ABSTRACT

Title of Dissertation:	THE ECONOMIC EFFECTS OF STORMWATER BEST MANAGEMENT PRACTICES (BMPS) ON HOUSING SALE PRICES IN WASHINGTON, D.C.
	Boyoung Park, Doctor of Philosophy, 2024
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The aim of this dissertation seeks to investigate the economic effects of stormwater best management practices (BMPs) on housing sale prices in Washington, D.C. Stormwater best management practices (BMPs) were designed to address flooding and water quality issues that impact environmental, social, and economic effects. As awareness of the BMPs increased, municipalities and local governments developed regulations to require developers and property owners to implement BMPs. Effective stormwater management was not merely a matter of environmental responsibility but may create significant economic incentives.

To study the economic effects of BMPs on housing prices, this study reviewed 32 years of research articles answering following questions: 1) How do BMPs affect housing prices? 2) What kinds of stormwater BMPs have been studied that affect housing prices? This review study used the PRISMA approach to conduct an in-depth systematic review. The search parameters included articles written in English and published between January 1990 and September 2022 using Google Scholar, ProQuest, and EBSCO host search engines. Initially, more than 20,000 studies were

identified. Ultimately, 23 Studies were selected for inclusion with specific search terms. The results of this study show that many BMPs (trees, detention basins, retention basins, parks, etc.) use various measurements (e.g., percent coverages, proximity) to estimate the economic impacts on housing prices. Our robust findings address that BMPs have more substantially positive (82.6%) than negative effects (52.2%) on housing prices. Trees and parks had an impact that is more positive on housing prices than detention and retention basins. While studies on the economic value of BMPs were limited, literature found that the capitalization of real estate can be affected by nearby stormwater BMPs using the hedonic pricing method.

To extend the economic effects of BMPs on housing sale prices in Washington, D.C., this study addresses research questions: Do stormwater BMPs positively impact housing sale prices? How do proximity and number or structural BMPs affect the housing sale prices? This study used the hedonic pricing method by applying hierarchical regression models to determine whether a set of independent variables significantly improved the models. The primary findings indicate that BMPs have positive, negative, or no effects on housing sale prices. Proximity to BMPs inside of parks increased housing sale prices in all buffers. In contrast, proximity to BMPs outside of parks and impervious roads decreased housing sale prices in all buffers. Percent tree canopy coverage negatively linked to a 50 m buffer and no relationship with other buffers on housing sale prices. This study implies that BMPs impact housing prices and can be improved by landscape architects, policy makers, and stakeholders.

To compare the economic effects of BMPs on housing sale prices in high-income and low-income wards in Washington, D.C., this study addresses how environmental, structural, neighborhood and locational variables hierarchically affect housing sale prices in high-income and low-income wards. The robust findings of this study conclude that environmental variables (e.g., proximity of houses to parks with BMPs, house to BMPs inside of parks, and house to BMPs outside of parks, impervious surfaces, and impervious roads) can be attractive factors for purchasing homes, according to model 1 and model 3 in high-income ward. In contrast, there was no evidence of the economic effects of environmental variables on housing sale prices in low-income ward. All structural variables in the high-income ward were statistically significant on housing sale prices. In contrast, limited structural variables in low-income ward were statistically significant on housing sale prices. Several locational and neighborhood variables (e.g., population density, unemployment rate, and poverty rate) in the high-income ward were statistically significant on housing sale prices. These results contribute to property owners considering how environmental, structural and neighborhood and locational variables could be beneficial between high-income and low-income communities. However, such disproportionate economic effects of factors concern remain. The intervention of green gentrification should be considered between local government and disparate community groups by supporting financial incentives for homeownership or having an equity project for existing residents to improve their communities. This could change the neighborhood composition which is associated with the availability of stormwater BMPs as well as the involvement of these efforts from landscape architects, urban planners, stakeholders, and government is essential to accelerate the strategies to fair distribution and effects of stormwater BMPs on housing sale prices.

