Opportunities for Self-Financing Flood Resilience Infrastructures in Boston, Massachusetts.

Radboud University Nijmegen

Matthijs Ham

Master thesis

Master Spatial Planning: Planning, Land and Real Estate Development

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Abstract

Flood risk is becoming more severe due to climate change. However, financing adaptations to climate change, like in the form of flood resilience infrastructures (FRIs), presents some challenges for local governments (Doeffinger & Rubinyi, 2023). Big investments are needed today, to avert even bigger future damage costs. Earlier studies have found that flood risk negatively affects housing prices (Bin & Landry, 2013). Conversely, by reducing flood risk through FRI implementation, housing prices are expected to increase because future damages are (expected to be) avoided (Kim, 2020). This research aims to provide a basis for arguing that FRI projects might be able to be (partially) self-financed through land value capture (LVC), by empirically testing the relationship between FRI construction and housing prices. If investments in FRIs yield increases in sales prices, these increases could subsequently be captured to get a return on investments; much like in a virtuous circle, as explained by Lord et al. (2019). This is analyzed for Boston, Massachusetts, via a hedonic price model with a difference-in-differences interaction term to estimate the effect of FRI construction. The model looks at sale transactions of residential condominiums between 2008 and 2021. Each sale is linked to its closest respective FRI project. In total, there were twelve projects that have been completed. The date of sale and the FRI completion date were used to distinguish between pre and post completion sales. FRI project characteristics were included to spot any differences between grey and green FRIs, as well as between more specific types of FRIs; e.g., shoreline stabilization and drainage infrastructures. Lastly, a plethora of structural, locational and neighborhood characteristics were included in the model to control for any confounding effects. The results show that there is a negative relationship between the distance to the nearest completed FRI project and the sale price per sf. On average, FRI projects increased post group sale prices by 2,7%. This effect was significant and found to be greater for properties in higher flood risk zones. These findings are in line with earlier accounts (Kelly & Molina, 2023). Based on these results, Boston might consider to start implementing LVC instruments to capture these price increases. This way, the City of Boston is better equipped to implement its climate resilience goals.

Key words: climate adaptation, flood risk, flood resilience, land value capture, hedonic price model

Preface

This thesis is the final hurdle to obtaining my master's degree. It is the labor of six years of studying at the Radboud University in Nijmegen and it marks the end of a chapter in my life that I have thoroughly enjoyed. This thesis feels like the crowning glory of my time as a student. Through a suggestion of Erwin van der Krabben, of the RU's Planning Department, I was able to get in contact with Enrique Silva, of the Lincoln Institute of Land Policy in Cambridge. With help of many thesis sessions with a group of friends – though some sessions more productive than others – I finished my research proposal. Then, after some back and forth with Enrique, I was lucky enough to get to travel to Boston for a fellowship at the LILP. The three months I spent there, allowed me to meet amazingly kind and helpful people that have contributed a great deal to this thesis, as well as to discuss my research with city and state officials, and to be able to see the resilience infrastructures I have studied.

Hence, I want to express my gratitude towards some people. First of all, to Erwin and Enrique for making this fellowship possible, and Enrique also for his supervision and guidance during my time at Lincoln. Secondly, to Lincoln's Climate Strategies team, Amy and Patrick, for including me in the team, discussing my work, and for letting me benefit from their network. Furthermore, to the Center for Geospatial Solutions, in particular Jeff and Margaret, for their invaluable help with all of my GIS questions and problems. I also want to thank the Valuation and Land Markets team, Joan, Semida and Sydney, for their amazing help in getting the data I needed and the great conversations. Additionally, I'd like to thank all Lincoln staff for welcoming me to Boston/Cambridge and the organization. Last but certainly not least, I of course want to thank my thesis supervisor, Ary Samsura, for his guidance, advice, and all the sparring sessions which made this thesis into what it is.

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1. Introduction

1.1 Research context

Climate change is exacerbating flood risk across the globe (Arnell & Gosling, 2014; Kundzewicz et al., 2013). Sea levels are rising even more swiftly than anticipated and together with heavier storms cause greater storm surges (IPCC, 2021), which put an enormous pressure on our flood risk management systems (Walsh et al., 2019). Climate mitigation will not be enough to solve this problem, as not much can be done to prevent the estimated short to mid-term scenarios (IPCC, 2022). Therefore, climate adaptation will become more important in the coming years to avert the disastrous consequences of climate change to some extent, as well as minimizing indirect consequences of climate change as much as possible (Biesbroek et al., 2010).

However, in order to implement a sufficient level of adaptation to climate hazards worldwide, enormous investments have to be made (Burgess & Rapoport, 2019). The United Nations Environment Progam (UNEP) estimated that by 2030, yearly adaptation costs are around $140-300 billion (Puig et al., 2016, p.40), whereas international public spending on climate adaptation was approximately only $22.5 billion in 2014 (Puig et al., 2016, p.23). Even if the target for the Paris Agreement for public adaptation spending ($100 billion per year) is fully met and is – again in accordance to the agreement – heightened after 2025, then it still needs to be roughly three to six times higher (Puig et al., 2016, p.41). Hence, some speak of a 'financing gap' that needs to be bridged for adequate adaptation to take place (Doeffinger & Rubinyi, 2023).

1.2 Problem statement

Many argue that a possible way of overcoming this financing gap is through land value capture (Sait, 2020). Land value capture (LVC) instruments aim to extract increases in land or real estate prices by public authorities to recoup public costs or unlock additional funds for public investments (Hui, Ho, & Ho, 2004). Many scholars point toward a negative relationship between flood risk and residential real estate prices, i.e., higher flood risk leads to reduced prices (see e.g., Bin & Landry, 2013; Lamond, Proverbs, & Hammond, 2010; McAlpine & Porter, 2018). Inversing this relationship would mean that a reduction of flood risk would lead to an increase in housing prices. This creates opportunities for LVC instruments to generate additional funding for flood resilience infrastructures (FRIs), like seawalls, levees, retention ponds or drainage systems (Beltrán, Maddison, & Elliot, 2018; Doeffinger & Rubinyi, 2023; Kim et al., 2020).

However, not much research has been done to definitively conclude that climate adaptations – or more specifically in this case, FRIs – are reflected in real estate values. Most of the LVC literature mainly focusses on the application of LVC instruments in cases of improved accessibility due to transport development (see e.g., Cervero and Murakami, 2009; Debrezion, Pels, & Rietveld, 2007; Du & Mulley, 2007). Yet, the capitalization of FRIs into real estate values is getting more attention in recent literature. For example, Walsh et al. (2019) studied the effect of FRIs on housing prices in Maryland. They recommend further research in this field, mostly to compare different FRIs, for different infrastructures were observed to yield different impacts on real estate prices. Furthermore, Mutlu, Roy and Filatova (2023) studied the effect of nature-based FRIs on housing prices in the Netherlands and found a positive effect, but indicated that because of institutional differences results of studies may vary across countries. Additionally, a study by Kelly and Molina (2023) found that property values in the Miami-Dade County (Florida) increased after completion of FRIs. However, they noted that their results might not be generalizable to real estate markets outside their sample. This relates to the argument of Lord, Van der Krabben and Dong (2022), namely that a major challenge for putting LVC instruments related to a reduction in climate hazards into practice is the need for "a carefully quantified account of this relationship" (p.46). This is necessary to more adequately assess how much value is exactly created by public investments in climate adaptation and to influence decision-making processes (Doeffinger & Rubinyi, 2023; Kelly & Molina, 2023). A further argument for this is that many LVC instruments are negotiable (McAllister, 2019). Therefore, the strategic use of information asymmetry by developers in these negotiations can lead to insufficient levels of value capture (Chen, Chau, & Yang, 2022; Muñoz Gielen & Van der Krabben, 2019).

Altogether, without a more in-depth study into this relationship, situations will continue to persist where either i) the increased value is not being captured to its full extent; or ii) values could have been raised more by implementing FRIs that are shown to affect real estate prices more, or, lastly, iii) information asymmetry in the negotiation process with developers about this effect remains too high and leads to suboptimal value capturing by public actors. In any case, (public) money is either left or lost, which does not help in bridging the adaptation financing gap.

The City of Boston (Massachusetts) has put considerable effort into an extensive adaptation strategy entitled 'Climate Ready Boston', making Boston a frontrunning city in the field of climate adaptation within the US (City of Boston, 2016a). One of three main focus points is flood risk protection against coastal and riverine flooding. According to the World Bank (2013), Boston is the eight most vulnerable city to sea level rise in terms of damage costs. The neighborhoods most at risk, see figure 1, are also some of the most populous as well as the most densely built neighborhoods. Hence, flood events would bring about tremendous costs, next to putting many citizens in danger (City of Boston, 2016b). To avoid this, Boston has worked out local adaptation plans for each of these neighborhoods, comprised of a package of cumulative resilience projects. Together, these interventions should protect Boston from the worst coastal and riverine flood scenarios (City of Boston, 2016a). Some of these projects are already being implemented, while others are still designed. Therefore, alternative or additional financing strategies for these plans will be helpful to reduce public spending.

Figure 1: Focus areas of the 'Climate Ready Boston' plan (City of Boston, 2016a, p.39).

1.2 Research aim and questions

The main aim of this research is to obtain better insight into the interplay of FRIs and housing prices; and to provide an argument for how this interplay might be utilized to expand available financing methods for FRIs. To do so, a hedonic price method together with a difference-in-difference design is implemented. Ultimately, this research aims to help Boston and other cities with acquiring adequate financial resources needed to finance climate adaptation in order to circumvent the consequences of climate change. Hence, the main research question is as follows:

"What is the effect of flood resilience infrastructures on housing prices in Boston, Massachusetts?"

To answer this question, additional sub-questions need to be answered. A first question is what FRIs were constructed. The main focus of this question is to uncover what types of projects were constructed and when they were completed. A second question is which residential real estate transactions have been made in the years before and after the implementation of these resilience projects. Close attention has to be paid to the characteristics of the real estate objects in question to account for any confounding effects. After these questions have been answered, the effect of FRIs can be determined. If evidence can be found for such an effect, then applying LVC instruments to the full extent means also accounting for these additional price increases. This will provide a basis for financing FRIs by the City of Boston. In summary, the sub-questions that have to be answered are:

- What flood resilience infrastructures projects are constructed and where?
- Which transactions took place before and after the implementation of the flood resilience infrastructure projects and what were their characteristics?

1.3 Societal relevance

Boston is vulnerable to flood risk. Different scenarios of sea level rise alter the severity of the consequences. It is estimated that in the period up to 2050, a severe flood – a 1% annual chance flood event – would affect 2.100 buildings with a total value of $20 billion, which includes residencies of 16.000 inhabitants (City of Boston, 2016a, p.18). From 2070 onwards, it is estimated that a significant area – about one fifth – of Boston would be flooded every month during the hightide, though this depends greatly on global carbon emissions (City of Boston, 2016a, p.21). Nevertheless, the flood scenarios up to 2050 are to a great extent locked-in and cannot be significantly altered through climate mitigation (IPCC, 2022). In addition, flood risk also poses broader negative consequences for society, like disruption of economic productivity, relocation costs, damage to transport, energy and digital infrastructure (City of Boston, 2016b). Moreover, Taylor and Aalbers (2022) have already observed evidence of ‘climate gentrification’ in Miami, Florida. These are essentially regular gentrification processes that are amplified by the risk climate change presents to urban communities. Leaving the most vulnerable groups of society to deal with the greatest hazards, while more affluent groups start moving towards less dangerous areas. FRI projects are crucial in preventing these consequences from happening. However, they are far from cheap; public spending would have to be increased drastically in the coming years (Puig et al., 2016). LVC instruments could leverage more funding and prevent letting created value by means of public spending slip away without allowing it to be reinvested (Burgess & Rapoport, 2019).

Furthermore, in the negotiation process between landowners or developers and the government, the effectiveness of LVC instruments might experience hinderances from information asymmetries in favor of developers (Chen et al., 2022; Viallon, 2018). Specifically, a lack of insight in the expected costs of infrastructure (the ‘viability charade’) and a lack of insight into the effect of infrastructure provision on real estate values, result in a weaker position of the government in this negotiation process (Lord et al., 2019; Lord et al., 2022). Therefore, a better understanding of the relationship of FRIs on real estate prices will help to reduce information asymmetry in this negotiation process. Better insight result in a more equal negotiation position for the municipality, which leads to more effective value capture.

1.4 Scientific relevance

The effect of flood risk on land and real estate values has also been studied in depth. An important distinction in the accounts lies in the independent variable, i.e., flood risk. Some studies use actual, calculated flood risk (see e.g., Shilling, Sirmans, & Benjamin, 1989; Harrison, Smersh, & Schwartz, 2001; Bin, Kruse, & Landry, 2008), while others use perceived flood risk (e.g., Bin & Polasky, 2004; Burningham, Fielding, & Thrush, 2008; Eves, 2002). Nevertheless, most studies conclude that a negative relationship is present. However, studies using perceived flood risk observed a decrease in property values in the time period after a flood event has occurred, which then slowly fades away as time goes by (see e.g., Atreya, Ferreira, & Kriesel, 2013; Husby et al., 2014; Lamond & Proverbs, 2006). Hence, Belanger and Bourdeau-Brien (2017) have performed a more all-encompassing study. They included both actual and perceived flood risk. They found a negative relationship exists between actual flood risk and property values – even if perceived flood risk is minimal – and that the severity of this effect is heightened in the months after major flood events, i.e., when perceived flood risk is greater.

Although research into the effect of flood risk on housing prices is quite ubiquitous, research looking into the capitalization of FRIs into the housing market, however, is scarce. Avner et al. (2022) have developed an urban economics model as a means to influence decision making about public FRI investments ex ante. They found a theoretical basis to justify upfront investments, but suggest that land market friction should be added to make the model more precise. Moreover, Mutlu et al. (2023) have studied the effect of nature-based FRIs on housing prices in the Netherlands. They have found evidence to support that these types of infrastructures increase housing prices more in comparison to traditional FRIs. However, the hedonic model they have used presumes perfect information. They recommend further research should focus on ways to account for information asymmetries on the housing market, since homebuyers can never be fully informed about the risks. Additionally, Walsh et al. (2019) have studied the influence of flood defense systems on real estate prices through a hedonic price model. They have found evidence of increased prices due to construction of bulkheads and ripraps, however they stress the importance of exploring the impact of other types of infrastructures. The same recommendations are proposed by the case study research of Kok et al. (2021); additionally, they state that attention needs to be given to multiple institutional and socio-economic instances across the globe in order to fully grasp the potential of LVC instruments for financing FRIs. Furthermore, Kelly and Molina (2023) performed an empirical study into the effect of FRIs on real estate values in the Miami-Dade County and found evidence to postulate a distance decay effect exists between the two. Yet they also stress that their results may not be generalizable to other instances. This relates to the point made by multiple scholars, who underline the importance of more studies on local and quantified results of the effect of climate adaptation on land and real estate prices ex post (Lord et al., 2022), as well as more ways to capture these land value increments (Doeffinger & Rubinyi, 2023).

This research contributes by providing empirical evidence for the model by Avner et al. (2022). It will also help to determine effect of resilience on land values on a longer term, which could be useful for fine tuning their model. Moreover, this research includes different kinds of FRIs, as was recommended by Walsh et al. (2019) and Kok et al. (2021). This research adds to generalizability of earlier results, such as Kelly and Molina (2023). Lastly, this study is a local and quantified account, which is necessary for municipalities to incorporate additional LVC instruments to capture resilience premiums, as mentioned by Lord et al. (2022).

1.5 Reading guide

The remaining parts of this research are structured as follows. In the next chapter a review of relevant scientific literature is given together with a theoretic framework, which serve as the basis for the conceptual model and the later formulated hypothesis. After this, the third chapter will elaborate on the methodology; or how this hypothesis was tested. In the subsequent chapter, the empirical results are shown and compared to findings by literature discussed earlier and they are also tested for their robustness. In the chapter thereafter, the main research question is answered, policy recommendations are presented and limitations of the research are discussed.

2. Literature review & theoretic framework

In this chapter the main theoretic concepts relating to the research questions will be explained. This will start by explaining the concept of climate adaptation in relation to flood risk. Then, the concept of LVC will be elaborated upon. Subsequently, the possibilities for application of LVC for FRIs will be explored. Finally, methods used to assess FRI premiums will be reviewed. Any inconclusiveness within the literature on these concepts will also be discussed. Through this framework, at the end of this chapter, a conceptual model is constructed and a hypothesis is formulated.

2.1 Climate adaptation to flood risk

This paragraph starts with describing basic concepts related to climate adaptation and explaining the nested hierarchy model of vulnerability. The second paragraph discusses multiple adaptation pathways for managing flood risk.

2.1.1 Climate adaptation, adaptive capacity, and climate resiliency

There are two approaches to address climate change; climate mitigation and climate adaptation. The former combats climate change by putting a stop to emissions, therefore addressing the root problem of climate change. The latter is concerned with minimizing the symptoms caused either directly or indirectly by climate change (Lee, Yang, & Blok, 2020). The IPCC defines climate adaptation as: "adjustments in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" (IPCC, 2007, p.6). Many scholars and policymakers adhere to this definition (Davoudi, Brook, & Mehmood, 2013; De Bruin et al., 2009; Füssel, 2007; Nelson, 2010).

When talking about climate adaptation, the concept of vulnerability deserves further clarification. Smit & Wandel (2006) note that vulnerability is the function of exposure, sensitivity and adaptive capacity. Exposure to an environmental hazard means that there is a likelihood of a system experiencing the effects of a particular climate risk (Kelly & Adger, 2000), whereas the sensitivity determines the magnitude of that exposure to the system (Turner et al., 2003). Sensitivity is influenced by all sorts of local and more regional characteristics of a system (Smit & Wandel, 2006).

Another important aspect is adaptive capacity, which refers to the ability of a system to adapt. Adaptive capacity is dynamic, because it is context specific and alters between countries, regions, and communities, as well as over time. Furthermore, adaptive capacity on a nation scale is also partially determined by the adaptive capacity on more local scales, and vice versa (Smit & Wandel, 2006). When assessing a systems adaptive capacity, one ought to look at coping ranges, which are the conditions to which a system can accommodate, deal with or recover from (Jones, 2001). Coping ranges can be altered depending on the duration of exposure, the magnitude of the consequences, and changes in economic, social, political, and institutional system factors. Therefore, adaptive capacity can stretch the coping ranges of a system (Smit & Wandel, 2006).

Finally, there is adaptation, which "[…] are manifestations of adaptive capacity, and they represent ways of reducing vulnerability" (Smit & Wandel, 2006, p.286). This is summarized in figure 2. The larger set of circles depict the broader factors that shape exposure, sensitivity, and adaptive capacity at the local level, represented by the smaller set of circles. These overlap, for these shaping processes are frequently interdependent. The small-scale interactions between these elements illustrate local vulnerability and local adaptations to that vulnerability.

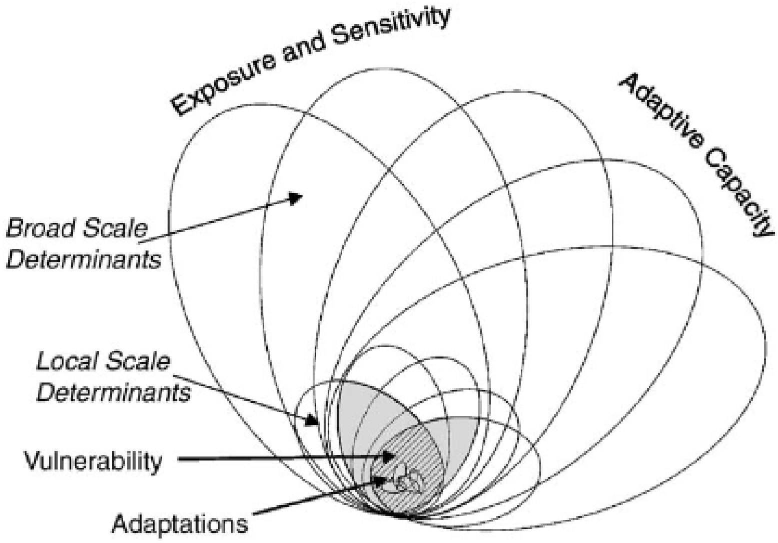

Figure 2: Nested hierarchy model of vulnerability (Smit & Wandel, 2006, p.286).

It should be noted, however, that this model does not allow for a quantifiable measurement of a community's vulnerability or adaptive capacity. Additionally, the model merely indicates that there can be an interaction between the factors, it does not imply that they have to always be interrelated. This means that even in the same system, vulnerabilities to different climatic hazards will likely vary (Smit & Wandel, 2006).

In the last few decades, the exposure to floods has been growing faster than the adaptive capacity, leaving societies more vulnerable to flood risk (Kundzewicz, 2002; Kundzewicz et al., 2013). Climate change is only exacerbating this vulnerability (Arnell & Gosling, 2014). In response, many policies are aimed at 'building resilience'. Davoudi (2012) distinguishes three types of resilience. Firstly, engineering resilience denotes the capacity of a system to return to its original state (or equilibrium state) after a disturbance (Holling, 1973). It is measured by the return time; i.e., how long it takes to bounce back (Davoudi et al., 2013). Secondly, ecological resilience entails the ability of a system to absorb disturbances or changes and still endure. Thus, this suggests that no sole equilibrium state exist, but rather multiple equilibria that systems can shift into (Gunderson, 2000). It is concerned with how much pressure it can take before shifting into a new equilibrium state (Davoudi et al., 2013). Finally, evolutionary resilience encompasses "the ability of complex social-ecological systems to change, adapt, and, crucially, transform in response to stresses and strains" (Davoudi, 2012, p.302). Therefore, rejecting the idea of an equilibrium state and suggesting that the inherent nature of the system itself may also change over time. These different definitions of resilience have implications for policies implemented by governments (Davoudi et al., 2013). This will become clear in the next paragraph.

2.1.2 Adapting to flood risk

This paragraph discusses different adaptation strategies to manage flood risk. After this, the flood defense and flood mitigation strategies are further elaborated, since these are the strategies of interest for this study.

Flood risk management strategies

In response to flood risk, governments can adopt several flood risk management strategies (FRMS). Hegger et al. (2014) distinguish five types of FRMS, which are summarized in table 1. These strategies are concerned with the probability of flooding (flood defense), the projected damages (flood risk prevention, flood risk mitigation, and flood preparation), or on the restoration of society after a flood event has occurred (flood recovery). It should also be noted that multiple strategies can be applied simultaneously; it is even argued that resilient urban communities – in the evolutionary sense – are those that have adopted multiple flood risk management strategies (Davoudi, 2012; Hegger et al., 2014).

Table 1: Five types of flood risk management strategies (Hegger et al., 2014, p.4130).

Strategy	Explanation
Flood defence	Flooding can be prevented by infrastructural works, such as dikes, dams, embankments and weirs, upstream retention or giving more space to the river within its current embankments ("keeping water away from people"), mostly referred to as "flood defence" or "structural measures". Main actors: generally governmental water management actors at national/ regional level.
Flood risk prevention	Negative consequences of flooding can be avoided by proactive spatial planning or land use policies ("keeping people away from water"), aimed at building only outside areas that are prone to flooding. Main actors: actors involved in planning processes (governmental actors, private parties). Flood insurance companies may influence planning decisions, for instance by (not) insuring properties in high-risk areas or the use of risk-based premiums (Kunreuther 2008).
Flood risk mitigation	Consequences of floods can be mitigated by a smart design of the flood-prone area. Measures include spatial orders, constructing flood compartments, or (regulations for) flood-proof building. Main actors: citizens, project developers, water managers and other public and private actors.
Flood preparation	Consequences of floods can also be mitigated by preparing for a flood event. Measures include developing flood warning systems, preparing disaster management and evacuation plans and managing a flood when it occurs. Main actors: governmental organisations like the meteorological office, flood forecasting centres, local and regional governments.
Flood recovery	This strategy facilitates a good and fast recovery after a flood event. Measures include reconstruction or rebuilding plans as well as compensation or insurance systems. Main actors: national governments establishing disaster relief funds, insurance companies as well as the affected citizens themselves.

Flood mitigation and defense: grey and green infrastructures

Flood mitigation and defense interventions can be further distinguished as either grey or green infrastructures. Grey infrastructures, sometimes also referred to as (hard) engineered interventions (Morris et al., 2018; Waryszak et al., 2021), include infrastructures aimed at i) impeding water through structures, ii) lessening the power of waves, and iii) rapidly flowing off water in urban areas (Chiu, Raina, & Chen, 2021). They use hard constructions such as concrete seawalls, breakwaters, or dikes (Waryszak et al., 2021). Green infrastructures, or nature-based solutions, aim at reducing flood risk by using the natural buffering capacity of ecosystems, such as barrier islands, bioretention ponds, and reefs (Waryszak et al., 2021). According to Morris et al. (2018), the distinction between grey and green infrastructures is sometimes blurry, and should therefore be regarded as a spectrum with many hybrid forms. In some instances, these hybrid forms are shown to harness the benefits of both grey and green infrastructures. Minimizing their weaknesses, whilst still being able to deliver adequate flood risk protection (Waryszak et al., 2021).

Important differences between grey and green infrastructures are that the construction, maintenance and restoration costs of grey infrastructures are often higher than those of green infrastructure, because green infrastructures are self-repairing (Gittman et al., 2014). This difference in costs is even more prominent since climate change is putting greater pressure on infrastructures, increasing the maintenance and restoration costs of grey infrastructures (Chiu et al., 2021). Furthermore, green infrastructures often provide additional co-benefits to local communities, such as improved biodiversity, mitigating heat stress, increased air quality, and providing space for recreation (Chausson et al., 2020; Kabisch et al., 2017; Narayan et al., 2016; Raymond et al., 2017). Nevertheless, it is also recognized that green infrastructures often demand more space than grey infrastructures (Waryszak et al., 2021). Hence, coastal protection using green infrastructures is not possible everywhere, especially in the case of densely populated coastal cities (Bouma et al., 2014).

2.2 Land value capture

One of the main challenges for implementing climate adaptation – and public infrastructure in general – is the (inadequate) availability of state- or local-level public funding (Alexander, 2012). Kresse et al. (2020) refer to this lack of funds as fiscal stress. In the literature, land value capture (LVC) is often proposed as a solution to fiscal stress. LVC refers to the process which allows the public sector to recoup the value that is created by public interventions – not the landowner – in order to be used for public purposes (Nguyen et al., 2017). The rationale behind LVC argues that public authorities are allowed to capture value increments because this increment cannot be ascribed to actions of the landowner, but rather to planning decisions, public investments in infrastructure, as well as to market forces (Vejchodská et al., 2022). Therefore, this added value is often referred to as the 'unearned increment' (Alterman, 2012).

