suggest that building construction emissions are between 5,527 gCO_2e/ft^2 and 5,570 gCO_2e/ft^2 depending on the energy standard adopted. Because the emission differences are exceedingly small, the initial construction emission is not an important factor in energy standard selection (optimization step 1).

2.3.2 Building operation emissions

Building operation energy consumption and associated carbon emissions are estimated using the Open

Studio Energy Plus module. The module computes energy consumption as a function of building type, climate condition, and energy standard. This study restricts building type to medium-sized office buildings and focuses on the impact of climate conditions and design standards on building emissions. The same prototype buildings as those used in Section 2.3.1 are used here. A linear regression model is created to express the change of building emissions with respect to climate conditions and energy standards. The model is expressed as follows:

$$z_i^0 = \alpha_1 {Ta_i}^2 + \alpha_2 Ta_i + \alpha_3 {Bn_i}^2 + \alpha_4 Dy_{1,i} + \alpha_5 Dy_{2,i} + \alpha_6 Ef_i \quad (2.4)$$

where α_1, α_2, α_3, α_4, α_5 and α_6 are the parameters to be estimated and they are constant across all buildings. Ta represents air temperature, Bn represents direct radiation, and Dy_1 and Dy_2 are dummy variables representing the energy standard. They are (-0.5, 1) for the Standard 90.1-2007, (-0.5,-0.5) for the Standard 90.1-2010 and (1,-0.5) for the Standard 90.1-2013. Ef represents the grid emission factor (gCO_2/Btu).

The emissions of the prototype office building z_i^0 are estimated in fourteen climatically consistent regions within the contiguous United States based on the International Energy Conservation Code. For each region, one city was selected to represent the climatic conditions of that region. The climate data of each city are collected from Meteonorm 7, which gathers hourly data on climate factors such as global radiation, direct radiation, temperature, precipitation, humidity, wind, etc. By plotting the emissions with respect to the climate data, it is determined that air temperature and direct radiation have a significant effect on building emissions. As evidenced from Figure 2.2, the impact of air temperature on emissions is quadratic. This quadratic relationship is due to the increases in energy consumption in summer and winter months because of the need to use air conditioners and heaters (Buzoianu et al., 2005). The deterministic variables are ${Ta_i}^2$ and Ta_i, where Ta_i denotes air temperature. It is further noted that emissions linearly correlate with the square of direct radiation, and thus the deterministic variable ${Bn_i}^2$ is adopted, where Bn_i denotes direct radiation.

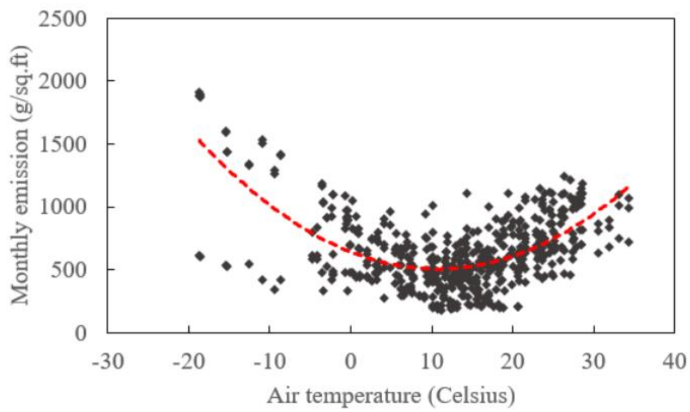


Figure 2.2 Change of Building Emissions with Air Temperature

Electricity in the selected cities is often supplied by different power grids that vary in fuel structures and in their generation and distribution efficiencies. Such situations lead to significant divergences in grid emission factors (gCO_2e/Btu) among cities. In other words, buildings that consume the same amount of energy may emit different amounts of carbon dioxide based on the power grids in which the buildings are located. Therefore, the grid emission factor (Ef_i) is selected as a deterministic variable of building emissions. The value of the emissions factor is obtained from the Climate Registry (TCR, 2015).

Table 2.1 summarizes the estimated coefficient values of building emissions in Equation 2.4. Building emissions are significantly affected by climate conditions (air temperature Ta and direct radiation Bn), the energy standard with which the building complies (Dy_1 and Dy_2) and the grid emission factor (Ef). On average, compared to the Standard 90.1-2007, emission savings are 230 gCO_2/ft^2 for the Standard 90.1-2013 and 52 gCO_2/ft^2 for the Standard 90.1-2010, conditional on the same climate conditions and power grids.

Table 2.1 Regression Result for Building Emission

Coefficient	Value	Standard deviation	P-value
α_1	1.044	0.400	0.000
α_2	-21.923	0.900	0.000
α_3	-0.001	0.000	0.002
α_4	-118.482	9.826	0.000
α_5	34.919	9.647	0.000
α_6	3449.389	142.440	0.000
Constant	84.481	25.838	0.001

Note: Number of observation is 528. F(6,521)=291.58.

R-squared is 0.7705. Adjusted R-squared is 0.7679.

Equation 2.4 is used to predict future emissions of the prototype building in a changing climate. The future climate data are provided by Meteonorm 7 and are based on General Circulation Models. The models combine with different emission scenarios presented in the IPCC Fourth Assessment Report: Climate Change 2007. The emission scenarios include A1FI, A1B, A1T, A2, B1 and B2. None of the emission scenarios represent a best guess of future climate change. The A2 scenario, which is used in this study, is characterized by a world of independently operating and self-reliant nations with continuously increasing populations and regionally oriented economic development (IPCC, 2000). This scenario represents a sustained increase in global emissions and includes the highest increase in temperature to occur by 2100 (Robert and Kummert, 2012). With temperature increase of approximately 0.4° Celsius in this scenario, the baseline emission of the prototype building is expected to increase by 4.4% from 2010 to 2030, as presented in Figure 2.3. The building constructed with the most stringent energy standard (90.1-2013) outperforms that with the more relaxed energy standards (90.1-2007 or 2010). However, a reverse situation may occur when the buildings are located in different climatic zones. The lower bound in Figure 2.3 represents the emissions of the most energy efficient building following a corresponding energy standard, and thus, it is often a building located in a region that has a mild climate and an efficient power grid. Conversely, the upper bound often represents the emissions of a building located in a region that has extreme cold or hot weather and a less efficient power grid.

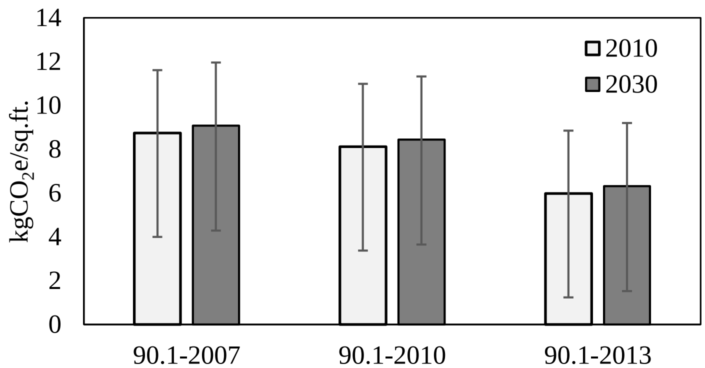


Figure 2.3 Prediction of Baseline Emissions for Different Energy Standards

2.3.3 Emission reduction techniques

Conventional ways of reducing emission often include the change of insulation materials and windows. Building emission is affected by the R-values of insulation materials, which differ in the type of material used and the thickness on both roof decks and walls. The R-values of wall insulation range from 10 to 15. The cavity R-values and continuous R-values of roof insulation range from 13 to 49 and from 15 to 25, respectively. Windows are altered in four ways: (*i*) number of panes, (*ii*) gas fill, (*iii*) tint, and (*iv*) low emission control. The U-values of the windows range from 0.17 to 0.76. The solar heat gain control (SHGC) values of the windows range from 0.26 to 0.67. Daylight control technique is also included. Conventional windows will be replaced with view and daylight windows as recommended by the Small to Medium Office AEDG Recommendations. Windows on the south facade will have exterior shading or light shelf surfaces depending on if they are view or daylight windows. East and west view windows will have internal shading controls. Daylight sensors are added in spaces with daylight control.

The prototypical building is designed with the alternative technologies of three wall insulation materials, five roof insulation materials and five windows, and daylight control. A total of 38 design alternatives are generated. Each of those designs adopts one or multiple emission reduction technologies. The designs are used in different climatic zones and their emissions are estimated using the OpenStudio Parametric Analysis Tool (PAT). Not all the designs are effective in any climatic zones. For example, the daylight control technique can save 41.8 Btu/ft^2 per year when it is used in Miami (zone 1A), while it increases the energy use by 40.9 Btu/ft^2 per year when it is used in Chicago (zone 5A). The main reason for this difference is that the use of daylight windows in Chicago significantly increases the heating load in winter. Energy used for heating far exceeds the lighting savings. Given that, the technologies that are not effective in a particular region are removed from the analysis of that region. Figure 2.4 summarizes the mitigation potential with the use of aforementioned technologies in different climatic zones. The technologies are generally more effective in cold regions (e.g., zones 5 to 7) than they are in mild or hot regions (e.g., zones 1 to 3).

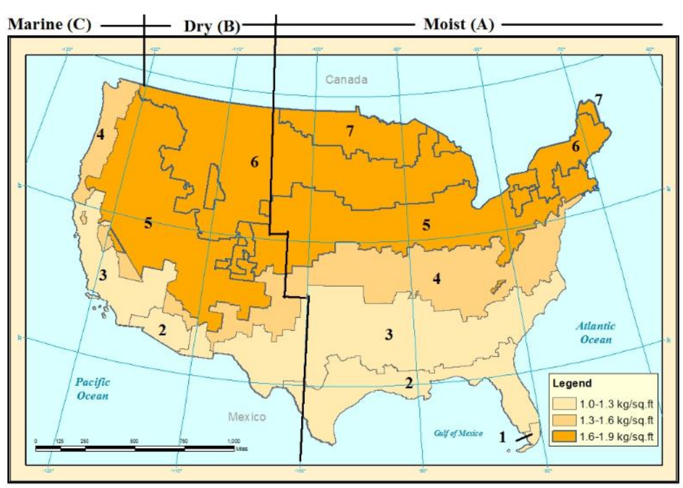


Figure 2.4 Technological Mitigation Potential of Buildings in Different Climate Zones

2.4 Estimation of Abatement Costs and Revenues

Empirical data are collected to estimate building retrofit costs $\mathbb{C}(q_{i,t})$ and initial construction costs $ic(x)$ and to determine parameter values for life cycle payoffs, e.g., γ_t and β.

2.4.1 Building retrofit cost

The building retrofit cost is described as a function of emission reduction and climate condition, as expressed in Equation 2.5. The retrofit cost is estimated using the cost analysis module of OpenStudio PAT. The technology cost parameters are obtained from the National Residential Efficiency Measures Database. It is implicitly assumed that the cost of insulation materials and windows are not significantly different between residential buildings and commercial buildings. The emission reduction has been estimated in Section 2.3.2. The climatic zones are grouped according to the differences in temperature and humidity. Temperature difference is denoted by Te. Te is 1 for zones 1 to 4 and 2 for zones 5 to 7. Humidity difference is denoted by *Hu*. *Hu* is 1 for the zones with the letter A (dry) and 2 for the zones with the letter B (moist) or C (marine).

$$\mathbb{C}(q) = \beta_1 q^2 + \beta_2 q^2 \cdot Te + \beta_3 q^2 \cdot Hu + constant \tag{2.5}$$

where β_1, β_2 and β_3 are the parameters to be estimated and they are constant across all buildings. $\mathbb{C}(\cdot)$ represents the retrofit costs in the unit of $\$/ft^2$, q represents the cumulative annual emission reduction in the unit of $gCO_2e/(ft^2 \cdot yr)$, Te represents the climatic zones differentiated by temperature, *Hu* represents the climatic zones differentiated by humidity. The regression results in Table 2.2 indicate that the cost is a convex function of the emission reduction, which is statistically significant at a 95% confidence level.

Table 2.2 Regression result for Building Retrofit Cost

Coefficient	Value	Standard deviation	P-value
β_1	1.86×10^{-2}	2.24×10^{-3}	0.000

β_2	-6.52×10^{-3}	1.14×10^{-5}	0.000
β_3	0.658	0.214	0.002
Constant	3.704	0.589	0.000

Note: Number of observation is 281. $F(3,277) = 49.59$.

R-squared is 0.3494. Adjusted R-squared is 0.3424.

It is emphasized that in practice, each project-based baseline should be monitored and verified by a standard organization and that there are additional fees applied to these processes compared to using a performance baseline. Normally, each project experiences two rounds of external reviews with average expenses of $5,000 per round. Therefore, the abatement cost is increased by $10,000 per project when implementing the project-based baseline.

2.4.2 Initial construction cost

The incremental costs for initial construction are estimated by PNNL(2013) and PNNL(2015). The studies analyze national cost-effectiveness of ASHRAE 90.1-2010 and 90.1-2013 compared to ASHRAE 90.1-2007. The cost estimates are tied to the changes in HVAC system, lighting, building envelope, power and other equipment. As the retrofit is limited to the building envelope in this study, only the cost associated with building envelope is considered. Table 2.3 displays the incremental initial costs of the changes in energy standard from ASHRAE 90.1-2007 to 90.1-2010 and 90.1-2013, respectively.

Table 2.3 Incremental Cost Estimate (unit: $/sq.ft)

Climate zone	90.1-2007	90.1-2010	90.1-2013
1~3	0	0.42	0.61
4	0	1.29	4.08
5~7	0	0.42	2.51

2.4.3 Life-cycle payoffs

The life-cycle analysis approach is based on the method used by the Federal Energy Management Program (PNNL, 2015). The method applied in this case consists of determining the payoffs from emission abatement, the year in which they occur, and their values in present dollars. Future payoffs are discounted to the present value based on a discount rate. The discount rate often reflects the interest that could be earned on another conventional investment with similar risk. The real discount rate of 3% used in this study is based on Rushing et al. (2013). Thus, $\beta = 1/(1 + 3\%) = 0.97$.

This chapter uses a 30-year study period, the same study period used for the cost-effectiveness analysis of the commercial energy code conducted by the PNNL (2015). The study period is a balance between capturing the impact of future inflation, energy and carbon price escalation and the increasing uncertainty of these factors in the future. Because technologies can be adopted anytime during the 30-year study period, the residual of the unused life is not negligible for the technology that is adopted later. Thus, it is inappropriate to define the terminal value as zero at the end of the study period. This study assumed that the payoffs continue to be discounted at β after the end of the 30th year. Therefore, the terminal value is $\pi_{i,t=30}/(1-\beta)$.

Electricity prices by state were obtained from EIA Monthly Electric Power Report 2015 (EIA, 2016). The escalation rate was estimated based on the price percentage change from 2014 to 2015. The price of voluntary carbon offset was obtained from Carbon Catalog at http://www.carboncatalog.org (access in October, 2015); a publicly available directory that contains the price information of 40 U.S. offset providers. Their average offset price is \$5 per metric ton, which is used as the initial price in this study. The increasing rate is assumed to be \$1 per year. A transaction fee is assumed to be 2% of the revenues from offset sales.

2.5 Results and Discussion

2.5.1 Program participation and mitigation decisions

The optimal problem is specified by plugging empirical function (Eq. 4 and 5) into objective functions (Eq. 1 and 2). A closed-form solution for the dynamic problem is derived in the Appendix. The model is then run in a dynamic pattern using AnyLogic 7.1.2 for two scenarios. The first is a scenario for new construction projects, where the project proponents first choose an energy standard for building construction (according to Eq.1) and then decide on the annual emission reductions during the operation phase (according to Eq.2). The second is a scenario for building retrofit projects, where the project proponents take building designs as given and decide on the annual emission reductions during the operation phase. In each scenario, two baseline rules are compared with respect to their effects on emission mitigation, cap extension and profit generation.

With respect to new construction projects, the construction and operation phases contribute differently to emissions mitigation over a building's life cycle. As displayed in Table 2.4, 9.6% of emission mitigation occurs in the construction phase due to optimally selected energy standards, while 91.4% of emission mitigation occurs in the operation phase through subsequent retrofit. ASHRAE 90.1-2013 is the optimal choice for 80% of the buildings with the project-based baseline and 64% of the buildings with the performance baseline. Even if more than half of the buildings follow the most cost-effective energy standard, subsequent retrofits are still likely to be profitable as energy and carbon prices are expected to increase. Compared to the project-based baseline, adopting the performance baseline enables the project proponents to earn \$4.64/ft^2 more from carbon trading at the expense of generating 13.3 kg/ft^2 non-additional offsets. The performance baseline can increase private profits mainly because it eliminates the need for verifying individual project baselines and saves the costs associated with project application, monitoring and verification. Considering the current carbon price, the monetary gains from using the performance baseline is attractive even when accounting for the slightly extended emission cap.

With respect to retrofit projects, buildings have been constructed following current commercial building energy codes in their corresponding states. According to the statistics of the U.S. Department of Energy, as of April 2016, 10% of the states have adopted ASHRAE 90.1-2013 or higher, 34% have adopted ASHRAE 90.1-2010 and 56% have adopted ASHRAE 90.1-2007 or lower. Accordingly, their as-built energy performances are lower than those for the new construction projects, for which 64% have optimally chosen to adopt ASHRAE 90.1-2013. As the adoption of energy codes are differentiated for existing buildings, the variances in BAU emissions over geographic regions are more obvious. These variances lead the use of a performance baseline to produce more non-additional offsets even though the emission mitigation remains roughly the same as that for new construction projects.

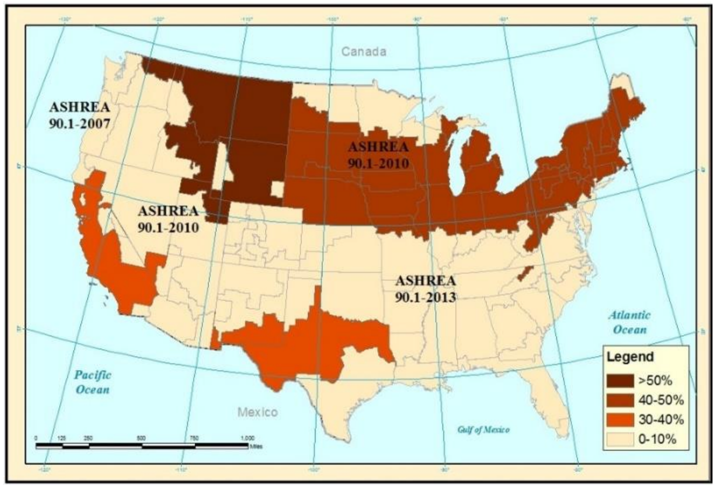
Table 2.4 Baseline Effects on New Construction and Retrofit Projects

		Emission mitigation (kg/ft^2)	Non-additional offsets (kg/ft^2)	Private profit ($\$/ft^2$)
New construction (cons./oper.)	Project-based	2.25/21.16	0/0	1.79/0.12
	Performance	1.97/21.28	-0.84/13.88	2.30/4.25
Retrofit projects (operation only)	Project-based	20.67	0	0.12
	Performance	21.01	20.95	5.93

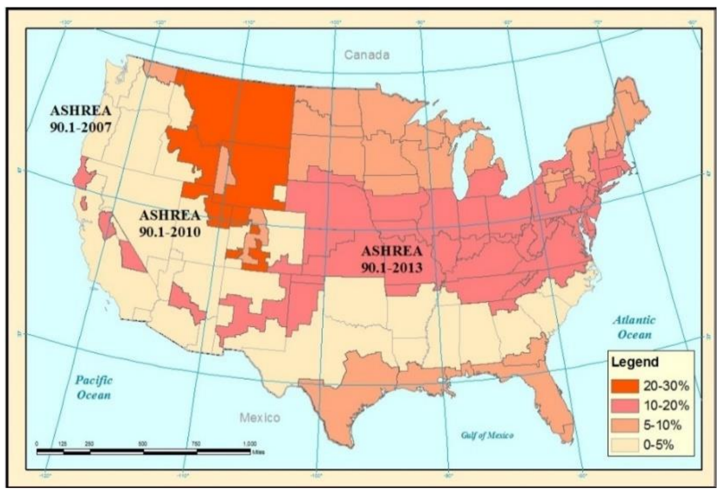
2.5.2 Baseline effects on offset allocation

Not every project proponent benefits from using the performance baseline. As a threshold uniformly applied to the whole sector, a performance baseline is theoretically certain to over-allocates offsets to some emitters and under-allocates offsets to others. This problem is extremely prominent in the building sector as emissions significantly vary according to geographic regions. Figure 2.5(a) displays the percentage of sold offsets of the total emissions over a building's life cycle. In climatic zone 6B (mainly states of Montana and Wyoming), more than half of the building emissions are verified as offsets, even though the actual reduction only accounts for 23% of the total. This finding is observed primarily because the buildings located in this climatic zone have BAU emissions that are far below the performance baseline. The difference between the BAU emissions and the baseline can guarantee a great deal of non-additional offsets even without any further emission mitigation. In contrast, buildings in climatic zones such as 1A, 2A, 2B and 3A, due to their high BAU emissions, are not qualified to earn offsets even though they have voluntarily reduced their emissions by approximately 10%. This allocation bias prevents high BAU emitters from participating and leads to a trading program that consists solely of low BAU emitters.