THE ECONOMIC EFFECTS OF STORMWATER BEST MANAGEMENT PRACTICES (BMPS) ON HOUSING SALE PRICES IN WASHINGTON, D.C.

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2024

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Acknowledgements

First, I would like to express sincere gratitude to my advisor, Professor Byoung-Suk, Kweon. One of the best things that happened to me was that I could be her student. She has offered various, more importantly, fascinating, and special research opportunities. Being my role model, she has continuously inspired, guided, and encouraged me with her intellectual and beyond academic insight. I must send my gratitude to my committee members, Professor Christopher D. Ellis, Professor Chengri Ding, Professor Laixiang Sun, and Associate Professor Masoud Negahban-Azar. I appreciate constant support and providing broader and deeper insights and feedback to my research.

Second, I would like to express special thanks to my fellow graduate students at the University of Maryland, Yvette Tamukong and Sherry Russell as well as my best friends, Dr. Hyein Jang and Dr. Minha Lee who held my hand passing through so many bumpy roads together.

Last but not least, I owe enormous thanks to my family. I would like to dedicate this dissertation especially to my parents Byung Koo Park and Jeong mi Kim, younger brother Dong Hyun, and Grandfather Se-jin Park and Grandmother Moosoon Yang, who always stand by me, protect me and are proud of me no matter who I am. Your unconditional love has been my best energy booster to go through this long journey.

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List of Abbreviations

BMPs	Best Management Practices
CI	Confidence Interval
CSOs	Combined Sewers Overflows
CSS	Combined Sewer System
EPA	Environmental Protection Agency
DOEE	Department of Energy & Environment – Washington, DC
MMU	Minimum Mapping Unit
MS4	Municipal Separate Storm Sewer System Permit
NPDES	National Pollutant Discharge Elimination System
USGS	United States Geological Survey
VIF	Variance Inflation Factors

Chapter 1: Introduction

1.1 Background

As land development progresses and precipitation event intensity, stormwater runoff has been considered a large problem in urban and suburban landscapes (Taguchi et al., 2020). Flooding and stormwater present a range of environmental threats, including the conveyance of pollutants, contamination of ecosystems, and degradation of water quality (National Research Council, 2009). Stormwater poses challenges when it comes to combined sewer overflows (CSOs), which occur when rainwater runoff, domestic sewage, and industrial wastewater are collected in a single pipe, leading to the discharge of untreated sewage into nearby water bodies (EPA, 2008). The management of combined sewer systems has garnered increased attention, with the Environmental Protection Agency (EPA) prioritizing this issue and mandating municipalities to adhere to the regulations outlined in the National Pollutant Discharge Elimination System (NPDES). NPDES oversees the issuance, modification, monitoring, and enforcement of stormwater pretreatment as part of the U.S. Clean Water Act (EPA, 2008).

Traditionally, the improvement of stormwater management has relied on conventional gray infrastructure such as a network of curb gutter-pipes or ditches (Fletcher et al., 2015). However, conventional practices of urban stormwater management have been increasingly proven to be unsustainable bypassing the treatment process that causes flooding, stream bank erosion, and water quantity and quality problems (Qi & Barclay, 2021).

For these reasons, to offset the limitations of gray infrastructure, the installation of stormwater BMPs has increasingly incorporated as green infrastructure (Irwin et al., 2017).

Stormwater best management practices (BMPs) indicate that they were practical strategies to prevent or reduce pollution in various environmental settings (EPA, 2008). Stormwater BMPs such as green roofs, rain gardens, vegetated swales, and permeable pavements have been widely used to mitigate runoff issues since the strategies of green infrastructures (e.g., stormwater design manual) have been adopted in the early 1990s by the U.S EPA (Fletcher et al., 2015).