Value capture literature is ubiquitous, but mostly discusses i) the value capture rationale (Alterman, 2012; Rodríguez-Bachiller, Thomas, & Walker, 1992), ii) the different LVC instruments and their effectiveness (Lee & Locke, 2020; Mathur, 2019; Walters, 2013), iii) the amount of value which can be captured (Cervero, 1994; Smith & Gihring, 2006), and iv) differences in institutionalizations of LVC in laws and regulations (Alexander, 2012; Muñoz Gielen, Maguregui Salas, & Burón Cuadrado, 2017). All these aspects will be discussed in the following paragraphs – except for the last aspect, since this research only focuses on Boston. In the next paragraph the principle behind LVC is explained first.

2.2.1 Henry George's theorem and virtuous circles

Henry George (1879) argued that if there is free access for private developers, then government spending on public amenities would, in equilibrium, generate value through increased land prices equal to the costs of those amenities. Should the government be able to capture this value, it could then be reinvested in public amenities, raising land prices, value capturing, reinvesting, etc. This would instate a virtuous circle, see figure 3 (Lord et al., 2019). To constitute such a virtuous circle, a development not only has to be viable but also create value (Lord et al., 2019; McAllister, 2019). There are different ways in which value can be added to land and properties other than by investments made by the landowner. A first way is through planning decisions made by governments, like changes in land use, land regulations, and building or development rights (Garza & Lizieri, 2016; Rebelo, 2017; Viallon, 2018; Wu et al., 2019). Secondly, externalities of investments in public infrastructure and public services increase housing prices, like the construction of higher quality infrastructure (Nguyen et al., 2017). Lastly, changes in market conditions also affect real estate prices, for example changes in demand (Rebelo, 2017). LVC deals with capturing value increases due to these three phenomena. Moreover, another crucial aspect to upkeep a virtuous circle, besides creating value, is the effective capture of that created value. Hence, LVC plays an essential role in George's theorem, for it closes the circle and prevents capital from slipping away. If either not enough value is created or value is not (adequately) captured, the opposite can transpire; a vicious circle, in which the invested capital keeps slipping away, which only complicates the development of the area (Lord et al., 2019).

However, today, George's theorem is mainly used to justify public value capture (Alterman, 2012). Nevertheless, if land value increments can be successfully captured by the public, it can create a situation alike a virtuous circle in which enough funds are generated to make public infrastructure and service provision self-financing (Doebele, 1982; Doebele, 1987; Hong & Needham, 2007).

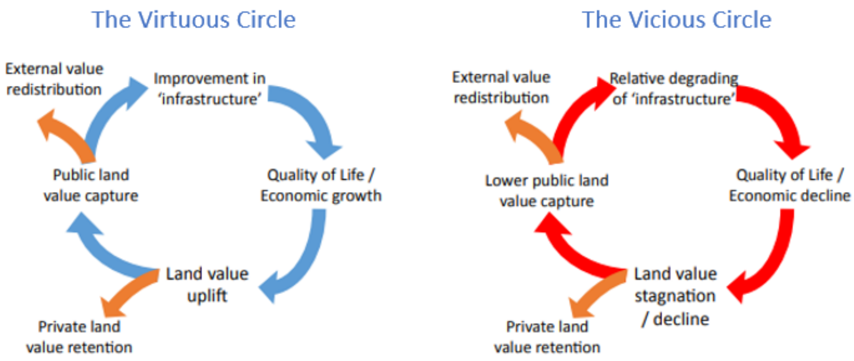

Figure 3: Schematic form of the logic that underpins the virtuous and vicious circles (Lord et al., 2019, p.247).

2.2.2 Types of LVC instruments

As mentioned earlier, many countries practice some type of LVC, however vast differences exist between and even within countries. As a result, many different LVC instruments and mechanisms exist. This paragraph does not intend to give a full overview of all existing LVC instruments, but rather to discuss different approaches to LVC instruments and different aspects and characteristics of LVC instruments. In the literature, different typologies can be found based on different aspects of LVC instruments; namely, direct and indirect LVC policy instruments, fiscal versus regulatory instruments, and negotiable and non-negotiable instruments. These will be discussed below. However, first different land management strategies will be discussed, because they can be regarded as LVC instruments themselves.

Land management regimes

When talking about LVC instruments, a first consideration to be made is the type of land management regime; i.e., the juridical regulations that steer the actions of governments in land development in regard to the management of property rights in land and buildings (Muñoz Gielen et al., 2017). Sometimes also referred to as macro policy instruments (Alterman, 2012). Different modes can be practiced in the same country depending on the situational characteristics of the development and additional LVC instruments can be used within specific regimes (Muñoz Gielen et al., 2017). These regimes can be categorized on the level of interventionism; i.e., more active to more passive regimes. The former describes the one end of this spectrum where governments create plans, regulate the land-uses, buy and assemble all the land, put the infrastructure in place, and eventually sell or lease the land to developers who can construct the real estate (Van der Krabben & Jacobs, 2013). The latter is the other end of the spectrum, where the governments merely create the plans and regulate the land-uses, then they permit market parties to assemble the land, put the infrastructure in place, and construct the real estate (Muñoz Gielen et al., 2017). It should be noted that these are the ends of this spectrum, many hybrid forms exist. In the literature, five main land management categories can be found: Nationalization of all land, public land banking, public-private partnership, land readjustment, and private land development. For conciseness these are not further elaborated here. Alterman (2012) and Muñoz-Gielen et al. (2017) discuss these more thoroughly.

Direct and indirect LVC policy instruments

Alterman (2012) distinguishes between direct and indirect LVC policy instruments. Direct policy instruments refer to a set of instruments that are directly aimed at capturing some or all of the value increment through the sole conviction that landowners ought to contribute a percentage of the increment to the public; no additional explanation to justify these instruments is required. Mostly, these take the form of taxes (Alterman, 2012), which often require a detailed legislative embedding either at the regional or national level (Muñoz Gielen et al., 2017). Furthermore, a division into either capture of the unearned increment and capture of betterment can be made. Capture of the unearned increment entails the capture of value ascribed to general developments in market forces, whereas capture of betterment is concerned with capturing the value ascribed to public action; i.e., planning decisions and construction of public infrastructure.

Conversely, indirect instruments aim to generate revenues for public services and do not directly aim to capture the created value but rather to mitigate the impacts of development by internalizing the costs. Alterman (2012) notes that they present ways of capturing value without imposing new taxes on the public. A general term for indirect instruments in the literature are developer obligations, but they can be referred to as exactions, planning gain, planning obligations or impact fees. Indirect instruments are most frequently deployed at the local level and are unique in that they do not have to be embedded in regional or national legislation, which makes them quite flexible (Muñoz Gielen & García Pastor, 2019).

Fiscal versus regulatory

Additionally, LVC instruments can be differentiated either as fiscal instruments or as regulatory instruments. Fiscal instruments are taxes or fees. Some common examples of taxes and fees include land value tax, capital gains tax, special assessment, or betterment contributions (Smolka & Amborski, 2000). Regulatory instruments can take the form of a land management regime or of developer obligations (DO). DOs are "contributions of landowners and developers in exchange for land use regulation decisions of any kind that increase the economic value of land" (Muñoz Gielen et al., 2017, p.126). Fiscal and regulatory instruments can be bounded to land use regulation decisions, for example with DOs or a betterment tax (Muñoz Gielen et al., 2017). They can also be independent from these decisions, either as a one-time charge – for example, a tax upon the transfer of ownership title – or recurring – for example, capital gains tax or annual property tax (Muñoz Gielen et al., 2017).

Negotiable and non-negotiable developer obligations

LVC instruments, especially DOs, can also be distinguished on the basis of the (in)ability of the landowners to decline their implementation, i.e., whether they are negotiable or not. Non-negotiable developer obligations (N-NDOs) are a priori prescribed by governments and unilaterally imposed on landowners or developers. Negotiable developer obligations (NDOs) depend on voluntary agreement between the government and the landowner (Muñoz Gielen et al., 2017). The effectiveness of N-NDOs is often higher compared to NDOs, because during the negotiation process developers will try to persuade the government to impose lower contributions (Hendricks et al., 2021). Developers mostly aim to do so by performing the 'viability charade', i.e., they will argue that the development is not viable should they need to pay for certain DOs (Lord et al., 2019). Furthermore, Muñoz Gielen and Van der Krabben (2019) state that N-NDOs and NDOs vary in their flexibility, legal requirements, and transparency. N-NDOs are more rigid compared to NDOs, because of their strict and very detailed legislative character. NDOs are more flexible and open in that regard, allowing them to better adapt to different situations and making them easier to be introduced by public authorities (Hendricks et al., 2021). Nevertheless, NDOs are also uncertain, as the outcome of the negation process will determine the amount of value being captured by the public. This negotiation process is associated with a lack of transparency from both the public party (Chen et al., 2022) as well as the private party (McAllister, 2019). Furthermore, LVC solely on the basis of N-NDOs is not favorable either, since N-NDOs might disincentivize development (Chen et al., 2022). A combination of N-NDOs with room for additional NDOs is also possible. Chen et al. (2022) are proponents of a combination of the two since they can cover each other's weaknesses.

2.3 Land value capture for climate adaptation

As mentioned earlier, LVC is often proposed as a method of (partly) financing flood – and other climate – resilience infrastructures. This section will provide the theoretical foundation for this argument. The first paragraph elaborates how flood risk affects land and real estate prices. In the second paragraph it is explained how this might be used to create value through FRIs.

2.3.1 Housing prices and flood risk

Much literature can be found on the effect of flood risk on land and real estate prices. For the most part, scholars have found similar results. However, discussion exists on the magnitude of this effect and there are also some scholars who have found opposing findings. Earlier contributions have a more neoclassical approach, while later research studies the effect from the angle of behavioral economics. These will be discussed below. This research focuses solely on residential real estate, as this type of real estate has widely been shown to be impacted negatively by flood risk. This presents the strongest case for price increases due to flood risk reduction; hence this focus.

Neoclassical explanations: measured flood risk

Neoclassical accounts would argue that flood risk negatively affects land and real estate prices (Harrison et al., 2001; Shilling et al., 1989). In the field of urban economic studies, this is explained through (adaptations of) the monocentric bid rent model of Alonso (1964). This model assumes there is one city center where all amenities and job opportunities are. Housing prices are a function of location, i.e., distance to the city center, and transport costs. Houses closer to the center have higher housing prices, for the transport costs to travel to the center will be lower; and vice versa. As a result, market actors search for houses, within their budgets, from which they can maximize their utility (Filatova, Mulder & Van der Veen, 2011). This means choosing a house at the location with the lowest transport costs, which they can still afford. This basic model can be shown in figure 4.

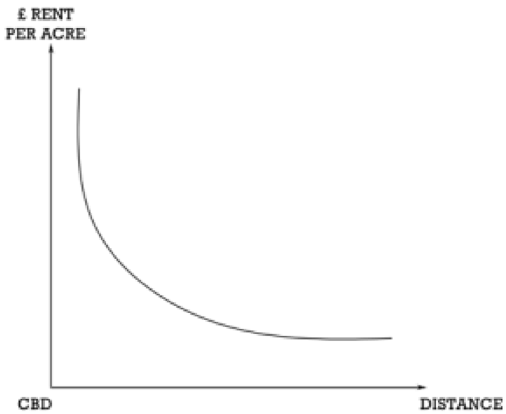

Figure 4: Alonso's bid rent curve (Narvaez, Penn, & Griffiths, 2013, p.4).

When any type of risk – such as flood risk – is involved, buyers choose between locating in a flood prone or safe area. This can be regarded as a trade-off in which future flood damage and recovery costs are weighed against future derived utility from a certain location; i.e., lower transport costs and access to amenities (Harrison et al., 2001; Tatano, Yamaguchi, & Okada, 2004). The buyers that still choose to locate in at-risk areas accept future damages due to floodings, but will internalize these future losses in their bid prices. Thus, houses in at-risk areas will have lower prices (Filatova et al., 2011). This is what Taylor and Aalbers (2022) call rent at risk; the anticipated loss due to flood risk.

When market prices for real estate reflect the chance these losses occur, then flood risk is internalized in the market (Bin & Landry, 2013; Hofmann, 2007). This was already shown to be the case in flood prone areas by some scholars, as they found that properties were valued lower than properties in safer areas (Shilling et al., 1989). Nevertheless, others demonstrate that risk is currently not accurately internalized. For example, Pommeranz and Steininger (2020) found that homebuyers ascertain flood risk on the basis of the average neighborhood risk, due to difficulty of doing so on a particular individual property. Additionally, Cohen, Barr and Kim (2021) state that certain storm events surpassed the anticipated flood zones in Texas and Florida, which took residents by surprise. More generally speaking, the exact consequences of the risks posed by climate change are uncertain (Termeer & Van den Brink, 2013). This makes it difficult for markets to internalize these risks, resulting in imperfect markets in which property prices can be either over- or undervalued (Cohen et al., 2021).

Behavioral economics: perceived flood risk

Behavioral economics provides an alternative explanation; perceived flood risk. This is different from actual, measured flood risk as it takes the perceptions of market actors into account. Risk perception can be defined as the personal assessment of the probability of the hazard and the probability of the resulting negative consequences perceived by society (Becker, Aerts, & Huitema, 2013; Bubeck, Botzen, & Aerts, 2012). If homebuyers perceive less risk from flooding, then the flood risk discount – the price decrease due to flood risk – is less apparent (Burningham et al., 2008). According to Pryce et al. (2011), market actors are myopic, i.e., risk averse, and suffer from amnesia, i.e., forget about past flood events over time. The flood risk discount is strongest right after a flood event has occurred, because such an event heightens risk awareness (Belanger & Bourdeau-Brien, 2017). Subsequently, over time, the flood risk discount starts to minimize. Bin and Landry (2013) found that prices return to a pre-flood event level after five to six years. Similar findings were reported by Atreya et al. (2013) and Multu et al. (2023) who found the flood risk discount completed faded away after four to nine years, and after nine to twelve years, respectively. Pryce et al. (2011) argue that such a price discount after a disaster is evidence of a deficiency in risk awareness of market actors, caused by information asymmetries. In cases of perfect risk information, risk would already be capitalized into the market. Therefore, a disaster event should not result in any consequences on housing prices. The time it takes for the price discount to fade away is an estimation of just how much risk is internalized by the market. The longer the return time, the less risk is internalized (Miller & Pinter, 2021).

The level of perceived flood risk is determined through a myriad of factors (Mutlu et al., 2023). However, the literature is often contradictory how different cognitive or emotional factors influence flood risk perception, for they are highly personal and many interrelationships between these factors exist (Lechowska, 2018). More consensus exist about which situational elements are of influence. The most important factors include flood experience, proximity to the hazard area, the nature of the flood, and the extent of the effects (Bradford et al., 2012; Lindell & Hwang, 2008; Montz & Tobin, 1997; Qasim et al., 2015).

Moreover, Samarasinghe and Sharp (2010) note that in regions where flood insurance is not obligatory, the magnitude of the price reducing effect of flood risk on land and real estate is significantly lower due to the lower perceived flood risk of homebuyers. Simultaneously, however, flood risk perceptions may also be affected by purchasing flood insurance, as it may lead to false feelings of preparedness or protection (Kim, 2020). Findings differ due to varying laws and regulations for damage recovery, flood risk management strategies, and insurance policies (Multu et al., 2023).

Furthermore, market conditions can shape the magnitude of the effect perceived flood risk has on prices (Belanger & Bourdeau-Brien, 2017). When demand for housing is high, buyers have less negotiation power (Harding, Rosenthal, & Sirmans, 2003). A consequence hereof, is that the flood risk discount almost entirely vanishes. On the contrary, in instances of low demand for housing, buyers are able to negotiate higher flood risk discounts (Belanger & Bourdeau-Brien, 2017).

2.3.2 Value creation through flood resilience infrastructure

As can be gathered from the previous paragraphs, the effect of flood risk on land and real estate prices can be ascribed to both actual flood risk and perceived flood risk (Belanger & Bourdeau-Brien, 2017; Filatova et al., 2011). On the one hand, actual flood risk affects real estate prices due to more rent at risk, which steadily increases due to climate change. On the other hand, the occurrence of flood events influences perceived flood risk, which results in fluctuations in the flood risk discount (Belanger & Bourdeau-Brien, 2017).

In response, governments aim to reduce flood risk by implementing flood risk management strategies (Hegger et al., 2014). Because flood risk can be defined as a function of the expected damage costs and the probability of the flood event, reducing flood risk is done through reducing either the damage or the probability (Filatova et al., 2011). One way of reducing the damage of a flood event is through what Hegger et al (2014) call flood risk prevention, i.e., restricting development in flood prone areas. However, if these areas continue to economically thrive, it remains interesting to keep developing these areas (Filatova et al., 2011). Another way of lowering the consequence of flood events is through flood mitigation strategies, for example through infiltration systems or water retention structures. Flood defense strategies, on the other hand, reduce flood risk by reducing the probability of a flood event from occurring. The implementation of both flood mitigation and flood defense infrastructure can reduce rent at risk and perceived flood risk (Mutlu et al., 2023; Walsh et al., 2019). This results a less severe persistence of risk in the utility maximizing trade-off, making properties protected by FRIs more attractive; thus, resulting in price increases (Kim, 2020).

Moreover, flood defense strategies can interconnect with flood recovery strategies (Hegger et al., 2014). The flood insurance premiums are often tied to the level of flood risk the property experiences. These premiums can also be internalized by the market. This means that properties with higher insurance premiums have lower market prices, and vice versa (Harrison et al., 2001). When FRIs are constructed to protect an area, flood risk decreases leading to lower flood insurance premiums, causing another uplift in property values (Belanger & Bourdeau-Brien, 2017).

When price increases occur, the notion of LVC becomes interesting. Value can be created through the implementation of FRIs, which can then be captured by the public to recoup costs or finance additional FRIs. However, because of its novelty of application in regard to this type of infrastructure, the implementation of LVC instruments benefits from more precise knowledge on just how much value can be ascribed to these kind of interventions (Lord et al., 2022). This makes it necessary to look deeper into what types of FRI create value and how much. This will be examined for both grey and green FRIs in the next paragraphs.

Grey infrastructure

For many places, grey infrastructures were the traditional approach to protect against flood risk (Beltrán et al., 2018). Several studies looked into the effect of grey infrastructures on real estate prices; however, these accounts differ in their results. Earlier studies that have found significant positive results include Damianos and Shabman (1976) and Thompson and Stoevener (1983), for dam construction and watershed protection projects. Beltrán et al. (2018) found a price increase between 12.6% and 16.7% for urban properties in the UK protected by grey FRIs. Furthermore, Walsh et al. (2019) found a positive effect between the implementation of bulkheads and property prices, as well as between ripraps and property prices; the price increase, however, was stronger for bulkheads than for ripraps. The remaining type of infrastructure, groinfields, held inconclusive results due to a lack of sufficient data. These results would suggest that different types of infrastructure lead to different changes in perceived risk of citizens. Jin et al. (2015) performed a hedonic analysis for three coastal towns in Massachusetts to investigate the effect of hard shoreline protection infrastructures and found a 10% increase in average real estate values.

Furthermore, Kelly and Molina (2023) studied the effect of grey and green FRIs on sale prices in Florida and find that both FRIs increase property values; this was particularly the case for projects that were visually identifiable by residents, i.e., the larger projects such as seawalls and raised streets. Presumably due to a greater reduction in risk perception. Kim (2020) also found a positive effect for both grey and green infrastructures, though green infrastructures were found to have a stronger effect likely due to secondary benefits. Contradictory, Kim et al. (2020) found no evidence of a price increasing effect of grey infrastructures on property prices. Similar findings by Mutlu et al. (2023) also suggest no increase in property prices due to grey infrastructure. Yet, this study looked at riverine flood defense and only one type of infrastructure was assessed; namely dike reinforcement. Presumably, these differences occur due to disamenity impacts; while grey infrastructures protect communities against flood risk, they can also obstruct ocean views or block physical access to the ocean, which are found to positively influence housing prices (Jin et al., 2015).

Green infrastructure

As explained earlier, next to reducing flood risk, green infrastructures provide multiple co-benefits, among which recreational amenities. As a consequence, some scholars argue that green infrastructures will often generate more value compared to grey infrastructures, which solely provide flood risk protection (Kim et al., 2020). However, little empirical evidence exists to support this. Research by Multlu et al. (2023) on fluvial flood defense found that green FRIs increased property prices by 6.5% due to flood risk defense and a further rise by 4.2% due to environmental amenities for properties 1 km away from the river; and a 15% total increase on average (Mutlu et al., 2023, p.10). Additionally, Kim et al (2020) have found an 12.6% increase in housing prices in closer proximity to green infrastructure projects. Furthermore, Bockarjova et al. (2020) performed a meta-analysis of the effect of urban green interventions on housing prices. They estimated a maximum premium of 20% for properties in the vicinity of those nature-based solutions. However, Bockarjova et al. (2020) warn that these nature-based solutions can unintentionally instigate green gentrification. This is a process where green urban renewal through nature-based solutions creates amenities that attracts affluent citizens, which capitalize the added value of green spaces into their house value, displacing less affluent citizens (Anguelovski et al., 2017).

2.4 Assessing value increments

Earlier studies have mainly used either a hedonic price model (HPM) or a difference-in-difference (DID) approach – or a combination of both methods – to assess the effect of flood risk or FRIs on housing prices. Both of these methods will be discussed in the following paragraphs.

2.4.1 Hedonic price models

The HPM is a method to estimate the value of certain attributes of houses by comparing the relative prices of houses and their bundles of attributes (Engström & Gren, 2017). For the most part, it rests on two theoretic grounds: Lancaster's consumer theory and Rosen's model. The former entails that consumers derive utility from house characteristics (Chau & Chin, 2003). The latter states that the joint bundle of house characteristics is represented by the offer functions of profit maximizing producers and the bid functions of utility maximizing homebuyers (Mei et al., 2020). In short, HPMs assume that property values are determined by the sum of their attributes. There are three types of house characteristics, structural, locational and neighborhood characteristics. The HPM estimates the added value of each specific attribute.

The application of HPM to the real estate market is widespread. Many studies have been performed to identify exactly which attributes influence real estate prices (e.g., Engström & Gren, 2017; Nicholls, 2019; Zhang & Dong, 2018). First, structural characteristics that are found to be of influence are lot size, floor space area, building age, floor level, and the amount of both bedrooms and bathrooms (Chau & Chin, 2003). Second, some important locational characteristics include distance or access to the CBD, availability of different public transport modes, and distance to the interstate (Zhang & Dong, 2018). Finally, research has shown that some of the neighborhood characteristics of influence are vandalism, public services like schools, noise, air quality, presence of urban green, availability of recreational areas, and environmental disturbances (Engström & Gren, 2017; Nicholls, 2019). Sometimes studies find alternative results for these characteristics, which are explained through secondary effects caused by these characteristics. For example, proximity to subway stations, bus stops and schools have also been shown to negatively impact home values in some instances, which is explained through increased traffic congestion and noise (Kim, 2020).

There are several different forms of HPMs, though all are variations on the basic hedonic price function, which look as follows:

$$P = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_v X_v + u$$

Where P is the housing price, β_0 the intercept, X_1 to X_v are all the characteristics of influence, β_1 to β_v are the coefficients to be estimated, and u is the error term. There are three types of different HPMs; parametric, nonparametric and semiparametric models. For the parametric model, the ordinary least square (OLS) method is used most often. This model is often critiqued, however, on problems of heteroscedasticity especially in multiple regression analysis (Fletcher, Gallimore, & Mangan, 2000).

This problem can cause bias in the estimations of the coefficients and in the standard error of these coefficients (Stevenson, 2004). In the nonparametric model different weights are given to the variables, allowing for more flexibility (Hastie & Loader, 1993). However, these models are often less precise even in cases of larger samples, because the coefficient estimates rely on the local averaging. This leads to sparsely distributed observations and difficulty in assigning weights to the variables (Owusu-Ansah, 2011). Finally, semi-parametric models apply features from parametric models into nonparametric models, allowing them to benefit from the advantages of both models (Anglin & Gençay, 1996). However, though the gravity of the problems associated with both parametric and nonparametric models is reduced in the semi-parametric model, they still persist (Owusu-Ansah, 2011).

Additionally, there are some more general caveats to the HPM. Some of the more practical critiques are the problem of spatial autocorrelation and omitted variables (Engström & Gren, 2017). Yet, there are also some critiques to the more fundamental principles on which the HPM is based. A first is that there should be freedom to enter the market for both buyers and sellers (Goodman, 1978). Buyers, however, are confronted with budget restrictions and, similarly, housing developers require starting capital. Developers also have to obtain development rights first and, therefore, are not fully free to enter the market (Chau & Chin, 2003). Next, the condition of perfect information can never fully be obtained. Finally, the assumption of market equilibrium is also contested, because market imperfections persist everywhere (Goodman, 1978).

2.4.2 Difference-in-difference designs

Alternatively, difference-in-difference (DID) designs are an option often applied in housing market research. This is a method that evaluates the efficacy of different policies or to assess the impact a certain event has caused; i.e., the treatment effect. DID is a type of quasi-experiment. Apart from the randomized field experiment, the quasi-experiment is one of the most reliable ways of estimating the (causal) effect of a certain treatment on a dependent variable (Clark et al., 2021; Wooldridge, 2019).

The method starts with dividing the study sample into a treatment group and a control group, where the treatment groups is affected by a certain treatment and the control group remains unexposed. Next, outcomes pre and post treatment for both groups are measured. The treatment effect is determined by looking at the difference between the treatment group's post treatment outcome and the estimated outcome of the treatment group had there been no treatment (Chun-Chang, Chi-Ming, & Hui-Chuan, 2020). The latter is known as the 'counterfactual'. The counterfactual is based on the trend of the control group. This is illustrated in figure 5.

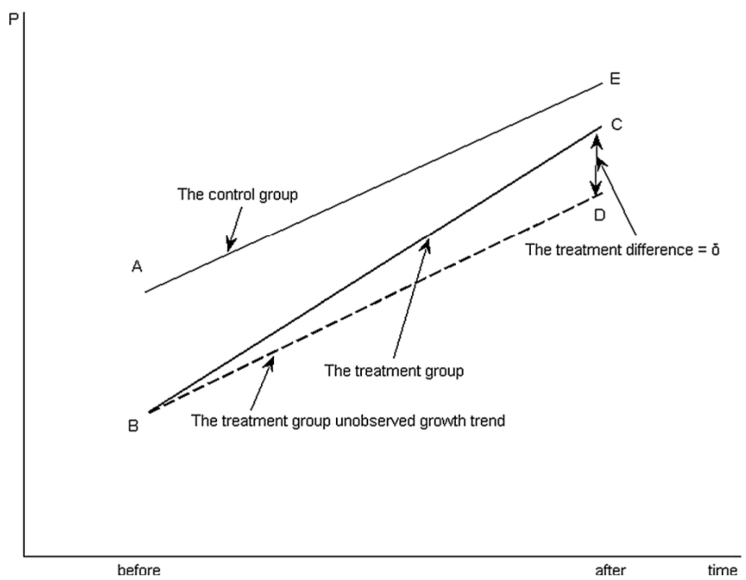

Figure 5: Schematic diagram of the difference-in-difference method (Lee, Liang, & Chen, 2017, p.412).