The offset allocation problem does not exist with the project-based baseline because it generates the offsets in accordance with individual emission reductions. Using this baseline greatly increases the participation rate because every unit of emission reduction is qualified to be traded as an offset. By comparing the offset sale percentages using different baseline rules (Figure 2.5 (a) vs. (b)), it is evident that more areas are willing to participate when using the project-based baseline than when using the performance baseline. For example, buildings located in zones 1A, 2A and 4A, which opt-out under the performance baseline, are qualified to sell offsets under the project-based baseline, with the amount equivalent to approximately 5% to 10% of their emissions. In addition, using the project-based baseline can avoid generating non-additional offsets, assuming the baseline is perfectly designed. For each individual building, the amount of offsets reflects its actual emission reductions. The offsets, therefore, are dispersed over different geographic regions as opposed to being highly concentrated in certain regions under the performance baseline.



(a) Performance Baseline



(b) Project-based Baseline

Figure 2.5 Percentage of Sold offsets on Total Building Emissions

2.5.3 The paradox of baselines adjusted for co-benefits

As suggested by the dynamic model solution in the Appendix, annual emission reductions are driven by the expected revenues from both offset sales and utility savings. This implies that utility savings may render the efforts of emission mitigation self-profitable even without a carbon price signal. The self-profitable portion of emission reduction, in theory, should not be claimed as carbon offsets. However, neither of the baseline approaches have taken this into account, which may lead to an overestimation of the offsets. The extent to which the emission reduction is driven by utility savings depends on the relative price of electricity to carbon dioxide. Based on the current average offset price, i.e., $5 per metric ton of carbon dioxide, the real offsets only account for approximately 3% of the actual emission reductions. Even at the end of the study period, when the offset price increases to $35, the effective offsets are only approximately 16% of the actual emission reductions. This means, if the baselines are adjusted to exclude all the self-profitable emission reductions, most of the previously qualified offsets will become non-additional and the voluntary trading will become a dispensable mechanism for the building sector.

The baselines that are thoroughly adjusted for profitability are not politically feasible in many cases because profitability is not the only factor that determines technology implementation in practice. Many mitigation technologies are commercially available and cost-effective, but they are often not fully implemented due to market barriers and policy constraints (Liu et al., 2013). The barriers include, but are not limited to, information asymmetries, bounded rationality, a lack of access to capital, burdensome transaction costs, institutional resistance to change current practices, etc. Significant economic incentives are often needed to enable the technologies to achieve what is expected. The incentives can be provided by baselines that are slightly more generous than their theoretical values, thus accounting for those hard-to-quantify barriers in the market.

2.5.4 Relaxing perfect information

The previous analysis considered the case where the regulator has perfect information of BAU emissions, and as such, the baselines can be set without any biases. As discussed in Section 2.2.1, some degree of information asymmetry is to be expected. At the least, the regulator may know the general trend and distribution of BAU emissions over different geographic regions but is unlikely to have accurate emissions information for each individual building. The assumption of perfect information always fails in practice. This section, therefore, relaxes the assumption through allowing uncertainties of baselines, electricity prices and carbon prices. The parameter uncertainties are modeled using triangular distributions and are assigned with the most likely values as well as upper and lower bounds. Specific assigned values are listed in

Table 2.5.

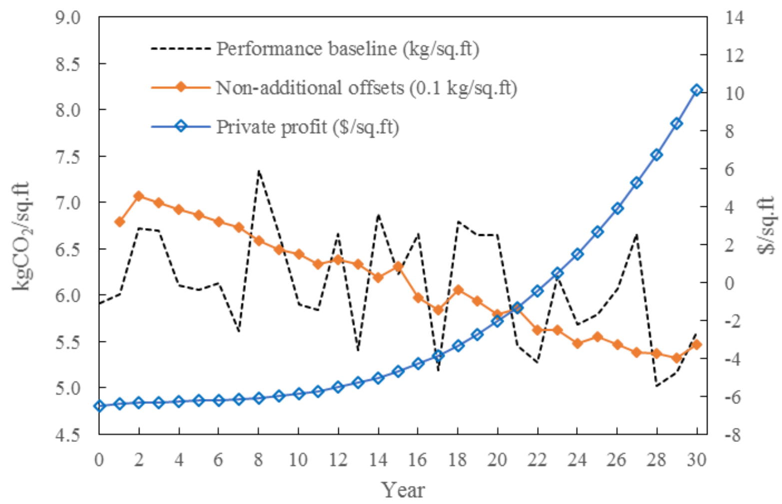
Table 2.5 Triangular Distribution Parameters for Baselines and Electricity and Carbon Prices

	Unit	Most likely value	Lower bound	Upper bound
Performance baseline	Percentile	80^{th}	90^{th}	50^{th}
Project-based baseline	Times of BAU emission	1	0.8	1.2
Increase of carbon price	$/year	1	-2	5

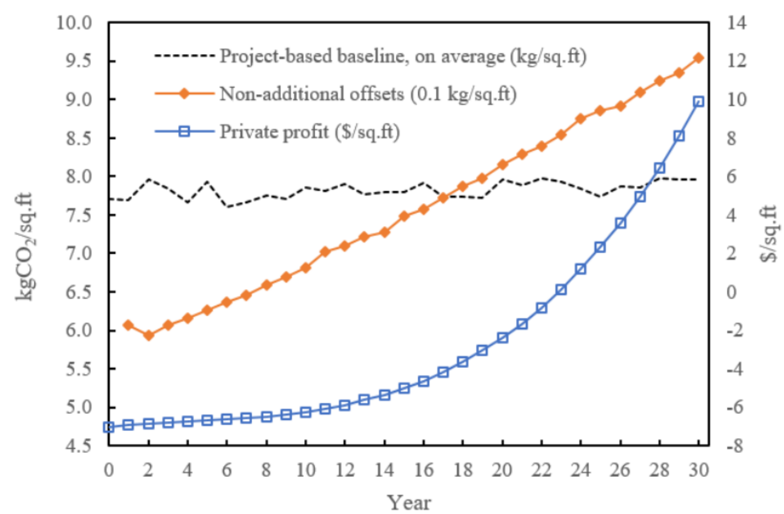
Increase of electricity price	\$/year	0.14	-0.1	0.5

Allowing for imperfect information about the performance baseline does not significantly change the overall mitigation decisions. As the baseline fluctuates around the unbiased 80^{th} percentile, over- and under-allocation in different years can compensate each other to some extent. The total non-additional offsets with imperfect information increase by 32.6% compared with the case with perfect information. The increased non-additional offsets drive up the private profit from \$4.25/ft^2 to \$10.14/ft^2. As presented in Figure 2.6(a), even though the amplitude of the baseline remains roughly the same, annual non-additional offsets decrease over time. This phenomenon can be explained by a diminishing difference of emissions from buildings across the country. As high emitters continuously optimize their emissions, they gradually narrow the emission gaps among different geographic regions. The population's emissions then become more homogeneous over time. Such a population has a small emission variance and thus produces less non-additional offsets with the performance baseline.

The imperfect information case, however, fundamentally changes the results of using the project-based baseline. The project-based baseline does not produce any non-additional offsets with perfect information. However, if the assumption is relaxed, non-additional offsets are generated when the baselines are positively deviated from the BAU emissions. As the temperature continues to rise in future, as presented in Figure 2.6(b), the amount of non-additional offsets sharply increases over time. As a result, the life cycle non-additional offsets amount to 22.8 kg/ft^2, thus exceeding the total of 18.4 kg/ft^2 with the performance baseline. This implies that the effect of the project-based baseline on emission mitigation is extremely sensitive to information accuracy and validity, and accordingly, the problem of non-additionality is easily exacerbated with imperfect information.



(a) Performance Baseline



(b) Project-based Baseline

Figure 2.6 Baseline Effects with Imperfect Information

2.6 Summary

This chapter evaluates the environmental and cost effects of two baseline approaches for voluntary carbon trading. A project-based baseline, in principle, is capable of providing effective incentives for emission mitigation and is strict in environmental integrity. However, the baseline's feasibility is conditional on the ability of an accurate prediction of BAU emissions. The results indicate that at least for the commercial building sector, the uncertainty in predicting BAU emissions can lead to a great deal of non-additional offsets generated by the voluntary program and selling the non-additional offsets to the compliance programs can result in one of the following consequences. If the compliance entities are not able to tighten their own emission caps in response, which is mostly likely to occur in practice, there will be a net increase of global emissions by approximately 53 million metric tons per year. If the compliance entities are tightened, increased emissions can be prevented but the payment for non-additional offsets will exceed $1 billion per year. These results assume the offsets include the self-profitable reductions due to utility savings. To the extent that these savings are treated to be non-additional, the potential for the project-based baseline may be even bleaker than suggested in this study.

The performance baseline, in contrast, is more adaptive to the uncertainty of the BAU emission prediction as the total amount of non-additional offsets does not significantly increase due to the allowance of imperfect information. The performance baseline also reveals a decreasing trend as the emission differences among individuals diminish over time. This is an obvious advantage because the inability to make precise predictions about building emissions, particularly over a 30-year time horizon, is to be expected. Even using an advanced energy demand model can err by up to 35% (Yu et al., 2010). In addition, the performance baseline streamlines the verification process by eliminating the need for project proponents to verify their individual project baselines. This characteristic further reduces transaction costs of emission mitigation and renders the performance baseline more attractive compared to the project-based baseline.

One of the concerns of the performance baseline is the inequity in offset allocation and a lower program participation rate. As a uniform emission threshold applied to the whole sector, the performance baseline inevitably over-allocates offsets to low BAU emitters and under-allocates offsets to the others.

The results presented in this chapter suggest that buildings in certain climate zones, due to their low BAU emissions, can obtain offsets four times more than their actual emission reductions, whereas many high BAU emitters opt out of the program even if they voluntarily reduce emissions. This allocation issue does not exist in a program with the project-based baseline because projects are awarded offsets against their self-customized baselines. One way to address the allocation issue is to propose multiple performance baselines stratified according to geographic characteristics. However, as this solution significantly increases the sample size requirements to form representative distributions for different geographic regions, it is costly to implement in practice.

The issue of baseline selection may also exist in other sectors. Even in those believed more transparent and data-rich, such as the power generating sector, emission prediction errors range from 0.48% to 11.32% depending on coal characteristics (Roy et al., 2009). As demonstrated by Winebrake and Sakva (2006), seemingly small errors in total energy forecasts actually hide more significant errors in specific sectors. In the U.S., the energy prediction conducted by the Energy Information Administration can err by as much as 3.55% for the residential building sector, 6.08% for the industrial sector and 11.09% for the transportation sector over a ten-year time horizon. While this chapter only demonstrates the results for the commercial building sector, similar attention should be given to the issue of baseline feasibility for other sectors.

As the project-based baseline has been widely used for mitigation projects, regulators are advised to be cautious regarding the prediction errors of their BAU emissions and implement the baseline while updating on the conservative side. For the projects that want to adopt the project-based baseline for future crediting, it is suggested that qualifications are evaluated based on the project nature and that permits are issued only to the projects whose emissions are relatively easy to predict. The performance baseline is more suitable to those sectors that have a complicated emission mechanism. Finally, regulators are advised to be cautious about the offset allocation issue and implement stratified baselines conditional on data availability.

Chapter 3 Baseline Manipulation in Voluntary Carbon Offset Programs

Abstract

Studies of voluntary carbon trading almost exclusively assume the additionality baselines are set by regulators who have either perfect or imperfect information about the costs and emissions of projects. In practice, regulators are often less informed than project proponents; therefore, the baselines are more likely to be privately defined even for sectoral crediting. The primary concern with privately defined baselines is that baseline developers may exert their powers to manipulate the baselines, leading to increases in sectoral emission caps. This study models baseline manipulation behaviors in the context of adverse selection, where participants can self-select into the market. The theoretical results show that the extent to which the baseline is manipulated is highly dependent on who is assigned as the baseline developer. The more the baseline developer emits, the more likely the developer manipulates the baseline. The results are further discussed in the context of the U.S. commercial building sector, where empirical methods are introduced to characterize cost and revenue functions. The empirical analysis reveals that, because of the notably low price elasticity of the offset supply, baselines are often positively biased even with third-party verifications. The biased baselines would produce up to 852 gram of non-additional offsets per square feet of building space and result in approximately 700 million metric tons of carbon leakage in compliance programs each year.

3.1 Introduction

Carbon offset is an intangible asset. The value of this asset is recognized through an additionality test that attempts to distinguish with a price signal the projects that achieve real carbon reduction from the projects that would have been undertaken anyway in the absence of the signal (UNFCCC, 2012). Only the projects that would not have occurred under a business-as-usual (BAU) scenario are considered additional. These additional projects are eligible to produce carbon offsets and sell them to the regulated entities that find it costly to reduce emissions. The additionality test is thus the centerpiece of carbon offset programs to ensure overall environmental integrity.

The additionality test is performed by setting a baseline against which the emission reduction is quantified. Setting the baseline requires rather detailed information about typical project practices over a wide range of sectors. Such information is usually privately owned and less accessible to the regulators. As one of the regulators, Verified Carbon Standard helped fill this information gap by engaging the efforts of industrial associations and private firms that are well placed to determine baselines for their own sectors (VCS, 2012). The privately defined baselines therefore served as thresholds for any projects within that sector to test additionality.

The main concern with the baselines is that the private firms, as baseline developers, may exert their power to manipulate the baselines and thus gain more from the offset programs. For example, baseline developers may lower the baseline to expel competitors from the offset programs. The decrease in offset supply drives up the offset prices, which creates more surpluses for the developers but risks forgoing the benefits of cost-effective offset projects. It is also possible that the developers increase the baseline above the counterfactual BAU emission, allowing themselves to sell non-additional offsets. The non-additional offsets either represent a damage cost due to global warming or an increase in the transaction costs within this sector. Even though such manipulation is reduced to some extent by third-party verifications, it plays a role in the programs that reward offsets based on additionality (Jack, 2008).

In the offset programs where participation is voluntary, the baseline manipulation relies not only on monopoly rents but also on complex incentives for other firms in the programs; they are potential participants. Because the participants have more information about their own abatement costs than the baseline developer, they can decide to participate if they are offered a favorable baseline (Fischer, 2005). This so-called adverse selection problem has been widely studied in the context of voluntary emission trading. Previous studies in this area focused on the impact of asymmetric information on the baseline efficacy and corresponding global emission reduction. As one example, the studies of Millard-Ball (2013) and Montero (1999, 2000) show that a generous baseline promotes participation but produces a large volume of non-additional offsets. These offsets result in significant social losses even with the consideration of abatement cost savings. However, the study of van Benthem and Kerr (2010) shows that a stringent assigned baseline may also reduce market efficiency because participants will self-select into the program. While the issue of adverse selection has spurred considerable discussion in the voluntary opt-in programs, its impact on the sector-wide baselines has yet to be studied in the context of market distortion induced by unregulated exercise of manipulation.

This chapter focuses on the motivation for manipulating baselines and its impact on the reduction of global emissions. The hypothesis is that baseline developers can always gain more by deviating from the unbiased baseline, which is an emission threshold that surpasses the 80^{th} percentile of comparable peers (UNFCCC, 2006). The analysis is performed in three steps: (*i*) a firm's abatement decision is modeled as a response to the sectoral additionality baseline. Observing the baseline, self-informed firms decide whether to participate and how much to reduce their emissions. Each firm's emission reduction is a function of the baseline, as depicted on the left side of Figure 3.1. (*ii*) One of the firms in the program is chosen to be the baseline developer who solves an optimization problem in the context of adverse selection. The developer takes firm's response functions as given and uses them to set the baseline that maximizes its expected payoffs, as depicted on the right side of Figure 3.1. (*iii*) The functional forms are specified in the context of the U.S. commercial building sector. Closed-form solutions for the optimal baseline are derived, which are compared against the unbiased baseline to demonstrate that the baseline manipulation has a high chance of occurring.

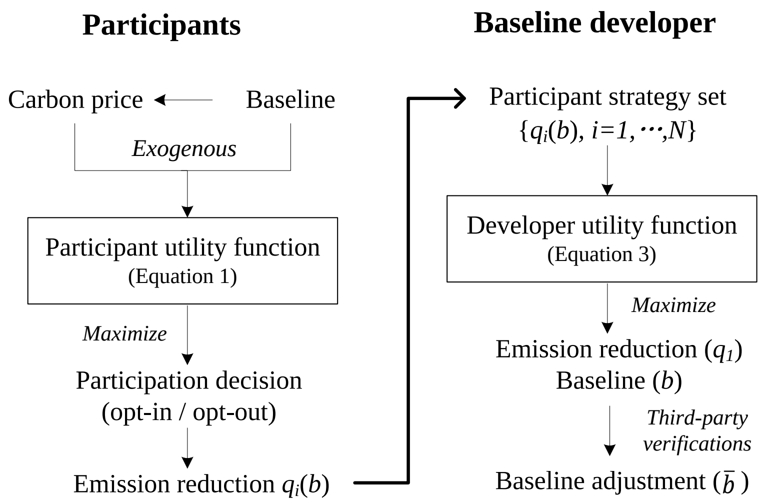


Figure 3.1 Framework of the adverse selection problem

3.2 Model Setup

3.2.1 Participation and abatement decision

The model proposed in this study is similar in the spirit to that of Millard-Ball (2013), who developed an adverse selection model in the context of the Clean Development Mechanism. There are firms $i = 1, \ldots, N$ that may choose to participate in an offset program. The firms are voluntary participants that do not face emission caps from compliance programs. For simplicity, I assume that, given an offset price and an additionality baseline, the firms make one-time decisions about the amount of emission reduction simultaneously.

Emission reduction brings two potential payoffs to the firms. The first is the revenue from selling carbon offsets to either the entities regulated in the compliance program or the individuals in the voluntary program. The second is the utility savings reflecting reduced energy consumption, which is proportional to the reduced emissions.

Each firm $\boldsymbol{i}$ has an annual BAU emission $z_i^0 \in R_+$. If the firm chooses to reduce emissions by $q_i \in R_+$, it needs to make a one-time investment $\mathbb{C}(q_i; z_i^0), R_+ \to R_+$ for technology upgrades and obtain annual revenue $\mathbb{R}(q_i; z_i^0), R_+ \to R_+$ from the reduced energy usage. The ultimate emission of the firm $\boldsymbol{i}$ is $z_i = z_i^0 - q_i$. Otherwise, the firm's emission remains z_i^0, and its abatement cost is zero. All firms are faced with a uniform baseline $b \in R_+$ set by a baseline developer. The difference between z_i and b can be sold as offset at price $p = \mathbb{P}(b), p \in R_+$. The annual revenue from the offset sale is $p(b - z_i^0 + q_i)$. It is assumed that firm $\boldsymbol{i}$ estimates its BAU emission z_i^0 and cost function $\mathbb{C}(q_i; z_i^0)$ with certainty. It can observe but not affect, the offset price p and the baseline b. A risk-neutral firm will decide to participate if and only if the gain, which is the combined offset sale and utility saving, outweighs the cost. Mathematically, net profit should satisfy

$$\pi_i = max_{q_i}\{\theta[p(b - z_i^0 + q_i) + \mathbb{R}(q_i)] - \mathbb{C}(q_i)\} \geq 0 \tag{3.1}$$

where $\theta = [(1+a)^n - 1]/[a(1+a)^n]$ represents a conversion of an n-year uniform annual revenue to a present value at interest a. It is a positive constant number.