The benefits of structural BMPs were that they were designed to mimic nature and consider not only the volume of runoff but also the quality of water that flows through our urban landscape. Landscape architects, with their expertise in environmental sustainability with design, play a critical role in crafting solutions that address the challenges while considering both functionality and the visual appeal of stormwater BMPs (Faggi & Caula, 2017). Driven by the challenges of urbanization to climate change, effective stormwater management was not merely a matter of environmental responsibility but also had significant economic implications, especially on housing prices.

Housing sale prices have emerged as a pivotal factor in the real estate market, significantly contributing to socio-economic development (Jia & Zhang, 2021). Regarding the economic effects of stormwater best management practices (BMPs) such as detention basins, green roofs, or permeable pavements, on neighboring properties, researchers aimed to understand the capitalization effects of these BMPs, which encompassed potential co-benefits and associated expenses including planning, design, construction, and maintenance costs (Irwin et al., 2017).

In this context, the hedonic pricing method, an empirical approach, has been widely utilized to assess the economic impact of proximity to nearby water features on property values. This method enables the estimation of the contribution of individual attributes to housing value, accounting for various physical and other heterogeneous features (Sheppard, 1999). By incorporating a range of factors such as environmental conditions (e.g., percentage of tree canopy coverage and proximity to detention basins), internal and external features of housing structures (e.g., number of bathrooms and age of the house), and neighborhood characteristics (e.g., occupancy rate and crime rate), researchers were able to estimate the relative impact of each variable on housing prices while controlling for other factors.

These analytical methods provided insights into how specific attributes like BMPs influence housing prices, aiding planners and policymakers in making informed decisions regarding the capitalization or regulation of BMP implementation based on their observed impact on property values.

1.2 Research Objectives and Contributions

This dissertation proposes the economic effects of stormwater BMPs on housing sale prices in Washington, D.C. The focus of the study used hedonic pricing method to explore the economic effects of environmental, structural, locational and neighborhood, and wards variables on housing sale prices. The contribution of the dissertation is organized as follows:

Chapter 2 provides a systematic literature review of the economic effects of stormwater BMPs on housing sale prices by using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA).

Chapter 3 demonstrates the findings of the economic effects of stormwater BMPs on housing sale prices in Washington, D.C. This research addresses specific questions to contribute to the existing literature: Do stormwater BMPs positively impact housing sale prices? How do proximity and number of structural BMPs affect the housing sale prices?

Chapter 4 addresses the comparison of economic effects of stormwater BMPs on housing sale prices between high-income and low-income wards in Washington D.C. This research addresses specific questions to contribute to the existing literature: How do the economic effects of stormwater BMPs affect housing sale prices between high-income and low-income wards in the District? How do proximity and number of structural BMPs affect the housing sale prices differently between high-income and low-income wards?

Chapter 2: A Systematic literature review of the Economic Effects of Stormwater Best Management Practices (BMPs) on Housing Prices

2.1 Introduction

In this literature review, I investigated 32 years (1990–2022) of research articles on the economic effects of stormwater best management practices (BMPs) on housing prices in any region of the world. As land development progresses and precipitation event intensity, stormwater runoff has been considered a large problem in urban and suburban landscapes (Taguchi et al., 2020). When stormwater is not adequately managed, the environment may be adversely affected by conveying pollutants, changing the volume, degrading ecosystems (National Research Council, 2009) as well as increased intensity of storm events contribute to flooding and damaging property.