The basic DID model is the following:

$$P = \beta_1 + \beta_2 TREATMENT_i + \beta_3 TIME_t + \delta(TREATMENT_i \times TIME_t) + \sum_{j=1}^{n} X_{jit} + e_{it}$$

Where P is the price; TREATMENT_i is a dummy variable that has the value 1 if the observation is in the treatment group and 0 if in the control group; TIME_t is a dummy variable for the time of the observation, being 1 for observations posttreatment and 0 for pretreatment; δ is the DID coefficient, which measures the interaction effect between treatment or control group and pre- or posttreatment on the treatment effect on the housing prices; X is a sum of control variables that also may affect housing prices; and finally, e is the error term of normal distribution. The main focus of the DID model is on $\delta(TREATMENT_i \times TIME_t)$, because this describes the treatment effect (Lee, Liang, & Chen, 2017).

The most important assumption of the DID model is that of parallel trends; i.e., the assumption that the treatment and the control group would show equal trends, had it not been for the intervention of the treatment (Ryan et al., 2019). Hence, it assumes that the difference between the trends of the treatment and control group is entirely caused by the treatment. Because of this, it is of critical importance to the internal validity of the model to make sure no critical differences exist between either the treatment and control group. If this is the case, the estimates of the effect will be biased (Gibson & Zimmerman, 2021). To avoid this, DID analyses are often paired with matching procedures, which select cases from the control group that most closely resemble cases from the treatment group. The result is observations that have similar characteristics, except for one; the treatment (Liang et al., 2020).

There are also many accounts that include the DID variables into an HPM, for example Walsh et al. (2019). This way, the variables of interest are still measured applying the DID methodology, but the HPM can determine the magnitude of the treatment effect and that of the other variables. The function of such a model would look the following:

$$P = \beta_1 + \beta_2 TREATMENT_i + \beta_3 TIME_t + \delta(TREATMENT_i \times TIME_t) + \sum_{a=1}^{n} (\beta_a X_a + \beta_b X_b + \cdots + \beta_v X_v) + e_{it}$$

Here, P is the housing price, $\beta_1$is the intercept, $\beta_2 TREATMENT_i$ and $\beta_3 TIME_t$ are dummy variables for treatment or control group and for pre or post exposure. The interaction term $(TREATMENT_i \times TIME_t)$ is the treatment effect and still the main variable of interest. Then the hedonic regression part is $\beta_a X_a + \beta_b X_b + \cdots + \beta_v X_v$ which is the sum of all the structural, locational and neighborhood characteristics. Finally, e_{it} is the error term. In comparison to the HPM, a well-performed DID analysis can more reliably determine the causal effect on an independent variable on a dependent variable (Wooldridge, 2019). On the one hand, by including the DID terms into the HPM, the effect of the variable of interest is therefore accurately determined. On the other hand, by applying a traditional DID analysis, the direction and the magnitude of the effect of the confounding variables cannot be determined. Whereas by combing the DID with the HPM, this is still possible.

2.5 Conceptual model & hypothesis

To summarize, housing prices are influenced by a myriad of factors. But the section above provides a theoretic foundation that suggests that a reduction of flood risk through FRIs has a positive influence on the value of residential real estate. Figure 6 is a schematic illustration of this relationship.

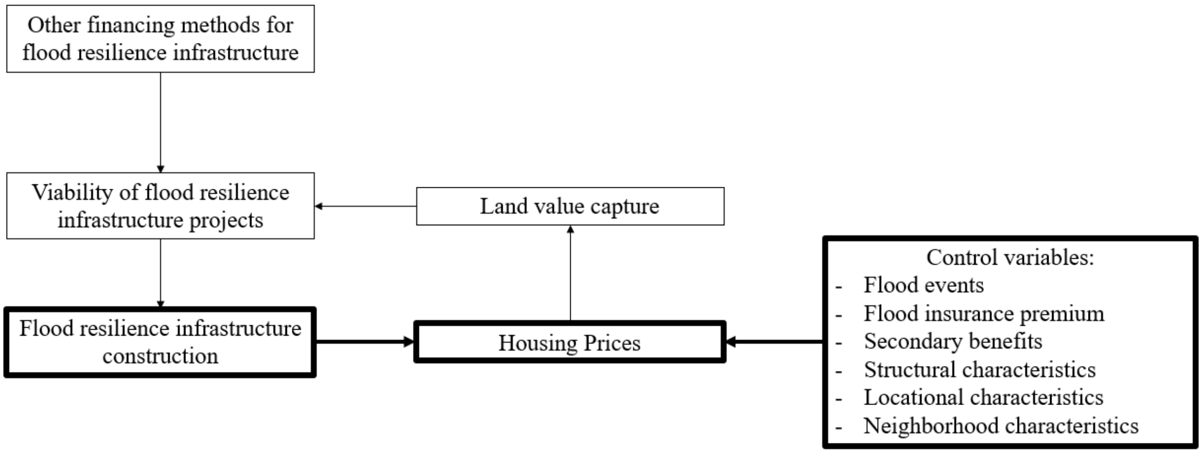

Figure 6: Conceptual model.

FRI construction is expected to have a price increasing effect on at-risk residential real estate. Due to this price premium, LVC can generate additional funds for reinvestment in FRI projects. This way, the viability of FRI projects is heightened. Resulting in a situation alike a virtuous circle, this enriches other financing strategies.

Then there are other factors of influence on housing prices. First of all are the occurrence of flood events which heighten perceived flood risk, decreasing housing prices for a period of time. Buyers suffer from amnesia and myopia, making them forget about the flood risk and making them unaware of long-term consequences of flood risk. Furthermore, in the US, homebuyers are in some cases required by law to have flood insurance. These insurance premiums are internalized by the market; thus, market prices reflect future flood insurance costs. By reducing flood risk through FRI implementation, flood insurance premiums may drop to a lower category, which will increase housing prices. Additionally, as can be concluded out of the few studies into green infrastructures, some FRI projects come with secondary benefits that will have a further price increasing effect on housing prices, for example a park which serves as an inundation zone and simultaneously as a recreational area. Finally, there are three categories of housing characteristics, structural, locational, and neighborhood characteristics that influence housing prices. Structural characteristics are variables like building age, number of bed and bathrooms, building materials, etc. Locational characteristics encompasses variables like distance to the city center and accessibility of public transport. Neighborhood characteristics include variables like accessibility of amenities, such as parks and schools, and greenery in the immediate area. All these types of characteristics can influence housing prices in their own way.

The main hypothesis of this research is the following: FRI construction increases housing prices for at-risk residential real estate after project completion in the protected area. This effect, along with the necessary control variables, are depicted in figure 6 in bolder font. This is the effect that will be quantitatively tested in this research. The remaining part of the conceptual model is to show the virtuous circle that could be the result of the effect of interest, this is, however, not tested but shown for completeness.

3. Methodology

This chapter delineates how the hypothesis was tested, i.e., how the research was performed. First, it discusses the broader applied research paradigm. The second paragraph describes the research design and operationalization of the studied concepts. This paragraph also aims to explain why this specific research design was chosen over other possible designs. The paragraph thereafter, elaborates the required data; how these were collected and subsequently analyzed. The final paragraph of this chapter discusses the validity and reliability of the research methodology. This paragraph will also present ways in which some of the pitfalls regarding validity and reliability can be accounted for.

3.1 Research paradigm: postpositivist approach

First and foremost, it should be noted that this research applies the postpositivist research paradigm. This entails certain assumptions about research ontology and epistemology (Van Thiel, 2014). Regarding the ontological question, this research assumes that there is one reality which can be observed and measured (Farthing, 2016). In other words, it is rooted in critical realism, where one "real" reality is postulated, but which simultaneously can never be fully understood; it can only be apprehended as closely as possible (Guba & Lincoln, 1994). Furthermore, the epistemological question is answered in a modified dualist or objectivist manner (Farthing, 2016). True dualism is forsaken in postpositivism, however there remains a "regulatory ideal". Meaning that there is no true independency between the investigator and the research object, however a certain level of independency still remains, which in turn is guarded by falsification (Guba & Lincoln, 1994). Hence, it is a more nuanced version of the positivist approach in which the researcher is assumed to observe phenomena behind a glass window. Finally, the methodological issue in the postpositivist approach is again a modified version of the positivist experimental and manipulative methodology (Guba & Lincoln, 1994). Hypotheses are empirically tested in order to verify them (Van Thiel, 2014). In this process, possible intervening factors are manipulated in such a way to prevent the biased outcomes. The postpositivist approach puts emphasis on triangulation in order to falsify – as opposed to verify, in the case of positivism – hypotheses (Farthing, 2016). Therefore, the postpositivist approach accommodates for both quantitative and qualitative research methods (Guba & Lincoln, 1994).

3.2 Research design

To test the hypothesis, this research analyzes the effect of FRIs on residential real estate prices, to provide a basis for the application of LVC instruments to capture price increases due to improved flood resilience. This relationship will be determined quantitatively through a quasi-experimental design rooted in an HPM. Establishing any type of causal effect is most preferably done through a randomized field experiment, because it has the highest level of reliability and validity (Rossi et al., 2004). It compares both a randomly assigned treatment and control group, where only one factor – the one of interest – differs between these two groups (Liang et al, 2020). However, in many cases, applying this research method is not possible, since most situations do not allow for randomized selection of the object of study for being included in the treatment or control group. For this research, that is also the case; it is not possible to randomly assign where FRIs will be constructed. Therefore, a quasi-experiment would be the next best approach.

In quasi-experiments the treatment and control groups are nonrandomly assigned (Maciejewski, 2018). They compare the object of study before and after the implementation of a certain policy or occurrence of an event, the treatment, between a treatment and a control group (Lan et al., 2020). The treatment group consists of cases that have been affected by the treatment, whereas the control group consists of cases that remain unaffected (Chun-Chang et al., 2020). However, nonrandomly assigning objects into either treatment or control group comes with some points of attention for the reliability and validity of the study (Rossi et al., 2004). This will be discussed in paragraph 3.4. However, the following paragraphs deal with the operationalization of the concepts used in this research.

3.2.1 The treatment: flood resilience infrastructure projects

The treatment in this study is the construction of FRI projects to reduce coastal or riverine flood risk of certain areas in Boston. After the completion of the construction, the home sales are considered to be 'treated'. FRIs are operationalized as physical interventions aimed at reducing coastal or riverine flood risk in an area, either through flood defense or flood mitigation approaches. FRIs can be either flood defense infrastructures or flood mitigation infrastructures. However, only area level interventions are considered because property level interventions will most likely only effect prices of the targeted properties. Hence, interventions like for example elevating properties or floodproofing properties are not incorporated. The completion date of the FRI is the moment after which treatment has occurred and the post-treatment period starts. The sample of resilience projects included in the analysis are projects that were completed between the period of January 1st 2009 to December 31st 2020. This is because detailed property characteristics are available from 2008 onwards. Thus prior to 2008, it would not be possible to control for other factors. Moreover, sales were available up to 2021. Therefore, to be able to look into the developments in sale prices up to one year before and one year after completion, this means that the resilience projects need to be finished in between 2009 and 2020.

3.2.2 The treatment and control groups: a continuum rather than a binary

The units of analysis are sales in residential properties. In a traditional DID design, the treatment and control groups are handled as separate groups which are then compared pre and post exposure to the treatment. This would require knowing the exact area which is exposed to treatment, or in this case, the precise area that is protects due to FRIs. However, studies determining this area are not included into any of the plan documents of the FRI projects. Thus, including the treatment and control groups as a strict binary may lead to possible discrepancies in the effect, particularly for sales of properties close to, but just outside, the treated area. Hence no effective distinction is made between treatment and control group, but rather, the distance of every sale to its closest respective FRI is calculated. The treatment effect then becomes the distance to the closest FRI project once that project has finished construction. This method is also applied by others in similar studies, for example Kelly and Molina (2023) and Walsh et al., 2019). The analysis determines whether a distance decay effect is present; i.e., whether sales closer to FRIs sell for higher prices after project completion than sales further removed from these projects.

The study period for which this is tested is between January 1st 2008 and December 31st 2021. Again, this period has to do with data availability. Additionally, the included sales must be located inside the projected flood zone of 2070 in a 36-inch sea level rise and 1 percent annual chance storm event scenario. This flood scenario is used for federal and local policy interventions. Properties have to face flood risk because any price effects caused by FRIs in areas that do not experience present or future flood risk will most likely be due to other theoretical explanations than flood risk reduction. Price increases that can be observed in these instances could for example be caused by secondary benefits of projects (Mutlu et al., 2023). Therefore, sales outside this flood zone are excluded.

For every sale, the sale date is compared against the completion date of its nearest FRI. Should the sale have occurred prior to project completion, then that sale will be categorized as pre completion group. Transactions occurring after FRI completion fall into the post completion group. In a traditional DID design, there is only one treatment, however, in this case, the treatment consists of a number of projects that all finish at different times, known as a staggered treatment roll-out of. Hence, units need to be individually analyzed on whether they belong to the pre or post completion group.

3.3 Data

This paragraph will elaborate the different datasets used in this study and how this data was collected. Hereafter, the data analysis will be explained in more detail; what kind of analysis was performed, and the treatment of outliers is discussed.

3.3.1 Dataset and data collection

The data necessary for the analysis consists of six different datasets, which will be elaborated below. This paragraph will talk about which data is incorporated in the analysis and how this data was gathered. Moreover, it also discusses the quality of the data.

Housing prices

First, the independent variable, housing prices. Transaction price data were preferred here, because they best reflect the actual market value; therefore, this value includes the hypothesized added value of FRIs, if any. Data on transaction prices are recorded by the Department of Revenue of the Commonwealth of Massachusetts and are made publicly available on their website. All arm's length sales between January 1st 2008 and December 31st 2021 for the City of Boston were extracted. Only sales of properties located in the 2070 36-inch sea level rise 1 percent annual chance flood zone are included, as explained earlier. Furthermore, seeming as the clear majority of sales were condominiums and other property types were not represented well enough to reliably analyze, only the condos were included. These do not include any type of subsidized housing because these may yield different results. Moreover, solely residential condos were incorporated, no multi-use condos were added, for the effect of FRIs on commercial properties was found to be non-significant (Fell & Kousky, 2015). Wholesales of entire condominium buildings were also not included, mostly due to a small number of these kinds of transactions. The included sales are depicted in figure 7. Note that this map shows the sales on parcel level rather than at the sub-parcel level the data actually is recorded on. This means that sales of condos in a multistory building and sales of the same property at different points in time are layered on top of each other. This figure is merely intended to give an overview of the spatial clustering of the sales data.

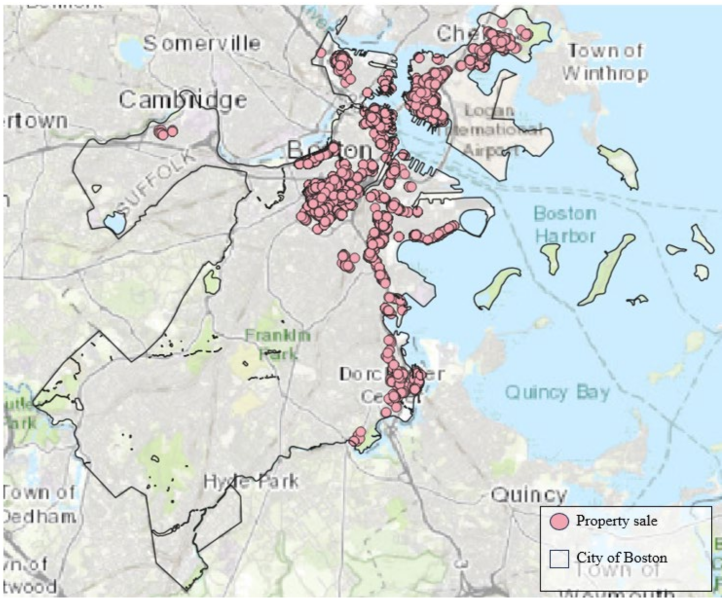

Figure 7: Arm's length home sales located in the 2070 36-inch sea level rise 1% annual chance flood zone between January 1st 2008 and December 31st 2021.

The sales data includes the date of sale, the seller and buyer, the sale price, the property type, and the location. In total there are 18.582 number of condo sales in the study period. The prices were transformed into real prices at the time of 2021 by using the Consumer Price Index (CPI). The CPI allows for price correction for inflation. It is calculated and published by the US Bureau of Labor Statistics (BLS). For this research the northeastern annual CPI for all urban consumers (CPI-U) was used, which is most commonly applied (U.S. BLS, 2021).

Flood resilience infrastructures

Second, the dataset on FRI projects was created by analyzing all the approved plans of the completed development projects between 2009 and 2020. The plans are listed on the website of the Boston Planning and Development Agency (BPDA). From the plans it was determined if a development included an FRI. All the plans that included any kind of flood defense interventions (e.g., seawalls, breakwaters, or raised streets) were included. For flood mitigation interventions (e.g., infiltration galleries, retention ponds, or raingardens) to be included in the database the plans needed to explicitly specify that the intervention affects a larger area than just the project site. By using the project site provided in the development plan, the resilience projects were mapped on project site level, enabling spatial analysis. Twelve projects completed in the study period were considered to include FRIs. Figure 8 shows the included projects. The table in Appendix I provides an overview with full descriptions of the FRI projects.

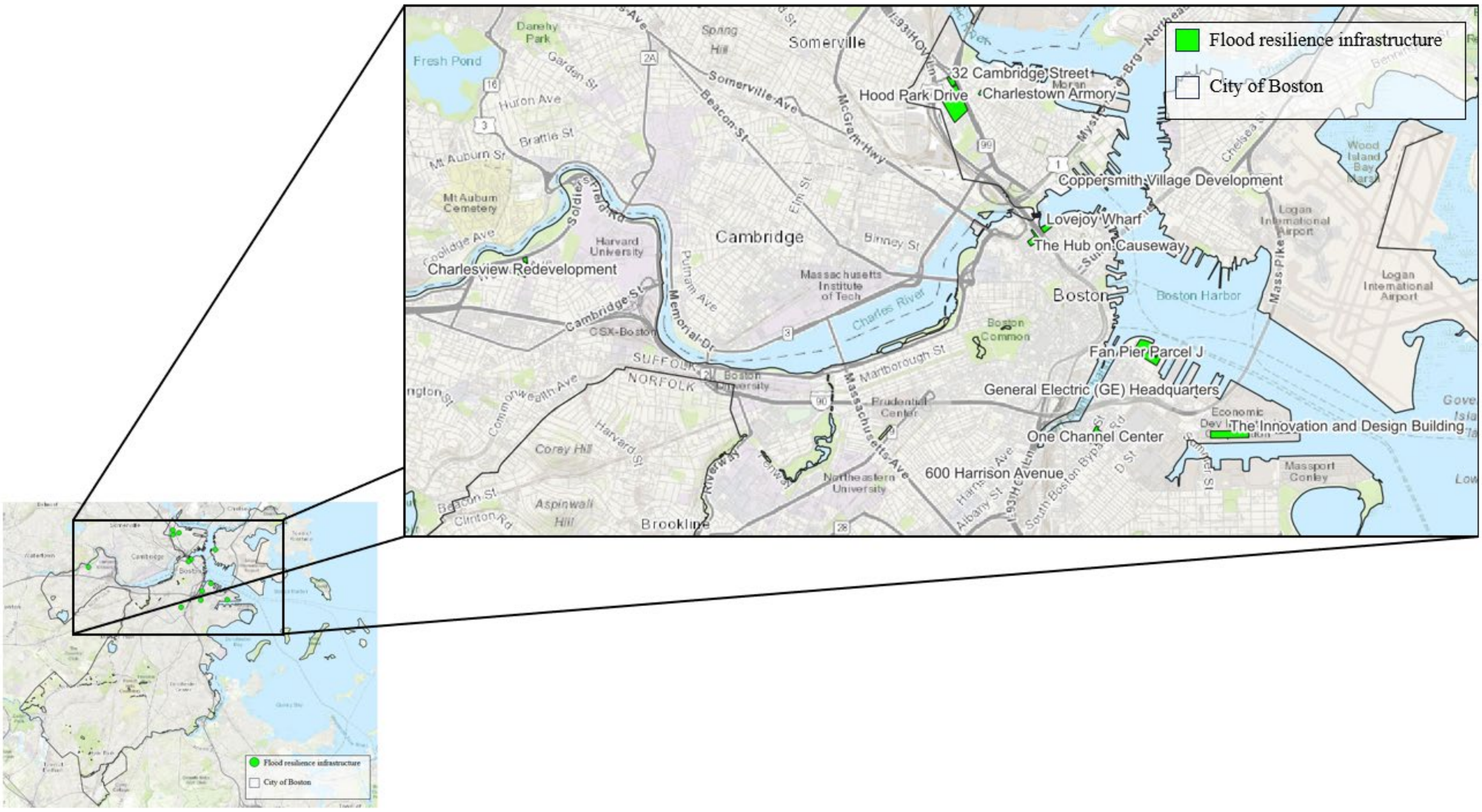

Figure 8: Flood resilience projects completed between January 2009 and December 2020 that target coastal and/or riverine flooding.

Unfortunately, the plans do not include a detailed study that determines what exact area is affected by the FRI. This same issue was noted by a similar study on the Miami-Dade County in Florida by Kelly and Molina (2023). To resolve this issue, they drew a buffer zone of 200 meters around the perimeter of the development project sites. All properties inside this buffer zone were considered as having received treatment. This research, however, calculates the distance of each sale to its closest FRI project and adds this as a continuous variable. This way, a distance decay effect can be accounted for, rather than making an arbitrary cut off. However, for an FRI to be included in the study, its 200m buffer zone has to intersect with the 2070 36-inch 1% annual chance flood zone. This is done so only infrastructures targeting either coastal or riverine floodings are incorporated. This meant that three projects were excluded. Furthermore, a typology used by Kelly and Molina (2023) is applied to place the FRIs into five categories, to be able to check for any differences in project types. These types include: i) shoreline stabilization interventions, like (fortification of) seawalls, breakwaters, and bulkheads; ii) elevation interventions, like raised streets or grading adjustments; iii) drainage interventions, like pumps or infiltration galleries; iv) small water holding infrastructures, like raingardens or bioswales; and lastly,

v) large water holding infrastructures, like retention ponds. Note that the first two categories are flood defense interventions, whereas the last three categories are flood mitigation interventions. Out of the twelve FRI projects one infrastructure improves drainage, two include increasing elevation or raising streets, three projects stabilize shorelines, five are small water holding infrastructures, and one is a large water holding infrastructure. Figure 9 depicts the categorization of FRIs as made by Kelly and Molina (2023).

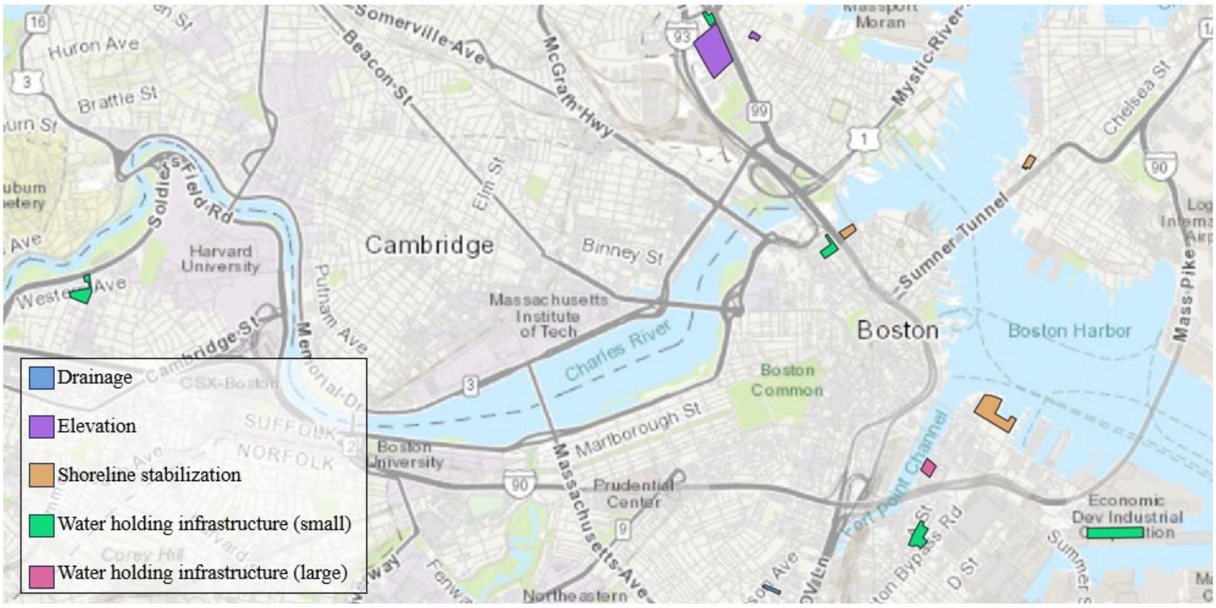

Figure 9: Flood resilience infrastructure projects categorized following typology of Kelly & Molina (2023).

Furthermore, the data on FRI projects includes the start date of the construction, which is denoted as the date on which the building permit was granted, as well as the date of project completion; both retrieved from the website of the BPDA. Finally, it includes a description of the FRI project and a categorization into either grey or green FRIs; of which there are eight and four respectively. This allows for an exploration into the differences for secondary benefits provided by green infrastructures. Figure 10 provides an illustration for this categorization.