Assuming each firm is a profit maximizer, the optimal reduction q_i^* should be reached when the marginal revenue (the sum of offset sale and utility saving per unit of emission reduction) equals marginal cost (the technology cost per unit of emission reduction). The ultimate emission level of firm i is therefore $z_i^* = z_i^0 - q_i^*$. Not all firms supply offsets. Only the firms whose optimal ultimate emissions z_i^* are less than the baseline will participate in the program and supply carbon offsets. The offset supplies from such firms are $b - z_i^*$. The firms with ultimate emissions higher than the baseline supply zero offset to the program. Therefore, the annual supply of carbon offset $s \in R_+$is expressed as follows:

$$s = \mathbb{S}(b; z_i^*) = \sum_{i=1}^{N} \max(b - z_i^*, 0) \tag{3.2}$$

3.2.2 Baseline setting

Any firm in the program could be the firm that sets the baseline. Because of technology differences and information asymmetry, some firms may have higher probabilities of becoming the baseline developer. There will be a game in which the firms compete for the developer position. For simplicity, instead of solving this game, the baseline developer is assumed to be given, for example, firm 1, with BAU emission z_1^0.

To apply the baseline to the entire sector, the developer needs to pay a fixed cost $f \in R_+$ to the standard organization to get the baseline verified. In return, the developer gets compensated in terms of collecting a certain fee for any unit of offset sold based on the baseline. This fee is denoted as $\tau \in (\bar{\tau}, \underline{\tau}) \in R_+$. Assuming offset demand always exceeds supply, the total compensation is $\mathbb{H}(b; z_i^*) = \theta\tau\mathbb{S}(b; z_i^*) - f$. The developer also benefits from its own offset sale and utility saving.

In contrast to the other firms that choose q_i and take b as given, the baseline developer determines both b and q_1 simultaneously. In this problem, b is used to affect the offset price p, which, in turn, affects the participation of the other firms. As one example, a more stringent b reduces the annual supply of offsets $s = \mathbb{S}(b; z_i^*)$. A decrease in supply drives up the offset price p according to the inverse supply curve $p = \mathbb{P}\big(\mathbb{S}(b; z_i^*)\big), R_+ \rightarrow R_+$. For the developer, the increased price contributes to its revenue from offset sale but reduces its compensation because of decreased offset supply (s). Therefore, the goal of the developer is to choose both b and $q_1$that can achieve the overall maximum profit that combines its own offset sale, utility savings and compensation from the other firms. The optimal b and q_1 satisfy

$$(b^*, q_1^*) = \text{argmax}\{b, q_1 |\ \theta\mathbb{P}(b)(b - z_i^0 + q_1) + \mathbb{H}(b) + \mathbb{R}(q_1)] - \mathbb{C}(q_i)\} \tag{3.3}$$

Given q_1^*, the baseline developer sets the baseline b^* by weighing the trade-offs between its own offset sale and the compensation as a baseline developer ($\mathbb{H}(b)$). Any deviations from the optimal baseline b^* will result in a loss of expected profit. Graphically, this is demonstrated in Figure 3.2. If the baseline developer sets $b = b^* - \Delta b$, a total of $N\Delta b$ emission reductions are not regarded as offsets anymore, and the annual supply of offset decreases, which, in turn, causes the offset price to increase by Δp. The change in the profit will be the extra offset sale (area A) minus the cost of non-additional reductions (area B). Meanwhile, the baseline developer receives less compensation because of the decrease in offset sales (here, all the offsets are assumed to be sold). The loss of compensation is the compensation fee (τ) times the change of offset sale ($\Delta s = s^* - s$), represented by area C. Because b^* maximizes the total expected profit, the impact of deviation (area A-B-C) must be negative.

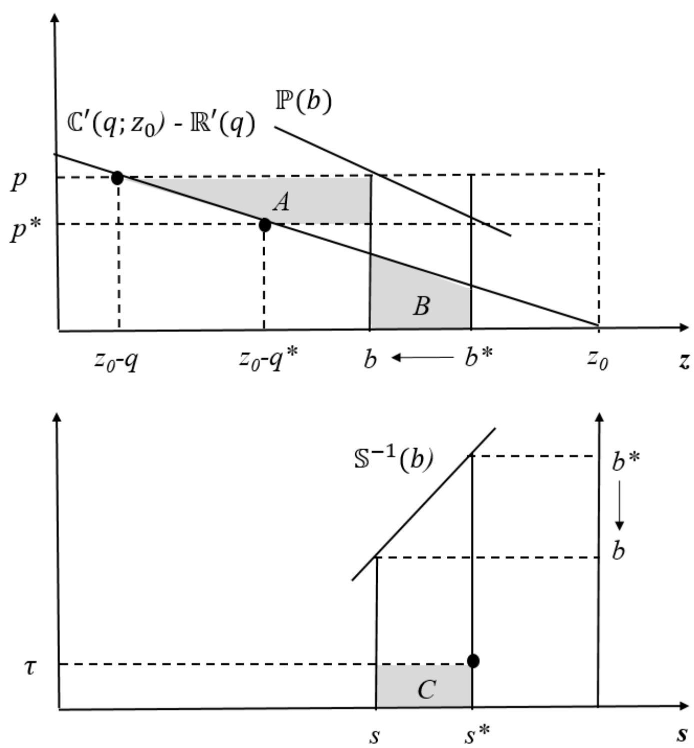


Figure 3.2 Analysis of the deviation from the optimal baseline

3.2.3 Baseline adjustment under verification

The privately defined baseline must be assessed and validated by independent verification bodies. The objective of the verification is to ensure that the baseline level provides both environmental integrity and sufficient financial incentive to potential projects. Therefore, in practice the optimal baseline b^* solved in Section 3.2.2 may not be the optimal value. It may requires some adjustments to account for the need for third-party verifications.

Carbon emissions are "fugitive events" that are not recorded by any party other than the emitter itself. They are not similar to conventional air pollutants that can be directly measured by monitoring devices. The verification bodies can only indirectly estimate the honesty of the baseline through the underlying data and dataset that are submitted by the baseline developer. Because of this limited monitoring ability, the possibly imperfect verification is characterized by the conditional probabilities (Malik, 1993).

$$\omega_j = \mathrm{P}(\ b \text{ at level } j \text{ passes verification} \mid b > b^0) \tag{3.4}$$

where ω_j represents the probability that the privately defined baseline b at level j can be verified even if it is higher than the unbiased baseline b^0 ($b < b^0$ is allowed in verification because of the principle of conservativeness). It is assumed that $\omega_{b=b_0} = 1$ and $\omega_{b=b^*} = 0$ where $b^* = \{b^* | z_1^0 = \max(z_i^0, i = 1, \dots, N)\}$. The value of ω_j changes linearly between 0 and 1.

If the baseline b does not pass the verification, the baseline developer needs to revise the baseline level and resubmit it for another round of review. The cost of resubmission is assumed to be the same as the verification fee f. The developer is allowed to revise the baseline infinite times until it is eventually verified. Because each round of revisions is associated with a cost f, it is more cost effective for the developer to only adjust the baseline once if necessary. A risk-neutral baseline developer will adjust the level of the baseline to maximize its payoffs:

$$\overline{b^*} = argmax\{b|\, \pi_{ad}, \pi_{noad}\} \tag{3.5}$$

$$\pi_{ad} = \omega_{b^{a*}} \cdot \pi_1^a + (1 - \omega_{b^{a*}})(\pi_1^0 - f) \tag{3.6}$$

$$\pi_{noad} = \omega_{b^*} \cdot \pi_1 + (1 - \omega_{b^*})(\pi_1^a - f) \tag{3.7}$$

where $\overline{b^*}$ represents the optimal baseline level under verification. The payoff is π_{ad} if the baseline developer decides to adjust the baseline from b^* to b^{a*}. The payoff is π_{noad} if the baseline developer decides not to adjust the baseline and directly submits the baseline b^* for verification.

The value of b^{a*} is determined through Monte Carlo simulation. The baseline developer begins with the baseline level b^* that is solved in Section 3.2.2. Submitting the baseline b^* has the probability $(1 - \omega_{b^*})$ that it is detected to be biased. If it is detected, the baseline developer will lower the baseline level until it passes the verification. The highest baseline level that passes the verification is recorded as b^a. This process is simulated 5,000 times. Each simulation outputs a b^a, and the value of b^{a*} is the average of all of the b^as. The payoff of setting the baseline to be b^{a*} is denoted as π_1^a.

The choice of b may have a positive or negative spillover effects on the net reduction of global emissions $\mathbb{G}(b)$. $\mathbb{G}(b)$ takes into account both the reduced emissions from participating firms and the increased emissions from the offset buyers, mostly the ones regulated in compliance programs. $\mathbb{G}(b)$ is the difference between the actual emission reductions and the offset supply, expressed in Equation 8. $\mathbb{G}(b) < 0$ suggests that there is a net increase of global emissions and that the offset program is considered to be ineffective.

$$\mathbb{G}(b) = \sum_{i=1}^{N} q_i^* - \mathbb{S}(b; z_i^*) \tag{3.8}$$

3.3 Empirical Estimates of Function Forms

The functions defined in Section 3.2 are specified in this section to derive closed-form solutions. The forms of the functions highly depend on the sector to be studied. In this study, the U.S. commercial building sector is chosen as an example. This sector is one of the pilot sectors that have implemented the additionality baseline in the United States.

3.3.1 Cost and revenue functions of emission abatement

The cost and revenue functions of emission abatement include one-time technology investment $\mathbb{C}(q_i; z_i^0)$ and annual utility saving $\mathbb{R}(q_i)$. The functions are constructed according to the outputs from the Open Studio Parametric Analysis Tool (PAT). The relevant data are collected in the following way: (i) Typical energy conservation measures are selected from the Open Studio Building Component Library and downloaded into the PAT; (ii) technological cost data are collected from the National Residential Efficiency Measures Database; (iii) medium-sized office prototype buildings are created using the Open Studio Energy Plus module and imported into the PAT, along with their cost and climate data; and (iv) the energy performances of the prototype buildings are simulated in the PAT to obtain data on the energy savings and corresponding technology costs. The data reveal a quadratic relationship between emission reductions (q_i) and technology costs ($\mathbb{C}(q_i)$); thus, $\mathbb{C}(q_i)$ is expressed as a quadratic function of q_i in Equation 3.9.

The annual utility saving $\mathbb{R}(q_i)$ is linear with respect to energy saving. Energy savings often convert proportionally to emission savings through a constant emission factor, i.e., 0.093 kg CO_2 per MJ electricity. Thus, $\mathbb{R}(q_i)$ is defined as a linear function of q_i in Equation 3.10.

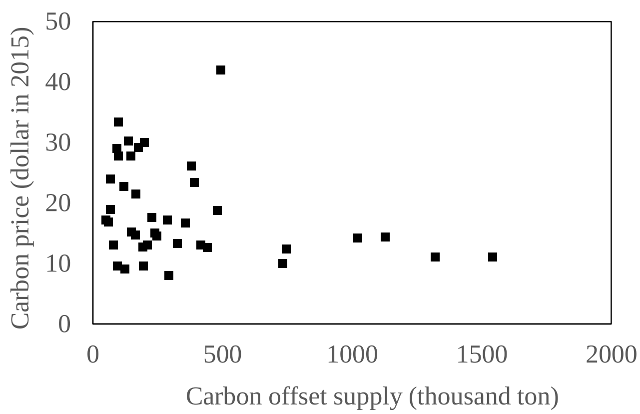
$$\mathbb{C}(q_i) = \eta q_i^2, \qquad \eta > 0 \tag{3.9}$$

$$\mathbb{R}(q_i) = \gamma q_i, \qquad \gamma > 0 \tag{3.10}$$

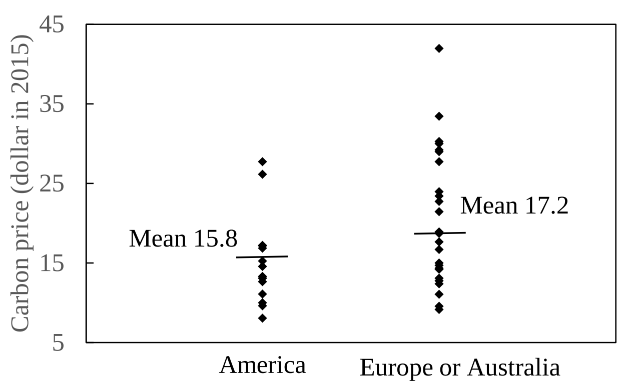
where η and γ are the parameters to be estimated. $\eta > 0$ given that technology costs are positive and often increase with the emission reductions, $\gamma > 0$, as it represents utility saving for one unit of emission reduction.

3.3.2 Carbon offset price-supply curve

The impact of supply on offset price is estimated based on the data from the Carbon Catalog at http://www.carboncatalog.org (access in October, 2015), which is a publicly available directory that contains the price information from 40 offset providers. Their annual offset supplies range from 50,686 tons to 154,303,000 tons. The offset providers with annual supplies less than 50,000 tons are excluded because most of them only have one offset project, which makes the prices depend highly on the nature of the project and fluctuate frequently. The only two offset providers with annual supplies larger than 400,000,000 tons are also excluded because the offset prices of these two providers are internally inconsistent, and often different from project to project. Among the providers recorded in the dataset, the reporting years range from 2007 to 2015. The CPI Inflation Calculator provided by the Bureau of Labor Statistics is used to convert the dollar values in different years to the year 2015.



(a) Changes in offset prices with the offset supply



(b) Changes in offset prices with provider locations

Figure 3.3 Changes in offset prices with respect to the offset supply and provider locations

Unlike regulated programs where price can be clearly predicted, voluntary programs display a wider range of price characteristics, which makes the price mechanism less clear. One explanation is that the offset price in the voluntary program may reflect not only the relationship between marginal cost and marginal benefit but also preference for associated co-benefits such as favorable public reputation (Conte, 2010). This characteristic is partially reflected in an unclear price-supply relationship, as shown in Figure 3.3. Nevertheless, the data still reveal a general trend that the offset prices decrease with the offset supply. In addition, the data reveal the differences between providers located in Europe or Australia and those located in America. For mathematical convenience, the change in the offset price is assumed to be linear with respect to the changes in the offset supply, as expressed in Equation 3.11. (Section 3.5.1 shows that the linear relationship is statistically significant).

$$p = v_1 s + v_2 Re \qquad , v_1 < 0 \tag{3.11}$$

where v_1 and v_2 are the parameters to be estimated and are constant across all buildings. p is the carbon offset price. *s* is the annual offset supply. *Re* is a dummy variable representing the region where the provider is located: 1 for Europe or Australia and 0 for America.

3.4 Participation and Baseline Setting Results

Firm participation problems are solved by plugging empirical Equations 3.9 and 3.10 into the objective function (Eq.3.1). Maximizing the objective function yields

$$q_i^* = \frac{\theta(p+\gamma)}{2\eta} \qquad , \theta, \eta, \gamma > 0 \tag{3.12}$$

$$z_i^* = z_i^0 - q_i^* = z_i^0 - \frac{\theta(p+\gamma)}{2\eta} \qquad , \theta, \eta, \gamma > 0 \tag{3.13}$$

With a given distribution of initial emission z_i^0, firms tend to reduce more when the offset price increases. The offset price is an exogenous variable to firms but an endogenous variable to the baseline developer. The baseline developer cannot directly set the offset price, but it can affect the price by changing the annual offset supply. Recall that the annual offset supply is $s = \mathbb{S}(b; z_i^*) = \sum_{i=1}^{N} \max(b - z_i^*, 0)$. Because this function has sharp corners, the feasible zone of this function is divided into two intervals, which are discussed separately.

- Interval 1: $b \geq \overline{z}^*$ - all the firms participate in the program

If baseline $b \geq \overline{z}^* = \max\{z_i^*, i = 1, \ldots, N\}$, all of the firms can sell at least some offsets. They supply offsets with the amount $\mathbb{S}^I(b; z_i^*) = \sum_{i=1}^{N}(b - z_i^*)$. Thus, the supply function becomes continuously differentiable.

In this context, the baseline developer solves b and q_1 simultaneously according to Equation 3.3. Solutions are presented in Equations 3.14 and 3.15 (refer to the Appendix B for the detailed calculation process).

$$b^{I*} = \frac{2\eta}{4\eta + \theta C} z_1^0 - \frac{\theta(D + \gamma)}{4\eta + \theta C} - \frac{4\eta}{4\eta + \theta C}\left(\frac{\tau}{2\nu_1} + \frac{D}{2C}\right) \quad , \tau > 0, \nu_1 < 0 \tag{3.14}$$

$$q_1^* = \frac{\theta}{2\eta}(Cb^{I*} + D + \gamma) \quad , \eta, \theta, \gamma > 0 \tag{3.15}$$

where

z_1^0= initial emission of the baseline developer

θ = a factor that convert a uniform annual revenue to a present value

τ = compensation fee

γ = utility saving for one unit of emission reduction

η = a parameter in Equation 3.9 showing the change of technology costs with emission reductions

ν_1= a parameter in Equation 3.11 showing the change of offset price with offset supply

C = an expression referred to Appendix Equation B4

D = an expression referred to Appendix Equation B4.

Equation 3.14 indicates that the baseline developer determines the baseline b^{I*} based on its initial emission level z_1^0, the price elasticity of offset supply ν_1, and its compensation fee τ. A low emission baseline developer tends to set a stringent baseline. The baseline will be more stringent in the program where either the offset price is more responsive to the supply changes (large $|\nu_1|$), or the compensation fee is low (small).

- Interval 2: $0 \leq b < \overline{z}^* -$ a proportion of firms participate in the program

If baseline $b < \overline{z}^* = \max\{z_i^*, \underline{i} = 1, \dots, N\}$, at least some firms choose to opt out and supply zero offsets. In this case, for mathematical convenience, the total supply of offsets is represented by $\mathbb{S}^{II}(b) = (b/b^{I*})\mathbb{S}^I(b^{I*})$. The expression of $\mathbb{S}^I(b^{I*})$ can be found in Appendix Equation B9. This function approximates the change in the offset supply with the baseline level. When the baseline b is equal to b^{I*}, the offset supply is the same as that for Interval 1. Because b is more stringent in Interval 2, the offset supply decreases as more firms opt out. Once b becomes zero, all of the firms opt out, and the offset supply decreases to zero.

The baseline developer uses the function of offset supply $\mathbb{S}^{II}(b)$ and solves the same problem that it solves for Interval 1. The results of b^{II*} and q_1^* are presented in Equations 3.16 and 3.17 (refer to the Appendix B for the detailed calculation process). b^{II*} displays similar properties to b^{I*}, that is, decreasing with price elasticity of supply ($|\nu_1|$) and increasing with compensation fee (τ).

$$b^{II*} = \frac{1}{2}(z_1^0 - q_1^*) - \frac{\tau}{2\nu_1} - \frac{Y}{2X} \qquad ,\tau > 0, \nu_1 < 0 \tag{3.16}$$

$$q_1^* = \frac{\theta}{2\eta}(Xb^{II*} + Y + \gamma) \qquad ,\eta, \theta, \gamma > 0 \tag{3.17}$$

where

z_1^0= initial emission of the baseline developer

θ = a factor that converts a uniform annual revenue to a present value

τ = compensation fee

γ = utility saving for one unit of emission reduction

η = a parameter in Equation 3.9 showing the change of technology costs with emission reductions

ν_1= a parameter in Equation 3.11 showing the change of offset price with offset supply

X = an expression referred to Appendix Equation B11

Y = an expression referred to Appendix Equation B11.

The baseline developer chooses $b^* \in (b^{I*}, b^{II*})$ that brings greater payoffs, satisfying Equation 3.3. The choice of b^* has a spillover effect on the net reduction of global emissions $\mathbb{G}(b^*)$ according to Equation 3.8. $\mathbb{G}(b^{\mathrm{II}*}) \geq \mathbb{G}(b^{\mathrm{I}*})$ given that $b^{I*} \geq b^{II*}$. This means that if $\mathbb{G}(b^{\mathrm{I}*}) > 0$, so is $\mathbb{G}(b^{\mathrm{II}*})$. The expression of $\mathbb{G}(b^{\mathrm{I}*})$ is presented in Equation 3.18.

$$\mathbb{G}(b^{I*}) = \left(\sum_{i=1}^{N} z_i^0 - \frac{2N\eta}{4\eta + \theta C} z_1^0\right) + \frac{\theta(D + \gamma)}{4\eta + \theta C} + \frac{4\eta}{4\eta + \theta C}\left(\frac{\tau}{2\nu_1} + \frac{D}{2C}\right), \tau > 0, \nu_1 < 0 \tag{3.18}$$

Equation 3.18 shows that given a fixed number of firms (N), $\mathbb{G}(b^{I*})$ positively correlates with the price elasticity of the offset supply ($|\nu_1|$) but negatively correlates with the compensation fee (τ). More importantly, this equation highlights the significance of answering a question, namely, who should be the baseline developer? This question is critical because the spillover effect, which is how the baseline affects the global emissions, highly depends on the relative emission level of the baseline developer in the program, which is represented by $\sum_{i=1}^{N} z_i^0 - \frac{1}{2} N z_1^0$ (the first term of Equation 3.18 is simplified here given that θC is very small). The more the baseline developer emits, the more likely the developer sets a baseline that results in a net increase in global emissions ($\mathbb{G}(b^{\mathrm{I}*}) < 0$). When the baseline developer behaves in this way, the offset trade will produce negative environmental externalities on a global scale.