Stormwater best management practices (BMPs) indicated that they were practical strategies to prevent pollution and manage the quality and quantity of runoff in various environmental settings (EPA, 2008). To combat stormwater-related flooding, BMPs such as green roofs, rain gardens, vegetated swales, and permeable pavements have been widely used to mitigate runoff issues since the strategies of green infrastructures (e.g., stormwater design manual) have been adopted in the early 1990s by the U.S EPA (Fletcher et al., 2015). As awareness of the BMPs increased, municipalities and local governments developed regulations to require developers and property owners to implement BMPs. The National Pollutant Discharge Elimination System (NPDES) permit, as a part of the Clean Water Act of the Environmental Protection Agency (EPA), has regulated water runoff from municipalities, construction activities, and industrial sources to mitigate overflows (Fletcher et al., 2015). After the birth of NPDES regulations, BMPs were defined as techniques, processes, activities, or structures to diminish the pollutant content of stormwater discharge and maximize its effectiveness (Fletcher et al., 2015). BMPs encompassed both structural control (engineered or built infrastructure, such as detention basins, rain gardens, and green roofs) and nonstructural control (operational or procedural practices, minimizing the use of chemical fertilizers) (EPA, 2008). Structural BMPs were called in many different terminologies, like green stormwater infrastructures, blue spaces, and low-impact development (LID), as a part of green infrastructure interchangeably (Struck et al., 2010). While conventional drainage approaches (e.g., gutters and storm drains) rapidly convey runoff through an extensive system of underground pipes, structural BMPs were designed to mimic nature and consider not only the volume of runoff but also the quality of water that flows through our urban landscape (Vogel et al., 2012). Landscape architects, with their expertise in environmental sustainability with design, play a critical role in crafting solutions that address the challenges while considering both functionality and the visual appeal of stormwater BMPs (Faggi & Caula, 2017).

By assessing how BMPs such as detention basins, green roofs, or permeable pavements impact nearby properties, the capitalization effects of stormwater BMPs indicated whether types of BMPs generated co-benefits, such as expenses associated with plannings, designs, constructions, and maintenances (Irwin et al., 2017). This phenomenon could be related to environmental gentrification in that housing prices a significant factor in the real estate market, contributed immensely to socio-economic development in nearby neighborhoods (Owusu-Ansah, 2011). For example, green infrastructure projects such as New York’s High Line (Loughran, 2014), Atlanta’s Beltline (Immergluck & Balan, 2018), and Cheonggyecheon stream restoration project converted abandoned places into popular green spaces, nearby land value or rental prices of neighborhoods drastically increased. However, vulnerable or marginalized communities have to be displaced due to rising rent (Chen et al., 2021).

With this respect to hedonic pricing method has been widely used for assessing the economic impacts of the proximity to the nearby water features on property value. This method allowed an estimation of contribution of individual attributes and housing value can be counted for physical and other heterogeneous features (Sheppard, 1999). A set of environments (e.g., percentage of tree canopy coverage and proximity to detention basins), internal and external housing structure (e.g., number of bathrooms and age of house), and neighborhood factors (e.g., occupancy rate and crime rate) were applied to estimate how much each variable contributed to the housing prices while controlling for other factors. Such methods allowed for understanding how specific attributes like BMPs impacted housing prices and helped planners and policymakers to make decisions about capitalizing or regulating the implementation of BMPs by valuing the nearby properties.

The following paper synthesized the evidence of the economic effects of BMPs on housing prices over 32 years of studies through the preferred reporting items for systematic review and meta-analyses (PRISMA). I addressed specific questions and described the broader literature. This systematic review approach aimed to summarize the “best available research” by collecting, critically evaluating, integrating, and presenting findings on the topic of interest.

2.2 Research Objective

This analysis has three goals associated with this review study. Through the literature review, I focused on studies addressing the following questions: First, what kinds of stormwater

BMPs have been studied that affect housing prices over 32 years? Second, how do BMPs affect housing prices economically? Third, to generate an agenda for further study based on the evidence from this assessment, what are the other factors that contribute to boosting the economic effects of BMPs on housing prices and improving the limitations?

2.3 Method

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) check list was used for the literature review (Moher et al., 2010). PRISMA was one of the advanced techniques, which consisted of a 27-item checklist and a four-phase flow diagram that enabled systematic review (Moher et al., 2010). This method identifies the relevant evidence by screening multiple resources with steps. I included articles written in English and were published since 1990 in any region of the world. The focus of the search was on original, primary peer-reviewed literature, articles from organization websites, conference proceedings, working papers, government and official publications, doctoral dissertations, and master's theses. Literature was excluded if it did not meet the range of our primary keywords.