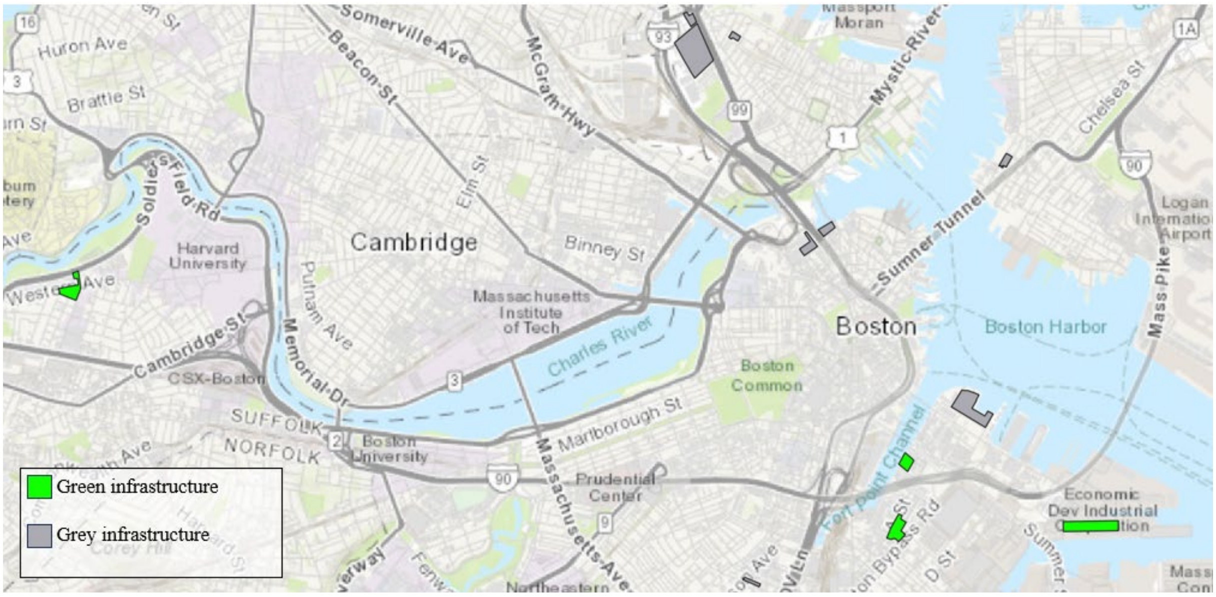

Figure 10: Flood resilience infrastructure projects categorized as green or grey nature.

Flood risk, -events, and -insurance

Third, are the data on the flood zones. The data on the present flood zones are publicly available through the Federal Emergency Management Agency (FEMA). Since the establishment of the National Flood Insurance Policy (NFIP) in 1968, the US government provides flood insurance to property owners. Flood insurance rates are based upon, among other things, the flood zone in which a property is located. This is determined and kept up to date by FEMA for the entire US. FEMA models the flood zones for a 1% annual chance storm and a 0.2% annual chance storm. Furthermore, they publish flood zone maps to showing the flood zone designations of all properties. A table of the flood zone categories and their meanings is illustrated in table 2. Owners of properties within any of the A or V zones – the 'Special Flood Hazard Area' (SFHA) – and who financed their properties through government backed mortgages are obliged to get flood insurance. For properties in zones B, C, or X this is not obligatory. Furthermore, developments in the A and V zones are required to adhere to certain building prescriptions, mostly relating to elevation. Therefore, the flood zone indications are, next to indications of actual flood risk, an important factor in citizen's perceived flood risk (Shao et al., 2017).

Over the course of the study period, there has been one true update in the flood zone status for Boston, which became effective in 2016 and is still currently in effect. In 2009 a 'new' flood map became effective, but this was only a digitized version of the 1992 study without any alterations in flood zone indications. This 2009 version was made available by FEMA for this research. For sales between the years 2008 up to 2015 the flood zone indications of the 2009 study are used. From 2016 onwards, the flood zone indications from the current effective 2016 study are used to denote flood risk. The future flood zone, that of 2070 with a 36-inch sea level rise and 1% annual chance storm scenario, is obtained through the Environment Department of the City of Boston. This is used to determine which sales are included in the sample, as elaborated in paragraph 3.2.2. The two flood zone studies of 2009 and 2016 by FEMA are illustrated in figures 11 and 12, respectively. In the figures, the flood zone indications were projected on parcels. Should a border of a flood zone indication be in a parcel, then the highest flood risk indication is shown. They are shown this way, for this is how the flood zones are ascribed to the property sales in the dataset that was used. As expected, the floodplain penetrates further land inwards in the map of 2016; especially in the neighborhoods Charlestown, East Boston, the North End, Downtown, South Boston Waterfront, South Boston and the South End. The changes in the southwestern part of city – the neighborhoods Rosindale, Hyde Park, West Roxbury, Jamaica Plain, and Brighton – from SFHA in 2009 to the 1% drainage area less than 1 square mile are due to a more detailed study methodology applied by FEMA, rather than a reduction in flood risk.

The data on flood events were found only on county level. Furthermore, these data were not very detailed; most specifications, like the amount of damage, were unknown. Hence, no data on flood events is added to this research's dataset. In similar studies by Kelly and Molina (2023) and Walsh et al. (2019) flood events were also excluded. The price increase related to FRIs will be noticeable despite any price discounts caused by flood events. If anything, flood events heighten flood risk perceptions and will therefore only further increase sale prices, though temporarily. Furthermore, by only looking at Boston, flood events will have impacts – either through actual damage or through heightened perceived flood risk – on the entire sample. Hence, it does not pose that much of a problem by omitting the variable.

Unfortunately, data on insurance premiums were not accessible, the height of the flood insurance premiums is, therefore, not known. However, with the FEMA flood zone indications it is still possible to determine which properties have the insurance mandate should the new owners have bought it by relying on a government backed mortgage, which is the case for 32.8% of buyers nationally (Consumer Financial Protection Bureau, 2022). Additionally, a conventional loan may also come with requirements, like buying flood insurance, but this can vary among lenders. Nevertheless, the FEMA data at least allow for incorporating nominal data on the mandate, indicating a 1 for properties with the insurance mandate and a 0 for no mandate. As of October 1st 2021, FEMA has started implementing a new method – called Risk Rating 2.0 – for calculating the insurance premium. Existing policies did not change, but new policies were calculated using the new method. However, this new methodology did not change anything about the way the insurance mandate works, it mostly resolved certain accuracy and equity issues of the prior system. Hence, Risk Rating 2.0 does not affect the data for this analysis.

Table 2: Description of flood zone indications (FEMA, 2023)

Flood zone	Full description
A	Areas with a 1% annual chance of flooding and a 26% chance of flooding over the life of a 30-year mortgage.
A99	Areas with a 1% annual chance of flooding that will be protected by a federal flood control system where construction has reached specified legal requirements.
AE	The base floodplain where base flood elevations are provided.
AH	Areas with a 1% chance of shallow flooding, usually in the form of a pond, with an average depth ranging from 1 to 3 feet. These areas have a 26% chance of flooding over the life of a 30-year mortgage.
AO	River of stream flood hazard areas, and areas with a 1% or greater chance of shallow flooding each year, usually in the form of sheet flow, with an average depth ranging from 1 to 3 feet. These areas have a 26% chance of flooding over the life of a 30-year mortgage.
AR	Areas with a temporarily increased flood risk due to the building or restoration of a flood control system (such as a levee or dam). Mandatory flood insurance purchase requirements will apply but will not exceed the rates for unnumbered A zones if the structure is built or restored in compliance with the zone AR floodplain management regulations.
VE	Coastal areas with a 1% or greater chance of flooding and an additional hazard associated with storm waves. These areas have a 26% chance of flooding over the life of a 30-year mortgage. Base flood elevations (BFE) derived from detailed analyses are shown at selected intervals within these zones.
V	Coastal areas with a 1% or greater chance of flooding and an additional hazard associated with storm waves. These areas have a 26% chance of flooding over the life of a 30-year mortgage. No BFE are shown within these zones.
B/X	Area of moderate flood hazard, usually the area between the limits of the 100-year and 500-year floods. Also used to designate BFE of lesser hazards, such as areas protected by levees from 100-year floods, or shallow flooding areas with average depths of less than one foot or drainage areas less than 1 square mile.
C/X	Area of minimal flood hazard, usually depicted on FIRMs as above the 500-year flood level. Zone C may have ponding and local drainage problems that don't warrant a detailed study or designation as base floodplain. Zone X is the area determined to be outside the 500-year flood and protected by levee from 100-year flood.
D	Areas with possible but undetermined flood hazards. No flood hazard analysis has been conducted. Flood insurance rates are commensurate with the uncertainty of the flood risk.

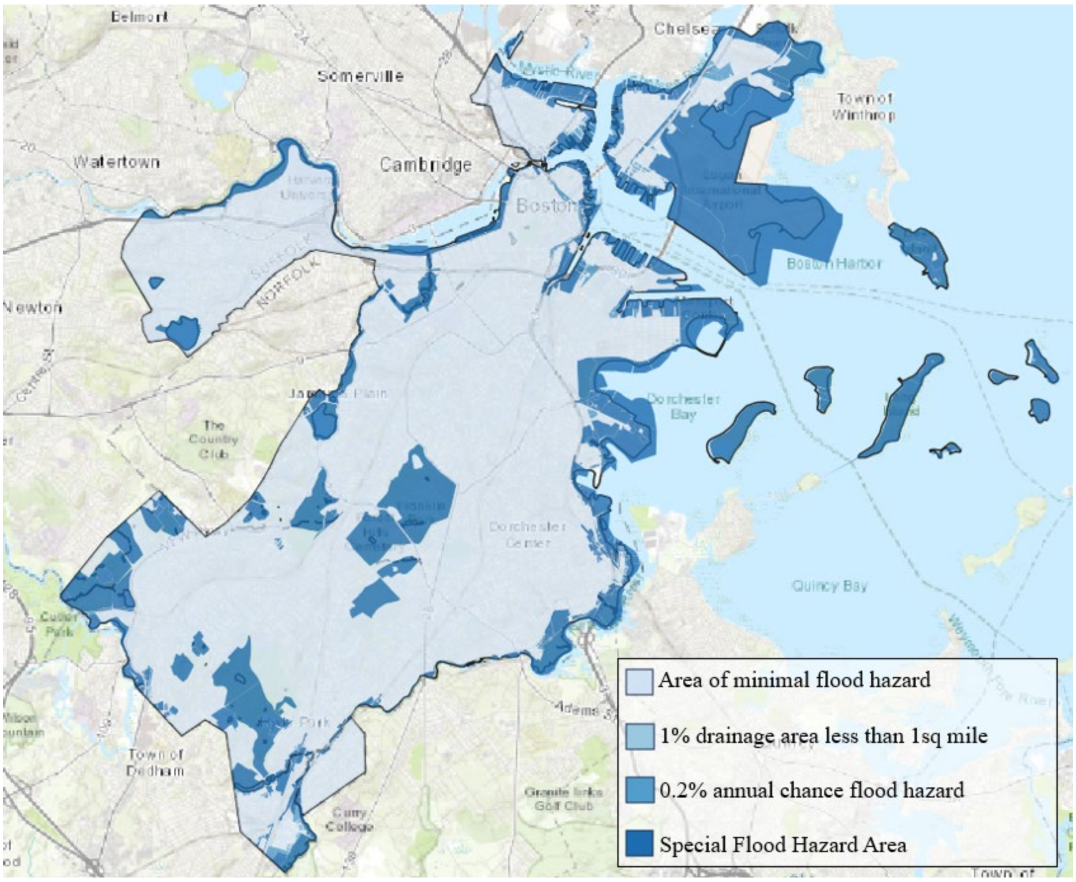

Figure 11: Highest flood zone indication of every parcel as of 2009 (FEMA, 2009).

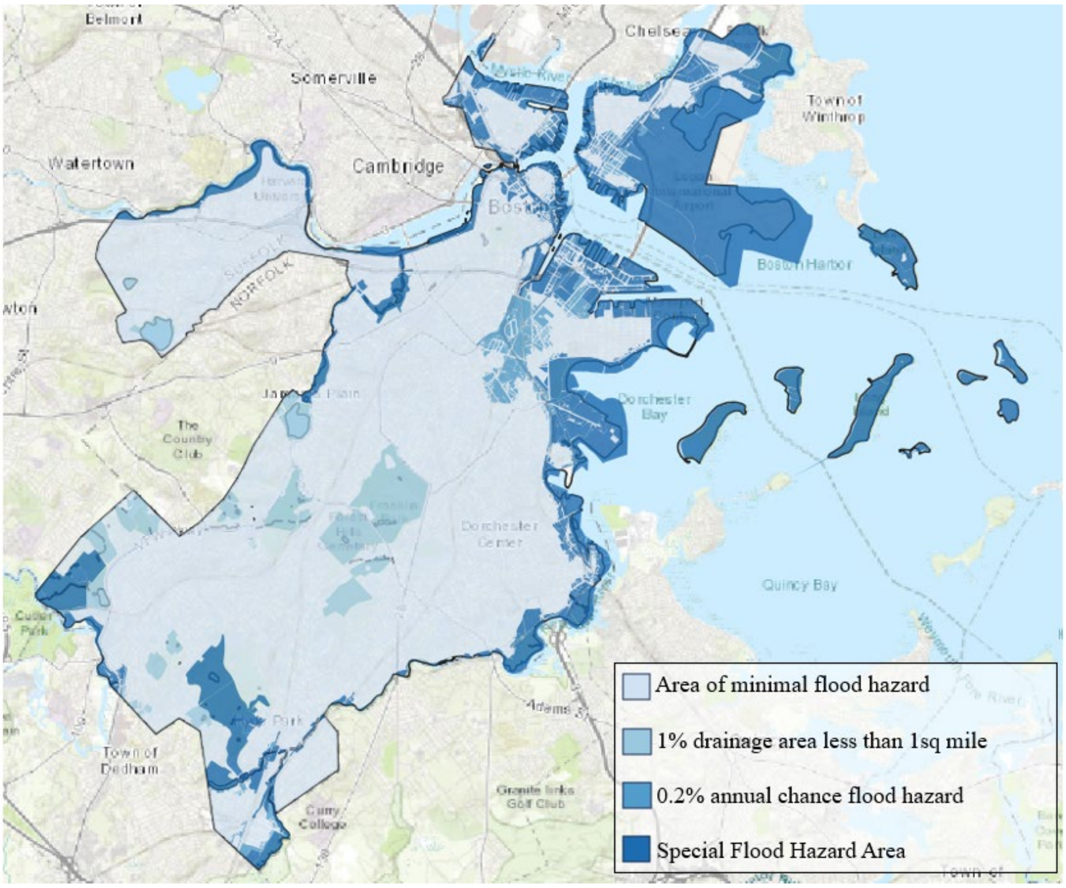

Figure 12: Highest flood zone indication of every parcel as of 2016 (FEMA, 2016)

Structural, locational and neighborhood characteristics

Lastly, the control variables. The structural characteristics are obtained through the Assessing Department of the City of Boston, which publishes yearly property assessments on their website. Each property has its own unique ID which is also present in sales dataset. This, together with the date of sale, allowed combining the sales data to the specific year of the property assessment. This entailed that the characteristics of all the sales were completely up to date. So, for example buildouts or renovations happened in between two sales of a single property are accounted for. Assessment data are recorded in accordance to assessing guidelines described in a manual, as a means to reduce bias. Furthermore, property owners can appeal the findings of the Assessing Department. If granted, the alterations are updated. The dataset includes, among other things land use, property type, gross living area, lot size, number of floors, building age, year of remodel, number of bedrooms, number of (half)bathrooms, style of (half)bathroom, number of kitchens, style of kitchens, construction material, roof material, heating type, presence of AC, building style, quality of exterior finish, quality of interior finish, number of available parking spots, property orientation, and property view. As years go by more characteristics were added. Hence the 2008 assessment is not as detailed as the 2021 assessment.

Moreover, the data on locational characteristics were obtained through spatial analysis in GIS by utilizing publicly available data of MassGIS, the transportation department of the Commonwealth of Massachusetts. For every sale, the distance to its nearest subway stop is calculated as well as the distance to Boston's Downtown. All these distances are measured in meters and as the crow flies. More sophisticated methods of measuring distances – e.g., distance measured as travel time – were not chosen, due to the lack of historical data needed to execute these analyses. For example, congestion data or road network data were not available all the way through to 2008. Thus, distance as the crow flies in this case allows for better comparison throughout the years.

Lastly, certain neighborhood characteristics were also included. This includes data on open spaces, public schools, and trees. The open space data are accessible through the Boston Parks and Recreation Department. Open spaces entail areas that are managed in order to be conserved or for recreational purposes. The data were filtered to only include open spaces that are accessible to the public. Additionally, only certain types of open spaces are included, namely: "malls, squares and plazas; "parkways, reservations and beaches"; "parks, playgrounds and athletic fields"; "urban wilds"; and, "open land". This means that "cemeteries and burying grounds" and "community gardens" are excluded. Most of the community gardens were already excluded because they were not publicly accessible. The remaining community gardens were also excluded, due to being closed for applicants or having to adhere to strict visiting rules and hours. Cemeteries and burying grounds are excluded, because these data are meant to serve as control for recreation areas, which is generally not a function of cemeteries and burying grounds. The data that were extracted from this dataset using GIS are nearest open space site name, nearest open space site type, nearest open space site acres, distance to nearest open space, and the number of open spaces in a 1km radius from the centroid of the real estate transaction. The dataset on public schools is published by Boston Maps, Boston's GIS department. It includes all public schools in the city in the year 2018-2019. This was the only available year and is used for the entirety of the real estate transactions dataset. Using GIS, this dataset provided the name of the nearest school, the type of that school, and the number of schools in a 1km radius from the centroid of the real estate transaction. Finally, Boston Maps also published a dataset on trees. In this it mapped all park and street trees in the city. Using GIS, the number of trees in a 100m radius from the real estate transaction is included in the dataset. This is used to have an indication of the amount of green in a neighborhood.

3.3.2 Data analysis

This paragraph delineates which analysis has been performed to test the hypothesis. Furthermore, the treatment of outliers will be discussed in this paragraph.

Hedonic (multiple regression) model with DID interaction term

The data analysis was executed via a multiple regression analysis. This model determines the nature of the relationship of each of the independent variables onto the dependent variable. Furthermore, it can also asses the gravity of these relationships. The main variables of interest are added to this model as DID interaction terms. Meaning a dummy variable for time is added, indicating whether a sale is in the pre or post treatment group. This variable has the value of one for sales post development and the value of zero pre-FRI development. The distance of the sale to its closest FRI project is also added. As explained, this was added as a continuous variable to allow for a distance decay effect. These two variables combined allow for the investigation of the treatment effect, since the distance to the closest FRI project is equal to the initial difference between the would be 'treatment' and 'control' group and distinction between pre and post development allows for turning on that treatment effect. Thus, to uncover the treatment effect, a final interaction variable of these earlier mentioned variables is added to the regression analysis. This variable only accounts for the effect of the distance to the nearest FRI project if that project is actually finished.

Moreover, the regression analysis was performed as a hierarchical model. This type of model runs the regression multiple times and with each new model additional variables can be added to the analysis. This allows for a comparison of certain sets of variables by looking at the differences in R^2. In the first model, only the variables of interest were added to the regression analysis. In the second model, some variables describing the characteristics of the FRI projects were added. In the last model, the structural, locational and neighborhood characteristics were added to the regression. Appendix II summarizes all the variables that were entered into the regression model. Furthermore, the table explains in which unit the variable was measured, what the level of measurement is – nominal, ordinal, interval or ration – and which resources were used to obtain these variables.

Data cleaning and outlier detection

Before running the model, the data had to be cleaned. First, any duplicates were removed from the dataset through the unique identifier and the date of sale. Next, sales with multiple missing values were removed. Furthermore, sales with suspiciously low or high prices per sf were checked for their square footage; some also did not have any gross area listed. These were also not included in the analysis. At the end of this first cleaning process, the dataset was complete in that all prior missing values were retrieved. After this, additional steps were taken to detect and treat outliers in the dataset.

The first step was to scan for outliers in the dependent variable. This was done for each year individually, because an exorbitant sale price for the year 2008 might have been not as conspicuous when compared to the sale prices by the time of 2021. Outliers were spotted by using the interquartile range (IQR). The IQR method is preferred over scanning for outliers by using the mean, because the mean is affected substantially by outliers itself, whereas outliers have less effect on the median (Rousseeuw & Hubert, 2011). When this method is applied, data points are often considered to be outliers when they fall outside either a lower or upper boundary. Commonly, these are the first quartile minus 1,5 times the IQR and the third quartile plus 1,5 times the IQR. However, debate exists in the literature whether the factor of 1,5 is too severe. Some prefer factors of 2,2 or even 3 (Hoaglin, Iglewicz, & Tukey, 1986). Here, a factor of 2,5 was applied, in order not to be too severe. When searching for outliers in sale prices, one has to acknowledge the fact that overbidding on the housing market is more common in times of scarcity in supply. Therefore, simply labeling these transactions as outliers would negate important market effects.

The last step of this process was to spot outliers in the independent variables. Detecting outliers in multivariate data is often done through the Mahalanobis distance. This is a metric which calculates Euclidian distances between each of the data points based on each variable (Li et al., 2019). Units with a more similar combination of independent variable values have smaller differences in Mahalanobis distance. Units with more uncommon combinations of independent variable values have a larger difference with the mean Mahalanobis distance and are therefore further removed from the center of the data cluster (Todeschini et al., 2013). This allows to spot for multivariate outliers. These were then not included in the sample. After this step, the total sample amounted to 13.229 sales.

3.4 Validity & reliability

Solid scientific research has to be both valid and reliable. Two forms of validity exist, internal and external validity. Internal validity is concerned with accurately measuring outcomes and the trustworthiness of the results, whereas external validity deals with the generalizability of the outcomes of the research. Reliability is about whether when the same research is reproduced the outcome will yield similar results (Clark et al., 2021). There are some points of discussion concerning the validity and reliability of the research methodology applied in this research. First the caveats of the HPM are discussed, whereafter the issues related to the difference-in-difference design are elaborated. Finally, some general points are discussed.

For the HPM, one of the main factors concerning internal validity is the choice of the form of the function (Engström & Gren, 2017). In a parametric model, a linear relationship is assumed. This, however, does not necessarily have to be the case. This is also one of the traditional assumptions on which a multiple regression analysis is based. This can be checked by seeing whether linearity exists in the scatterplot of the standard residuals versus the predicted values. If there exists linearity between the dependent and the independent variables then no curve should be observed in this scatterplot. This assumption is tested in chapter 4. The parametric model is chosen over the nonparametric model, since the former is associated with less precise estimations for larger datasets due to difficulties in the assignment of the weights for each variable. Semi-parametric models are also not chosen because even though they can resolve some of the gravity of the issues considered with parametric models these issues can still persist (Owusu-Ansah, 2011). As for the external validity, the HPM assumes certain market conditions to be present. These are freedom to enter the market, perfect information, and market equilibrium. These assumptions are already contested (Chau & Chin, 2003; Goodman, 1987). However, they also bring about consequences for the generalizability of the results. Depending on the instance, these assumptions might be present to either a lesser or higher degree than for this research. Thus, these assumptions should always be considered when transferring the results of this research.

Next the DID, and therefore the quasi-experimental, approach are discussed. In theory, experimental designs would yield the highest internal validity, however, it is suggested that quasi-experiments – when performed well – are a good alternative (Shadish, Cook, & Campbell, 2002). Nevertheless, these designs should be carefully performed and even then, there are certain threats to the internal validity of these designs. The first of these has to do with the difference between a randomized experiment and the quasi-experiment; the selection into the treatment and control group. With a randomized experiment, this assignment is completely random. In the case of a quasi-experiment, this cannot be randomized (Rossi et al., 2004). Therefore, it should be checked whether there are no critical differences – other than the between these groups that determine selection into either treatment or control group. For example, whether the houses that are protected through FRI projects are not only old houses, but also newer ones. This is important, because the DID analysis ascribes all the difference between the real outcome and the projected outcome (the counterfactual) to the variable of presence of a FRI. If any other variable differs between treatment and control groups, this will lead to either over- or underestimation of the effect of the solely the treatment variable. Thus, leading to a decreased internal validity. This concern is mitigated through the addition of the DID design into the HPM. In the HPM, the structural, locational and neighborhood characteristics act as control variables for these critical differences. A second issue, as pointed out by Rossi et al. (2004), is the trade-off in quasi-experimental designs between upkeeping a high level of either internal validity or preferring a good external validity. For a high internal validity rests on a sample of local spatial scale, because it is assumed that houses close to each other, in the same state in the same city, will experience similar external shocks. This reduces the number of critical differences between observations. However, because of this local spatial scale, external validity can suffer. Conversely, if a larger spatial scale is chosen, the generalizability of the analysis will be higher as the observations in the study cover a larger part of the country, and therefore can be better used to make predictions on the nation as a whole. However, the possibility of critical differences between the treatment and control group rises significantly. Here, a higher level of internal validity is preferred, because from recommendations found in the literature, a carefully quantified basis is needed to solidify the effect of interest into planning practices (Lord et al., 2022). Additionally, a solid methodology can always be replicated and applied to other instances to increase the external validity. This will be, however, beyond the scope of this research.

Then there are issues that arise due to the research being of longitudinal nature. First, due to the use of secondary data, the risk of instrumentation, i.e., changes in the way tests are administered between pre and post observation, should be accounted for (Clark et al., 2021). Mainly this might be prevalent in the structural characteristics. Over time the recording methods of these characteristics are subject to change. Secondly, there is the possible problem of attrition. This encompasses problems that arise due to drop-out of study objects (Rossi et al., 2004). Since houses are the object of study in this case, attrition could occur in the form of demolition or transformation to other uses. If this drop-out is not random, problems with the internal validity can occur (Clark et al., 2021). However, due to relatively short period of this study compared to the average longevity of houses, this will most likely not be a problem. Furthermore, as pointed out by Bertrand, Duflo and Mullainathan (2004), panel data should be checked for serial correlation. As they have shown, not checking for serial correlation, the significance levels of the outcome can be grossly overestimated. To solve this issue, Bertrand et al. (2004) recommend using block bootstrapping when the number of observations is sufficiently big enough to maintain an adequate level of internal validity.

4. Results

This chapter describes the results of the earlier explained data analysis. First, the descriptive statistics of all the variables that entered in the regression are presented. Second, the results of the model are interpreted and elaborated. Finally, the underlying assumptions used for a multiple regression model are tested, to assess the robustness of the presented results.

4.1 Descriptive statistics

The variables are elaborated in groups, first the dependent variable – sale prices – will be elaborated. Hereafter, the main variables of interest, mostly the variables related to flood risk and FRIs will be described in detail. Lastly, the control variables will be briefly discussed. In Appendix III, a table summarizing the full descriptives statistics of each of the variables is given.

4.1.1 Housing prices

The dataset included all the transaction prices for condominiums in Boston between the years 2008 and 2021. The total prices are divided by the square footage of living area noted in the property assessment of the year in which the sale occurred. Moreover, prices are real prices for 2021 using the annual CPI-U for the northeastern area (US Bureau of Labor Statistics, 2021). In total, there are 13.229 sales that were included in the analysis. For the total study period, 2008 to 2021, the sale prices have a mean of \$819,02 per square foot, with a minimum of \$122,68 and a maximum of \$1734,45 per square foot; the median is at \$797,03.

One of the main assumptions of regression analysis is whether the dependent variable is normally distributed. Following the central limit theorem, in analyses with high numbers of cases, this assumption will almost always hold. This can also be tested with statistical tests, like the Kolmogorov-Smirnov test or the Shapiro-Wilk test. However, these tests are heavily critiqued, especially when applied to large datasets like this one (Field, 2013). Hence, the assumption of normality is only checked visually in this case. Figure 13 shows a distribution histogram of the sale prices per sf. It shows a distribution that is slightly positively skewed, but more or less normal. This can be further checked through the normal quantile-quantile plot, shown in figure 14. If the distribution was very skewed, then the observed quantiles – the points – would 'snake' along the line. However, they do not seem to exhibit this. Additionally, from this figure, it is clear that the observations do not suffer much from kurtosis, since the observed quantiles do not deviate much from the expected quantiles; i.e., the line.