3.5 Case Study

3.5.1 Parameter estimation

The theoretical results in Section 3.3.4 are applied to the U.S. commercial building sector, which constitutes approximately one third of the national carbon emissions. OpenStudio is used to create prototype buildings and estimate their annual carbon emissions. A total of 48 prototype buildings are created according to the ASHRAE 90.1-2013 Standard and placed in fifteen climatically consistent regions based on the International Energy Conservation Code. For each region, one city is selected to represent the climate conditions of that region. The climate data for each city are collected from Meteonorm 7 and used as input data for Open Studio Energy Plus to estimate the hourly emission of each building. All of the buildings are three-floor office buildings with 53,660 ft^2. Their emissions range from 1,240 gCO_2e/ft^2 to 8,851 gCO_2e/ft^2, depending on the climate regions in which they are located.

Building retrofit cost is described as a function of emission reduction in Equation 3.9. The retrofit cost is estimated using the cost analysis module of OpenStudio PAT. The technology cost parameters are obtained from the National Residential Efficiency Measures Database. It is implicitly assumed that the costs of abatement technologies are not significantly different between residential and commercial buildings. The regression result shows that the relationship between retrofit cost ($\mathbb{C}(\mathrm{q})$) and the square of emission reduction (q^2) is statistically significant at the 95% confidence level. The coefficient η is 4.50×10^{-6} (P-value is 0.000). The R-squared is 0.3353.

Utility saving is described as a function of emission reduction in Equation 3.10. Because electricity is a major energy source for buildings, electricity saving is used to approximate utility saving from emission abatement. The electricity price for each climate region is obtained from EIA(2016) and ranges from 7.8 cent/kWh to 17.8 cent/kWh. The electricity emission factor for each climate region is obtained from TCR(2015) and ranges from 1,001 lbs/MWh to 1,896 lbs/MWh. The electricity saving per unit of emission reduction (γ) is therefore estimated to be from \$$1.17\times10^{-4}$ to \$$3.16\times10^{-4}$ per gram of emission reduction.

The carbon offset price is described as a function of the offset supply in Equation 3.11. The parameter estimation is presented in Table 3.1. On average, each gram increase in offset supply drives down the carbon offset price by \$$6.99\times10^{-9}$. The relationship is statistically significant at the 95% confidence level, with R-squared 0.2106.

Table 3.1 Regression result for carbon offset price

Coefficient	Value	Standard deviation	P-value
v_1	-6.99×10^{-9}	3.26×10^{-9}	0.039
v_2	5.69×10^{-6}	2.36×10^{-6}	0.021
Constant	1.73×10^{-5}	2.13×10^{-6}	0.000

Note: The number of observation is 40. F (2, 37) = 4.93

R-squared is 0.2106. Adjusted R-squared is 0.1679.

3.5.2 Result analysis

In this case study, one of the 48 building owners is selected as the baseline developer. The developer solves for the optimal baseline and emission reductions according to the equations in Section 3.3.4, where the parameters are set according to Section 3.5.1. As shown in Figure 3.4, the optimal baseline varies with the initial emission of the baseline developer. The developers who own the buildings with higher emissions tend to set the baseline at a higher level. This trend implies that the level of baseline manipulation depends on who is selected as the baseline developer.

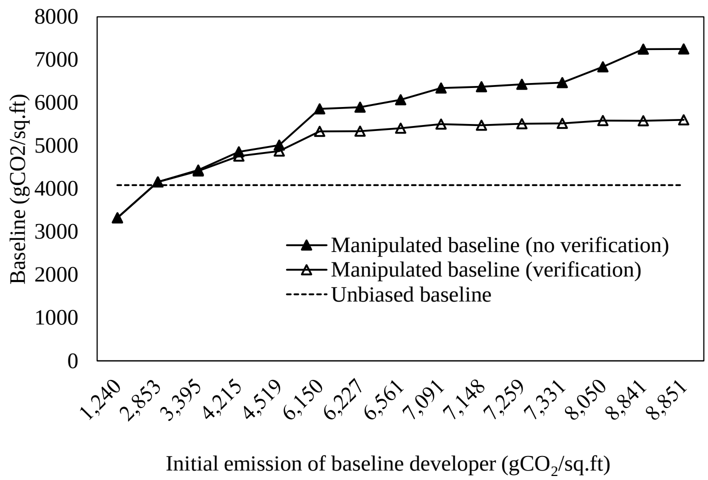


Figure 3.4 Comparison of manipulated baselines with unbiased baselines

Compared with the unbiased baseline, privately defined baselines often deviate positively and produce more carbon offsets. The unbiased baseline shown as the dotted line in Figure 3.4 represents the 80th percentile threshold of all building BAU emissions. This threshold follows the spirit of UNFCCC (2006) that requires the baseline to surpass the 80th percentile of comparable peers. Depending on the initial emission of the baseline developer, privately defined baselines deviate from the unbiased baseline to different extents. With the exception of the extremely low emissions case, the baseline developer is more likely to increase the baseline level and enjoy extra revenue from selling non-additional carbon offsets. This inclination can be explained by the very low price elasticity of the offset supply, which means that a significant increase in the offset supply will not substantially reduce the revenue from selling a unit of carbon offset. This low price elasticity motivates the baseline developer to increase the baseline level to benefit from larger offset supply in the program.

Even with third-party verifications, the baseline developer still tends to deviate from the unbiased baseline. As presented in Figure 3.4, although the acts of manipulation can be restricted to some extent by verifications, they occur almost with certainty when one of the high emitters is assigned to be the baseline developer because, for high emitters, the gains from manipulated baselines outweigh the losses from being detected and revising the baseline level. These emitters are more willing to take the risk of submitting dishonest baselines during the first round review. Because the probability of being detected increases with the degree of baseline deviation, monitoring is generally more effective in restricting the manipulation behaviors of high emitters compared to low emitters.

The direct impact of baseline increases is producing more non-additional carbon offsets from the program. Once these offsets are sold to the entities regulated by compliance programs, the emission caps are implicitly extended, resulting in an increase in global emissions. As shown in Figure 3.5, if the baseline is unbiased, the offset trading in this case can, on average, reduce global emission by 771 gCO_2e/ft^2. However, if the baseline is allowed to be privately defined, it is highly likely to be manipulated to produce large amounts of non-additional offsets, even exceeding the reduced emissions from firms participating in the program. Even with third-party verification, the manipulation can still result in a net increase in global emissions as high as 852 gCO_2e/ft^2. Considering a total of 87 billion square feet of floor space for commercial buildings in the United States, the emission caps in the compliance programs will be extended by up to 738 million metric tons of carbon dioxide solely from commercial building offset trading.

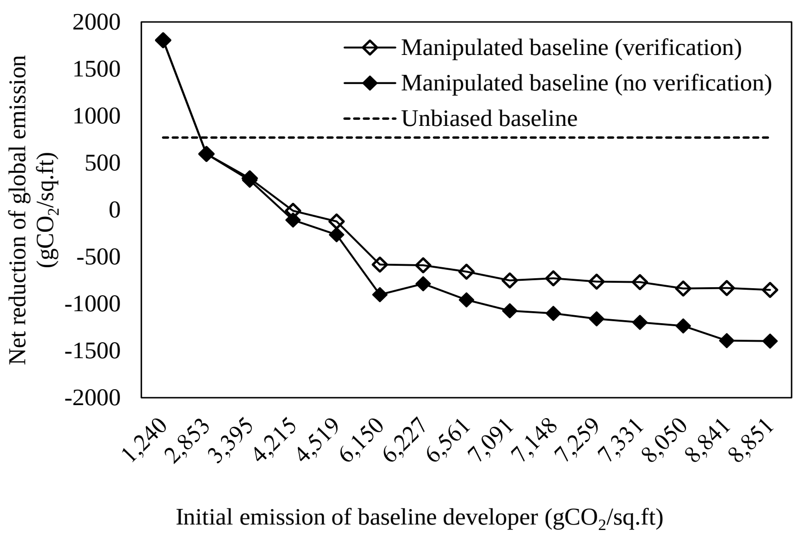


Figure 3.5 Comparison of global emission reductions between using unbiased and manipulated baselines

3.6 Summary

The issue of additionality baselines is studied in the context of adverse selection, where firms self-select to participate in carbon offset programs. One of the firms is assigned as a baseline developer who takes firms' strategies as given and decides on the baseline that is applied to all of the firms in the program. Because the baseline is privately defined, it represents a level that maximizes the expected benefit of the baseline developer instead of our long-believed social welfare maximum. Such a privately defined baseline is suspected to run a risk of extending sectoral emission caps and resulting in a net increase of global emissions.

My theoretical results show that the extent to which the baseline is manipulated highly depends on who is assigned to be the baseline developer. The more the baseline developer emits, the more likely the developer exerts its power to manipulate the baseline. The result is further discussed in the context of the U.S. commercial building sector, where the empirical methods are introduced to characterize the cost and revenue functions. The empirical analysis reveals that, because of the notably low price elasticity of the offset supply, the privately defined baseline is often positively deviated and produces more non-additional carbon offsets.

To the extent that policymakers wish to allow baselines to be privately defined, they might be advised to focus on the firms that emit less than their peers in the sector. This implies that an "open to all" policy might not be the most plausible option. Instead, baseline setting might be implemented on an invitation-only basis to specific emitters that have relatively lower historical emissions. In the case studied here, inviting the firms whose emission performances are among the top 20% of comparable peers as the baseline developers can enable the offset program to achieve a net reduction of global emissions.

In practice, the consequence of the privately defined baseline is restricted due to third-party verification. Any proposed baseline should be reviewed by independent verification bodies not involved in monitoring and reporting, who check that the baseline is determined in compliance with the relevant guidelines.

Nevertheless, any verification body needs to address the necessary trade-offs between cost and uncertainty, especially when faced with multiple small emission sources, e.g., single buildings. The allowance for uncertainty leaves the baseline developer with a chance to benefit from a manipulated baseline. This study indicates that even with the third-party verification, the baseline developer still has strong motivation to deviate from the unbiased baseline and produce non-additional carbon offsets. Once the offsets are sold to the entities regulated by compliance programs, the emission caps are implicitly extended, which can result in approximately seven 700 metric tons of carbon leakage each year. Therefore, it is pivotal for regulators to be cautious about these potential risks even if the baselines are technically verified by a third party.

Chapter 4 Balancing Climate Mitigation and Adaptation Goals: Decision Making on Building Retrofits in Hurricane-Prone Regions

Abstract

Increased climate risks pose challenges of combining climate mitigation and adaptation goals into building designs. These two goals are often misaligned, as adaptation measures use additional materials and equipment that are sources of greenhouse gas (GHG) emissions. This phenomenon causes building design to involve tradeoffs between enhancing structural resilience and reducing GHG emissions. This chapter addresses the need to identify the optimal investment allocation mechanisms between climate mitigation and adaptation measures for the design of buildings in hurricane-prone regions. A dynamic decision-making model is developed for individual investors to maximize their expected payoffs over a building's lifecycle. The model is based on the evaluation of non-stationarity hurricane damages and building emission performance under different mitigation scenarios. The results reveal a transition from long-advocated low-carbon investments to risk-oriented portfolios for building retrofits. The value of enhancing structural resilience is demonstrated through a case study on Anne Arundel County, MD, for which a "60-40" resilience/abatement portfolio is recommended. It is suggested that risk mitigation efforts should be supported with discretion on the accuracy of insurance premium discounts. Meanwhile, subsidies for emission abatements are recommended to accommodate existing emission trading schemes and building property values.

4.1 Introduction

Historically, climate policies on sustainable buildings have almost exclusively focused on greenhouse gas (GHG) mitigation (Aldy, 2015). Emissions trading schemes have been formed as climate policy instruments at national and regional levels to control global warming by creating economic incentives for achieving GHG reductions (Ju et al., 2014). These schemes are economically efficient in an environment where projects can achieve stable revenues in the presence of carbon price signals; however, they are suspected to be less attractive in areas at substantial risk of experiencing catastrophic events such as hurricanes and floods (Guikema, 2009). These events damage local buildings and result in significant direct costs such as restoration and indirect costs such as losses of business revenue and economic growth in impacted areas. To balance future costs of structural failures, project proponents have been advised to pay extra up-front costs to enhance structural resilience and to prepare, absorb, recover from and adapt to natural disasters (Linkov, 2014).

Much of the early work on resilient buildings focused on the design of single buildings with an emphasis on soil-foundation-structure-building envelope systems to improve performance in disasters (e.g., for a new development to be built in a hurricane-prone area) (Ellingwood et al., 2004; Lee et al., 2005; Li & Ellingwood, 2006; Van de Lindt & Dao, 2009). Traditional design practices involve slab-on-grade construction, which is susceptible to hurricanes. A new modular building system that involves the use of precast concrete elements combined with light-frame wood sub-systems (including basements) is proposed. This modular system reduces risks of hurricane damage by providing a stiffer living area through the addition of precast concrete elements and by providing occupants shelter in the basement (Chang, 2009). Resilience studies have recently been extended to a focus on the performance of building networks (Filippini & Silva, 2014; Chopra & Khanna, 2015; Rochas et al., 2015). Relevant studies have sought to optimize the performance of building networks exposed to a spectrum of natural disasters that can be matched to community resilience goals. They thus consider resilient building networks as a necessary component of resilient communities.

With several exceptions, enhancing structural resilience inevitably aggravates global warming, as it not only requires additional construction materials and installation activities, but it also tightens budgets for emission abatements. Strengthening costs, depending on construction specifications and the availability of materials, range from 5% to 10% of the total property value (Li, 2012). This cost makes project proponents with limited leveraging abilities tighten their expenditures on emission abatement measures, e.g., envelope insulation, daylight control, window upgrades, etc. Meanwhile, additional construction materials and activities are required to improve building element capacities to withstand natural disasters. For example, more resilient buildings are now constructed on modified, elevated foundations, and materials are stronger and more resistant to mold and hurricane straps (Guikema, 2009). These retrofitted elements emit GHGs throughout their production, transportation and installation and thus become additional emission sources that are not a factor in non-retrofit cases (Li et al., 2007).

Therefore, ways of properly addressing climate risks depend on investment decisions that trade off, at least implicitly, emission abatement (slowing down global warming) for resilience management (adapting to global warming). As a traditional solution, adopting emission abatement measures can reduce energy costs and generate revenues from carbon offset sales. Kneifel (2010) showed that these measures can be used to limit energy use in new commercial buildings by 20-30% on average. Life-cycle costs can be reduced by 3% on average and by up to over 6% for some building types and locations. However, these revenue sources can be interrupted due to structural failures resulting from disasters, rendering abatement investments less attractive. As global temperatures continue to increase and as more areas are subjected to severe natural disasters, the vast majority of property and wealth is now at risk of significant damages. UNISDR (2012) reported that the annual loss induced by infrastructure failures amounted to roughly $55 billion in the United States. This number is expected to increase due to the combined effects of climate change and increased coastal inventories of assets (Ayyub et al., 2012). These expected damages highlight the need to enhance resilience to sustain building operation and to accelerate post-disaster recovery. According to ULI (2015) studies on the South Florida Resort, the use of hurricane resilience measures can lower annual expected damages by an estimated $500,000, thus significantly reducing annual operation expenses. This makes resilience management an important addition to traditional low-carbon development pathways, and if it is properly managed in conjunction with emission abatements, it will lead to a more sustainable and resilient community.

This chapter attempts to identify optimal investment allocation between climate mitigation and adaptation measures for the design of buildings in hurricane-prone regions. A dynamic decision-making model is developed for individual investors to maximize their expected payoffs over a building's lifecycle. The model is based upon an evaluation of non-stationarity hurricane damages and building emission performance under different mitigation scenarios. Optimal investment allocation is determined by characterizing individual investment behaviors on emission abatements, hurricane mitigation, and interactions between these two actions. This chapter supports the following outcomes: (*i*) the development of a hybridized decision model that facilitates a balance between resilience and sustainability objectives, (*ii*) the ability to reflect resilience goals in building design, construction and maintenance, and (*iii*) the model's application to a selected county to demonstrate its capacity to manage a broad range of building cases and to determine policy implications for a county's environmental and economic sustainability.

4.2 Model

4.2.1 Overview

As discussed above, climate mitigation and adaptation are two approaches available to project proponents in the design of sustainable buildings. Climate mitigation is often achieved by implementing energy-efficient technologies to reduce electricity and natural gas use during building operation. Climate adaptation is often achieved by reinforcing a building's structure, allowing it to better defend against future catastrophic events such as hurricanes. Both approaches involve additional up-front technology investment while also offering financial benefits owing to reduced expenditures dedicated to energy usage and structural restoration.

The use of emission abatement measures generates financial benefits mainly through voluntary carbon trading markets. Markets enforce emission thresholds for individual buildings that are referred to as additionality baselines. Differences between baselines and actual building emissions are qualified to be traded in markets as carbon offsets. The prices of carbon offsets are determined by auction and thus vary among projects and offset providers. Revenues from carbon offset sales are earned on an annual basis and often last over remaining building years.

The use of adaptation measures strengthens building structures and helps reduce property damages during catastrophic events. Catastrophic events induced by climate change can include hurricanes, floods, earthquakes, etc. This study restricts attention to hurricanes for illustration purposes. The probability and intensity of hurricane winds is expected to increase in a changing climate. Using hurricane mitigation measures in buildings can reduce the chances and severity of damages, thus reducing expenditures on restoration. Expected cost savings are dependent on many factors such as building values, hurricane intensity levels, damage severity levels, and recovery periods. This information is assumed to be known by individual project proponents amidst some uncertainty surrounding hurricane occurrence.

In this context, the goal of a project proponent is to maximize expected payoffs by determining investment allocation between emission abatement and hurricane mitigation. As shown in Figure 4.1, each project proponent is modeled as a forward-looking decision maker. He is a potential participant in voluntary carbon trading markets and has perfect information on any technologies that are applicable to his building to reduce energy consumption or enhance structural strength. Restricted by a fixed annual budget, he aims to allocate the budget on different measures to achieve maximum lifecycle payoffs. He is given the right to adjust allocation practices on an annual basis as he continues to observe changes in market environments and climate risks. Each project proponent makes decisions independently and the performance of one building has no effect on the performance of another building during hurricane events. The results of this model exhibit dynamic investment allocation between emission abatement and hurricane mitigation measures throughout a building’s life cycle.

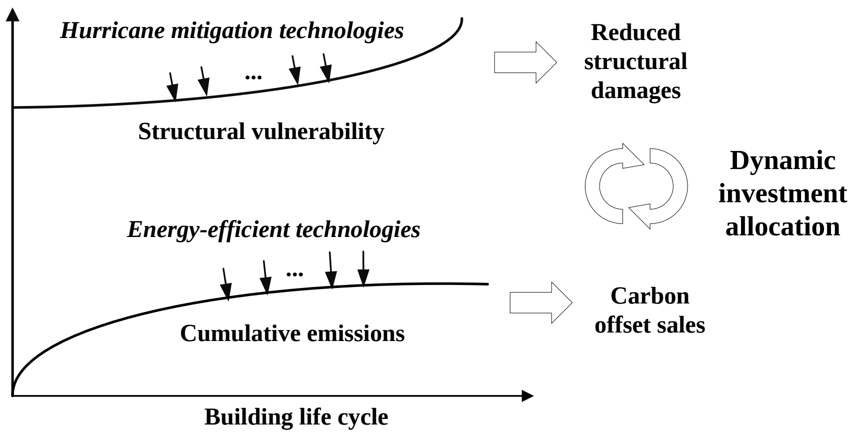


Figure 4.1 Diagram of model framework

4.2.2 Model setup

Project proponents, designated as $i = 1, \ldots, N$, design, construct and operate buildings. Each building has initial emissions $z_{i,0}$ and expected annual damages $M_{i,0}$ due to hurricane risks. For a business-as-usual (BAU) case, at year $t = 1$, a building's emissions are designated as $z_{i,1} = z_{i,0} + \epsilon_{i,1}$ and expected annual damages are designated as $M_{i,1}$, where $\epsilon_{i,1}$ reflects BAU emission adjustments due to an external environment change from $t = 0$ to $t = 1$. Such changes follow the same pattern for remaining building years.