2.3.1 Search Strategy and Database Selection

Databases were selected based on their relevance and journal coverage. I used three database search engines: Google Scholar, ProQuest Dissertations and Theses, and EBSCOhost. Google Scholar was a major database with freely accessible articles, ProQuest was one of the broad interdisciplinary databases, and EBSCOhost was the leading provider of research databases. The initial literature search was conducted between July and September 2022 using databases from January 1990, with updates to the searches run in September 2022. The search was initially conducted using full titles and abstracts without any geographical or language limitations in the selected database. The search results were de-duplicated using Excel, followed by four steps in the PRISMA flow diagram.

I used a variety of search terms using keywords and terms from papers known to be relevant to the review. The eligibility criteria for the assessed literature were: “Green infrastructure” and “Property values” and “Hedonic pricing model” and “Single family housing sale prices” and “Best management practices” and “Stormwater.” Searches were conducted using a combination of keywords from various databases. Following testing in the selected databases, the following terms were used in all search engines: Google Scholar, ProQuest, and EBSCOhost (Table 1).

Table 1 Search strategy with keywords and number of articles from database.

Search strategy with keywords	Google Scholar	ProQuest	EBSCOhost	Total
“Green infrastructure”	1,900,000	1,616,267	26,066	3,542,333
“Green infrastructure” and “Property values”	368,000	982,201	273	1,350,474
“Green infrastructure” and “Property values” and “Hedonic pricing models”	17,200	10,822	7	28,029
“Green infrastructure” and “Property values” and “Hedonic pricing models” and “Single-family housing sale prices”	15,600	1,185	3	16,788
“Green infrastructure” and “Property values” and “Hedonic pricing model” and “Single-family housing sale prices” and “best management practices”	15,400	1,111	0	16,511

"Green infrastructure" and "Property values" and "Hedonic pricing model" and "Single-family housing sale prices" and "best management practices" and "stormwater"	1,950	81	0	**2,031**

2.4 Results

2.4.1 PRISMA Summary

To evaluate the screening process, I used a flow chart of the screening and selection process of stormwater BMPs reporting economic outcomes (Figure 1). I adopted and modified the PRISMA format. First, 2,031 articles were chosen after screening with a combination of key terms: "Green infrastructure" and "Property values" and "Hedonic pricing model" and "Single-family housing sale prices" and "best management practices" and "stormwater" from Google Scholar, ProQuest, and EBSCOhost search engines. Second, 331 of 2,031 papers were selected in screening step after detecting duplicates and searching "Hedonic" and "Property" and "Housing" and "Stormwater" and "Green infrastructure" in both titles and short description in databases. Third, 85 of 331 papers were selected after searching "Hedonic" and "Property" and "Housing" and "Price" and "Stormwater" and "Green" in abstract. Fourth, 23 of the 85 papers were selected after screening the variables, measurements, and results in full-text articles. Ultimately, 23 papers were selected after excluding the review articles and adding them to the reference examination. Once the final 23 papers were determined, we entered summary information into the table, which became a literature matrix (Appendix A).