However, looking at these statistics per year provides a better insight into the price dynamics. Table 3 shows the descriptives per year. The number of sales per year ranges between 707 and 1.221. Both the mean and median of the sample are decreasing up until 2011, whereafter they start increasing every year until they stagnate in 2018 and then remain relatively stable. This is illustrated graphically by the line between the boxplots in figure 15. The initial decrease makes sense in relation to the economic crisis, when the economy started to recover, demand increased relative to supply resulting in high price increases. This was also noted by Anthony (2018) and Burgess (2019) in investigating Boston's housing market. The halt of this increase around 2020 might be due to the COVID-19 pandemic; this is also found by Liu and Su (2021) for the US housing market. The boxplot also shows each year's range and observations that are considered possible outliers. However, these are not further addressed, since outliers were already screened for as explained in paragraph 3.3.2. Additionally, the distribution of the total is no reason for concern. Thus, these remaining 'outliers' are considered to be the consequence of outbidding on the housing market, which is interesting to inspect further. Therefore, they are included. The sale price ranges show a slight growth and also some more variance as years go by. Finally, the values for skewness and kurtosis in each of the individual years are no reason for concern, since no value is greater than 1,0 or lower than -1,0.

Figure 13: Distribution histogram of sale price per sf.

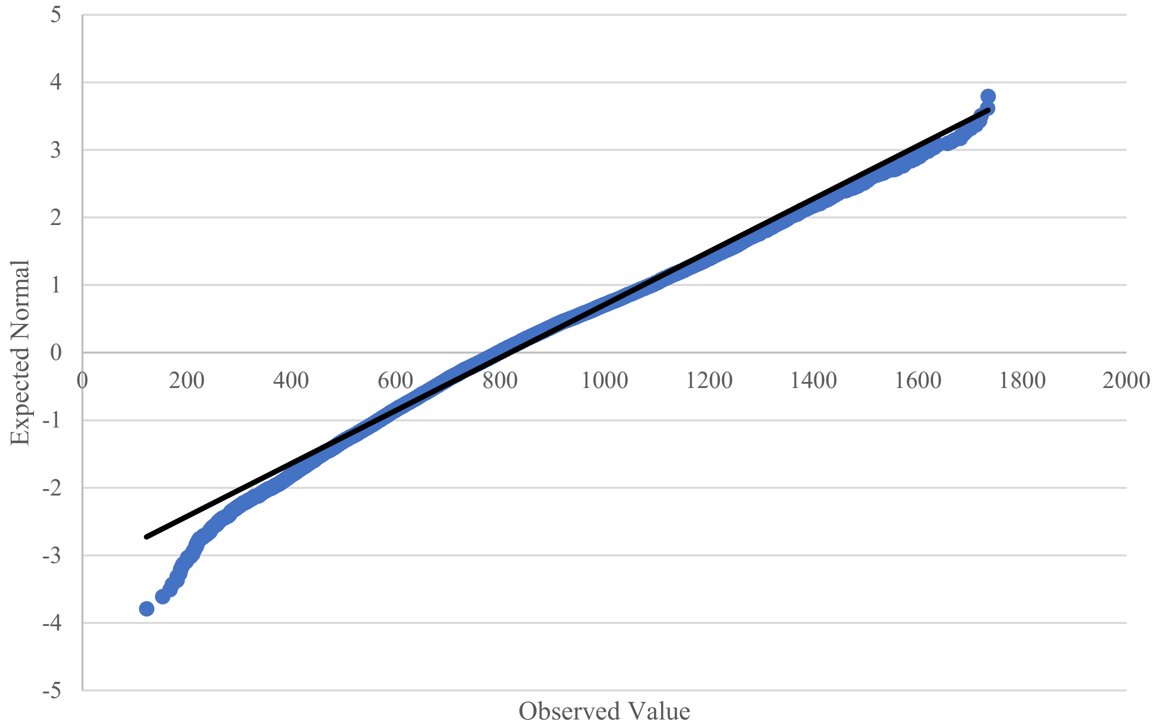

Figure 14: Normal Q-Q plot of sale price per sf.

Table 3: Sale price per sf total and yearly descriptive statistics.

Year	Number of sales	Mean	Min.	Max.	Median	Standard deviation	Standard error	Skewness	Kurtosis
Total	13.229	$819,02	$122,68	$1.734,45	$797,03	254,12	2,21	0,319	-0,167
2008	774	$712,32	$201,29	$1.292,36	$717,34	179,86	6,46	-0,086	0,192
2009	707	$684,54	$171,72	$1.283,04	$692,49	186,74	7,02	0,194	0,486
2010	834	$681,89	$167,77	$1.258,37	$679,07	182,33	6,31	0,101	0,181
2011	802	$674,74	$122,68	$1.269,96	$673,47	179,28	6,33	0,145	0,406
2012	1.100	$675,16	$185,90	$1.304,12	$663,32	189,30	5,71	0,239	0,160
2013	1.128	$726,99	$190,46	$1.352,80	$726,61	199,99	5,95	0,033	0,038
2014	1.042	$771,33	$193,77	$1.479,02	$776,76	228,63	7,08	0,036	-0,123
2015	1.011	$840,90	$181,23	$1.448,75	$846,38	236,30	7,43	-0,073	-0,398
2016	965	$897,22	$259,16	$1.574,95	$895,64	259,16	7,72	-0,006	-0,426
2017	921	$941,04	$286,67	$1.720,89	$954,18	260,99	8,60	-0,070	-0,396
2018	920	$968,25	$241,28	$1.681,36	$969,32	260,83	8,60	-0,066	-0,284
2019	951	$949,04	$327,30	$1.606,12	$962,89	247,68	8,03	-0,061	-0,611
2020	853	$949,57	$282,14	$1.717,87	$968,52	257,76	8,83	-0,036	-0,604
2021	1.221	$931,37	$284,41	$1.734,45	$910,31	264,12	7,56	0,295	-0,333

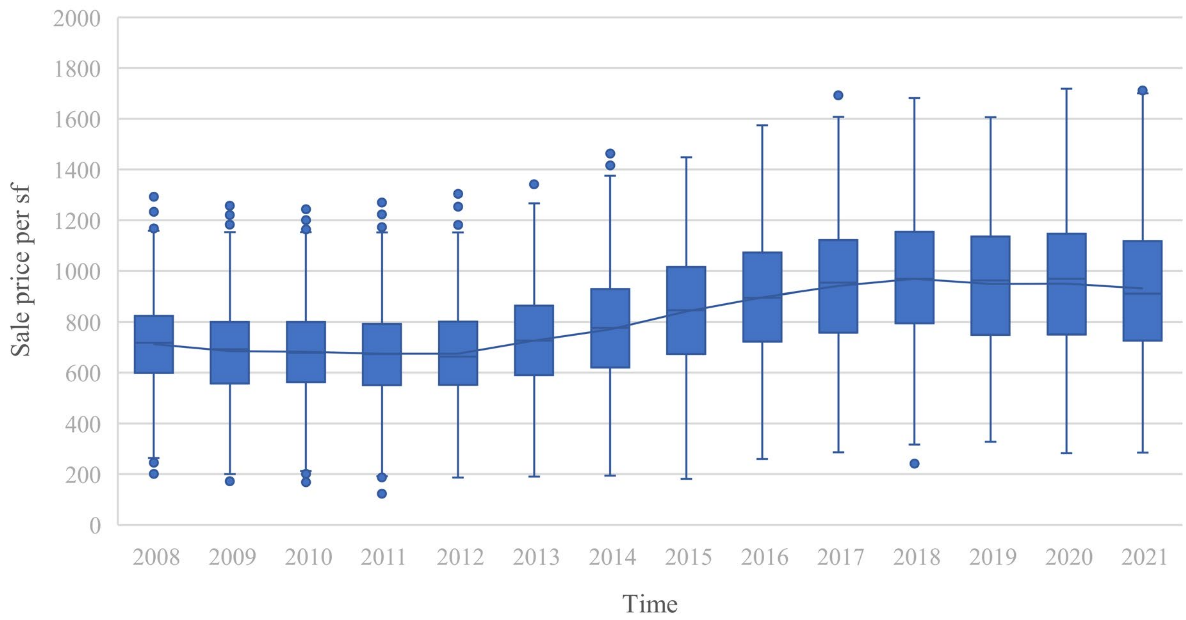

Figure 15: Boxplot of sale price per sf per year; showing range, first and third quantile, mean trendline, and "outliers".

4.1.2 Variables of interest: flood risk and resilience infrastructures

In figure 16, the mean sale price per sf is depicted for each of the flood zone categories. For reference, the mean of all sales in the study is also shown. The sales are ascribed the flood zone category at the time of the transaction. On average, properties in the C zone – areas with minimal level of flooding – are sold at the highest price points; slightly higher than the mean. Then, just below the mean, are the properties in either A or V flood zones. These are the properties with a possible flood insurance mandate. The lowest average sale prices are found for properties in the X flood zone, which are at risk to 0.2% annual chance floodings. The number of sales is highest for properties in the C flood zone, however, after 2016 – when FEMA updated the FIRM for Boston – the number of sales for the X and A/V categories significantly increase, as is shown in table 4.

Table 4: Number of sales per flood zone category per year.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
C	684	608	744	685	952	971	902	854	635	621	634	590	561	790	10.231
X	33	44	32	44	54	70	65	72	123	106	93	116	85	154	1.091
A/V	57	55	58	73	94	87	75	85	207	194	193	245	207	277	1.907

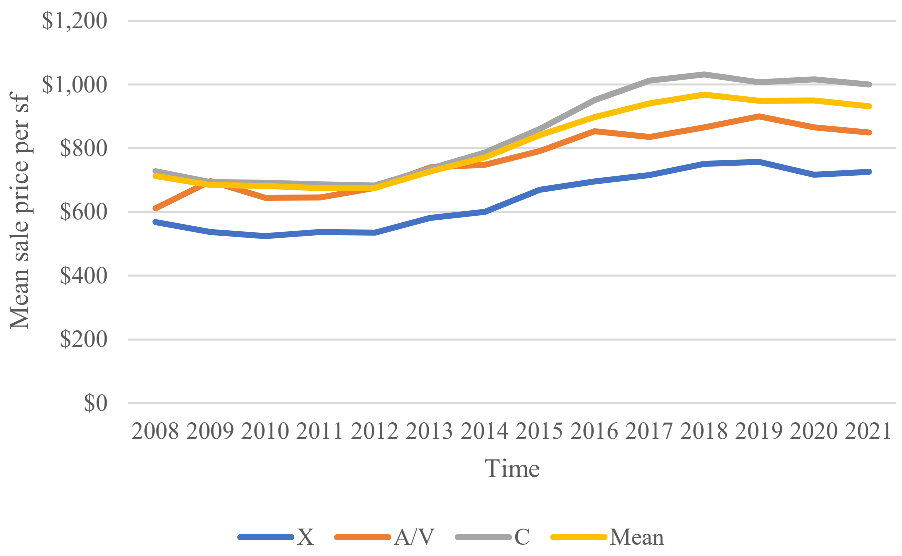

Figure 16: Mean sale prices per sf for each flood zone and the overall mean.

In table 5, the number of sales and mean prices are given for a number of sample groups. A division is made between pre and post completion of the nearest FRI of the sale, as explained in chapter 3. In total, there are 8.592 sales in the pre group and 4.637 in the post group. The pre group mean sale price is $747,06 and for the post group it is $952,35. However, the difference in mean sale price between these groups is not conclusive here; it is tested with the multiple regression analysis.

As explained in paragraph 3.2.2, the control group consists of sales in the 2070 36-inch sea level rise 1% annual chance flood event scenario, outside a buffer zone of 200m around each of the FRI projects. The treatment group includes the sales, that have happened inside the same flood zone, but inside a buffer zone of 200m around each of the FRI projects. However, in the regression analysis, rather than using this binominal variable, the distance to the closest FRI project is used. The control and treatment group in the table do use this binary, in order to give an indication of the number of sales closer to and further from FRI projects; which are 667 and 12.562 sales for the treatment and control group, respectively. The mean distance to the nearest FRI project is 92,05m and 869,10m, for the treatment and control group respectively. In figure 17, the mean sale price of the treatment and control groups are plotted against time. The figure also indicates the years in which an FRI project is completed. Because not all projects finish at the same time, sales can still fall in the pretreatment group if their closest FRI is not yet developed. The last project – Hood Park Drive – finishes in 2020, yet no sales are recorded as closest to that project in that year. Therefore, the pretreatment group stops after 2019. In 2020 and 2021, the post treatment group consists of all transactions made around a 200m buffer zone around the FRI projects. Again, in the regression analysis, the buffer zone method is replaced by an absolute distance variable. Here, this is solely done for the purposes of visualization and scanning for potential problems. Before any FRI project had been completed, the mean sale prices between the treatment and the control group trend fairly similar. After treatments start happening, the trend of the mean sale price seems to start increasing faster for the treated sales. It is, however, too prematurely to draw any conclusions from this given.

Table 5: Number of sales, mean sale price, and mean distance to nearest FRI project per group.

	Number of sales			Mean sale price per sf			Mean dist. to
	Pre	Post	Total	Pre	Post	Total	nearest FRI
Control group	8.215	4.347	12.562	$754,071	$956,07	$823,97	869,10m
Treatment group	377	290	667	$594,20	$896,67	$725,71	92,05m
Green infra.	1.124	911	2.035	$617,85	$763,43	$683,02	611,10m
Grey infra.	7.468	3.726	11.194	$766,50	$998,54	$843,74	869,70m
Drainage	4.804	2.667	7.471	$812,36	$1.054,09	$898,65	974,85m
Elevation	266	119	385	$554,63	$735,10	$610,41	101,63m
Large water holding infra.	506	97	603	$720,57	$928,55	$754,02	396,47m
Shore stabilization	2.233	868	3.101	$684,02	$859,39	$733,11	709,51m
Small water holding infra.	783	886	1.669	$608,66	$768,96	$693,76	729,48m
Total	8.592	4.637	13.229	$747,06	$952,35	$819,02	829,92m

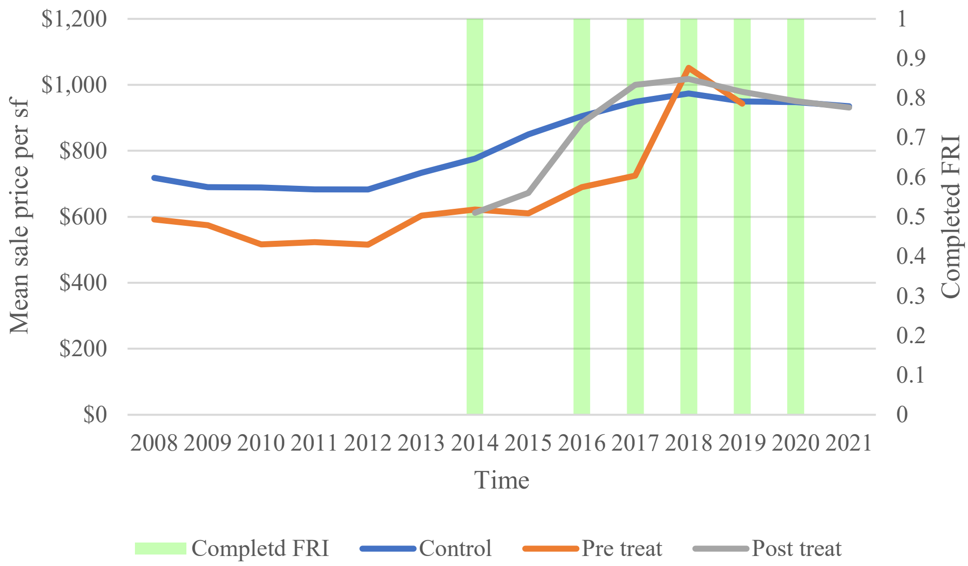

Figure 17: Mean sale price for treatment and control group, pre and post completion of FRI projects.

Figure 18 shows the mean sale prices of properties closest to either grey or green FRIs. The mean of the grey infrastructures is almost equal to the mean of the entire dataset. A larger share of the sales also occurs near grey infrastructure projects, relative to green infrastructures; 11.194 against 2.035, respectively. Even though the mean sale price of properties near green infrastructures is lower than the mean of the grey infrastructure group, the two groups trend very similar. This might entail that the distinction implies no differences in posttreatment effect. This will be further explored with the regression analysis.

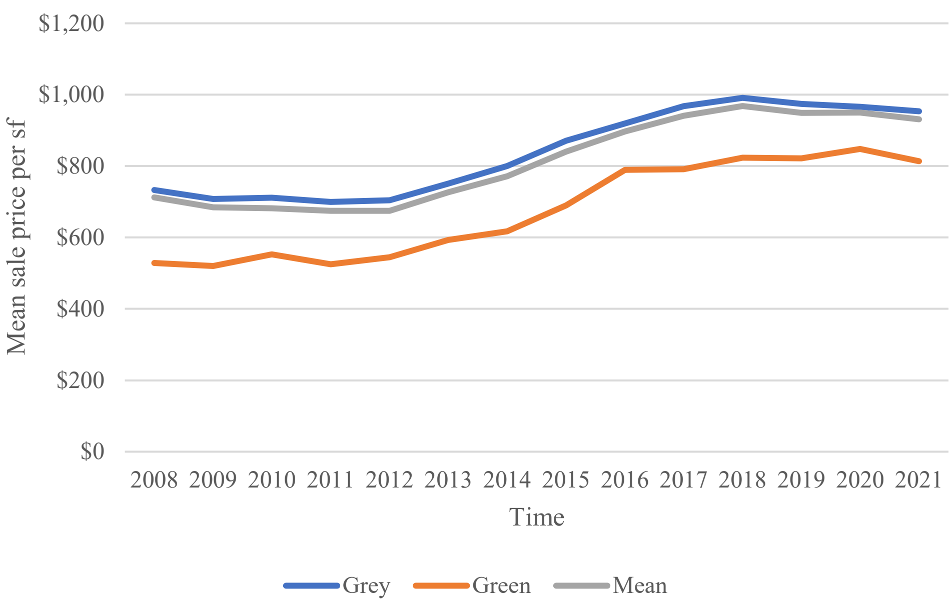

Figure 18: Mean sale price per sf of sales closest to either grey or green FRIs.

The last set of sub groups in which the sales can be categorized – with respect to flood risk and resilience – are the resilience categories. More than half the sales, 7.471, are closest to a drainage FRI, followed by shoreline stabilization projects, 3.101, and then the small water holding infrastructures at 1.669. The large water holding infrastructure and elevation groups are the smallest at 603 and 385, respectively. In figure 19, their mean sale prices are depicted. The sales that have occurred near drainage projects have the highest prices on average. This is the only group for which its mean is higher than the total mean. The other groups are all below the mean, yet seem to trend rather similar to the total mean. Despite the trend lines for the large water holding and elevation infrastructures being more capricious, a similar evolution of mean prices can be distilled. This might again indicate that the effect of the different categories is negligible, but this will be studied further in paragraph 4.2.

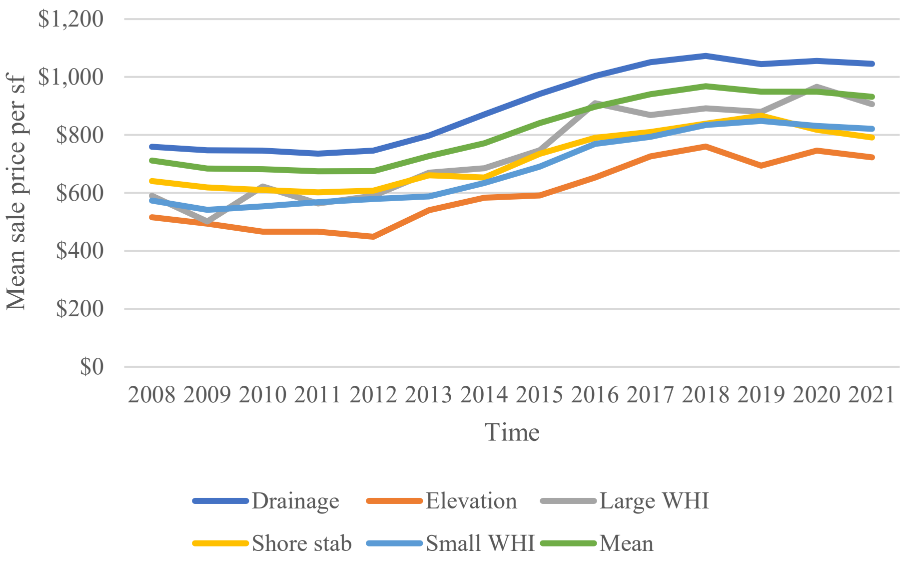

Figure 19: Mean sale price per sf over time per resilience category.

4.1.3 Control variables: structural, locational and neighborhood characteristics

The set of control variables consists of structural, locational and neighborhood characteristics. In this paragraph, the differences in descriptive statistics for these variables will be compared for the treatment and control group. Even though treatment and control group are not entered in the analysis as this binary, but based on a continuous distance variable, this is still presented in order to pick up on any differences that might be of importance. In the subsequent paragraphs, the relation between the control variables and sale prices is also explored. The descriptives statistics of these variables will be described per characteristics group, beginning with the structural characteristics.

Structural characteristics

All the descriptive statistics for structural characteristics are summarized in table 6. The prevalence of the respective structural characteristics is also noted for the treatment and control group, as a means to spot differences more easily.

Table 6: Descriptives of structural characteristics for treatment and control group.

	Mean year built	Mean gross area	Percentage brick	Mean num. bedrooms	Mean num. bathrooms	Percentage remodel after 2007	Percentage owner occupied	Percentage with AC
Treat	1938,36	1176,67sf	56,8%	1,7	1,5	20,2%	65,8%	71,1%
Control	1923,55	1065,15sf	84,8%	1,6	1,4	10,6%	58,9%	65,9%
Total	1924,29	1070,77sf	83,4%	1,6	1,4	11,1%	59,3%	66,1%

A first structural characteristic is building age. The mean building age is 90,5 years. In figure 20, the mean sale price per sf is plotted against the construction year of the properties sold. To generalize, properties built before the 1900s often sell at higher price points, however, there is a lot of variances among the individual construction years. A small dip in the mean sale price occurs at houses built mid-2000s, after 2010, the mean sale price starts to climb back up. Treatment properties are on average only 15 years older than the control group.

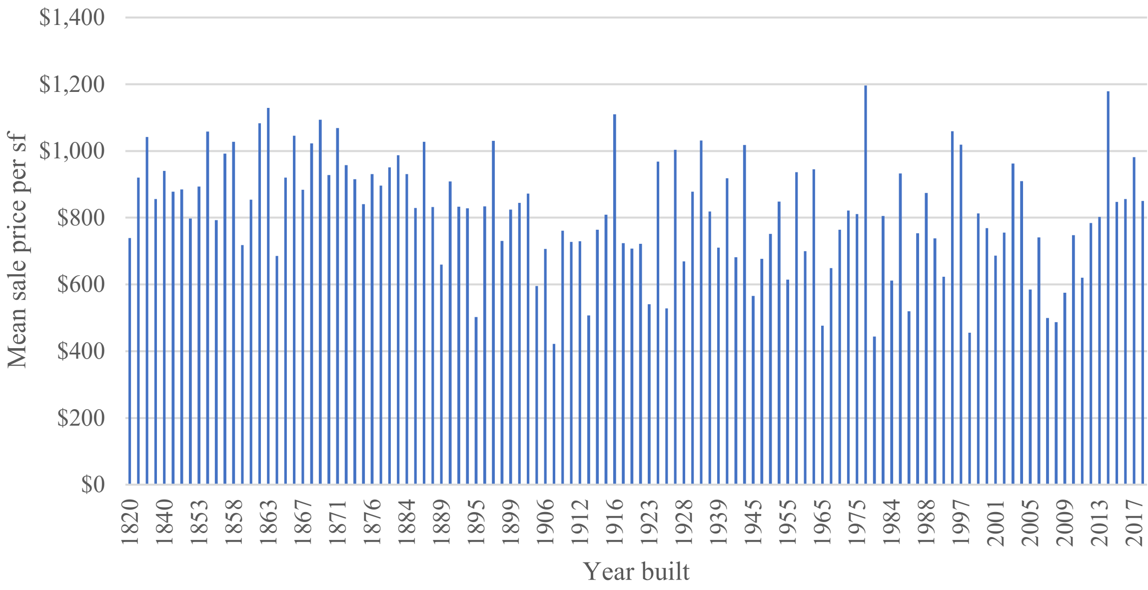

Figure 20: Mean sale price per year of construction.

Secondly, looking at the gross area, condos are on average 1.071 sf, with the smallest property in the study at 200 sf and the largest at 5.168 sf. Sales belonging to the treatment group are circa 110 sf larger than sales in the control group. According to Kelly and Molina (2023), larger properties are found to sell at higher prices per sf. In this case, it seems this is not only true for larger properties, but also for smaller properties, which may be due to their location. In figure 21, this is illustrated for this sample.

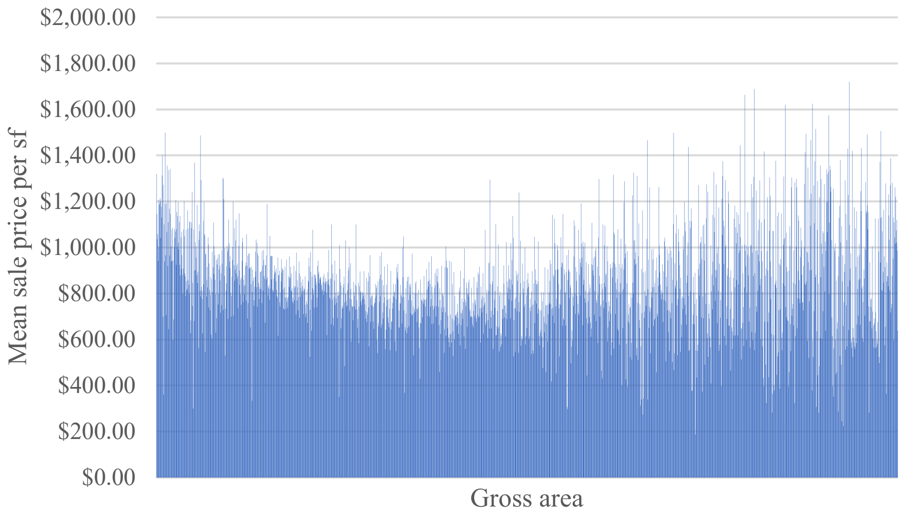

Figure 21: Mean sale price per sf per gross area.