For any year t, the building can be retrofitted in two ways. The first involves improving energy efficiency levels and reducing GHG emissions. At $t = 1$, if the building reduces $r_{i,1} > 0$, it emits $z_{i,1} = z_{i,0} - r_{i,1} + \epsilon_{i,1}$, saves utility bills $y_{i,1} = \mathbb{Y}(r_{i,1})$ and incurs an abatement cost $c_{i,1} = \mathbb{C}(r_{i,1})$. $z_{i,1}$ is compared against an additionality baseline b_1, and only emissions below b_1 can be sold as offsets at an exogenous price p_1. Revenues from carbon sales are $p_1(b_1 - z_{i,1})$. At $t = 2$, the building is faced with a new carbon price p_2 and determines whether emissions must be reduced further. If emissions are not reduced further, the abatement cost remains at $c_{i,1}$ and emissions are $z_{i,2} = z_{i,1} + \epsilon_{i,2}$. Otherwise, the building reduces $r_{i,2} > 0$ and has a cumulative abatement such that $q_{i,2} = r_{i,1} + r_{i,2}$. The associated utility savings are

$y_{i,2} = \mathbb{Y}(q_{i,2})$ and abatement costs are $c_{i,2} = \mathbb{C}(q_{i,2})$. Emissions are thus reduced to $z_{i,2} = z_{i,1} - q_{i,2} + \epsilon_{i,2}$. Similar decisions will be made each year until the building reaches its end of life.

The second retrofit plan involves reinforcing the building's structure and reducing future hurricane damages. At $t = 1$, if $a_{i,1}$ is invested in the building to install hurricane mitigation measures, the expected annual damage is reduced from $m_{i,0} = M_{i,0}$ to $m_{i,1} = M_{i,1} \cdot \mathbb{A}(a_{i,1})$, where $\mathbb{A}(a_{i,1})$ represents the percentage of building damages that can be avoided due to investments $a_{i,1}$. At $t = 2$, the building is faced with an increase in hurricane risks and whether additional mitigation measures must be adopted is determined. If there no further investments are made, the mitigation cost remains at $a_{i,1}$ and the expected annual damage is $m_{i,2} = M_{i,2} \cdot \mathbb{A}(a_{i,1})$. Otherwise, $a_{i,2}$ is invested in the building and the cumulative investment becomes $k_{i,2} = a_{i,1} + a_{i,2}$. The expected annual damage is reduced to $m_{i,2} = M_{i,2} \cdot \mathbb{A}(k_{i,2})$. Similar decisions will be made each year until the building reaches its end of life.

The annual retrofit investment is bounded by F_t, implying that $c_{i,t} - c_{i,t-1} + a_{i,t} \leq F_t$. In this context, a risk-neutral project proponent will maximize life cycle payoffs by balancing investment between emission abatement and hurricane mitigation. The optimization problem is expressed as follows.

$$\max_{r_{i,t}, a_{i,t}} \Pi_{i,t} = p_t\left(b_t - z_{i,t}\right) + y_{i,t} - c_{i,t} + c_{i,t-1} - m_{i,t} + \beta \Pi_{i,t+1} \tag{4.1}$$

$$\begin{aligned} \boldsymbol{s.t.}\quad & q_{i,t} = q_{i,t-1} + r_{i,t} \\ & z_{i,t} = z_{i,0} - q_{i,t} + \sum \epsilon_{i,t} \\ & k_{i,t} = k_{i,t-1} + a_{i,t} \\ & c_{i,t} - c_{i,t-1} + a_{i,t} \leq F_t \end{aligned}$$

The additionality baseline (b_t) is a sector-wide emission threshold that is uniformly applied to all buildings without considering individual differences. The United Nations Framework Convention on Climate Change (UNFCCC) established in its Marrakech Accords that a baseline is sufficient when it surpasses the 80th percentile of comparable peers (UNFCCC, 2006). Comparable peers include project activities undertaken in the previous five years in similar social, economic, environmental and technological contexts. For the sake of simplicity, it is assumed herein that all buildings examined in this study are comparable peers and therefore comprise the bundle for the baseline. It is also assumed that initial emissions $(z_{i,0})$ follow a normal distribution with a mean $(\bar{z}_0)$ and standard deviation (σ). Given this, the baseline is $\bar{z}_0 - 0.84\sigma$ and is adjusted for external environment change $(\epsilon_{i,t})$ as expressed in Equation 4.2. This represents the 80th percentile threshold for all BAU emissions.

$$b_t = \bar{z}_0 - 0.84\sigma + \sum \epsilon_{i,t} \tag{4.2}$$

4.3 Structural Resilience Evaluation

The expected annual damage $(m_{i,t})$ is an important model input that represents a building's ability to adapt to future hurricane risks. This ability is often referred to a building's resilience and can be quantified using a resilience metric. This section presents a practical resilience metric that allows one to track building structural performance over time. The value of resilience is calculated based on a probabilistic method that describes a non-stationary Poisson process of hurricane occurrence. This method also involves determining the value of $m_{i,t}$ to solve for optimal investment allocation in Equation 4.1.

4.3.1 Resilience metric

Several reputable entities have focused on defining the notion of resilience for infrastructure and on the development of resilience metrics. The National Research Council for instance defined resilience as the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events (NRC, 2013). This concept can be illustrated through a resilience triangle as shown in Figure 4.2. The triangle area represents the loss of infrastructure functionality after an external shock until initial levels of functionality are achieved. The percentage of functionality loss versus the area of full performance is used as a measure of infrastructure resilience (Ayyub, 2014).

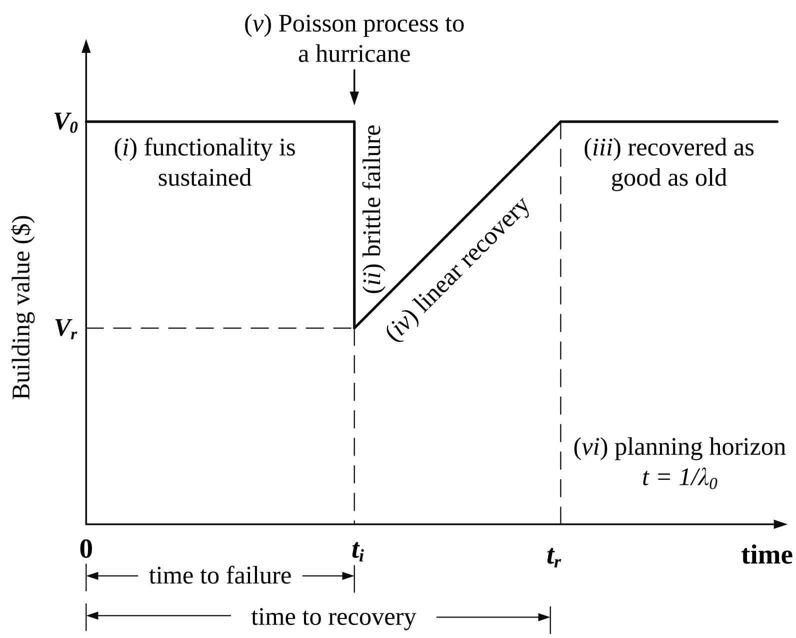


Figure 4.2 Diagram of the resilience triangle with basic assumptions

The resilience metric described in this chapter is consistent with practical metrics proposed by Ayyub (2015) that simplifies complicated system performance during disasters while maintaining intent, comprehensiveness and accuracy. The following assumptions are made: (*i*) the functionality of a building is sustained without any aging effects until a hurricane occurs; (*ii*) building failure is brittle; (*iii*) after a hurricane, a building recovers to previous performance levels; (*iv*) the recovery pattern is linear; (*v*) hurricane occurrence follows a Poisson point process with a mean occurrence rate (λ_t); (*vi*) the planning horizon relates to the initial mean occurrence rate as $t = 1/\lambda_0$; and (*vii*) building failures are independent.

The resilience metric is defined as the ratio of a building's residual value after failure to its counterfactual value without any incidents. More specifically, the ratio is the rectangular area ($V_0 \cdot t_r$) subtracted from the triangular area ($0.5(t_r - t_i)(V_0 - V_r)$) over the rectangular area ($V_0 \cdot t_r$). It is expressed in Equation 4.3 for a single failure-inducing hurricane event. Methods for determining building value (V_0) and extended time ($t_r - t_i$) are explained in Appendix C (Chock, 2005).

$$R_f = 1 - \frac{0.5(t_r - t_i)(V_0 - V_r)}{V_0 \cdot t_r} \tag{4.3}$$

4.3.2 Hurricane damage evaluation

In the resilience metric, the loss of building value ($V_0 - V_r$) is determined by hurricane damage evaluation. Hurricane hazard is often expressed through wind speed probability for a standard average time, exposure and elevation (Li *et al*., 2016). The wind speed cited in this chapter refers to 1 min sustained wind speed denoted as v. According to Georgiou (1986), the maximum wind speed achieved during a hurricane can be effectively modeled by a Weibull distribution. The cumulative density function (CDF) of wind speed is described in Equation 4.4. A non-stationary hurricane wind process is used to characterize the time variance of storm intensities due to climate change. The two Weibull parameters u_t and α_t in Equation 4.4 are treated as functions of time.

$$F(v, t) = 1 - \exp[-\left(\frac{v}{u_t}\right)^{\alpha_t}] \tag{4.4}$$

As no evidence has been presented to describe future changing patterns of hurricane winds, it is assumed that the mean speed increases linearly with time while the coefficient of variation remains unchanged (Bjarnadottir *et al.*, 2011). Assuming that r_u is the annual increment rate in parameter u_t, corresponding Weibull parameters are described as follows.

$$u_t = u_0 + r_u t \tag{4.5}$$

$$\alpha_t = \alpha_0 \tag{4.6}$$

Based on Huang *et al*. (2001) and Li *et al*. (2016), expected annual damages caused by hurricanes ($M_{i,t}$) are derived and presented in Equation 4.7 (refer to Appendix D for detailed information). $h(x,t)$ is the probability of the damage ratio exceeding a threshold x.

$$M_{i,t} = V_{i,0} \int_{t-1}^{t} \left\{ h(1,t) - \int_{0}^{1} x \cdot \frac{\partial h(x,t)}{\partial x} dxdt \right\} \tag{4.7}$$

The use of hurricane mitigation measures can reduce expected annual damages ($M_{i,t}$) and the expected loss of building value ($V_0 - V_r$) during hurricane events. Mitigation measures are categorized depending on the building component they improve. These include *(i)* roofing, (*ii*) decking, (*iii*) roof-to-wall connections, (*iv*) opening protection, and (*v*) water resistance. The costs of these measures are estimated by Pinelli *et al.* (2009) as applied to typical timber and masonry buildings of different ages and construction quality levels. Cost data are presented in Table 4.1 in terms of replacement cost ratios, which are defined as costs of replacing a particular component or assembly divided by the cost of constructing an entire building.

Table 4.1 Costs and premium discounts associated with using mitigation options

Building component	Mitigation options	Averaged cost ratio	Premium discount
Roofing	Strong shingles/tiles/roof Extra underlayment Joint tape/sealing	8.2%	26%
Decking	Improved decking nailing Bracing of gable ends	1.5%	9%
Roof-to-wall connection	Clip/strap/lumber plate	4.1%	10%
Opening	Shutters	4.7%	15%

protection	Laminated/impact glasses		
	Security film		
Water resistance	Joint sealing / taping	1.7%	4%

Data sources: Torkian et al. (2014), Pinelli et al. (2009), and FDEM (2005)

As hurricane events are inherently uncertain, the effects of such measures on building value preservation can be neither directly observed nor accurately estimated by engineering professionals. Hurricane insurance data for buildings can be used to infer the cost savings of using mitigation measures. In theory, the expected loss in building value due to hurricanes should be equal to the premium paid for hurricane insurance policies. Thus, any premium discount offered to mitigation measures should represent the expected cost savings associated with hurricane events. Let $d_{i,t}$ denote the premium discount. In turn, through the use of mitigation measures, adjusted annual building damages ($m_{i,t}$) should be BAU annual damages ($\mathrm{M}_{i,t}$) discounted at $d_{i,t}$ as expressed in Equation 4.8.

Different mitigation measures are offered with different discounts depending on their effectiveness at reducing hurricane hazards. The discount data shown in Table 4.1 serve as an example of Florida's insurance policies. Other states also use premium discount policies, but discounts employed are not disclosed to the public. As indicated by the data shown in Table 4.1, the change in premium discounts offered to insured buildings ($d_{i,t}$) is linearly correlated with the change in the replacement cost ratio ($\rho_{i,t}$). This suggests that a change in the premium discount should also be linearly correlated with a change in mitigation investments ($k_{i,t}$) given that construction costs are constant. Thus, $d_{i,t}$ is determined from Equation 4.9, where ω is a constant coefficient representing this linear relationship.

$$m_{i,t} = M_{i,t} \cdot \mathbb{A}\left(k_{i,t}\right) = M_{i,t} \cdot \left(1 - d_{i,t}\right) \tag{4.8}$$

$$d_{i,t} = \omega \cdot k_{i,t} = \omega \cdot \rho_{i,t} \cdot V_{i,0} \tag{4.9}$$

4.4 Emission Abatement Evaluation

Cost and revenue functions of emission abatement include one-time technology investments $c_{i,t} = \mathbb{C}(q_{i,t})$ and annual utility savings $y_{i,t} = \mathbb{R}(q_{i,t})$. Ideally, these variables should be estimated for individual buildings, as buildings always respond differently to adopted technologies. To develop an analytical model for a general case, costs are assumed to depend only on building types and on emission reductions, and revenues are assumed to depend only on energy savings. Numerical relationships are estimated through Energy Plus simulations supported by the OpenStudio. A detailed description of the estimation process is presented in Section 3.3.1. The data reveal a quadratic relationship between emission reductions ($q_{i,t}$) and technology costs ($\mathbb{C}(q_{i,t})$), and thus $\mathbb{C}(q_{i,t})$ is expressed as a quadratic function of $q_{i,t}$ in Equation 4.10.

Annual utility savings $\mathbb{R}(q_{i,t})$ are linear with respect to energy savings. Energy savings are often proportionally converted to emissions savings through a constant emission factor, *i.e.*, 0.093 kg CO_2 per MJ electricity. Thus, $\mathbb{R}(q_{i,t})$ is defined as a linear function of $q_{i,t}$ in Equation 4.11.

$$c_{i,t} = \mathbb{C}(q_{i,t}) = \beta_1 {q_{i,t}}^2 + \sum_k \beta_k Dy_k q_{i,t}^2 \tag{4.10}$$

$$y_{i,t} = \mathbb{R}(q_{i,t}) = \gamma q_{i,t} \tag{4.11}$$

where β_k and γ are the parameters to be estimated, and these parameters are constant across all buildings. $c_{i,t}$ represents retrofit costs in \$/sq.ft; $q_{i,t}$ represents the cumulative annual emission reduction in gCO$_2$e/(sq.ft · yr); and Dy_k are dummy variables representing building types (e.g., office, school, restaurant, hospital, hotel, etc.).

We employ a 30-year study period, which is the same study period used in the cost-effectiveness analysis of the commercial energy code conducted by the PNNL (2015). The study period captures impacts of future inflation, energy and carbon price escalation in the midst of increasing uncertainties associated with these factors in the future. As technologies can be adopted any time over the 30-year study period, the residual of the unused life is not negligible for the technology that is adopted later on. Thus, it is assumed that payoffs continue to be discounted at β after the end of the 30th year. The terminal value is $\Pi_{i,t=30}/(1-\beta)$. The values of key modeling parameters are described in Section 2.4.3.

4.5 Case Study

The analytical model employed is described in the above sections for a general case. Closed-form solutions for annual emission reduction ($r_{i,t}$) and mitigation investment ($a_{i,t}$) are derived in Appendix E. In this section, the analytical results are applied to Anne Arundel County, Maryland to demonstrate the model's applicability in guiding regional climate action plans. Numerical simulations are performed to illustrate how project investment, participation and outcomes vary with respect to the occurrence of hurricane winds in this county.

Historical hurricane data for Anne Arundel County were obtained from the U.S. National Hurricane Center (http://coast.noaa.gov/hurricanes). Over a radius of 50 miles, a total of 25 hurricanes directly affected this county from 1861 to 2008. On average, 0.174 hurricanes occurred annually over this period. The hurricane season runs from the beginning of June through the end of October. The most active months are August and September, which account for 60% of all hurricanes occurring in this county.

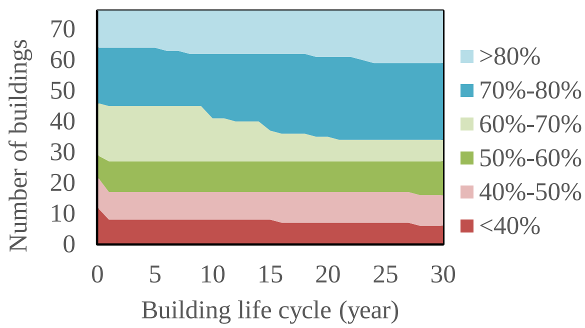
Building energy consumption data were provided by the Anne Arundel county government. The data include annual electricity and natural gas usage levels for 76 commercial buildings for 2008 to 2014. These buildings include administrative offices, warehouses, courthouses, fire departments, public libraries, road operation buildings, senior centers, etc. Based on the building typologies provided by the U.S. Department of Energy, they can be categorized into: *i*) 66 small offices including buildings with floor spaces of less than 50,000 square feet, *ii*) 9 medium-sized offices including buildings with floor spaces of between 50,000 to 200,000 square feet, and *iii*) 1 warehouse. The average annual electricity usage levels for the above three categories are 15.9, 23.9 and 3.0 kWh/sq.ft, respectively. The average annual natural gas usage levels are

0.3, 0.6 and 0.3 thm/sq.ft, respectively. The modeling parameter values for this county are described in SI-F.

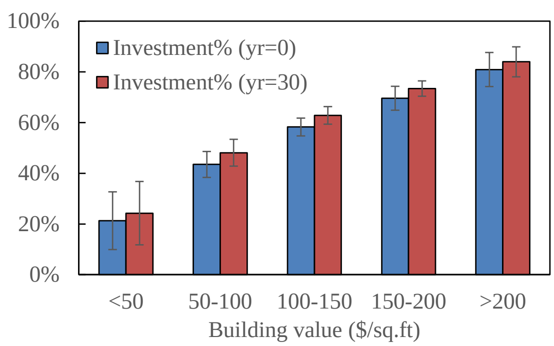
4.5.1 Results of dynamic investment in resilience

Optimal investment allocations are estimated for a total of 76 commercial buildings in Anne Arundel County for a period of 30 years. As indicated by Figure 4.3(a), project proponents invested more in structural resilience when faced with an increase in hurricane hazards over time. Investment in resilience increases from 62.6% to 66.4% over the 30-year period. In the initial year, 31 buildings invest more than 70% of their retrofit budgets into structural resilience. This number increases to 43 by the end of the 30th year. This increasing trend suggests that reinforcing building structures can deliver more payoffs than pure emission abatements. Traditional retrofit plans emphasize energy conservation that reduces life-cycle costs and GHG emissions. These plans are less cost-effective when buildings are subject to structural damages induced by climate hazards. Instead, investment portfolios that balance trade-offs between emission abatement and hazard mitigation can generate higher payoffs in the long run. In general practice, a "60-40" resilience/abatement portfolio could be recommended without access to any detailed building information.

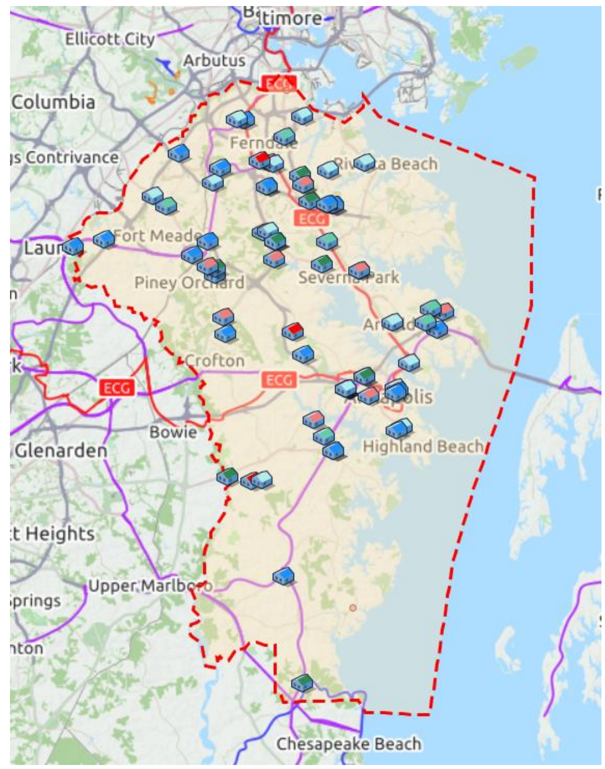
Optimal resilience/abatement portfolios change with building characteristics. They are often reflected in differences in property values. As shown in Figure 4.3(b), project proponents of buildings with higher property values invested more in structural resilience than those of buildings with lower property values. For example, in the initial year, investment in resilience reached 80.9% for buildings worth more than $200/sq.ft, while this portion is only 21.3% for buildings worth less than $50/sq.ft. This trend underscores the importance of customizing investment portfolios according to property values. High-valued buildings suffer from more serious economic losses when their structures are damaged, requiring more up-front investments in structural resilience to preserve property values. Structural damages constitute the main driver behind optimal portfolio differences among buildings, as payoffs from investing in emission abatements are relatively independent of property values. Therefore, in regards to recommendations on individual buildings, optimal resilience/abatement portfolios could reach as high as “80-20” or as low as “40-60” depending on a building’s property value.