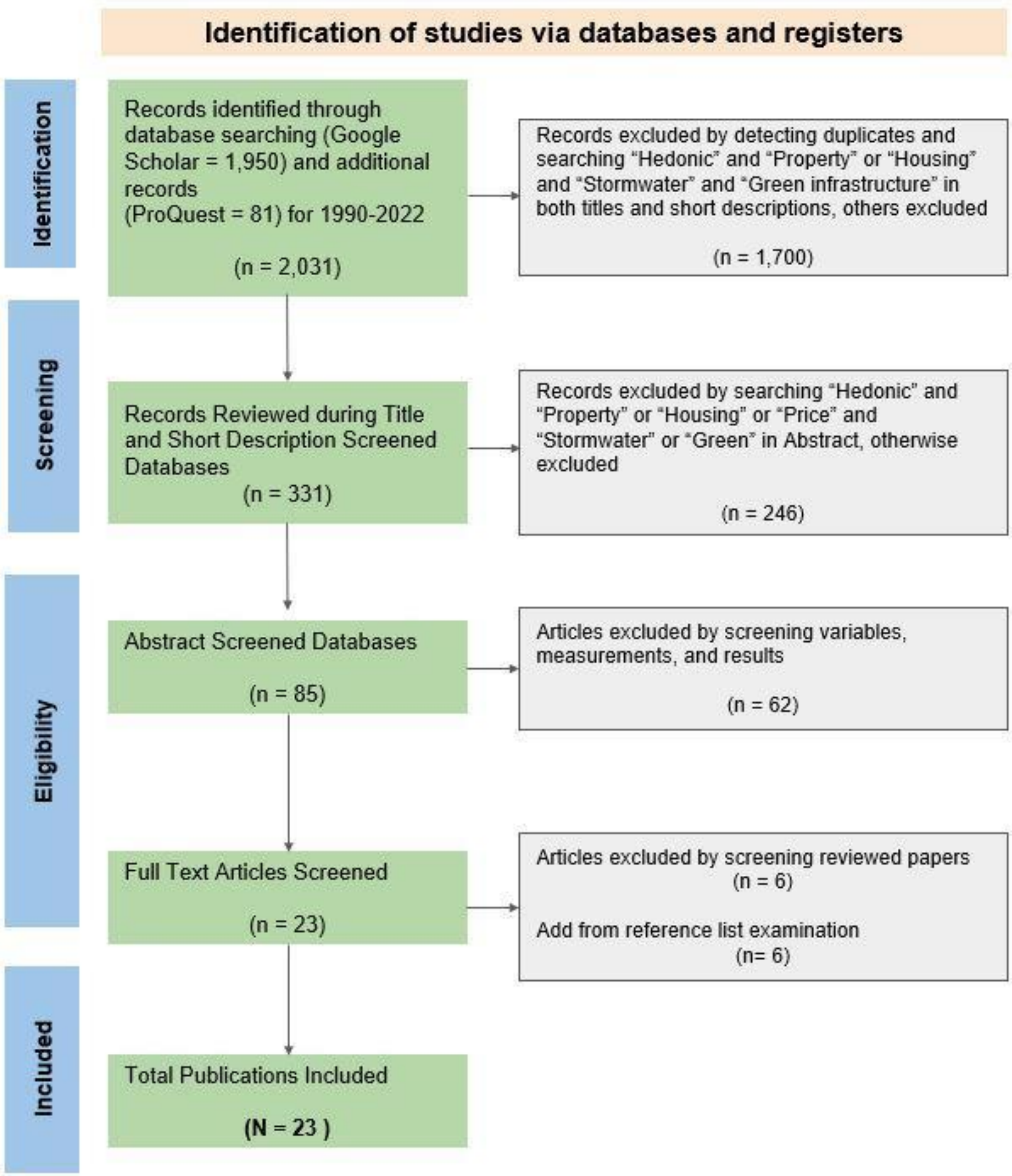

Figure 1 Preferred Reporting Items for PRISMA flow chart.

2.4.2 Patterns in study topics and methods

By reviewing 23 articles, I found the following stormwater BMPs categories: (1) trees, (2) detention basins, (3) retention basins, (4) parks, (5) rainwater tanks, (6) more than one BMPs. These articles used the hedonic pricing method to investigate various effects of BMPs on housing prices. The hedonic pricing method enables deconstruction of the price of an asset into the asset's various component parts: environmental, structural, locational, and neighborhood attributes by using the ArcGIS analysis tool to measure percentage (e.g., tree canopy coverage), proximity/distance buffer (e.g., proximity to parks and distance to retention basins), size, and count (e.g., count of rainwater tanks) of BMPs.