A number of structural characteristics are included in the analysis as dummy variables. A first is the material of the property's exterior. Due to the fact that a large share of the recorded sales, 11.036, have a brick or stone exterior and the rather low shares of the remaining materials, this variable is included as a binominal variable. The value 1 is awarded to properties that have a brick/stone exterior and a 0 to properties having any other exterior finish. However, to still provide some insight into the remaining categories, figure 22 shows the mean sale price per sf for each of the exterior materials. Glass finishes clearly have the highest mean sale price, namely $1.142 per sf. However, only 103 of the recorded sales have this type of finish, meaning it might not be the most reliable. The next highest mean sale price is found at brick or stone finishes, namely $857 per sf. All the other materials have means lower than the total mean of $819 per sf. Looking at the differences in brick or stone and other materials between sales in the treatment and control group, it should be noted that treated sales are less likely to have a brick or stone exterior. However, still more than half the sales are brick properties for the treatment group.

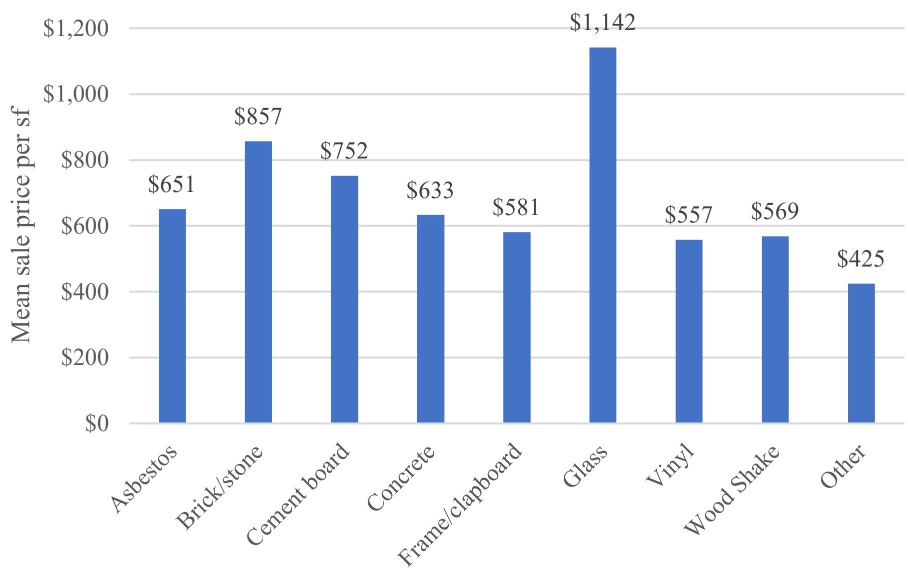

Figure 22: Mean sale price per sf for each exterior building material.

Next are the number of bedrooms and full bathrooms, shown in table 7. The mean sale price per sf seems to react quite capriciously to an increasing number of bedrooms. However, for the number of full bathrooms, the mean sale price per sf seems to increase for each additional full bathroom. The 16 properties sold with 4 bathrooms are too few to draw any solid conclusions from. Treated sales have an average of 1,7 and 1,5 bedrooms and full bathrooms respectively, which is almost the same for the control properties, which have 1,6 and 1,4 bedrooms and full bathrooms respectively.

Table 7: Number of sales and mean sale price for number of bed- and full bathrooms.

	Bedrooms			Bathrooms		
	Number of sales	Percentage	Mean sale price	Number of sales	Percentage	Mean sale price
0*	335	2,53%	$882,55	-	-	-
1	5.509	41,64%	$823,43	8.763	66,24%	$810,26
2	6.165	46,60%	$811,82	4.069	30,76%	$825,82
3	1.120	8,47%	$822,32	381	2,88%	$942,71
4	94	0,71%	$775,38	16	0,12%	$937,98
5	5	0,04%	$616,78	-	-	-
6	1	0,01%	$986,94	-	-	-
Total	13.229		$819,02	13.229		$819,02

*Zero bedrooms refers to studio condos.

Then there is the dummy variable of whether a remodel happened after 2007. The variable will have the value 1 if a remodel did happen after 2007 and the value 0 if no remodel after 2007 has happened. In total, 1.462 sales have had a remodel after 2007. In the treatment group 20,2% of the sales have had a remodel after 2007, for the control group this is 10,6%. The mean of the remodeled condos is clearly higher than that of the non-remodeled properties, namely $979,09 and $799,13 respectively. Figure 23 presents the mean sale price per sf against the number of years that has gone by ever since a remodel has happened at the moment of sale. Especially properties that were just recently remodeled have higher price points. The climb of the sale price at higher number of years since remodels, might be explained by comparing this figure to figure 20, of the building age. That figure also shows an increase in sale prices for older buildings. By including this variable as a dummy variable for before or after 2007, the interference of the age effect is mostly negated, as the number of years since the remodel is 14 at maximum.

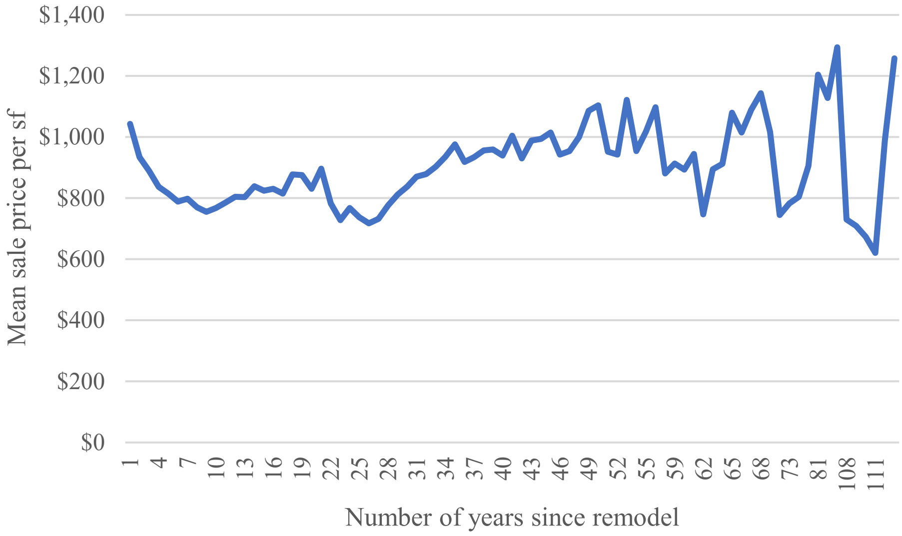

Figure 23: Mean sale price per sf for number of years since remodel.

Next is yet another dummy variable: owner occupied. It has the value 1 for an owner-occupied home and 0 for a non-owner-occupied home. In total, there are 7.844 sales made in owner occupied condos and 5.385 sales for non-owner-occupied, making owner occupied the default with about 60%. This percentage stays relatively stable throughout the study period, as illustrated in figure 24. Comparing the treatment and control group, the treatment group has a slightly higher percentage of owner-occupied homes, namely 65,8% versus 58,9% for the control group. The overall mean sale price of owner-occupied homes is just slightly above the price point of the non-owner-occupied homes, with $824,60 and $810,89 respectively.

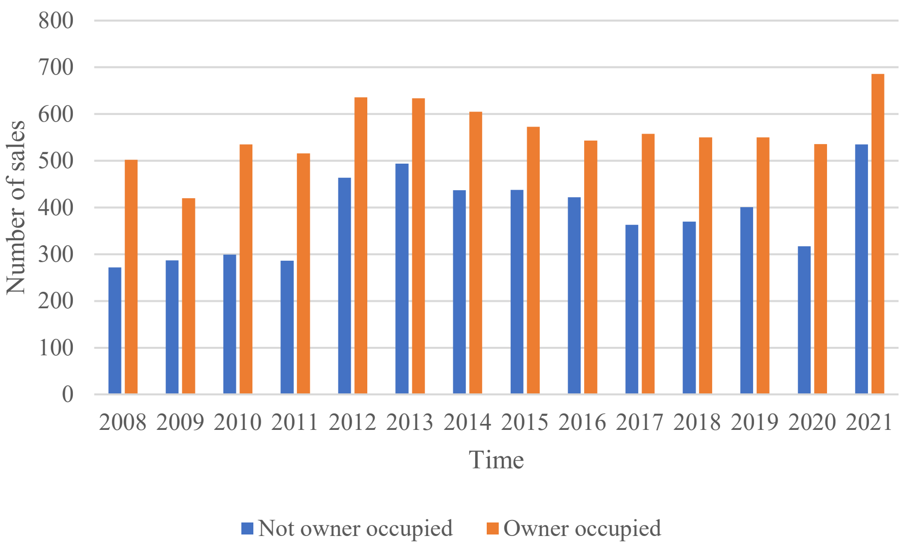

Figure 24: Number of sales for owner-occupied and non-owner-occupied homes

The last variable for structural characteristics is presence of air-conditioning. In total, there are 8.750 sales in the sample with AC, versus 4.479 without. The number of homes with air-conditioning has increased of the years, as shown in figure 25. That being said, however, they do not sell for higher prices. This variable is added as a dummy variable, with a value of 1 for properties with AC and 0 for properties without. In the treatment group, the percentage of properties with AC is 71,1% which is slightly higher compared to the 65,9% of properties in the control group.

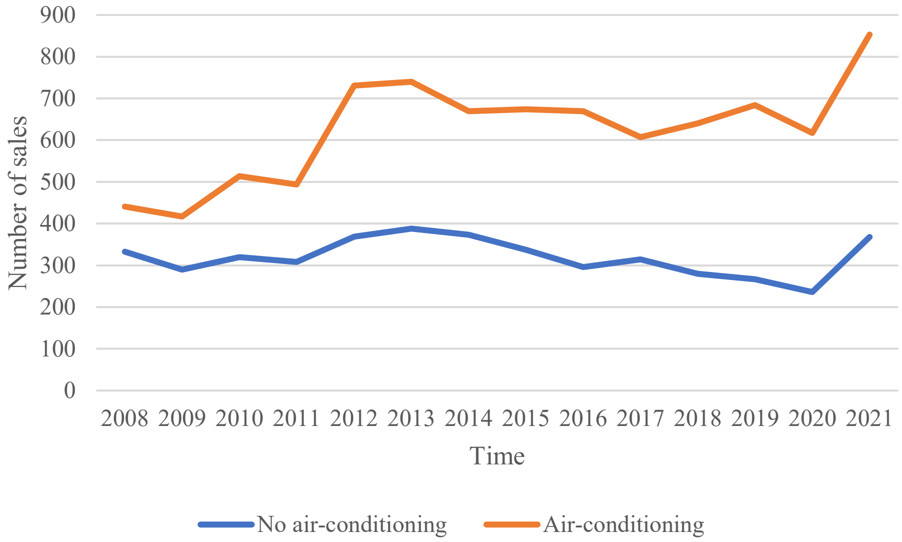

Figure 25: Number of sales for properties with and without AC.

Locational characteristics

The locational characteristics consist of two variables: distance to nearest subway stop and distance to Boston's Downtown area. In table 8, the minimum, maximum and mean distances are given for these two variables. Again, to provide insight in any differences between the treatment and control groups, the descriptives are also given for these groups. In both cases, the range of the control group is bigger than the range of the treatment group. On average, treated sales are 134 meters further from a subway stop, and 410 meters further from the Downtown area than control sales. The scatterplots in figures 26 and 27 capture the calculated distances of both groups in relation to the mean sale prices. From both figures it seems that the closer to either a subway stop or to Downtown, the higher the sale price per sf, which is in accordance to bid rent theory and earlier findings on improved accessibility and housing prices (Alonso, 1964; Cervero & Murakami, 2009).

Table 8: Minimum, maximum and mean distance to nearest subway stop and Downtown area.

	Minimum distance	Maximum distance	Mean distance
Subway stop	28,29m	1880,90m	409,99m
Treatment group	*54,19m*	*870,81m*	*537,10m*
Control group	*28,29m*	*1880,9m*	*403,24m*
Downtown	0,00m	7.282,18m	1021,75m
Treatment group	*241,65m*	*2400,40m*	*1411,31m*
Control group	*0,00m*	*7282,18m*	*1001,06m*

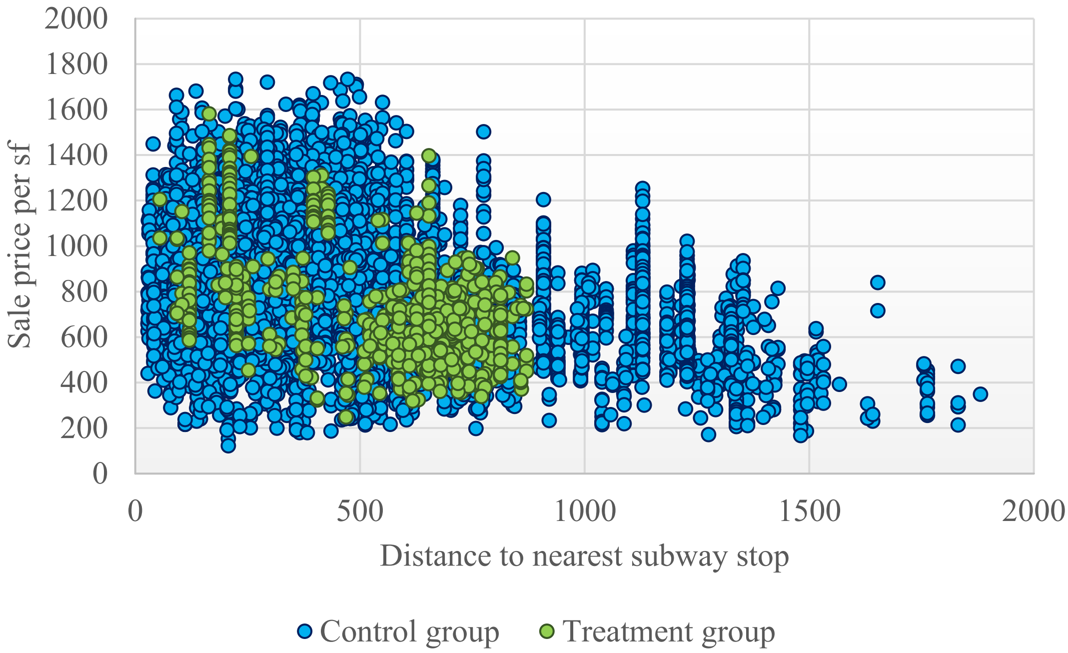

Figure 26: Distance to nearest subway stop related to sale price per sf.

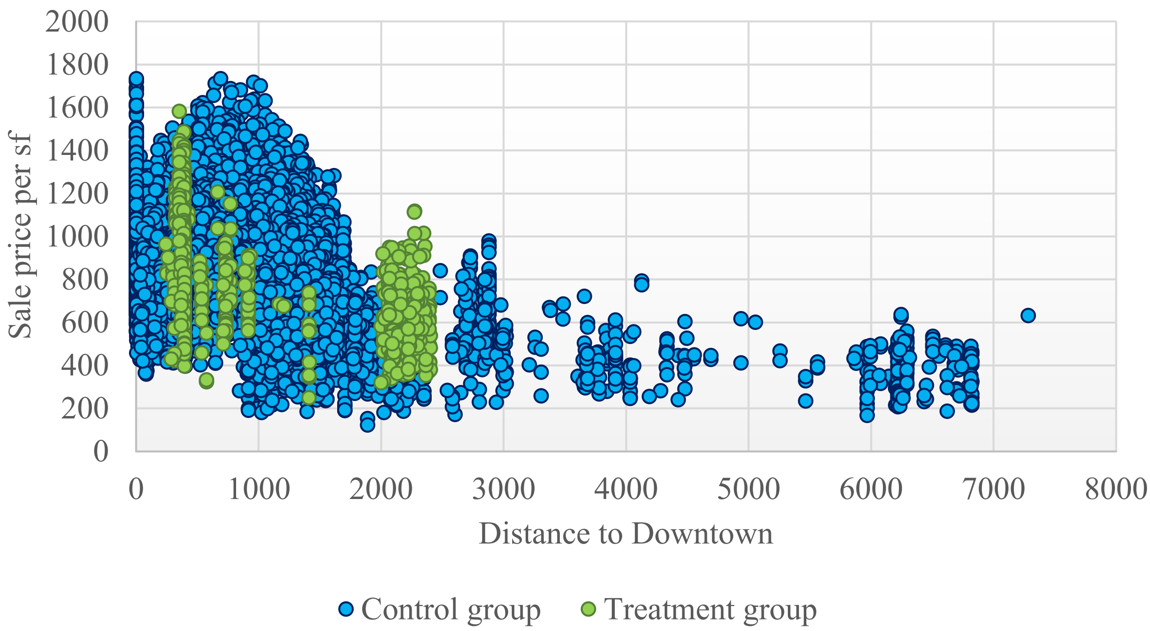

Figure 27: Distance to Downtown related to sale price per sf.

Neighborhood characteristics

Lastly is the set of neighborhood characteristics. These include number of parks and schools in a 1km radius around the sale and number of trees in a 100m radius around the sale. Table 9 provides an overview of the descriptives. Concerning number of parks, the treatment and control group are quite equal. This is also the case for the number of schools. The number of trees is also rather equal across both groups. These groups being fairly similar is beneficial to the analysis, for it will cause less nuisance in the estimation of the treatment effect.

Table 9: Minimum, maximum and mean of neighborhood characteristics.

	Treatment group	Control group	Minimum	Maximum	Mean
Num. parks 1km	16	24	2	38	24
Num. schools 1km	3	5	0	9	5
Num. trees100m	87	77	0	199	78

4.2 Regression analysis results

In this paragraph, the results of the multiple regression analysis are presented and interpreted. The multiple regression analysis was carried out through a hierarchical model. As explained in chapter 3, this type of analysis was chosen in order to see the relative explanation power of each set of variables. In a hierarchical model, the analysis is performed multiple times, whilst additional variables enter the analysis at each of the different stages. The first model (I) consisted of year of sale (YOS) dummy variables, dummies for flood zones, the distance to the nearest FRI (initial difference between 'treatment' and 'control' group), a dummy for time (pre or post project completion), the interaction effect between the time dummy and the distance to the nearest FRI (the treatment effect), and dummies for the interaction effects between each of the flood zones, the time dummy and distance to the nearest FRI project. In the second model (II), dummies for FRI categories and grey or green infrastructures were added, as well as the interaction variables for both the categories and the grey/green variables with the time dummy and the distance to the closest FRI. However, the grey/green dummy variable was removed from the analysis due to multicollinearity. In the last model (III), the structural, locational and neighborhood variables were added.

In table 10, the summary of the hierarchical analysis is shown. The variables included in the models correspond to the explanation above. The R^2 indicates how much of the variance in the dependent variable is explained through the model. This can – especially in cases of lower sample sizes – be biased to some extent, which is why the adjusted R^2 is also reported. However, in this analysis the shrinkage, or the difference between the R^2 and the adjusted R^2, is very small.

Table 10: Summary of regression model of hierarchical regression analysis.

Model	R	R^2	Adjusted R^2	Standard error of the estimate	R^2 change	F change	Df1	Df2	Significance of F change
I	0,570	0,324	0,323	209,029	0,324	317,160	20	13208	<0,001
II	0,698	0,487	0,486	182,176	0,163	465,515	9	13199	<0,001
III	0,820	0,672	0,671	145,839	0,184	569,978	13	13186	<0,001

The following paragraphs go through each of these models and interpret each model. The results of model III are also compared with earlier findings in the literature. This is done solely for model III, seeming as this is the most complete one and controls for the influence of other variables. Therefore, the findings by model III will be the most accurate.

4.2.1 Hierarchical model I: flood risk zones, distance to resilience and difference-in-difference

The first model included only the main variables of interest. Table 10 indicates that this model has an R^2 of 0,324; meaning that 32,4% of the variance in the data can be explained through the variables in this model. Table 11, summarizes the coefficients for model I. The constant is the intercept with the y-axis, or in other words, the predicted base value for the dependent variable when all other variables are zero. Because there are dummy variables included into the analysis, this means that the constant is the point when the values of all dummy variables are zero. In this case, it would mean the instance were a sale has occurred during 2008, in the C zone and pre completion of the nearest FRI project, with zero distance to the closest FRI project.

The individual effects of the variables in model I can also be gathered from table 11. The unstandardized B indicates the effect on sale price when a variable has a one-unit increase, ceteris paribus. The dummy variables for YOS are all significant for the p<0,05 level. The dummy variables compare the price increases to the base year 2008. From 2009 to 2012, the sale prices per sf are found to be lower than those in 2008. From 2013 onwards, the unstandardized coefficients are all positive, indicating that the sale prices per sf are higher as compared to 2008. Furthermore, the model found that when properties are located in flood zone X, they are sold for $205,58 per sf less than a sale in flood zone C. Sales occurring to properties in flood zone A or V are lower by $76,24 per sf. Both of these effects are significant, since p<0,001. All the variables relating to the DID effect are also significant for p<0,001. First of all, model I found a negative effect between sale price and distance to the nearest FRI project; i.e., the smaller the distance to an FRI project, the higher the sale price. Moreover, sales occurring after project completion are found to be more expensive than sales taking place prior to project completion. However, this was expected since housing prices in general have grown tremendously over the years. Then for the treatment effect – the interaction effect between the time dummy and the distance to the nearest FRI – is found to be negative. Again, indicating that the closer to an FRI project after it was completed, the higher the sale price. Looking for any changes in this effect when comparing flood zones, the effect is found to be even greater for properties in the higher flood risk zones.

The standardized beta coefficients measure the effect of each individual variable as Euclidian distances. Or in other words, the effects when the mean of each variable is set to zero, with a standard deviation of one. This way, the relative strength of the variables can be estimated better. This shows that, apart from the YOS, the dummy for location in flood zone X, the dummy for time, and the distance to the nearest FRI are the variables with the highest relative effect on the dependent variable. Furthermore, all variables have acceptable levels when it comes to multicollinearity. Tolerance values should not fall below 0,1 and for the Variance Inflation Factor (VIF) values should stay below 10.

Table 11: Coefficients for model I.

	Unstandardized B	Coefficients standard error	Standardized coefficients beta	T	Sig. (p)	95% confidence interval for B		Collinearity statistics	
						Lower bound	Upper bound	Tolerance	VIF
Constant	760,536	7,957		95,578	<0,001	744,94	776,13		
YOS 2009	-24,465	10,876	-0,022	-2,249	0,024	-45,78	-3,15	0,552	1,812
YOS 2010	-32,536	10,433	-0,031	-3,119	0,002	-52,99	-12,09	0,514	1,947
YOS 2011	-35,844	10,535	-0,034	-3,402	<0,001	-56,49	-15,20	0,523	1,914
YOS 2012	-36,463	9,808	-0,040	-3,718	<0,001	-55,69	-17,24	0,450	2,220
YOS 2013	20,449	9,758	0,022	2,096	0,036	1,32	39,58	0,445	2,249
YOS 2014	58,219	9,951	0,062	5,851	<0,001	38,72	77,72	0,460	2,175
YOS 2015	130,647	10,021	0,137	13,037	<0,001	111,00	150,29	0,466	2,146
YOS 2016	201,752	10,288	0,206	19,611	<0,001	181,59	221,92	0,461	2,167

YOS 2017	218,091	11,599	0,218	18,803	<0,001	195,40	240,83	0,379	2,638
YOS 2018	232,698	12,088	0,233	19,250	<0,001	209,00	256,39	0,349	2,863
YOS 2019	219,450	12,272	0,223	17,883	<0,001	195,40	243,50	0,329	3,042
YOS 2020	207,928	13,058	0,201	15,924	<0,001	182,33	233,52	0,321	3,114
YOS 2021	197,961	12,463	0,225	15,884	<0,001	173,53	222,39	0,254	3,940
Flood zone X	-205,584	8,323	-0,223	-24,699	<0,001	-221,90	-189,27	0,630	1,587
Flood zone AV	-76,241	5,990	-0,105	-12,728	<0,001	-87,98	-64,50	0,746	1,340
Distance FRI	-0,043	0,003	-0,133	-13,222	<0,001	-0,049	-0,036	0,507	1,974
Time pre/post	97,080	8,523	0,182	11,390	<0,001	80,374	113,79	0,200	5,007
Int. time & distance FRI	-0,029	0,005	-0,079	-5,779	<0,001	-0,038	-0,019	0,276	3,625
Int. Flood zone X & time & distance FRI	-0,065	0,013	-0,047	-5,068	<0,001	-0,09	-0,04	0,601	1,663
Int. Flood zone A/V & time & distance FRI	-0,047	0,006	-0,067	-7,442	<0,001	-0,06	-0,04	0,640	1,562

4.2.2 Hierarchical model II: addition of resilience project categories and infrastructure type

In model II, some characteristics of the FRI projects were added in order to investigate whether any differences are present in the treatment effect when controlling for distinctions in grey and green infrastructures and for the resilience categories. The results hereof are shown in table 12. Again, the constant represents the intercept with the y-axis or the baseline when all variables are zero, including all the dummy variables. In this model, this means that the intercept is the predicted value for properties sold in 2008, that are in the C flood zone, pre development of their nearest FRI project, that project is a grey infrastructure, and is in the small water holding infrastructure category, as well as all remaining continuous variables being zero.

Looking at the individual coefficients, it becomes clear that in model II, not all YOS dummies are significant anymore. This goes for 2009, 2010 and 2012. The nature of the relationships has stayed the same; from 2013 onwards, sale prices per sf are higher than those in 2008. A reason for this is further elaborated in the next paragraph. Furthermore, compared to model I, the flood zone dummy indicating an A or V flood zone has changed. In the first model, prices for either of the higher risk zones were lower as compared to zone C, but now properties with A or V indications have higher sale prices. Both dummies are still significant for $p<0,001$. The findings for the DID terms have remained fairly similar. Again, a negative relationship exists between the distance to the closest completed FRI and the sale price, which is stronger for sales in higher flood risk zones.

Additionally, the model tested the effects of the type of FRI. The dummy solely to distinguish between grey and green infrastructures showed severe signs of multicollinearity and was therefore left out of the analysis. An interaction variable that tests the relationship between sale price and the distance to green, completed FRI projects was also added. The model suggests a negative relationship; i.e., the closer to a green, completed FRI, the higher the sale price per sf. This effect is significant and just inside the boundary for multicollinearity. Hence, it is kept in the analysis, but it should be interpreted with some caution. Moreover, the resilience categories are also tested as compared to the baseline of the small water holding infrastructures. However, the effect of the shoreline stabilization projects is found to be not significant, the others are all significant for the $p<0,05$ level. Sales taking place near elevation projects are found to be sell for lower sf prices, but sales near either large water holding infrastructures or drainage projects are selling for higher prices. Again, the interaction effect was also tested for each resilience category, to estimate for which category the treatment effect is the strongest. The model would suggest that the distances to completed shoreline stabilization projects and elevation projects, so flood defense infrastructures, are negatively correlated with sales prices. Thus, sales with either of those types of completed projects as nearest FRI, sell for higher sf prices for each meter closer to these projects. However, distance to completed small water holding infrastructures were found to have a positive effect on sale prices; so, the further removed from these types of projects, the higher the sale price. The effect for distance to completed large water holding infrastructures was found to be non-significant. And finally, the effect for distance to completed drainage projects was excluded from the analysis due to strong levels of multicollinearity. Again, the cause for these findings is further examined in the next paragraph.