(a) Change in resilience investment percentages



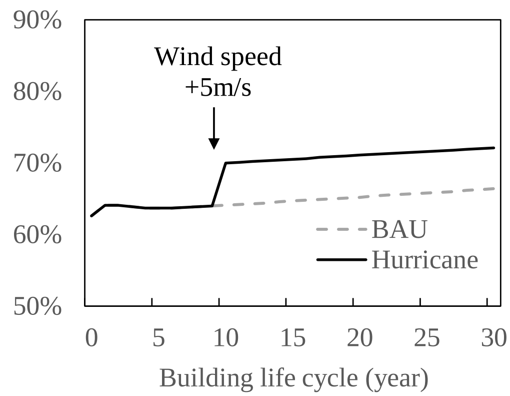
(b) Relationship between building value and resilience investment percentage



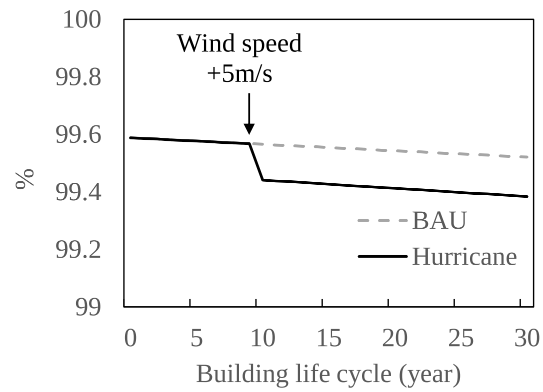
(c) Map of the studied buildings and of their resilience investment values by the end of 30th year

Figure 4.3 Optimal investment portfolios for building retrofits in Anne Arundel County

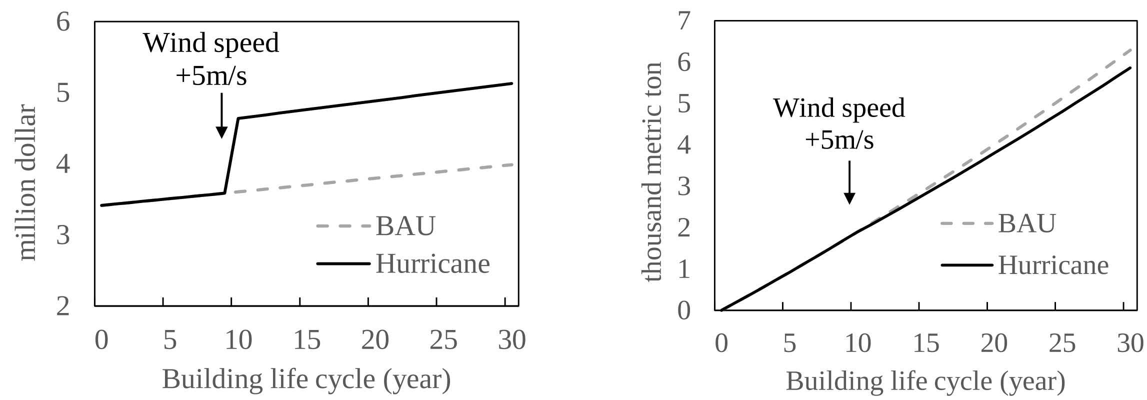
The occurrence of hurricane winds significantly affects optimal portfolios and property damages in the county. As indicated by Figure 4.4, in the BAU case, where the expected 1 min sustained wind speed is 22.4 m/s with a mean occurrence rate of 0.17, the total expected property damage level is 3.99 million dollars with 66.4% investment in structural resilience. The remaining 33.6% investment used for emission abatement can achieve a reduction of 6,290 metric tons of GHGs. The average resilience metric is 99.52%, meaning that 0.48% of the property values are expected to be lost due to hurricane winds occurring in the coming 30 years. If the expected wind speed increases over this period (e.g., the speed increases by 5 m/s from the 10th year), investment in resilience will increase to 72.1%. The total expected property damage level will increase to 5.13 million dollars while the total emission abatement level will decrease to 5,861 metric tons of GHGs. In turn, average resilience metric becomes 99.38%, meaning that an extra 0.14% of property values will be lost due to an increase in hurricane wind speeds. Therefore, hurricane hazards can alter the relative weight between structural resilience and emission abatement. A higher wind speed motivates building structure reinforcement but discourages efforts to reduce GHGs. Despite this, payoffs from improved resilience can barely compensate for the increase in property damages induced by stronger hurricane winds. Higher hurricane hazards in the future will inevitably increase financial losses and total GHG emissions.



(a) Resilience investment percentage



(b) Average resilience metric



(c) Total expected damage value

(d) Total GHG reduction

Figure 4.4 Changes in county resilience and emission performance with increased hurricane winds

4.5.2 County climate policy implications

As suggested by the results of the previous section, structural resilience can be effectively enhanced by providing insurance premium discounts for hurricane mitigation measures. A key underlying assumption is that premium discounts must be equal to property damages avoided through hurricane mitigation measures. If this assumption does not hold (e.g., a higher discount is offered), the avoided property damages may be unable to compensate for the county's increased expenditures on insurance subsidies. The county will suffer from a deficit even with a more resilient building network. As indicated by Figure 4.5, if the premium discount is increased by 20%, the county's expenditures on insurance subsidies will reach $112,280, which is 18.7% higher than the avoided property damages. This will result in an annual deficit of $18,700 due to subsidies for hurricane mitigation measures. However, if the premium discount is reduced by 20%, the county will gain from subsidy savings but will run risks of incurring higher property damages. Thus, it is pivotal for the county's policy makers to accurately estimate expected property damages and thereby tailor premium discounts to individual buildings. As property damages often change with hurricane occurrence, premium discounts should be adjusted to reflect changes in expected hurricane wind speeds in the future.

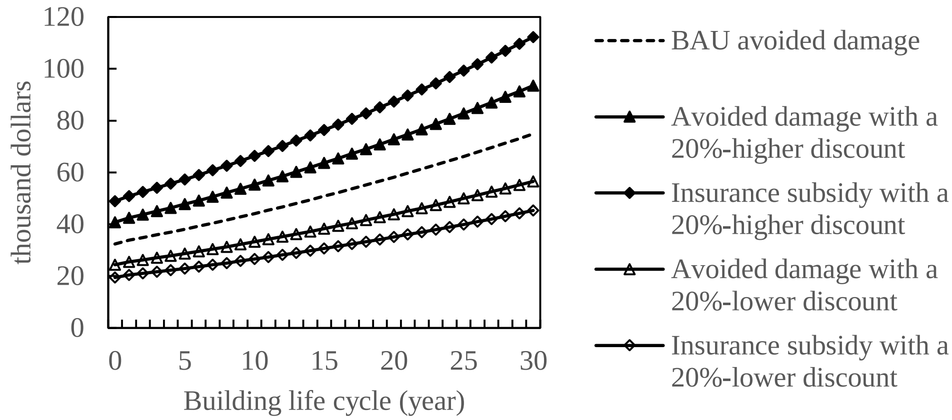


Figure 4.5 Impacts of premium discounts on property damages and insurance subsidies

In addition to enhancing structural resilience, the county's climate policies should also focus on cost-effective ways to reduce GHG emissions in the long run. As indicated by the results shown in Figure 4.3, on average, a mere 33.6% retrofit budget is used for emission abatement. This share is even lower for buildings with high property values. If viewed over a 30-year period, the share of investments in emission abatement show a decreasing trend when future hurricane risks are accounted for. This trend will be more notable when risks are higher than expected as suggested by Figure 4.4(d). Existing low and fluctuating carbon prices in voluntary trading markets do not create sufficient incentives for project proponents to invest in GHG abatements. There is a need to introduce new policies at the county level to engage abatement efforts, and especially for buildings with high property values. As part of incentive policies, financial subsidies can be provided for emission abatement measures that are voluntarily installed on buildings. Subsidies could strictly target high-valued buildings that are subject to serious economic losses when hurricane events occur. As illustrated by Figure 4.6, total GHG emissions can be reduced by 11.7% when a 5% discount on technology investments is offered for buildings with property values of more than $150 per square feet. The reduction percentage can reach 24.1% when a 20% discount is offered. The county's expenditures on technology subsides increases from $29,224 to $134,493 when the discount increases from

5% to 20%. Costs for each unit of emission reduction increase from \$4.16/MT CO_2 to \$17.2/MT CO_2. Costs are closed to current carbon prices in voluntary markets, and thus technology subsidies can be considered as a cost-effective way to further reduce this county's GHG emissions. As a higher discount level corresponds to less GHG emissions but larger government expenditures, the county is advised to choose a discount that can reconcile both economic and sustainable objectives in the long run.

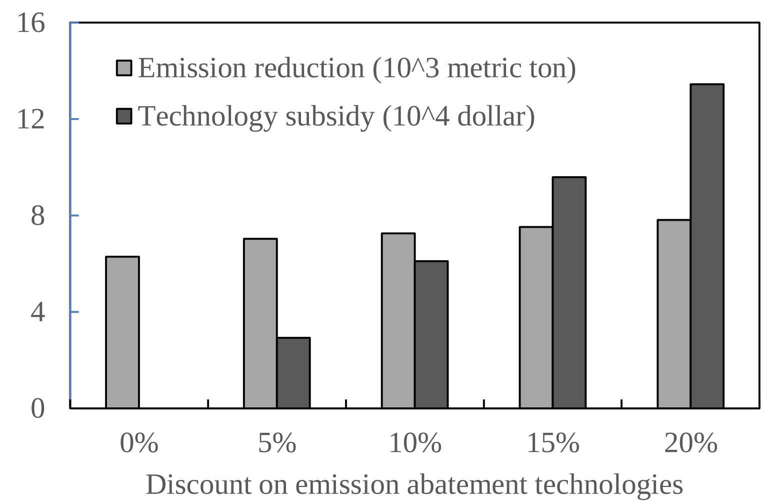


Figure 4.6 Changes in emission reductions and subsidies with technology discounts

4.6 Summary

Increased climate risks present challenges of combining climate mitigation and adaptation goals into building designs. These two goals are often misaligned, as adaptation measures use additional materials and equipment that are sources of GHG emissions. In turn, the design of buildings involves making tradeoffs between enhancing structural resilience and reducing GHG emissions. In this study, tradeoffs are made by determining optimal investment allocation between emission abatement and hurricane mitigation measures. The results reveal a transition from long-advocated low-carbon investment to a risk-oriented portfolio for building retrofits in hurricane-prone regions. The value of enhancing structural resilience is demonstrated through a case study on Anne Arundel County. When property damages induced by hurricane winds are accounted for, the county prioritizes the need for adaptation measures over traditional emission abatements. On average, 66.4% of the budget for building retrofitting is used to improve structural resilience, and this percentage is expected to increase as hurricane risks continue to rise in this county. For the 76 commercial buildings studied herein, the optimal portfolio generates $77,000 in revenue from carbon sales, saves $76,000 in utility bills, and reduces $70,000 in property damages each year, far exceeding payoffs when solely invested in emission abatement.

Structural resilience investment is motivated by providing insurance premium discounts for hurricane mitigation measures. The effectiveness of this policy approach mainly depends on whether discounts can truly reflect property damages avoided by using such measures. If discounts are offered at higher rates than they should be, the county will suffer from a deficit even with a more resilient building network in place. The deficit could reach approximately $18,000 per year when discounts are positively deviated by 20%. However, lower premium discounts lead to less resilient building networks and higher property damages, although the county saves expenditures on insurance subsidies. Thus, it would be wise to be cautious about premium discounts offered on mitigation measures and to make sure they are adjusted to reflect changes in hurricane-induced damages.

As damage control is favored in investment decision making, engaging emission abatement efforts constitute a new challenge faced by this county in further reducing its total GHG emissions. The results of this study show that existing low and fluctuating carbon prices in voluntary trading markets have failed to create sufficient incentives, causing only 33.6% of the retrofit budget to be used for emission abatement. This share is even lower for buildings with high property values. There is a need to offer financial subsidies for emission abatement measures that are voluntarily put in place for buildings. The results also show that total GHG emissions can be further reduced by up to 24% through reasonable expenditures on technology subsidies. This policy helps reconcile low-carbon and resilience goals without compromising the economic viability of this county.

While this study only analyzes the case of Anne Arundel County, similar policy implications may be applied to other communities that are exposed to hurricane storm damages. Based on historical hurricane records, the expected annual damage ratio for Miami-Dade County, Florida is 0.072, which is 4 times higher than the damage ratio for Anne Arundel County. Even for those areas that are considered more "safe" such as Washington D.C., there are still non-negligible risks of property damages (the damage ratio is 0.007). The success of the county's climate actions are dependent on good policy design and integration with local climate environments. Our study results could help guide a climate policy design that maximizes payoffs of emission abatement and risk mitigation. The results suggest that risk mitigation efforts should be pursued with discretion on the accuracy of insurance premium discounts. Meanwhile, subsidies for emission abatements should complement existing emission trading schemes and should be customized according to building property values.

Chapter 5 Conclusions

5.1 Major Findings

This dissertation evaluates the environmental and cost effects of two baseline approaches for voluntary carbon trading. A project-based baseline, in principle, is capable of providing effective incentives for emission mitigation and is strict in environmental integrity. However, the baseline's feasibility is conditional on the ability of an accurate prediction of BAU emissions. The results indicate that at least for the commercial building sector, the uncertainty in predicting BAU emissions can lead to a great deal of non-additional offsets generated by the voluntary program and selling the non-additional offsets to the compliance programs can result in one of the following consequences. If the compliance entities are not able to tighten their own emission caps in response, which is mostly likely to occur in practice, there will be a net increase of global emissions by approximately 53 million metric tons per year. If the compliance entities are tightened, increased emissions can be prevented but the payment for non-additional offsets will exceed $1 billion per year. These results assume the offsets include the self-profitable reductions due to utility savings. To the extent that these savings are treated to be non-additional, the potential for the project-based baseline may be even bleaker than suggested in this study.

The performance baseline, in contrast, is more adaptive to the uncertainty of the BAU emission prediction as the total amount of non-additional offsets does not significantly increase due to the allowance of imperfect information. The performance baseline also reveals a decreasing trend as the emission differences among individuals diminish over time. This is an obvious advantage because the inability to make precise predictions about building emissions, particularly over a 30-year time horizon, is to be expected. Even using an advanced energy demand model can err by up to 35% (Yu et al., 2010). In addition, the performance baseline streamlines the verification process by eliminating the need for project proponents to verify their individual project baselines. This characteristic further reduces transaction costs of emission mitigation and renders the performance baseline more attractive compared to the project-based baseline.

However, the effectiveness of the performance baselines relies on an important assumption that the baselines are set by regulators who have either perfect or imperfect information about the costs and emissions of projects. In practice, regulators are often less informed than project proponents; therefore, the baselines are more likely to be privately defined even for sectoral crediting. The primary concern with privately defined baselines is that baseline developers may exert their powers to manipulate the baselines, leading to increases in sectoral emission caps. The theoretical results show that the extent to which the baseline is manipulated is highly dependent on who is assigned as the baseline developer. The more the baseline developer emits, the more likely the developer manipulates the baseline. The results are further discussed in the context of the U.S. commercial building sector, where empirical methods are introduced to characterize cost and revenue functions. The empirical analysis reveals that, because of the notably low price elasticity of the offset supply, baselines are often positively biased even with third-party verifications. The biased baselines would produce up to 852 gram of non-additional offsets per square feet of building space and result in approximately 700 million metric tons of carbon leakage in compliance programs each year.

In practice, the consequence of the privately defined baseline is restricted due to third-party verification. Any proposed baseline should be reviewed by independent verification bodies not involved in monitoring and reporting, who check that the baseline is determined in compliance with the relevant guidelines. Nevertheless, any verification body needs to address the necessary trade-offs between cost and uncertainty, especially when faced with multiple small emission sources, e.g., single buildings. The allowance for uncertainty leaves the baseline developer with a chance to benefit from a manipulated baseline. This study indicates that even with the third-party verification, the baseline developer still has strong motivation to deviate from the unbiased baseline and produce non-additional carbon offsets. Once the offsets are sold to the entities regulated by compliance programs, the emission caps are implicitly extended, which can result in approximately seven 700 metric tons of carbon leakage each year.

In addition to the baseline issues, the trouble of voluntary emission trading programs also exists when they are implemented in the areas that exposure to significant risks of catastrophic events such as hurricanes and floods. The result indicates that existing low and fluctuant carbon prices in the voluntary trading markets failed to provide sufficient incentives, leading to only 33.6% of the retrofit budget used for emission abatement. The share is even lower for the buildings with high property values. When hurricane damages are accounted for, there is a transition from long-advocated low-carbon investment to a risk-oriented portfolio for building retrofits in hurricane-prone regions. The values of enhancing structural resilience are demonstrated in a case of Anne Arundel County, which prioritizes the need for adaptation measures over traditional emission abatements. On average, 66.4% of the budget for building retrofit is used to improve structural resilience, and this percentage is expected to increase as hurricane risks continue to rise in this county. For the 76 commercial buildings studied herein, the optimal portfolio generates $77,000 in revenues from carbon sales, saves $76,000 in utility bills, and reduces $70,000 in property damages each year, far exceeding payoffs when solely invested in emission abatement.

5.2 Policy Implications

As project-based baselines have been widely used for mitigation projects, regulators are advised to be cautious regarding the prediction errors of their BAU emissions and implement the baseline while updating on the conservative side. For the projects that want to adopt the project-based baseline for future crediting, it is suggested that qualifications are evaluated based on the project nature and that permits are issued only to the projects whose emissions are relatively easy to predict. Performance baselines are more suitable to those sectors that have a complicated emission mechanism.

When performance baselines are allowed to be privately defined, regulators should focus on the buildings that emit less than their peers in the sector. This implies that an “open to all” policy might not be the most plausible option. Instead, baseline setting might be implemented on an invitation-only basis to specific emitters that have relatively lower historical emissions. In the case studied here, inviting the project proponents whose emission performances are among the top 20% of comparable peers as the baseline developers can enable the offset program to achieve a net reduction of global emissions.

Increased climate risks emphasizes the need for tradeoffs between enhancing structural resilience and reducing GHG emissions. Structural resilience can be enhanced by providing insurance premium discounts for hurricane mitigation measures. The effectiveness of this policy mainly depends on whether the discounts can truly reflect the property damages avoided by using those measures. When the discounts are offered higher than they should be, the county will suffer from a deficit even with a more resilient building network. The deficit could reach approximately $18,000 per year when the discounts are positively deviated by 20%. However, lower premium discounts lead to less resilient building network and higher property damages although the county saves expenditures on insurance subsidies. Thus, it would be wise to be cautious about premium discounts offered on the mitigation measures and to make sure they are adjusted to reflect changes in hurricane-induced damages.

As damage control is favored in investment decision making, engaging emission abatement efforts constitute a new challenge faced by this county in further reducing its total GHG emissions. The results of this study show that existing low and fluctuating carbon prices in voluntary trading markets have failed to create sufficient incentives, causing only 33.6% of the retrofit budget to be used for emission abatement. This share is even lower for buildings with high property values. There is a need to offer financial subsidies for emission abatement measures that are voluntarily put in place for buildings. The results also show that total GHG emissions can be further reduced by up to 24% through reasonable expenditures on technology subsidies. This policy helps reconcile low-carbon and resilience goals without compromising the economic viability of this county.