2.4.3 Study findings

Findings showed that 23 studies addressed the economic effects of BMPs on housing prices. Eighteen studies (78.3%) were based in the U.S. and the locations of studies were present in urban or suburban settings. They investigated a variety of BMPs, such as trees, detention basins, retention basins, parks, rainwater tanks, etc. Two studies (8.7%) were in Europe with trees and parks, two studies were in Oceania (8.7%) with lakes and rainwater tanks, and one study was in Asia with lakes and parks (4.3%) (Appendix A).

Five single types of BMPs (e.g., trees, retention basins) and five more than one type of BMPs (e.g., trees + parks, detention basins + retention basins) were studied (Table 2). The economic effects of BMPs showed that different types of BMPs had positive (n = 19, 82.6%), negative (n = 12, 52.2%), and no relationships (n = 6, 26.1%) on housing prices (Table 2).

Trees. Trees were beneficial for residential communities that improved air quality, enhanced aesthetic appeal, and reduced the heat island effects (H. Sander et al., 2010). Such benefits were attractive to the neighborhood and residents, which led to higher property values.

Among twenty-three studies, four literatures (17.4%) studied only trees for the economic effects on housing prices (Donovan & Butry, 2010; Netusil et al., 2010; Li, 2019; Overwater, 2020). All four studies addressed the positive effects of trees on housing sale prices. Donovan & Butry (2010) found that the percent coverage/number of street trees within 100ft (30.5 m) positively impacted housing prices and street trees increased housing sale prices by an average of $8,870. Netusil et al. (2010) found that increased tree canopy coverages increased per-property benefits from 7.21% to 8.21% ($149-$528). The value of properties near tree planting locations (e.g., within 10 m buffer) increased by 1.2% in housing sale prices (Li, 2020). A 10% increase in trees per street (per 100 m) added a 0.03% to 0.05% premium to property prices (Overwater, 2020). This author also found that trees within 10-50 meters of property added a 0.02%-0.05% premium to property prices.

In contrast, a study showed that the increase in tree canopy coverages on the west side of Portland decreased property sale prices or tree canopy coverage within a quarter mile of properties had a significantly negative impact on housing sale prices (Netusil et al., 2010).

Table 2 Literature Review Matrix by types of BMPs and the effects on housing prices.

BMPs	n	Positive	Negative	No Relationship
Trees	4	Donovan & Butry ('10) Netusil et al. ('10) Li ('20) Overwater ('20)	Netusil et al. ('10)	
Detention Basins	1	Lee & Li (' 09)	Lee & Li ('09)	Lee & Li ('09)
Retention Basins	3	Natarajan et al. ('18)	Irwin et al. ('17) Jauregui et al. ('21)	Jauregui et al. ('21)
Parks	6	Espey & Owusu-Edusei ('01) Crompton ('04) Troy & Grove ('08) Cebula ('09) Larson & Perrings ('13)	Troy & Grove ('08) Larson & Perrings ('13) Kashian et al. ('18)	
Rainwater Tanks	1	Zhang et al. ('15)		
More than one BMPs				
Trees + Parks	2	Boslett ('12): **T** Franco & Macdonald **(**'18): **T, P**	Boslett ('12): **T, P** Franco & Macdonald **(**'18): **P**	
Trees + Retention Basins + Parks	3	Sander et al. ('10): **T, RB** Saphores & Li ('11): **T, P, RB** Jia & Zhang ('21): **T, P**	Saphores & Li ('11): **T, P** Jia & Zhang ('21): **T, RB**	Sander et al. ('10): **T**, **P**
Trees + Green street facilities	1	Netusil et al. ('14): **T, GF**		Netusil et al. ('14): **GF**
Detention Basins +	1	Sohn et al. ('20): **RB**	Sohn et al. ('20): **RB, DB**	Sohn et al. ('20): **DB**