As can be seen in table 10, this model explains 48,7% of the variance in the dependent variable. This means that the added variables account for an extra 16,3% of explained variance. By looking at the standardized beta coefficients, it becomes clear that the most important variables driving this explanation power are the dummy variable for drainage projects, the treatment effect for green FRI projects, and the distance to the nearest FRI. Furthermore, all the statistics to control for multicollinearity are still within acceptable ranges; i.e., all values for tolerance are higher than 0,1 and all values for VIF are less than 10.

Table 12: Coefficients for model II.

	Unstandardized B	Coefficients standard error	Standardized coefficients beta	T	Sig. (p)	95% confidence interval for B		Collinearity statistics	
						Lower bound	Upper bound	Tolerance	VIF
Constant	631,060	8,974		70,323	<0,001	613,47	648,65		
YOS 2009	-15,394	9,481	-0,014	-1,624	0,104	-33,98	3,19	0,552	1,813
YOS 2010	-14,322	9,106	-0,014	-1,573	0,116	-32,17	3,53	0,512	1,952
YOS 2011	-26,200	9,185	-0,025	-2,853	0,004	-44,20	-8,20	0,522	1,915
YOS 2012	-12,137	8,565	-0,013	-1,417	0,157	-28,93	4,65	0,449	2,229
YOS 2013	43,368	8,517	0,048	5,092	<0,001	26,67	60,06	0,443	2,255
YOS 2014	90,801	8,708	0,096	10,427	<0,001	73,73	107,87	0,456	2,193
YOS 2015	160,640	8,764	0,168	18,239	<0,001	143,46	177,82	0,463	2,161
YOS 2016	210,436	8,996	0,215	23,392	<0,001	192,80	228,07	0,458	2,182
YOS 2017	213,747	10,325	0,214	20,702	<0,001	193,51	233,99	0,363	2,753
YOS 2018	231,869	10,792	0,232	21,484	<0,001	210,72	253,02	0,333	3,004

YOS 2019	215,236	10,977	0,219	19,608	<0,001	193,72	236,75	0,312	3,204
YOS 2020	213,558	11,744	0,206	18,184	<0,001	190,54	236,58	0,302	3,316
YOS 2021	202,842	11,221	0,231	18,076	<0,001	180,85	224,84	0,238	4,205
Flood zone X	-35,595	8,209	-0,039	-4,336	<0,001	-51,69	-19,51	0,492	2,032
Flood zone AV	84,829	6,678	0,117	12,702	<0,001	71,74	97,92	0,456	2,193
Distance FRI	-0,079	0,003	-0,247	-27,179	<0,001	-0,09	-0,07	0,472	2,120
Time pre/post	111,211	8,326	0,209	13,357	<0,001	94,89	127,53	0,159	6,291
Int. time & distance FRI	-0,022	0,004	-0,059	-4,899	<0,001	-0,03	-0,01	0,267	3,742
Int. Flood zone X & distance FRI	-0,087	0,012	-0,063	-7,552	<0,001	-0,11	-0,06	0,560	1,785
Int. Flood zone A/V & distance FRI	-0,045	0,006	-0,064	-7,825	<0,001	-0,06	0,03	0,581	1,722
Int. grey/green & time & distance FRI	-0,367	0,025	-0,279	-14,737	<0,001	-0,42	-0,32	0,109	9,198
Shoreline stabilization	-13,248	7,623	-0,022	-1,738	0,082	-28,19	1,70	0,241	4,157
Elevation	-153,148	12,107	-0,101	-12,650	<0,001	-176,88	-129,42	0,606	1,651
Drainage	208,900	6,458	0,408	32,349	<0,001	196,24	221,56	0,245	4,086
Large water holding infrastructure	20,504	10,174	0,017	2,015	0,044	0,56	40,45	0,557	1,795
Int. shoreline stabilization & time & distance FRI	-0,062	0,010	-0,049	-6,253	<0,001	-0,08	-0,04	0,620	1,613
Int. elevation & time & distance FRI	-0,471	0,153	-0,022	-3,081	0,002	-0,77	-0,17	0,788	1,268
Int. small water holding infra. time & distance FRI	0,261	0,024	0,208	10,949	<0,001	0,22	0,31	0,108	9,269

Int. large water holding infra. time & distance FRI	0,116	0,062	0,014	1,875	0,061	-0,01	0,24	0,701	1,426

4.2.3 Hierarchical model III: addition of structural, locational and neighborhood variables

In the last model performed through a hierarchical analysis, the structural, locational and neighborhood variables are added. With this addition, all variables are now entered in the model. Therefore, in this paragraph, the results will be examined more in-depth and also be compared to findings by others. This final model explains 67,2% of the variance in the sale price per sf. The last set of variables adds another 18,4% of explanation power, as shown in table 10. The constant is now the point for properties sold in 2008, that are in flood zone C, pre development, near a drainage infrastructure project, non-owner-occupied, did not have a remodel after 2007, nor an AC, nor a brick exterior finish; as well as all remaining continuous variables being equal to zero.

Starting again by looking at the dummies for year of sale, the results are fairly similar to the findings by model II, see table 13. The years 2009, 2010 and 2012 are, once again, non-significant. All of the other years are for the $p<0,05$ level. Again, from 2009 to 2012, the sale prices per sf are found to be lower than those in 2008; though for three years this is not significant. A possible explanation for this is the aftermath of the global financial crisis. From 2013 onwards, the unstandardized coefficients are all positive, indicating that the sale prices per sf are higher as compared to 2008. This effect can be explained through a recovering economy, and later, a through a tighter housing market where less supply relative to demand drives up prices, and an increasing influx of capital towards the housing market which drives prices up through outbidding (Anthony, 2018; Burgess, 2019). Furthermore, the stagnation of the prices in the last few years is also found by Liu and Su (2021), who postulate this has to do with the impact of COVID-19 on the US housing market. They find that demand for housing shifted towards less dense and cheaper areas.

Furthermore, the influence of flood risk is tested again through the dummy variables for flood zone X and for zone A or V. The results are quite similar to those of model II; however, in this model the effect of zone X is found to be non-significant. Properties located in either zone A or V are found to be sold for higher prices as compared to properties in zone C. Zone A/V are indicated to have the highest flood risk and property owners who bought their homes inside this zone through a government backed mortgage are required to have flood insurance. It is, therefore, striking to see that sale prices are higher compared to flood zone C. A possible explanation for this finding is that properties in zones A and V are often closer to either the ocean or the river, see figures 11 and 12. Waterfront properties are often found to have higher values due to ocean views or good accessibility to beaches; i.e., buyers derive additional utility from being located near the ocean (Jin et al., 2015). This additional utility might outweigh risks associated with that location for these buyers; a tradeoff described by Filatova, Mulder and Van der Veen (2011). A study by Jin et al (2015) on homeowners in Massachusetts also found that in this tradeoff, accessibility to the oceans wins over flood risk. The results of this research provide evidence that these findings are also true for denser urban settings. Another explanation for this finding would be that risk perception is lower in the A and V zones, due to alternative personal assessments of the risk as noted by Becker et al. (2013) and by Bubeck et al. (2012). Homebuyers may perhaps have the feeling of protection as a result of buying flood insurance as explained by Kim (2020), or due to the fact that waterfront properties are mostly multistory buildings and home buyers located in higher level condos being less worried about the consequences of a flood event. It was not possible to control for these explanations due to data limitations. In any case, this finding can be explained by both (neo)classical and behavioral explanations on flood risk.

Moreover, the variables related to the treatment effect are all significant. The initial difference for the distance to the nearest FRI project is positive. Meaning that, without looking at whether projects are completed or not, properties further away from FRI projects sell for higher prices. However, when controlling for project completion – and thus, estimating the treatment effect – this relationship turns negative, which entails that the closer to a completed FRI project, the higher the sale price. The beta coefficient is equal to -0,029; meaning that, ceteris paribus, for every additional meter further removed from the project, the sale price per sf decreases with $0,029. Using the average distance of the post group sales to their nearest FRI – 887,01 meters – and the average post group sale price per sf for all years – $952,35 – this effect amounts to 2,7% of added value on average due to the FRI projects. This effect is stronger for sales occurring to properties located in higher risk flood zones, so X, A or V. This is in line with neoclassical theory on the influence of flood risk on housing prices. Since the rent at risk is greater in higher risk zones, property owners are willing to pay more for FRIs. The influence of flood risk perception on these results is difficult to grasp exactly. However, findings in the literature would suggest that the FEMA flood risk zone indications are important factors in flood risk perceptions (Shao et al., 2017). These findings suggest that the hypothesis can be confirmed. This result is also in line to empirical findings of other accounts, for example Beltrán et al. (2018), Kelly and Molina (2023), and Walsh et al. (2019). The magnitude of the effect found here is similar to the 1,4%–1,7% price increase found by Kelly and Molina (2023), but lower than the 12,6% – 16,7% increase found by Beltrán et al. (2018) and the 21% found by Walsh et al. (2019). However, Kelly and Molina (2023) argue that due to the fact that most projects included in their analysis were marginal improvements, i.e., projects that do reduce flood risk but do not completely negate it (e.g., pumping stations and drainage systems), their findings were logical. In this research, no extremely large-scale infrastructure projects, like a dam or large seawalls, are in the sample either, making these results plausible.

Furthermore, this effect is also greater for properties near completed green infrastructures. Again, meaning that the closer a property was located to a completed green infrastructure, the higher the sale price per sf. This can be explained through the influence of secondary benefits. However, it should be noted that the secondary benefits of this sample are mostly limited to enhanced greenery in the area. No infrastructures such as big parks, with the added benefit of increased recreational space, were constructed during the study period. These findings are in line with results by Kim et al. (2020) and Mutlu et al. (2023), as well as to empirical evidence in the wider nature-based solution literature, for example Bockarjova et al. (2020).

Moreover, differences were found between the resilience categories. The effects for projects regarding shoreline stabilization, elevation and large water holding infrastructure are also found to be negative. Meaning that after completion, the closer to one of these types of projects, the higher the sale price per sf, ceteris paribus. This effect is especially strong for elevation projects. However, the small water holding infrastructures were found to have an opposite effect; so, the further removed from these projects, the higher the sale price. Findings by Kelly and Molina (2023) suggested that larger FRIs had bigger impacts on sale prices. They postulated that this had to do with flood risk perceptions. Infrastructures which are bigger or which are more noticeable to citizens reduce flood risk perceptions to a greater extent than smaller infrastructures. These findings align with this explanation, for the small water holding infrastructures are more likely to go unnoticed.

Newly added to model III were the variables concerning the structural, locational and neighborhood characteristics. The variable with the strongest influence on sale price, as indicated through the standardized beta coefficient, is the distance to the Downtown area. This is a negative relationship, meaning that the closer to Downtown, the higher the sale price. This is in line with (neo)classical explanations of housing prices, like Alonso's bid rent model (Alonso, 1964), and empirical findings by Tatano et al. (2004). Other control variables with strong influences are number of parks in a 1km radius, the more parks nearby, the higher the sale price; number of full bathrooms, the more full bathrooms present, the higher the sale price; and gross area, the smaller the area, the higher the sale price. This last finding is striking, since earlier accounts would suggest that larger properties sell for higher prices per sf (Kelly & Molina, 2023). Furthermore, age at the YOS and number of bedrooms are found to have non-significant effects. Finally, even though it was expected that the distance to the nearest subway station would negatively impact housing prices – the further removed from the nearest subway station, the lower the price – and the number of schools in the area would positively impact housing prices – the higher the number of schools, the higher the price – this is not the case. This can be explained through negative consequences these characteristics may cause, like noise from the subway and traffic congestion at rush hours near schools, which is also found by Kim (2020).

Table 13: Coefficients for model III.

	Unstandardized B	Coefficients standard error	Standardized coefficients beta	T	Sig. (p)	95% confidence interval for B		Collinearity statistics	
						Lower bound	Upper bound	Tolerance	VIF
Constant	494,918	10,471		47,267	<0,001	474,39	515,44		
YOS 2009	-7,687	7,594	-0,007	-1,012	0,311	-22,57	7,20	0,551	1,815
YOS 2010	-11,303	7,295	-0,011	-1,549	0,121	-25,60	3,00	0,511	1,955
YOS 2011	-25,994	7,359	-0,024	-3,532	<0,001	-40,42	-11,57	0,521	1,918
YOS 2012	-16,463	6,866	-0,018	-2,398	0,017	-29,92	-3,00	0,447	2,236
YOS 2013	52,505	6,832	0,058	7,685	<0,001	39,11	65,90	0,442	2,264
YOS 2014	98,976	6,992	0,105	14,155	<0,001	85,27	112,68	0,453	2,207
YOS 2015	165,744	7,047	0,173	23,519	<0,001	151,93	179,56	0,459	2,180
YOS 2016	218,817	7,250	0,224	30,182	<0,001	204,61	233,03	0,452	2,211
YOS 2017	258,028	8,349	0,258	30,904	<0,001	241,66	274,39	0,356	2,808
YOS 2018	274,962	8,740	0,275	31,462	<0,001	257,83	292,09	0,325	3,074
YOS 2019	266,689	8,912	0,271	29,925	<0,001	249,22	284,16	0,303	3,296
YOS 2020	267,323	9,531	0,258	28,049	<0,001	248,64	286,00	0,293	3,408
YOS 2021	253,509	9,109	0,289	27,832	<0,001	235,66	271,36	0,231	4,323
Flood zone X	-11,885	7,207	-0,013	-1,649	0,099	-26,01	2,24	0,409	2,444
Flood zone AV	47,345	5,916	0,065	8,003	<0,001	35,75	58,94	0,372	2,686
Distance FRI	0,075	0,004	0,233	20,352	<0,001	0,07	0,08	0,190	5,250
Time pre/post	41,812	6,762	0,079	6,183	<0,001	28,56	55,07	0,154	6,574
Int. time & distance FRI	-0,029	0,003	-0,080	-8,374	<0,001	-0,04	-0,02	0,292	3,426
Int. flood zone X & time & distance FRI	-0,069	0,010	-0,050	-7,051	<0,001	-0,09	-0,05	0,503	1,988

Int. Flood zone A/V & time & distance FRI	-0,028	0,005	-0,040	-6,085	<0,001	-0,04	-0,02	0,571	1,751
Int. grey/green & time & distance FRI	-0,084	0,020	-0,064	-4,120	<0,001	-0,12	-0,04	0,103	9,688
Shoreline stabilization	-71,745	6,606	-0,120	-10,861	<0,001	-84,69	-58,80	0,205	4,871
Elevation	169,805	11,731	0,112	14,475	<0,001	146,81	192,80	0,413	2,419
Drainage	202,771	6,545	0,396	30,982	<0,001	189,94	215,60	0,154	6,549
Large water holding infrastructure	-74,405	8,587	-0,061	-8,665	<0,001	-91,24	-57,57	0,501	1,995
Int. shoreline stabilization & time & distance FRI	-0,024	0,008	-0,019	-2,954	0,003	-0,04	-0,01	0,609	1,642
Int. elevation & time & distance FRI	-0,495	0,123	-0,023	-4,034	<0,001	-0,74	-0,25	0,785	1,273
Int. small water holding infra. time & distance FRI	0,099	0,019	0,079	5,152	<0,001	0,06	0,14	0,106	9,447
Int. large water holding infra. time & distance FRI	-0,132	0,050	-0,016	-2,639	0,008	-0,23	-0,03	0,694	1,441
Distance subway stop	0,077	0,007	0,097	11,681	<0,001	0,06	0,09	0,360	2,775
Distance Downtown	-0,165	0,003	-0,617	-61,331	<0,001	-0,17	-0,16	0,246	4,062
Number of parks in 1km	3,866	0,225	0,139	17,156	<0,001	3,42	4,31	0,377	2,654
Number of schools in 1km	-10,037	0,804	-0,101	-12,485	<0,001	-11,61	-8,46	0,382	2,615
Number trees in 100m	0,208	0,042	0,034	4,941	<0,001	0,13	0,29	0,519	1,926
Owner occupied	15,290	2,661	0,030	5,745	<0,001	10,07	20,51	0,940	1,063

Gross area	-0,072	0,004	-0,134	-17,157	<0,001	-0,08	-0,06	0,408	2,449
Remodel after 2007	58,459	4,322	0,072	13,525	<0,001	49,99	66,93	0,875	1,142
AC	25,862	3,155	0,048	8,196	<0,001	19,68	32,05	0,721	1,387
Age at YOS	0,014	0,032	0,003	0,426	0,670	-0,05	0,08	0,691	1,448
Brick exterior finish	63,914	4,665	0,094	13,701	<0,001	54,77	73,06	0,534	1,872
Number of bedrooms	2,815	2,363	0,008	1,191	0,234	-1,82	7,45	0,575	1,740
Number of full bathrooms	57,262	3,414	0,123	16,774	<0,001	50,57	63,95	0,463	2,158

4.3 Testing regression assumptions

Multiple regression analysis is based upon five main assumptions. For the results of the analysis to be robust, all of the assumptions should hold. The assumptions are linearity, homoscedasticity, independence of errors, normality, and absence of multicollinearity. These will be checked and discussed in this paragraph in the aforementioned order.

A first assumption multiple regression analysis makes is the assumption of linearity between the dependent and the independent variables. In the case of multiple predictors, it also assumes additivity; i.e., the effect of two or more variables on the dependent variable can be described by adding the effects together. Should linearity be absent, then the model which is used will not fit the observed results. This assumption can be tested by looking at the scatterplot of standardized residuals against the standardized predicted values, see figure 28. If linearity is present, there should be no sign of curvature in the scatterplot, which is the case here. This would indicate that linearity is present and no other for the model unspecified relationship, e.g., quadratic or logarithmic, exists between the dependent variable and the independent variables.

Moreover, the next assumption is also tested by using the same scatterplot, namely that of homoscedasticity. Homoscedasticity is the situation in which the variance in errors is constant and is not related to any (combined) variable(s) in the model. Equal variance in errors is necessary for robust confidence intervals and significance tests for the independent variables. However, should the homoscedasticity assumption be violated, then the model will still produce unbiased estimates of parameters (Field, 2013; White, 1980). Heteroscedasticity is present when the residuals are not evenly distributed in the scatterplot, but rather they can be seen to follow a pattern. In figure 28, there is a slight cone shape noticeable in scatterplot, which would indicate a degree of heteroscedasticity. According to Hayes and Cai (2007) the gravity of the posed problem resulting from heteroscedasticity depends on the type and severity of the heteroscedasticity. Furthermore, they note that "relatively mild heteroscedasticity is not going to produce profound problems and is unlikely to swing the outcome of an analysis dramatically one way or the other" (Hayes & Cai, 2007, p.710). Additionally, heteroscedasticity most often leads to reduced statistical power (Shadish, Cook, & Campbell, 2002). Hence, in this case, this is not addressed further but merely noted.

The next assumption is the independence of errors. A common situation in which there is dependence of errors is in cases where data of longitudinal nature is used. One way to test for this is through the Durbin-Watson test. This test measures correlation between the residuals of an individual case and the case coming after that case in the dataset. Therefore, to adequately check for autocorrelation, the cases have to be ordered according to their date of sale. For Durbin-Watson test scores goes: the closer to 2 the better. The Durbin-Watson score for this ordering of the cases is 1,846, which is quite close to 2. Therefore, the independence of errors assumption can be justified.

The fourth assumption is concerned with the normality of the residuals. Residuals should be normally distributed for a number of reasons. A first is that this is necessary for accurate confidence intervals, another reason is for the accuracy of the significance tests, and a final reason is that the model parameters are most optimally estimated if normality is present. This assumption can be checked using two figures. The histogram in figure 29 shows that the standardized residuals are normally distributed. This would indicate that the assumption of normality is tenable. Additionally, the standardized residuals in the normal probability plot of the expected probability against the observed probability all fall very close to the regression line (dotted) and the points do not 'snake' around the line either, see figure 30. This strengthens the case for normal distributed residuals.

The last assumption is that there should be absence of multicollinearity. Multicollinearity describes a situation where two or more variables are strongly correlated. This can cause three problems. The first is that it results in unreliable estimations of the beta coefficients, due to higher standard errors. A second is that it inhibits the explanatory power of the model; if two predictors are strongly interrelated, they explain little unique variance. A last problem is that the relative importance of the predictors is difficult to know. Two of the independent variables that were supposed to be included were subsequently removed from the analysis due to high levels of multicollinearity. These were the dummy for grey or green infrastructures and the distance to completed drainage projects. In model III, there are also two more variables that are just within the critical values for the tolerance and VIF. These are the distance to completed green FRI projects and the distance to completed small water holding infrastructures. This is due to the fact that more than half of the small water holding infrastructures, also happen to be green infrastructures. This would probably have been no problem if the number of FRI projects would have been higher. Therefore, the results on the resilience categories and the distinction between grey and green infrastructures should be interpreted with caution. For all other variables, the Pearsons collinearity values (<0,7), the tolerance (>0,1) and the VIF (<10) scores are all within reasonable limits to assume no further multicollinearity is present.

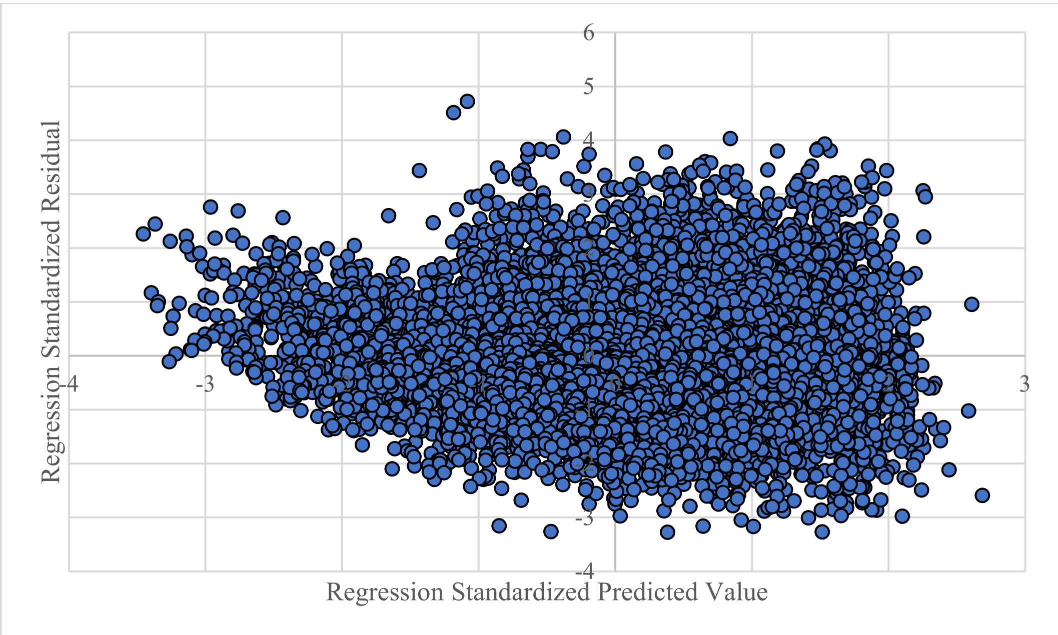

Figure 28: Standardized residuals and standardized predicted values.

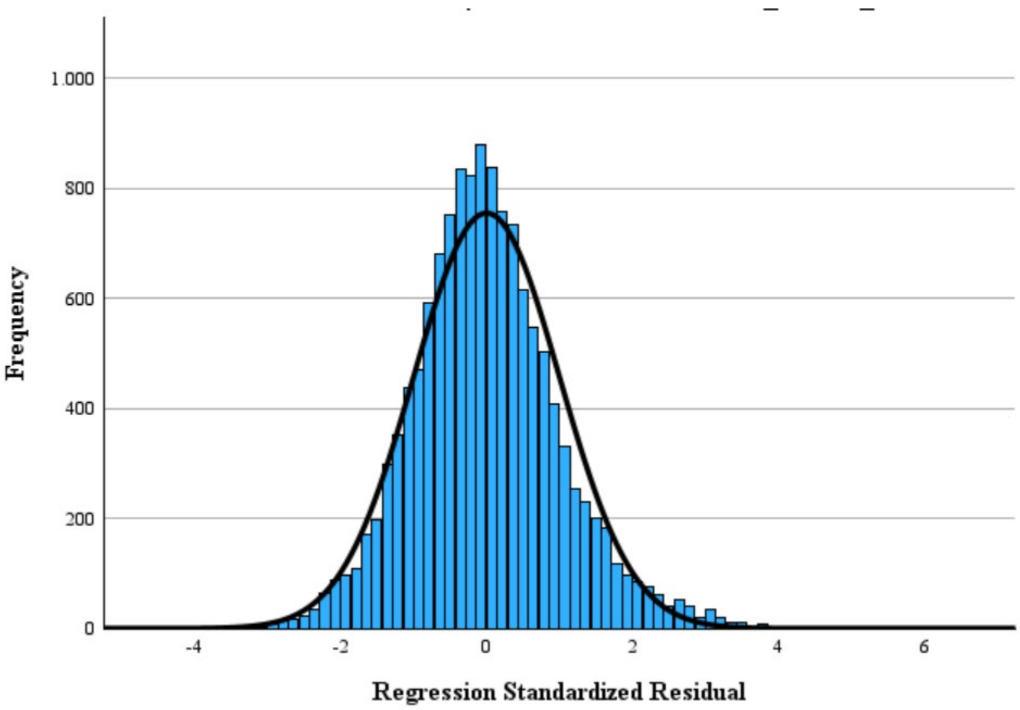

Figure 29: Frequency histogram of standardized residuals.

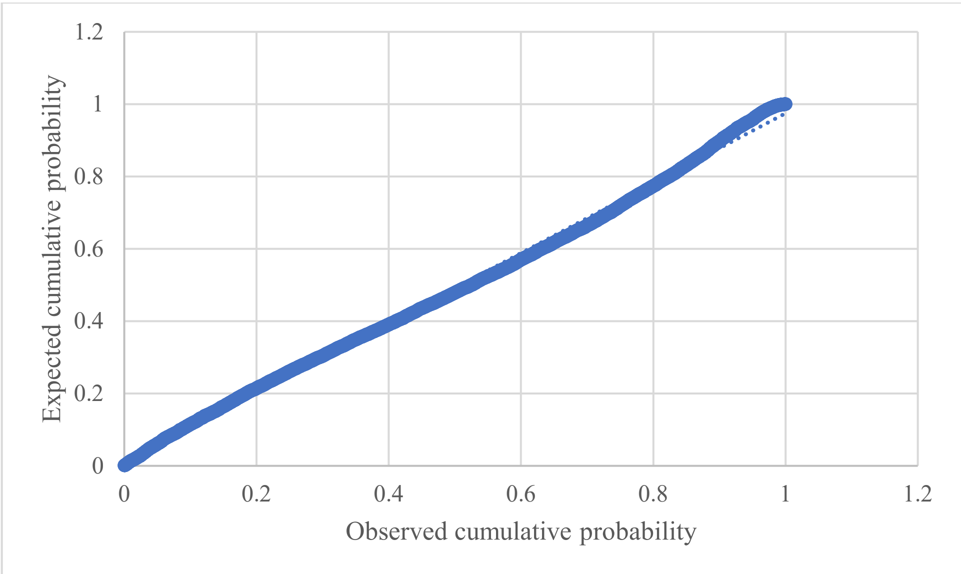

Figure 30: Normal probability plot of regression standardized residual.