Appendices

Appendix A: Solving for the Optimal Emission Reduction

Recall the optimization problem in Equation 2.2:

$$\max_{r_{i,t}} \pi_{i,t} = p_t\left(b_{i,t} - z_{i,t}\right) + \gamma_t q_{i,t} - \mathbb{C}\left(q_{i,t}\right) + \mathbb{C}\left(q_{i,t-1}\right) + \beta \pi_{i,t+1}$$

$$\text{s.t. } q_{i,t} = q_{i,t-1} + r_{i,t} \tag{A1}$$

$$z_{i,t} = z_{i,0} - q_{i,t} + \sum \epsilon_{i,t}$$

The cost function in Equation A1 is specified in Equation 2.5 as the follow.

$$\mathbb{C}(q) = \beta_1 q^2 + \beta_2 q^2 \cdot Te + \beta_3 q^2 \cdot Hu + constant \tag{A2}$$

For a given firm i, Te and Hu are constant. Thus, Equation A2 can be rewritten as the follow.

$$\mathbb{C}(q_i) = \kappa q_i^2 + constant, \text{ where } \kappa = \beta_1 + \beta_2 \cdot Te + \beta_3 \cdot Hu \tag{A3}$$

Plugging Equation A.3 into Equation A.1, the optimization problem becomes

$$\max_{r_{i,t}} \pi_{i,t} = p_t\left(b_{i,t} - z_{i,0} + q_{i,t-1} + r_{i,t} - \sum \epsilon_{i,t}\right) + \gamma_t(q_{i,t-1} + r_{i,t}) - \kappa(q_{i,t-1} + r_{i,t})^2 \tag{A4}$$

$$+ \kappa(q_{i,t-1})^2 + \beta \pi_{i,t+1}$$

Equation A4 is solved as a finite-period problem (*t = 1, …, N*). The firms make abatement decisions only within the N periods. The technologies that have been adopted continue to reduce emissions beyond *t = N*, but no more technology will be added beginning from *t = N+1*. Thus, the cumulative annual emission reduction $q_{i,t=n+1,\ldots,\bowtie} = q_{i,N}$. The terminal value $\pi_{i,N+1}$ is defined as the follow.

$$\pi_{i,N+1} = \sum_{t=N+1}^{\bowtie} \beta^t [p_N\left(b_{i,t} - z_{i,0} + q_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_t q_{i,N}] \tag{A5}$$

$$= \frac{1}{1-\beta}[p_N\left(b_{i,t} - z_{i,0} + q_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_t q_{i,N}]$$

The optimization problem is solved backward. When *t = N*, the value function is

$$\max_{r_{i,N}} \pi_{i,N} = p_N\left(b_{i,N} - z_{i,0} + q_{i,N-1} + r_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_N(q_{i,N-1} + r_{i,N}) - \kappa q_{i,N}{}^2 + \kappa q_{i,N-1}{}^2 + \tag{A6}$$

$$\beta\pi_{i,N+1} = p_N\left(b_{i,N} - z_{i,0} + q_{i,N-1} + r_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_N(q_{i,N-1} + r_{i,N}) - \kappa(q_{i,N-1} + r_{i,N})^2 +$$

$$\kappa q_{i,N-1}{}^2 + \frac{\beta}{1-\beta}[p_N\left(b_{i,t} - z_{i,0} + q_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_t q_{i,N}]$$

Taking the first order condition of Equation A6 with respect to $r_{i,N}$ yields the following solutions.

$$r_{i,N}^* = \frac{p_N + \gamma_N}{2\kappa(1-\beta)} - q_{i,N-1} \tag{A7}$$

$$q_{i,N}^* = q_{i,N-1} + r_{i,N}^* = \frac{p_N + \gamma_N}{2\kappa(1-\beta)} \tag{A8}$$

$$z_{i,N}^* = z_0 - \frac{p_N + \gamma_N}{2\kappa(1-\beta)} + \sum \epsilon_{i,t} \tag{A9}$$

Plugging Equations A.7 to A.9 into Equation A.6 yields the following optimal value function at *t*=*N*.

$$\pi_{i,N}^* = p_N\left(b_{i,N} - z_{i,0} + \frac{p_N+\gamma_N}{2\kappa(1-\beta)} - \sum \epsilon_{i,t}\right) + \gamma_N\left(\frac{p_N+\gamma_N}{2\kappa(1-\beta)}\right) - \kappa\left(\frac{p_N+\gamma_N}{2\kappa(1-\beta)}\right)^2 + \kappa q_{i,N-1}{}^2 + \tag{A10}$$

$$\frac{\beta}{1-\beta}\left[p_N\left(b_{i,t} - z_{i,0} + \frac{p_N+\gamma_N}{2\kappa(1-\beta)} - \sum \epsilon_{i,t}\right) + \gamma_t \frac{p_N+\gamma_N}{2\kappa(1-\beta)}\right]$$

Given $\pi_{i,N}^*$, the objective function at $t = N\text{-}1$ can be expressed as the follow.

$$\max_{r_{i,N-1}} \pi_{i,N-1} = p_{N-1}\left(b_{i,t} - z_{i,0} + q_{i,N-2} + r_{i,N-1} - \sum \epsilon_{i,t}\right) + \gamma_{N-1}(q_{i,N-2} + r_{i,N-1}) \tag{A11}$$

$$- \kappa q_{i,N-1}{}^2 + \kappa q_{i,N-2}{}^2 + \beta\pi_{i,N}^*$$

where $\pi_{i,N}^*$ satisfies Equation A10. Taking the first order condition of Equation A11 with respect to $r_{i,N-1}$ yields the following solution.

$$r_{i,N-1}^* = \frac{p_{N-1} + \gamma_{N-1}}{2\kappa(1-\beta)} - q_{i,N-2} \tag{A12}$$

Based on the expression of $r_{i,N-1}^*$ (Eq. A12) and $r_{i,N}^*$ (Eq. A7), the form of $r_{i,t}^*$ is guessed as

$$r_{i,t}^* = \frac{p_t + \gamma_t}{2\kappa(1-\beta)} - q_{i,t-1} \tag{A13}$$

Plugging Equations A13 into Equation A.4 yields the following optimal value function at *t*.

$$\pi_{i,t}^{*} = p_t\left(b_{i,t} - z_{i,0} + \frac{p_t+\gamma_t}{2\kappa(1-\beta)} - \sum\epsilon_{i,t}\right) + \gamma_t\left(\frac{p_t+\gamma_t}{2\kappa(1-\beta)}\right) - \kappa\left(\frac{p_t+\gamma_t}{2\kappa(1-\beta)}\right)^2 + \kappa {q_{i,t-1}}^2 + \beta\pi_{i,t+1}^{*} \tag{A14}$$

The value function at *t -1* can be expressed as

$$\max_{r_{i,t-1}} \pi_{i,t-1} = p_{t-1}\left(b_{i,t-1} - z_{i,0} + q_{i,t-2} + r_{i,t-1} - \sum\epsilon_{i,t-1}\right) + \gamma_{t-1}(q_{i,t-2} + r_{i,t-1}) - \kappa {q_{i,t-1}}^2 + \kappa {q_{i,t-2}}^2 + \beta\pi_{i,t}^{*} \tag{A15}$$

where $\pi_{i,t}^{*}$ satisfies Equation A14. Taking the first order condition of Equation A.15 with respect to $r_{i,N-1}$ yields the following solution.

$$r_{i,t-1}^{*} = \frac{p_{t-1} + \gamma_{t-1}}{2\kappa(1-\beta)} - q_{i,t-2} \tag{A16}$$

The guessed form is verified. Therefore, the optimal emission reduction $r_{i,t}^{*}$ is expressed as

$$r_{i,t}^{*} = \frac{p_t+\gamma_t}{2\kappa(1-\beta)} - q_{i,t-1}, \text{ where } \kappa = \beta_1 + \beta_2 \cdot Te + \beta_3 \cdot Hu \tag{A17}$$

Appendix B: Solving for the Optimal Baseline

1. Interval 1: $b \geq \bar{z}^*$ - all the firms participate in the program

According to Equation 3.13, the ultimate emission of firm *i* is

$$z_i^* = z_i^0 - q_i^* = z_i^0 - \frac{\theta(p+\gamma)}{2\eta}, \qquad \theta, \eta, \gamma > 0 \tag{B1}$$

Rewrite this equation as a function of price:

$$z_i^* = A_i \cdot p - B_i = -\frac{\theta}{2\eta} p + z_i^0 - \frac{\gamma\theta}{2\eta}, \qquad \theta, \eta, \gamma > 0 \tag{B2}$$

According to Equation 3.11, the relationship between offset price and offset supply is

$$p = \mathbb{P}(\mathrm{b}; z_i^*) = v_1 s + v_2 Re, \qquad v_1 < 0 \tag{B3}$$

Plugging Equations B2 and B3 into the supply function $s = \mathbb{S}(b; z_i^*) = \sum_{i=1}^{N} \max(b - z_i^*, 0)$, the offset price *p* can be expressed as a function of baseline b^I.

$$p = \mathbb{P}(b^I) = Cb^I + D = \frac{v_1 N}{1 + v_1 N \sum_{i=1}^{N} A_i} b^I - \frac{v_1 \sum_{i=1}^{N} B_i + v_2 Re}{1 + v_1 N \sum_{i=1}^{N} A_i} \tag{B4}$$

According to Equation 3.3, the optimal baseline b^I satisfies

$$\begin{aligned} &\max_{b^I, q_1} \theta \mathbb{P}(b^I)(b^I - z_i^0 + q_1) + \mathbb{H}(b^I) + \mathbb{R}(q_1)] - \mathbb{C}(q_i) \\ &\text{s.t.} \quad \mathbb{H}(b^I; z_i^*) = \theta\tau\mathbb{S}(b^I; z_i^*) - f \\ &\qquad \mathbb{C}(q_i) = \eta q_i^2, \; \eta > 0 \\ &\qquad \mathbb{R}(q_i) = \gamma q_i, \; \gamma > 0 \\ &\qquad b^I \geq \bar{z}^* \end{aligned} \tag{B5}$$

Plugging Equation B4 into the objective function B5 and taking the first order condition with respective to b^I and q_1 yields:

$$b^{I*} = \frac{1}{2}(z_1^0 - q_1^*) - \frac{\tau}{2v_1} - \frac{D}{2C} \tag{B6}$$

$$q_1^* = \frac{\theta}{2\eta}(Cb^{I*} + D + \gamma) \tag{B7}$$

The expressions of *C* and *D* can be found from Equation B4. Combining Equations B6 and B7, the optimal baseline level is expressed in Equation B8.

$$b^{I*} = \frac{2\eta}{4\eta + \theta C} z_1^0 - \frac{\theta(D + \gamma)}{4\eta + \theta C} - \frac{4\eta}{4\eta + \theta C}\left(\frac{\tau}{2\nu_1} + \frac{D}{2C}\right), \qquad \tau > 0, \nu_1 < 0 \tag{B8}$$

$$\mathbb{S}^I(b^{I*}) = \left(N - C\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{A_i}\right) b^{I*} - D\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{A_i} - \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} B_{\boldsymbol{i}} \tag{B9}$$

where *C* and *D* can be found from Equation B4. A_i and B_i can be found from Equation B2.

2. Interval 2: $\mathbf{0} \leq \boldsymbol{b} < \overline{\boldsymbol{z}}^*$ – a proportion of firms participate in the program

The total offset supply is

$$s^{II} = \mathbb{S}^{II}(b) = \frac{b}{b^{I*}}\mathbb{S}^I(b^{I*}) \tag{B10}$$

Plugging Equation B10 into Equation B3, the offset price becomes

$$p = \mathbb{P}(b^{II}) = Xb^{II} + Y = \frac{\mathbb{S}^I(b^{I*})}{b^{I*}} b^{II} + \nu_2 Re, \qquad X < 0 \tag{B11}$$

According to Equation 3.3, the optimal baseline b^{II} satisfies

$$\begin{aligned}
&\max_{b^{II}, q_1} \theta\mathbb{P}(b^{II})(b^{II} - z_i^0 + q_1) + \mathbb{H}(b^{II}) + \mathbb{R}(q_1)] - \mathbb{C}(q_i) \\
&\text{s.t.} \quad \mathbb{H}(b^{II}; z_i^*) = \theta\tau\mathbb{S}^{II}(b^{II}; z_i^*) - f \\
&\qquad \mathbb{C}(q_i) = \eta q_i^2, \ \eta > 0
\end{aligned} \tag{B12}$$

$\mathbb{R}(q_i) = \gamma q_i,\ \gamma > 0$

$0 \leq b^{II} < \overline{z}^*$

Plugging Equation B11 into the objective function B12 and taking the first order condition with respective to b^{II} and q_1 yields the following:

$$b^{I*} = \frac{1}{2}(z_1^0 - q_1^*) - \frac{\tau}{2\nu_1} - \frac{Y}{2X} \tag{B13}$$

$$q_1^* = \frac{\theta}{2\eta}(Xb^{I*} + Y + \gamma) \tag{B14}$$

The expressions of X and Y can be found from Equation B11. Combining Equations B13 and B14, the optimal baseline level is expressed in Equation B15.

$$b^{II*} = \frac{2\eta}{4\eta + \theta X} z_1^0 - \frac{\theta(Y + \gamma)}{4\eta + \theta X} - \frac{4\eta}{4\eta + \theta X}\left(\frac{\tau}{2\nu_1} + \frac{Y}{2X}\right), \qquad \tau > 0, \nu_1 < 0 \tag{B15}$$

Appendix C: Methods for determining building value ($\boldsymbol{V_0}$) and extended time ($\boldsymbol{t_r - t_i}$)

Building values (V_0) are estimated using the sales comparison approach. The premise of this approach is that a buyer would pay no more for a building than others are paying for similar buildings in the current market. The similar buildings chosen in this chapter are the buildings that are the same type, similar floor space (differences are less than 20%), and they are located within a radius of 5 miles. The sales prices of the similar buildings are adjusted for differences with the subject building. The differences relate to size, age and market conditions at the time of sale. The values of comparable transactions are adjusted upward (downward) for undesirable (desirable) differences with the subject building. The value adjustment are based on the following:

- Building age: properties are assumed to depreciate at 2% per annum. If a comparable building is sold at $5,000,000 and is five years older than the subject, an upward adjustment of $500,000 is made [$500,000 × 2% × 5 years].
- Sale year: the sale prices are assumed to appreciate 0.5% per month over the past three years. If a comparable building is sold at $5,000,000 a year ago, an upward adjustment of $300,000 is made [$500,000 × 0.5% × 12 months].
- Floor space: The adjusted sales price of each comparable building is divided by its size in square feet. The results of all the comparable buildings are averaged and applied to the subject building.

Post-disaster restoration involves processes of estimating damage, determining work load, obtaining funding, cleaning up, and construction. The extended time required for these processes ($t_r - t_i$) is often determined by a combination of complicated project-specific factors. They may include level of damages, funding availability, accessibility to work zones, local policies, etc. In a situation that the information is not fully accessible, the estimation of extended time can be simplified to only rely on the level of damage. Relevant data has been reported in the study of Chock (2005), which tracked 1,398 Hawaii buildings for the time required for substantial completion of repairs and reconstruction after Hurricane Iniki. The average extended times are listed in Table C-1 and can be used as inputs of the resilience metric when project-specific data are not available.

Table C- 1 Extended time required for post-hurricane restoration

Loss of building value	Average extended time (months)
Complete demolition without rebuild	10
$20\% \leq (V_0 - V_r)/V_0 < 40\%$	14
$40\% \leq (V_0 - V_r)/V_0 < 50\%$	15
$50\% \leq (V_0 - V_r)/V_0 < 90\%$	17

Appendix D: Hurricane damage evaluation

The building damages caused by hurricanes are estimated based on the study of Huang *et al*. (2001), who proposed a calculation formula for building damage ratio using Southeastern U.S. insurance data from Hurricanes Hugo and Andrew. The damage ratio is defined as the total premium paid by the insurer over the total insured value. The damage ratio is calculated as follows.

$$E(x) = \begin{cases} 0.01\exp(0.252x - 5.823), & x \le 41.4m/s \\ 1, & x > 41.4m/s \end{cases} \tag{D1}$$

where $E(x)$ is the expected building damage ratio caused by a hurricane. x is the ten-minute sustained wind speed. As the wind speed (v) in Section 4.3.1 refers to the 1-min sustained wind speed, a factor of $c = 0.9$ is used to convert v to x, expressed as $x = 0.9v$.

In a very short time interval $(t, t + dt]$ in which at most one hurricane could occur, the probability that the hurricane damage (E) exceeds e is as follows (Li *et al*., 2016).

$$\Pr(E > e, t) = \lambda_t \cdot [1 - F_E(e, t)] \cdot dt \tag{D2}$$

where $F_E(\cdot)$ is the CDF of damage ratio $E(\cdot)$. According to Equations 4.4 and D1, $F_E(\cdot)$ can be expressed as follows.

$$F_E(x, t) = \begin{cases} F\left(\frac{1}{c}E^{-1}(x), t\right), & x < 1.0 \\ F\left(\frac{1}{c}41.4, t\right), & x = 1.0 \end{cases} \tag{D3}$$

where $E^{-1}(\cdot)$ is the inverse function of the damage ratio. c=0.9 is a factor that converts the 1-min sustained wind speed to 10-min wind speed.

Let $h(e,t)$ denote the probability of the damage ratio exceeding a threshold e. Based on Equations D2 and D3, $h(e,t)$ is derived and presented in Equation 4.10. The expected annual damage at year t, $M_{i,t}$, is presented in Equation 4.11. Therefore, without any hurricane mitigation measure being adopted, the loss of building value should be equal to the expected annual damage ($V_0 - V_r = M_t$).

$$h(e,t) = \frac{\Pr(E > e)}{dt} = \lambda_t \left[1 - F\left(\frac{1}{c}E^{-1}(e), t\right)\right] \tag{D4}$$

where λ_t is the hurricane occurrence rate and assumed to be time-varying due to climate change, $\lambda_t = \lambda_0 + r_\lambda t$. The failure rate function $h(e,t)$ describes the probability of a prescribed hurricane damage within $(t, t+dt]$ as $dt \to 0$. It accounts for the variation of the damage probability over time through the non-stationarity description of wind speeds.

To estimate the expected hurricane damage ($M_{i,t}$), a time period $(T_1, T_2]$ is divided into N equal time intervals $(T_1, t_1], (t_1, t_2] \cdots (t_{N-1}, T_2]$. The duration of each interval is $\Delta T = (T_2 - T_1)/N \to 0$ as $N \to \infty$. Let E_i denote the damage ratio caused by the hurricane wind during the k^{th} time interval. The CDF $F_{E_k}(x,t)$ can be obtained in Equation D-5. The shape of $F_{E_k}(x,t)$ has a “jump” at x=1, corresponding to the probability $\Pr(E_t = 1)$ that is the probability of the 10-min sustained wind speed exceeding 41.4 m/s according to Equation D3. Thus, the expected hurricane damage ratio during the k^{th} time interval can be obtained in Equation D6.

$$F_{E_k}(x,t) = \Pr(E_k < x) = 1 - h(x,t) \cdot \Delta T \tag{D5}$$

$$E(E_i) = \Delta T \left\{h(1,t) - \int_0^1 x \cdot \frac{\partial h(x,t)}{\partial x} dx\right\} \tag{D6}$$

Let denote E_t the total damage ratio during a time period $(T_1, T_2] = (t-1, t]$ where t represent year. E_t is the integration of E_i during this period. The total expected damage at year t $M_{i,t} = E(E_t) \cdot V_0$. Thus, $M_{i,t}$ is expressed as follows.

$$M_{i,t} = V_{i,0} \int_{t-1}^{t} \left\{h(1,t) - \int_0^1 x \cdot \frac{\partial h(x,t)}{\partial x} dxdt\right\} \tag{D7}$$

Appendix E: Solving for the Optimal Investment Allocation

Recall the optimization problem in Equation 4.1:

$$\max_{r_{i,t}, a_{i,t}} \Pi_{i,t} = p_t\left(b_t - z_{i,t}\right) + y_{i,t} - c_{i,t} + c_{i,t-1} - m_{i,t} + \beta \Pi_{i,t+1}$$

$$\begin{aligned} \boldsymbol{s.t.}\quad & q_{i,t} = q_{i,t-1} + r_{i,t} \\ & z_{i,t} = z_{i,0} - q_{i,t} + \sum \epsilon_{i,t} \\ & k_{i,t} = k_{i,t-1} + a_{i,t} \\ & c_{i,t} - c_{i,t-1} + a_{i,t} \leq F_t \end{aligned} \tag{E1}$$

The functions of utility saving ($y_{i,t}$), abatement cost ($c_{i,t}$) and expected annual damage ($m_{i,t}$) are specified in Equations 4.11, 4.10 and 4.8, respectively. They are listed as follows.

$$y_{i,t} = \mathbb{Y}\left(q_{i,t}\right) = \gamma q_{i,t} \tag{E2}$$

$$c_{i,t} = \mathbb{C}\left(q_{i,\mathrm{t}}\right) = \beta_1 {q_{i,\mathrm{t}}}^2 + \beta_2 {q_{i,\mathrm{t}}}^2 \cdot Dy_1 + \beta_3 {q_{i,\mathrm{t}}}^2 \cdot Dy_2 \tag{E3}$$

$$m_{i,t} = M_{i,t} \cdot \mathbb{A}\left(k_{i,t}\right) = M_{i,t} \cdot \left(1 - d_{i,t}\right) = M_{i,t} \cdot (1 - \omega \cdot k_{i,t}) \tag{E4}$$

For a given building i, Dy_1 and Dy_2 are constant. Thus, Equation E3 can be rewritten as the following.

$$c_{i,t} = \mathbb{C}(q_i) = \kappa q_i^2, \text{ where } \kappa = \beta_1 + \beta_2 \cdot Dy_1 + \beta_3 \cdot Dy_2 \tag{E5}$$

Plugging Equations E2, E4 and E5 into Equation E1, the optimization problem becomes

$$\begin{aligned} \max_{r_{i,t},\ a_{i,t}} \Pi_{i,t} = {} & p_t\left(b_{i,t} - z_{i,0} + q_{i,t-1} + r_{i,t} - \sum \epsilon_{i,t}\right) + \gamma_t\left(q_{i,t-1} + r_{i,t}\right) \\ & - \kappa(q_{i,t-1} + r_{i,t})^2 + \kappa(q_{i,t-1})^2 - M_{i,t} \cdot \left[1 - \omega \cdot (k_{i,t-1} + a_{i,t})\right] \\ & + \beta \Pi_{i,t+1} \end{aligned} \tag{E6}$$

Equation E6 is solved as a finite-period problem ($t = 1, \ldots, N$). The project proponents make abatement decisions only within the N periods. The technologies that have been adopted continue to reduce emissions beyond $t = N$, but no more technology will be added beginning from $t = N+1$. Thus, the cumulative annual emission reduction $q_{i,t=n+1,\ldots,\bowtie} = q_{i,N}$ and the cumulative mitigation investment $k_{i,t=n+1,\ldots,\bowtie} = k_{i,N}$.

The terminal value $\pi_{i,N+1}$ is defined as the following.

$$\Pi_{i,N+1} = \sum_{t=N+1}^{\bowtie} \beta^t [\, p_N \left(b_{i,t} - z_{i,0} + q_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_t q_{i,N} - M_{i,t} \cdot (1 - \ \omega \cdot k_{i,N})]$$

$$= \frac{1}{1-\beta} [p_N \left(b_{i,t} - z_{i,0} + q_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_t q_{i,N} - M_{i,t} \cdot (1 - \ \omega \cdot k_{i,N})] \tag{E7}$$

The optimization problem is solved backward. When $t = N$, the value function is

$$\max_{r_{i,N},\ a_{i,N}} \Pi_{i,N} = p_N \left(b_{i,N} - z_{i,0} + q_{i,N-1} + r_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_N (q_{i,N-1} + r_{i,N}) - \kappa {q_{i,N}}^2$$

$$+ \kappa {q_{i,N-1}}^2 - M_{i,N} \cdot \left[1 - \ \omega \cdot (k_{i,N-1} + a_{i,N})\right] + \beta \pi_{i,N+1}$$

$$+ \lambda_N \left[\kappa {q_{i,N}}^2 - \kappa {q_{i,N-1}}^2 + a_{i,N} - F_N\right]$$

$$= p_N \left(b_{i,N} - z_{i,0} + q_{i,N-1} + r_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_N \left(q_{i,N-1} + r_{i,N}\right) \tag{E8}$$

$$- \kappa (q_{i,N-1} + r_{i,N})^2 + \kappa {q_{i,N-1}}^2 - M_{i,N} \cdot \left[1 - \ \omega \cdot (k_{i,N-1} + a_{i,N})\right]$$

$$+ \frac{\beta}{1-\beta} \Big[p_N \left(b_{i,t} - z_{i,0} + q_{i,N} - \sum \epsilon_{i,t}\right) + \gamma_t q_{i,N} - M_{i,N}$$

$$\cdot \left(1 - \ \omega \cdot k_{i,N}\right)\Big] + \lambda_N \left[\kappa (q_{i,N-1} + r_{i,N})^2 - \kappa {q_{i,N-1}}^2 + a_{i,N} - F_N\right]$$

Taking the first order condition of Equation E8 with respect to $r_{i,N}$ and $a_{i,N}$ yields the following solutions.

$$r_{i,N}^* = \frac{p_N + \gamma_N}{2\kappa(1 - \beta + \omega M_{i,N})} - q_{i,N-1} \tag{E9}$$

$$a_{i,N}^* = F_{i,N} - k_{i,N-1} - \kappa \left[\frac{p_N + \gamma_N}{2\kappa(1 - \beta + \omega M_{i,N})}\right]^2 \tag{E10}$$

$$\lambda_N^* = -\frac{\omega}{1-\beta} M_{i,N} \tag{E11}$$

$$q_{i,N}^* = q_{i,N-1} + r_{i,N}^* = \frac{p_N + \gamma_N}{2\kappa(1 - \beta + \omega M_{i,N})} \tag{E12}$$

$$z_{i,N}^* = z_0 - \frac{p_N + \gamma_N}{2\kappa\left(1 - \beta + \omega M_{i,N}\right)} + \sum \epsilon_{i,t} \tag{E13}$$

$$k_{i,N}^{*} = k_{i,N-1} + a_{i,N}^{*} = F_{i,N} - \kappa\left[\frac{p_N + \gamma_N}{2\kappa(1 - \beta + \omega M_{i,N})}\right]^2 \tag{E14}$$

Plugging Equations E9 to E14 into Equation E8 yields the following optimal value function at *t=N*.

$$\begin{aligned}
\Pi_{i,N}^{*} = {} & p_N\left(b_{i,N} - z_{i,0} + \frac{p_N + \gamma_N}{2\kappa\left(1 - \beta + \omega M_{i,N}\right)} - \sum \epsilon_{i,t}\right) + \gamma_N\left(\frac{p_N + \gamma_N}{2\kappa\left(1 - \beta + \omega M_{i,N}\right)}\right) \\
& - \kappa\left(\frac{p_N + \gamma_N}{2\kappa\left(1 - \beta + \omega M_{i,N}\right)}\right)^2 + \kappa {q_{i,N-1}}^2 \\
& + \frac{\beta}{1-\beta}\left[p_N\left(b_{i,t} - z_{i,0} + \frac{p_N + \gamma_N}{2\kappa\left(1 - \beta + \omega M_{i,N}\right)} - \sum \epsilon_{i,t}\right)\right. \\
& + \gamma_t \frac{p_N + \gamma_N}{2\kappa\left(1 - \beta + \omega M_{i,N}\right)} - M_{i,t} \\
& \left. \cdot\left(1 - \omega \cdot \left\{F_{i,N} - \kappa\left[\frac{p_N + \gamma_N}{2\kappa\left(1 - \beta + \omega M_{i,N}\right)}\right]^2\right\}\right)\right] \\
& - \frac{\omega}{1-\beta} M_{i,N}\left[\kappa\left(\frac{p_N + \gamma_N}{2\kappa\left(1 - \beta + \omega M_{i,N}\right)}\right)^2 - \kappa {q_{i,N-1}}^2 - k_{i,N-1}\right. \\
& \left. - \kappa\left[\frac{p_N + \gamma_N}{2\kappa\left(1 - \beta + \omega M_{i,N}\right)}\right]^2\right]
\end{aligned} \tag{E15}$$

Given $\pi_{i,N}^{*}$, the objective function at *t = N-1* can be expressed as the following.

$$\begin{aligned}
& \max_{r_{i,N-1}, a_{i,N-1}} \Pi_{i,N-1} \\
& = p_{N-1}\left(b_{i,t} - z_{i,0} + q_{i,N-2} + r_{i,N-1} - \sum \epsilon_{i,t}\right) + \gamma_{N-1}(q_{i,N-2} \\
& + r_{i,N-1}) - \kappa {q_{i,N-1}}^2 + \kappa {q_{i,N-2}}^2 - M_{i,N-1} \cdot \left[1 - \omega \cdot (k_{i,N-2} + a_{i,N-1})\right] \\
& + \beta \Pi_{i,N}^{*} + \lambda_{N-1}\left[\kappa {q_{i,N-1}}^2 - \kappa {q_{i,N-2}}^2 + a_{i,N-1} - F_{N-1}\right]
\end{aligned} \tag{E16}$$

where $\Pi_{i,N}^{*}$ satisfies Equation E15. Taking the first order condition of Equation E16 with respect to $r_{i,N-1}$ and $a_{i,N-1}$ yields the following solutions.

$$r_{i,N-1}^{*} = \frac{p_{N-1} + \gamma_{N-1}}{2\kappa(1 - \beta + \omega M_{i,N-1})} - q_{i,N-2} \tag{E17}$$

$$a_{i,N-1}^{*} = F_{i,N-1} - k_{i,N-2} - \kappa \left[\frac{p_{N-1} + \gamma_{N-1}}{2\kappa(1 - \beta + \omega M_{i,N-1})}\right]^2 \tag{E18}$$

Based on the expression of $r_{i,N-1}^{*}$ (Eq. E17) and $r_{i,N}^{*}$ (Eq. E9), and the expression of $a_{i,N-1}^{*}$ (Eq. E18) and $a_{i,N}^{*}$ (Eq. E10), the forms of $r_{i,t}^{*}$ and $a_{i,t}^{*}$ are guessed as

$$r_{i,t}^{*} = \frac{p_t + \gamma_t}{2\kappa(1 - \beta + \omega M_{i,t})} - q_{i,t-1} \tag{E19}$$

$$a_{i,t}^{*} = F_{i,t} - k_{i,t-1} - \kappa \left[\frac{p_t + \gamma_t}{2\kappa(1 - \beta + \omega M_{i,t})}\right]^2 \tag{E20}$$

Plugging Equations E19 and E20 into Equation E15 yields the following optimal value function at *t*.

$$\begin{aligned} \Pi_{i,t}^{*} = {} & p_t \left(b_{i,t} - z_{i,0} + \frac{p_t + \gamma_t}{2\kappa\big(1 - \beta + \omega M_{i,t}\big)} - \sum \epsilon_{i,t} \right) + \gamma_t \left(\frac{p_t + \gamma_t}{2\kappa\big(1 - \beta + \omega M_{i,t}\big)} \right) \\ & - \kappa \left(\frac{p_t + \gamma_t}{2\kappa\big(1 - \beta + \omega M_{i,t}\big)} \right)^2 + \kappa {q_{i,t-1}}^2 - M_{i,t} \\ & \cdot \left\{ 1 - \omega \left\{ F_{i,t} - \kappa \left[\frac{p_t + \gamma_t}{2\kappa(1 - \beta + \omega M_{i,t})} \right]^2 \right\} \right\} + \beta \Pi_{i,t+1}^{*} \end{aligned} \tag{E21}$$

The value function at *t* - 1 can be expressed as

$$\begin{aligned} \max_{r_{i,t-1}, a_{i,t-1}} \Pi_{i,t-1} = {} & p_{t-1} \left(b_{i,t-1} - z_{i,0} + q_{i,t-2} + r_{i,t-1} - \sum \epsilon_{i,t-1} \right) + \gamma_{t-1} (q_{i,t-2} + r_{i,t-1}) \\ & - \kappa {q_{i,t-1}}^2 + \kappa {q_{i,t-2}}^2 - M_{i,t-1} \cdot \big[1 - \omega \cdot (k_{i,t-2} + a_{i,t-1}) \big] + \beta \Pi_{i,t}^{*} \end{aligned} \tag{E22}$$

where $\Pi_{i,t}^{*}$ satisfies Equation E21. Taking the first order condition of Equation E22 with respect to $r_{i,N-1}$ and $a_{i,N-1}$ yields the following solutions.

$$r_{i,t-1}^{*} = \frac{p_{t-1} + \gamma_{t-1}}{2\kappa(1 - \beta + \omega M_{i,t-1})} - q_{i,t-2} \tag{E23}$$

$$a_{i,t-1}^{*} = F_{i,t-1} - k_{i,t-2} - \kappa \left[\frac{p_{t-1} + \gamma_{t-1}}{2\kappa(1 - \beta + \omega M_{i,t-1})} \right]^{2} \tag{E24}$$

The guessed form is verified. Therefore, the optimal emission reduction $r_{i,t}^{*}$ and the optimal mitigation investment $a_{i,t}^{*}$ are expressed as

$$r_{i,t}^{*} = \frac{p_t + \gamma_t}{2\kappa(1 - \beta + \omega M_{i,t})} - q_{i,t-1} \tag{E25}$$

$$a_{i,t}^{*} = F_{i,t} - k_{i,t-1} - \kappa \left[\frac{p_t + \gamma_t}{2\kappa(1 - \beta + \omega M_{i,t})} \right]^{2} \tag{E26}$$

where $\kappa = \beta_1 + \beta_2 \cdot Dy_1 + \beta_3 \cdot Dy_2$.

Appendix F: Modelling parameters for Anne Arundel County

Based on the recorded hurricane data in this county, it is found that the two Weibull parameters are: $u = 23.3m/s$ and $\alpha = 3.5$. As indicated by Figure F-1, the fitted Weibull distribution can well represent the actual wind speed data for this county. A 10% increase in the average wind speed u is assumed for the next 50 years, which suggests that the annual increment rate is $r_u = 0.0466$. The annual number of hurricane λ_t is also assumed to increase by 10%. Given $\lambda_0 = 0.174$, the annual increment rate $r_\lambda = 0.0003$.

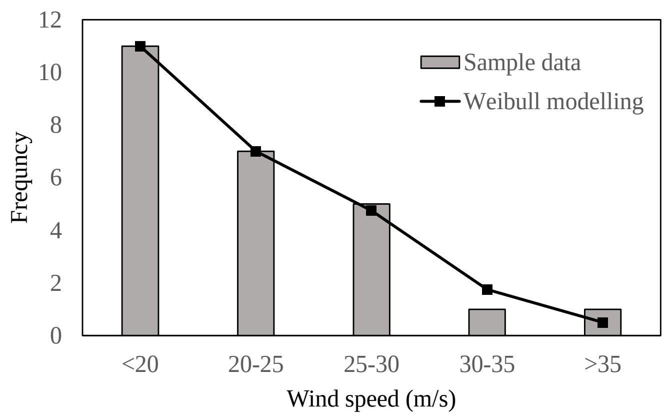


Figure F-1 Maximum sustained 1-min wind speed of Anne Arundel's hurricanes

The emission abatement measures described in Section 2.3.3 are applied to the buildings in this county to estimate emission reduction cost ($c_{i,t}$) using the OpenStudio PAT. The cost is described as a function of emission reduction ($q_{i,t}$) and building types (Dy_1, Dy_2) in Equation 4.10. The dummy variables for building types are (-0.5, 1) for medium offices, (1, -0.5) for small offices, and (-0.5, -0.5) for warehouses. The regression result shows that the model is statistically significant at the 95% confidence level and the R-squared is 0.9193. The coefficient of each variable is listed in Table F-1.

Table F-1 Estimated coefficients for emission abatement cost function

Variables	Coefficient	Standard error	P-value
$q_{i,t}^2$	2.74×10^{-4}	3.24×10^{-5}	0.000
$q_{i,t}^2 \cdot Dy_1$	-4.27×10^{-4}	6.47×10^{-5}	0.000
$q_{i,t}^2 \cdot Dy_2$	-4.66×10^{-4}	6.45×10^{-5}	0.000

Note: The number of observation is 63. F(3,60)=227.75.

R-squared is 0.9193. Adjusted R-squared is 0.9152.

Utility saving ($y_{i,t}$) is described as a function of emission reduction ($q_{i,t}$) in Equation 4.11. As electricity is a major energy source for building, electricity saving is used to approximate utility saving from emission abatement. Electricity price in Anne Arundel County is 12.5 cent/kWh. The electricity emission factor is 1,002 lbs/MWh (TCR, 2015). Electricity saving per unit of emission reduction (γ) is therefore estimated to be \$$2.77\times10^{-4}$ per gram of emission reduction.

Glossary

Variables	Unit	Description
$b_{i,t}$	$gCO_2e/(sq.ft \cdot yr)$	Additionality baseline
x	NA	ASHRAE Energy Standard
z	$gCO_2e/(sq.ft \cdot yr)$	Annual GHG emission
ic	\$/sq.ft	Incremental technology cost
$q_{i,t}$	$gCO_2e/(sq.ft \cdot yr)$	Cumulative emission abatement
$r_{i,t}$	$gCO_2e/(sq.ft \cdot yr)$	Annual emission abatement
$\pi_{i,t}$	\$/sq.ft	Total lifecycle payoffs
s	$gCO_2e/(sq.ft \cdot yr)$	Annual supply to carbon offset
ω_j	NA	Probability that the privately defined baseline b at level j can be verified even if it is higher than the unbiased baseline b^0
$\overline{b^*}$	$gCO_2e/(sq.ft \cdot yr)$	The optimal adjusted baseline under verification
b^a	$gCO_2e/(sq.ft \cdot yr)$	Adjusted baseline output from Monte Carlo simulation
$m_{i,t}$	\$/(sq.ft·yr)	Expected annual damage due to hurricanes
$M_{i,t}$	\$/(sq.ft·yr)	Expected annual damage without mitigation measures
R_f	NA	Resilience metric
$h(x,t)$	NA	Probability of the damage ratio exceeding a threshold x
$k_{i,t}$	\$/(sq.ft·yr)	Annual hurricane mitigation investment
$a_{i,t}$	\$/(sq.ft·yr)	Incremental hurricane mitigation investment

Parameters	Unit	Description
p	\$/g CO_2e	Carbon price
γ	\$/g CO_2e	Utility bill for each unit of GHG emission

$\epsilon_{i,t}$	g CO_2e/sq.ft	Emission adjustment due to an external environment change
β	NA	Discount factor
α_i	NA	Parameters to be estimated in Equation 1.4
Ta	F	Air temperature
Bn	NA	Direct radiation
Dy_k	NA	Dummy variables representing the energy standard
Ef	gCO_2/Btu	Grid emission factor
Te	NA	Temperature difference. 1 for zones 1 to 4 and 2 for zones 5 to 7
Hu	NA	Humidity difference. 1 for the zones with the letter A (dry) and 2 for the zones with the letter B (moist) or C (marine).
θ	NA	A factor that convert a uniform annual revenue to a present value
τ	\$/gCO_2e	Compensation fee
η	NA	A parameter in Equation 3.9 showing the change of technology costs with emission reductions
ν_1	NA	A parameter in Equation 3.11 showing the change of offset price with offset supply
ν_2	NA	A parameter in Equation 3.11 showing the change of offset price with offset supply
C	NA	An expression referred to Equation B-4
D	NA	An expression referred to Equation B-4
X	NA	An expression referred to Equation B-11
Y	NA	An expression referred to Equation B-11
N	NA	Total number of buildings
f	NA	Verification fee
Re	NA	A dummy variable representing the region where the provider is located: 1 for Europe or Australia and 0 for America

F_t	\$/(sq.ft·yr)	Total annual retrofit budget
V	\$/sq.ft	Building value
t_i	year	Time to failure
t_r	year	Time to recovery
λ_t	NA	Mean occurrence rate of hurricane
u_t	NA	Weibull parameter for Equation 4.4
r_u	NA	Annual increment rate in parameter u_t
α_t	NA	Weibull parameter for Equation 4.4
v	m/s	1 min sustained wind speed
$\rho_{i,t}$	NA	Replacement cost ratio
ω	NA	A constant coefficient for Equation 4.9
$d_{i,t}$	NA	Premium discounts offered to insured buildings

Functions	Unit	Description
$\mathbb{N}(\cdot)$	NA	Net present value of the annual paybacks
$\mathbb{C}(\cdot)$	NA	Building retrofit costs
$\mathbb{S}(\cdot)$	NA	Annual supply of carbon offset
$\mathbb{P}(\cdot)$	NA	Carbon price as a function of baseline
$\mathbb{H}(\cdot)$	NA	Baseline developer's compensation as a function of baseline
$\mathbb{R}(\cdot)$	NA	Utility savings as a function of cumulative emission
$\mathbb{G}(\cdot)$	NA	Net increase of global emission
$\mathbb{A}(\cdot)$	NA	Percentage of building damages that can be avoided

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