5. Conclusion & discussion

To summarize, this research sought empirical evidence for the presumed relationship between flood resilience infrastructures (FRIs) and housing prices, to find additional ways to fund these kinds of projects in order to bridge the financing gap that exists with resilience infrastructures. This was done through a quantitative research design, which entailed including a DID approach – for the estimation of the effect of interest – into an HPM. The HPM was performed so any confounding effects and possible interaction effects could be accounted for. In the subsequent paragraphs, the research questions shall be answered, the contribution of these findings to the development of the theories on this subject will be elaborated, some policy recommendations are set forth, and, lastly, the limitations of this research are presented as well as any recommendations for further research.

5.1 Answers to research questions & main findings

The aim of this research was to find possible additional sources which could leverage funding for the City of Boston in order to finance FRIs to adapt the city to rising levels of flood risk. Flood risk was shown to negatively affect housing prices by earlier studies (Bin & Landry, 2013; McAlpine & Porter, 2018). This led to believe that LVC instruments could be a possible source of funding, through lowering risk by the construction FRIs. As such, a virtuous circle might be instated, where value uplift due to reduced risk can be captured and reinvested (Lord et al., 2019). This research sought empirical evidence for this, by investigating the effect of FRIs on housing prices in Boston.

To be able to do so, two subquestions needed investigation. The first task was to see where and what kind of FRIs were constructed. There were found to be twelve FRI projects in Boston between 2009 and 2020, which are illustrated in figure 8. This number is probably greater, but a strict inclusion process was chosen in order to upkeep the internal validity. Plans needed to very explicitly state that the infrastructure affects a wider area than merely the project area. However, since it is not required to mention this for the plan process, more than the twelve included projects probably addressed flood risk. The second task was to see which transactions had taken place in residential real estate and what kind of properties these were. Only residential real estate transactions in the period of 2008 to 2021 were considered for this analysis, which were obtained through the Department of Revenue of the Commonwealth of Massachusetts. They are depicted in figure 7. This research focused solely on condominium sales, since this type of houses made up the clear majority of sales. The characteristics were drawn from the property assessments published by the Assessing Department of the City of Boston, as well as some publicly available databases of various departments of the City of Boston and the Commonwealth of Massachusetts.

With this, the subsequent HPM could determine the relationship between the FRIs and housing prices. The outcome of the analysis would suggest that there is a negative effect between the distance to the nearest completed FRI project and the sale price per sf. Meaning that, ceteris paribus, the closer to such a project, the higher the sale price per sf. This effect was greater in higher flood risk zones compared to zones of minimal flood risk. This is in line with other findings in the literature (Kelly & Molina, 2023). However, the magnitude of this effect was found to be smaller as compared to some of the other accounts in the literature (Kim, 2020; Walsh et al.,2019). This might be due to differences in perceived flood risk and the type of infrastructure that was constructed. The latter was the case in for example Kim (2020), who found higher price increase due to FRIs in Miami-Dade County than in New York City, due to higher levels of risk perception of the Miami-Dade County residents. The former argument was made by Kelly and Molina (2023), who found a lower price increases in the Miami-Dade County than Kim (2020). This was speculated to be caused by the type of infrastructure they were looking at. Smaller infrastructures, like drainage systems, that improve resilience but not fully take risk away the way levees would, resulted in lower price increases. Both these arguments may also apply here, since Boston faces lesser flood risk than the Miami-Dade County and the infrastructures that were constructed are not on such a large scale.

Moreover, the effect was also assessed considering the distinction between grey and green infrastructures. There was a negative effect between the distance to the nearest completed green infrastructure project and the sale price. Meaning that the closer to a green infrastructure project, the higher the sale price per sf, ceteris paribus. This is also consistent with earlier findings (Kim, 2020; Mutlu et al., 2023). This finding could inform future cost-benefit analysis used in deciding between grey or green alternatives. Future price premiums as a result of green infrastructures in the form of higher real estate values should be accounted for in cost benefit analyses. Although, the notion of green gentrification should be kept in mind when implementing these results.

Furthermore, the effect was also assessed considering the distinction between different resilience infrastructure categories. The ones included were shoreline stabilization projects, elevation projects, drainage projects, small water holding infrastructures and large water holding infrastructures. The flood defense infrastructure categories – shoreline stabilization and elevation infrastructures – were found to have a greater effect on the sale price than the flood mitigation infrastructures – drainage, small and large water holding infrastructures (ceteris paribus). However, this finding is probably not very reliable. One of the resilience categories showed large levels of multicollinearity and in general, the number of flood resilience projects investigated in the study was already small but even worse so for the resilience subcategories. Therefore, a topic for future research is investigating the different types of resilience infrastructures. This could be done, for example, by looking at a wider geographical area.

The outcomes of this research are useful for the realization of the flood resilience endeavors of the City of Boston in a sufficient and efficient manner. It provides a step towards more accurately pricing FRIs by the market, even though imperfections still persist due to imperfect risk pricing (Pryce et al., 2011). Nevertheless, these results provide evidence that – even in an imperfect market – resilience investments in Boston create value and could therefore yield returns when applying value capture strategies. This can inform decision-making processes about the actual costs and benefits of FRIs. As a result of this, the viability of FRI projects may be positively affected, which benefits the implementation of FRIs by the City of Boston and results in a better protected Boston in the face of flood risk.

5.2 Reflections and contribution to further development of theories

The findings of this research confirm the hypothesis formulated in paragraph 2.5; FRI construction increases housing prices of at-risk residential real estate. This is empirical evidence to support (neo)classical theories and behavioral theories on the internalization of flood risk in the housing market. The latter argues that homebuyers make a trade-off between their derived utility from being located in a flood prone area and the risk they subsequently face. When flood risk is lowered through flood resilience infrastructures, properties in the flood zone become more attractive. This leads to a higher willingness-to-pay for these properties, and thus increased prices. This is in line with the finding that the effect of the FRIs was stronger for properties located in higher risk areas; the X and A or V flood zones. The former theory moves that flood risk perceptions influence property prices. The same trade-off still persists, only with flood risk perception instead of actual calculated risk. Since the FRIs that were more noticeable in the built environment were shown to lead to higher price increases than FRIs that were smaller; however, that finding was not the most robust and therefore should be carefully reviewed. Nevertheless, this conclusion validates the relationship between FRI construction and housing prices as illustrated in the conceptual model depicted in figure 6.

As explained in chapter 2, flood risk is imperfectly internalized into the housing market due to unknown consequences of climate change (Cohen et al., 2021; Pommeranz & Steininger, 2020) and information asymmetries about the risk (Pryce et al., 2011; Miller & Pinter, 2021). Yet, as the results show, proximity to FRIs is positively valued in the market, despite these imperfections. This indicates that homebuyers in Boston are aware of flood risk, at least to some extent. Due to the fact that this effect was shown to be stronger in higher flood risk zones, this would also entail that flood risk is internalized in the market to, again, some extent. Underestimation of risk leads to overestimation of real estate values. A more accurate internalization of risk will result in lower prices, but presumably also to a stronger effect of the vicinity to FRIs.

More generally speaking, these results verify the notion that climate resilience investments yield returns in the form of increased land and or real estate prices, as also found for other climate adaptation investments for example investments to improve air quality (Lord et al., 2022). This fortifies the notion that land value capture instruments are efficient tools to use in implementing resilience infrastructure (Doeffinger & Rubinyi, 2023), as they are able to close the virtuous circle and prevent invested capital from slipping away. Thus, the schematic illustration of this circle, as depicted in the conceptual model, is empirically validated.

5.3 Recommendations for practice

Based on these conclusions, some policy recommendations can be drawn for the City of Boston and the US as a whole. Since this research suggests that the implementation of FRIs increases housing prices, it is recommended that LVC instruments are implemented in order to capture these increases and to make the most of the public investments in flood resilience. A good way to start is in instances of new developments that also include FRIs. In these cases, try to experiment with LVC instruments – particularly NDOs, like exactions or impact fees – aimed at capturing resilience premiums. To close the virtuous circle, the value uplift resulting from implementing FRIs must be captured. NDOs are a good to start with because of their flexibility and adaptability without the need for an extensive legislative framework, which makes them easier to introduce according to Hendricks et al. (2021). The full internalization of flood risk and the cost of flood insurance by real estate markets needed to effectively capture the value accruing in already developed areas will take quite some time. The introduction of new NDOs in new developments, on the other hand, can be achieved relatively quickly. By doing so, the viability of FRI projects can be positively affected. This way, the City of Boston can begin to address the imminent threat of flood risk, whilst making the most of its investment.

Secondly, another recommendation would be to implement green infrastructures over grey infrastructures where possible. The results show that the price increasing effect of green infrastructures is higher as compared to grey infrastructures. Therefore, when applying value capture instruments, more value can be captured when implementing green FRIs. This can lead to a positive effect for the viability of green FRIs, which is necessary in preparing Boston for flood risk. Nevertheless, it should be kept in mind that green infrastructures often take up more space than grey ones, which is not possible everywhere or viable everywhere when right of way has to be bought for numerous plots first. Furthermore, equity considerations should be kept in mind, as the implementation of additional green in the city can lead to green gentrification if not fairly distributed.

Moreover, as mentioned earlier, the number of FRI projects between 2009 and 2020 was probably higher than twelve. However, due to the choice for a rather strict inclusion process, the plan needed to state explicitly that they affected a wider area than just the project site. Presumably, more FRIs were constructed that affected a larger area, but their plans did not state so. The research could have benefitted from a higher number of FRI projects that could have been included, specifically in investigating the differences between different project categories. Hence, another recommendation for the City of Boston – and the US at large – is to start the collecting as much data as possible on FRIs. This also goes more in general for all climate adaptation investments. In the Climate Ready Boston policy program, addressing coastal and riverine flood risk is one of three parts. Meaning that other problems have to be addressed as well. To do so adequately and efficiently, more data will be necessary for research. Boston already possesses quite advanced databases and data collection infrastructures. Expanding on this by including more detailed climate adaptation investment data could lead to robust climate adaptation research which could benefit not only the city but the US and world as a whole.

5.4 Limitations and further studies

The results and conclusions of this research should be critically evaluated and, as in any research, certain points and caveats should be considered. These will be elaborated in this paragraph. As each point leads to consequences for either the reliability or the internal or external validity, they are grouped by the aspect that they present consequences for. This will start by discussing the reliability of the results, then the internal validity of this research will be reviewed, and subsequently the external validity.

Furthermore, during the evaluation of these aspects, ways to overcome some of these issues will be suggested. Finally, recommendations for further research on this subject are put forward.

To review the reliability of the results, certain aspects can be taken into consideration. Firstly, when comparing the results of this research to earlier studies on this effect, it seems that these results are similar, as elaborated in chapter 4. Differences in the magnitude of the found effect are explained through different levels of (perceived) flood risk and the type of infrastructure that is implemented. Another point was already elaborated in paragraph 4.3, which is that the results were shown to have some degree of heteroscedasticity. This may lead to an over- or underestimation of the explanatory power of the applied model. A possible way of fixing this might be to apply a log transformation on the dependent variable. Moreover, should this research be reproduced for Boston, similar results are expected to be found. However, it should be noted that risk is not static. In the face of climate change, flood risk will only increase and the occurrence of flood events will become more likely; influencing both actual flood risk and perceived flood risk. Therefore, future studies of the same locality are more likely to find a stronger effect. Furthermore, it should be considered that other factors are also at play, which can influence the magnitude of the effect. Overall, the similar results found by others and the given that flood risk will only increase, insinuate that the results are fairly reliable.

When critically reviewing the internal validity, some points for improvement can be found. A first concern has to do with the operationalization of the FRI projects. In this analysis, FRIs are essentially development projects that included FRIs. This, however, means that other elements were constructed in the built environment. Newly developed areas often include landscaping, repair or development of roads, new amenities, etc. These elements are not controlled for in this analysis. Hence, for a more robust analysis of the effect of FRIs on housing prices, the analysis should only include the construction of an FRI. However, from 2009 to present day, no sole FRI project was developed in Boston. Therefore, this could not have been avoided for this locality. A second caveat is that currently it was not possible to control for the floor the property is located on. This can be problematic because the effect the FRIs have on housing prices stems from flood risk. This was the reason to focus on property sales in the (future) flood risk zone. However, the severity of flood risk depends on elevation. Condos on higher floors might not even experience any sort of flood risk, that is, to their own individual unit. It can still be argued that owners living on higher floors still perceive flood risk and experience disamenity from for example their entrances or parking garages being flooded. Nevertheless, it would be expected that houses on lower levels would experience a stronger effect from being near an FRI. This distinction cannot be made, since this data is lacking. Furthermore, a closely related point to the last one is that of unaccounted spillover effects. This mostly distorts the magnitude of the effect and less so the presence of it. When an FRI finishes, the performed analysis found that it affects the sale prices of properties that are closest to this project out of all the FRI projects. This can be due solely to reduced flood risk, or, according to Kelly and Molina (2023), can also be due to increases in sale prices of properties near the FRI project which then by default increase the sale prices of all residences in the neighborhood; i.e., the price increase spills over to properties in the same neighborhood. The current analysis is not able to separate the actual effect of reduced flood risk from the probable spillover effect. Nevertheless, even though these increases may not be justified by an actual reduction of flood risk, the increase is empirically happening in these properties; therefore, it is still relevant.

A possible way to improve on the analysis when the aforementioned discussion points are accounted, would be by applying a repeat sales approach. This is a kind of research design which would enable to estimate this effect on an individual property level, therefore being better able, for example, to determine differences between first floor properties and properties on floor higher up. This approach was actually preferred here and all the other data allowed for such an analysis, but the number of twice, or even three times, sold properties in the sample was too small to yield any robust results. A concern covered by the repeat sales approach is accounting for continued growth over time. Now the analysis estimates the treatment effect as the average treatment effect. It does not account for further increases which could be the result of increased future risk. The amount of risk is not static, in the face of climate change it will in most instances only increase in the future. Theoretically, this could mean that resilience for this risk becomes even more valuable. Through a repeat sales approach this effect can be estimated on the individual property level. Additionally, a repeat sales approach could also uncover anticipation effects by the market. Development projects get announced by the local government, which already sends signals to the market. These signals could then already start to affect prices before the construction is completed. The extent of this signaling effect could be interesting for the decision-making process for resilience investments. However, according to Kelly and Molina (2023) this does not pose any problems for the estimation of the effect, since an increase in price should still be observed after completion because not all of the increases are internalized immediately.

Although this research mainly focused on maintaining high levels of interval validity, some arguments can definitely be made for the generalizability of the results found. The analysis was performed on Boston's residential condominium market, and evidence for the effect of FRIs on the sale prices was only found for this instance. Extrapolating to other property types, like single-family homes, apartments or even mixed-use condominiums, might not be the most reliable due the possible influence of certain other interfering factors. Furthermore, extrapolating these results to other localities should also be done with careful consideration. The risk profile of every city or town is different, as well as flood risk perceptions and how this plays out on their respective housing markets. Nevertheless, as mentioned earlier, similar results were found in Florida and Maryland (Kelly & Molina, 2023; Walsh et al., 2019). This could solidify the argument that this is the case with any coastal city facing flood risk. However, since LVC instruments require a local analysis anyway, it would be wiser to only extrapolate the methodology applied here.

On the basis of the findings of this research and the abovementioned considerations, some recommendations for future research can de distilled. First, as explained earlier in this chapter, this research would have benefitted from the application of the repeat sales approach and the inclusion of elevation data. Thus, for an even more robust analysis, this is a first recommendation for future research endeavors. Also, it would be interesting to see this outcome compared to the costs of the FRIs. No data was found on the costs of solely the FRI part of the development projects, so currently this was not possible. Secondly, further research could more robustly investigate the differences in the effect of the different resilience categories on property values. This research had too little FRIs included in the analysis in order to make any reliable statements about any possible underlying differences in the effect of types of FRIs on housing prices. This can provide useful results for determining what kind of FRI will best fit in a certain development scenario. Next, another route would be to investigate the effect of FRIs on other types of real estate. It is suggested that the commercial real estate market has a different way of internalizing flood risk and resilience. It may be interesting to investigate how it differs from the residential real estate market, since many older coastal cities typically have commercial center in high flood risk zones. This is also the case for Boston's Downtown (and with it, its Financial District). Furthermore, to promote the external validity, three other points require further investigation. Firstly, future research should focus on localities outside the US. Some research on this topic has been performed in Europe, but relatively little is known about this effect for geographies in the Global South. Since these countries will likely experience the brunt of climate change, local research in this field can greatly benefit them. Secondly, since risk is not static, it is interesting to see how much risk is needed for this effect to be present in the market. This would also require qualitative assessments of risk perceptions and the behavior of homebuyers under those circumstances. A last question of interest would be how this effect responds to changing market conditions; i.e., are resilience dividends a reliable funding source when crises hit? Should the effect not persist in times of crisis, then additional funding sources are still necessary in order to guarantee the timely implementation of FRIs. This holds true not only for Boston, but many other coastal cities; all should reap what they sow.

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Appendix I: Flood resilience infrastructure projects

Name	Construction started	Construction completed	FRI description	Infrastructure	Grey/green	Category
32 Cambridge Street	6-9-2017	20-8-2019	"To minimize the impact of flooding, the parking garage (partially below grade) will be able to be inundated in the event of flooding […]" (BPDA, 2016a, p.4-8).	Retention area	Grey	Small water holding infrastructure
600 Harrison Avenue	8-1-2015	13-10-2016	"Reducing stormwater run-off with below-grade stormwater infiltration systems for not only the new building and related site areas, but also the adjacent St. Helena's House property" (BPDA, 2013c, p.1-5).	Infiltration system	Grey	Drainage
Charlestown Armory	30-1-2015	28-9-2017	"The project will restore existing buildings and grounds allowing abutters to talk directly with design team engineers to resolve drainage, grading and retaining wall design issues." (BPDA, 2014a, p.1-8).	Grading adjustment	Grey	Elevation
Charlesview Redevelopment	18-10-2013	29-1-2016	The proposed project will decrease the amount of impervious area on the Brighton Mill and Telford Streets by approx. 2.2 and 0.1 acres, respectively (BPDA, 2008, p.3-25). This will be accomplished through the creation of vegetated pervious surfaces such as grass lawns and rain gardens in areas that are now paved or built upon (BPDA, 2008).	Retention area	Green	Small water holding infrastructure
Coppersmith Villiage Development	29-12-2015	14-8-2019	"The front portion of the Liverpool building, as well as yards for about 10 feet in front of the building, will also be lifted about 2'-6'above existing grade. This elevation is currently understood to be accomplished by means of retaining walls and structural fills." (BPDA, 2013a, p. 11).	Seawall	Grey	Shoreline stabilization
Fan Pier Parcel J	*	7-3-2018	"The cove will be made suitable for water transportation and water recreation uses by the construction of a wave attenuation structure (breakwater) and by dredging the cove to an appropriate depth." (BPDA, n.d.-b, p.4).	Breakwater	Grey	Shoreline stabilization
General Electric Headquarters	*	16-12-2019	"[…] The project site will consist of building coverage and pedestrian areas with landscape and bioretention areas to collect and treat stormwater." (BPDA, 2016b, p.10-4).	Retention pond	Green	Large water holding infrastructure

Hood Park Drive	22-10-2018	21-7-2020	The grading creates a street network that is generally 2-3 feet above the existing elevation of the site, enabling first floor elevations of all proposed buildings to be set at approximately elevation 20 (BCB) (BPDA, n.d.-a).	Raised streets	Grey	Elevation
Lovejoy Wharf	10-7-2015	19-10-2017	A steel sheetpile cut off wall was installed 10 to 15 feet outboard of the 131 Beverly Street and 160 North Washington Street building foundation walls (about 2 to 5 feet outboard of the original timber bulkhead along the projects site's north side). Concrete was then poured into the cavity between the sheet steel and the foundations (BPDA, 2004)	Bulkhead	Grey	Shoreline stabilization
One Channel Center	15-8-2012	31-1-2014	"The project will have less impervious area in the developed condition, due to the construction of the New Park in an area that is currently an impervious parking lot. […] almost all of the hardscape portion of the New Park will be either permeable paving or sloped so that the stormwater will run to permeable landscaped areas" (BPDA, 2012, p.3-18).	Retention area	Green	Small water holding infrastructure
The Boston Garden (The Hub on Causeway)	1-9-2016	1-11-2018	"The lower parking garage levels will be able to be inundated during storms." (BPDA, 2013, p.5-13).	Retention area	Grey	Small water holding infrastructure
The Innovation and Design Building	17-1-2014	5-10-2016	"This includes installation of new, green landscaped plazas at each of the four new building entries. These plazas will incorporate extensive planting of native and adaptive plant species, and natural landscaping design to improve the on-site absorption of stormwater and reduce runoff." (BPDA, 2014b, p.4-11).	Retention area	Green	Small water holding infrastructure

*Starting date was not listed on the website of the BPDA.

Appendix II: Variable matrix

Variable	Unit / values	Measurement level	Resources
Sale price per sf	$	Interval	Department of Revenue
Dummy year of sale	2008 – 2021	Nominal	Department of Revenue
Flood zones 2009 & 2016	C X A/V	Ordinal	FEMA
Dummy time pre/post	1 for post, 0 for pre	Nominal	BPDA and Department of Revenue
Distance to FRI	Meter	Interval	BPDA
Dummy grey/green	1 for green, 0 for grey	Nominal	BPDA
Dummy resilience category	Shoreline stabilization Elevation Drainage Small water holding infra. Large water holding infra.	Nominal	BPDA
Distance to nearest subway station	Meter	Interval	MassGIS & GIS computation
Distance to Downtown	Meter	Interval	MassGIS & GIS computation
Number of parks in 1km radius	Number	Interval	Boston Parks and Recreation Department

Number of schools in 1km radius	Number	Interval	Boston Maps
Number of trees in 100m radius	Number	Interval	Boston Maps
Dummy owner occupied	1 for owner occupied, 0 for not owner occupied	Nominal	Assessing department
Gross area	Square foot	Interval	Assessing department
Dummy remodel after 2007	1 for remodel, 0 for no remodel after 2007	Nominal	Assessing department
Dummy presence of AC	1 for AC present, 0 for not present	Nominal	Assessing department
Building age	Number of years	Interval	Assessing department
Dummy brick exterior	1 for brick exterior, 0 for other material	Nominal	Assessing department
Number of bedrooms	Number	Interval	Assessing department
Number of full bathrooms	Number	Interval	Assessing department

Appendix III: Descriptive statistics full overview

	Minimum	Maximum	Mean	Standard error	Standard deviation
Sale price per sf	122,68	1734,45	819,02	2,21	254,12
Dummy 2009	0,00	1,00	0,05	0,00	0,22
Dummy 2010	0,00	1,00	0,06	0,00	0,24
Dummy 2011	0,00	1,00	0,06	0,00	0,24
Dummy 2012	0,00	1,00	0,08	0,00	0,28
Dummy 2013	0,00	1,00	0,09	0,00	0,28
Dummy 2014	0,00	1,00	0,08	0,00	0,27
Dummy 2015	0,00	1,00	0,08	0,00	0,27
Dummy 2016	0,00	1,00	0,07	0,00	0,26
Dummy 2017	0,00	1,00	0,07	0,00	0,25
Dummy 2018	0,00	1,00	0,07	0,00	0,25
Dummy 2019	0,00	1,00	0,07	0,00	0,26
Dummy 2020	0,00	1,00	0,06	0,00	0,25
Dummy 2021	0,00	1,00	0,09	0,00	0,29
Dummy flood zone X	0,00	1,00	0,08	0,00	0,28
Dummy flood zone A/V	0,00	1,00	0,14	0,00	0,35
Dummy time pre/post	0,00	1,00	0,35	0,00	0,48
Interaction flood zone X, time, distance to nearest FRI	0,00	2666,94	32,44	1,60	183,61
Interaction flood zone A/V, time, distance to nearest FRI	0,00	6339,91	52,48	3,12	358,46
Distance to nearest FRI	1,00	6796,64	829,92	6,88	791,75
Interaction distance to nearest FRI and time	0,00	6796,64	310,91	6,06	696,43
Interaction distance to nearest FRI and green infrastructures	0,00	1587,76	94,00	2,27	260,78
Dummy shoreline stabilization	0,00	1,00	0,23	0,00	0,42
Dummy elevation	0,00	1,00	0,03	0,00	0,17
Dummy drainage	0,00	1,00	0,56	0,00	0,50
Dummy small water holding infrastructures	0,00	1,00	0,13	0,00	0,33
Dummy large water holding infrastructures	0,00	1,00	0,05	0,00	0,21
Interaction shoreline stabilization, time, distance to nearest FRI	0,00	3534,70	43,56	1,76	202,82

Interaction elevation, time, distance to nearest FRI	0,00	430,14	0,87	0,10	11,67
Interaction drainage, time, distance to nearest FRI	0,00	6796,64	216,95	5,82	668,96
Interaction small WHI, time, distance to nearest FRI	0,00	1683,34	47,26	1,76	201,95
Interaction large WHI, time, distance to nearest FRI	0,00	762,17	2,28	0,26	30,48
Distance to nearest subway station	28,29	1880,90	409,99	2,80	322,34
Distance to Downtown	0,00	7282,18	1021,75	8,24	948,04
Number of parks in 1km	2,00	38,00	24,05	0,08	9,17
Number of schools in 1km	0,00	9,00	4,70	0,02	2,55
Number of trees in 100m	0,00	199,00	77,65	0,36	41,84
Dummy owner occupied	0,00	1,00	0,59	0,00	0,49
Gross area	200,00	5168,00	1070,77	4,13	474,98
Dummy remodel after 2007	0,00	1,00	0,11	0,00	0,31
Dummy presence AC	0,00	1,00	0,66	0,00	0,47
Age year of sale	2,00	198,00	90,50	0,41	47,17
Dummy brick exterior finish	0,00	1,00	0,83	0,00	0,37
Number of bedrooms	0,00	6,00	1,63	0,01	0,71
Number of full bathrooms	1,00	4,00	1,37	0,00	0,55