Retention Basins				
Detention Basins + Rain gardens + Bio-retentions	1			Hoover et al. ('20): **DB, RG, BR**
Total	23 (100%)	19 (82.6%)	12 (52.2%)	6 (26.1%)

Note: Marks indicate T (Trees), DB (Detention Basins), RB (Retention Basins), P (Parks), GF (Green Street Facilities), RG (Rain Gardens), BR (Bio- Retentions)

These findings indicate that studies with only trees have more positive than negative effects on housing sale prices.

Detention Basins. Detention basins, called dry ponds, temporarily store stormwater and drain downstream gradually until completely drained (Shon et al., 2020). They can be stand-alone facilities or can be located within parks. Among twenty-three studies, one literature studied only detention basins for the economic effects of detention basins on housing property value (Lee & Li, 2009). They found positive, negative, and no effect of detention basins. Findings showed that proximity to detention basins within parks increased housing property values. As the 10-m distance was far away from the detention basins within parks, the residential property values decreased by $164.82 but properties with a view of detention basins located outside of the park decreased property value. Meanwhile, there was no evidence of the effect of detention basins on housing property value beyond 274 m (900 ft).

These findings indicated that a study only on detention basins had positive, negative, and no effects on housing property value.

Retention Basins. Retention basins, called wet ponds, were designed to hold stormwater permanently and functioned to store stormwater to remove the pollutants from runoff (Sohn et al., 2020). We included studies on lakes and ponds in this category because the functions of these BMPs are defined as retention ponds (Clar et al., 2004). Among twenty-three studies, three literature (13.0%) studied only retention basins for the economic effects on housing prices (Irwin et al., 2017; Jauregui et al., 2021; Natarajan et al., 2018). One study found that retention basins positively impacted housing prices (Natarajan et al., 2018). They addressed that every 100 m distance closer to the lakes, housing sale prices increased by AU$17.33.

In contrast, two studies showed that retention basins negatively impacted housing prices (Irwin et al., 2017; Jauregui et al., 2021). Proximity to stormwater retention basins decreased housing sale prices by $28,185 - $30,579 (13% - 14%) and the age of the retention basins decreased housing sale prices (Irwin et al., 2017). Jauregui et al. (2021) found proximity to retention basins from houses sold at discount prices compared to properties located further away. They also suggested that the view with stormwater retention basins from houses had no significant effect on housing prices (Jauregui et al., 2021).

These findings indicate that studies only on retention basins had positive effects, negative effects, and no relationship with housing prices.

Parks. The presence of parks in nearby residential areas was a crucial element to communities, residents, and the environment (Jia & Zhang, 2021). Parks offer recreation and leisure opportunities, social engagement and promote a healthy life and social engagement. Corresponding services include a sense of place, air quality enhancement (Escobedo et al., 2008), and attractiveness of view (Jim & Chen, 2006) for nearby residents.

Among twenty-three studies, six literature (26.1%) studied only parks for the economic effects on housing prices (Ceula, 2009; Crompton, 2004; Espey & Owusu-Edusei, 2001; Kashian et al., 2018; Larson & Perrings, 2013; Troy & Grove 2008). Five of six literature addressed that park had positive impacts on housing sale prices (Ceula, 2009; Crompton, 2004; Espey & Owusu-Edusei, 2001; Larson & Perrings, 2013; Troy & Grove, 2008). Homes adjacent to parks increased housing sale prices by 14% (Cebula, 2009) or received an approximate price premium of 22% relative to properties a half-mile away (Crompton, 2004). House sold for 6.5% higher price when the park was within 1,500 feet of the location compared to a house greater than 1,500 feet (Espey

& Owusu-Edusei, 2001). They also found that houses within 1,500 feet of the smaller size of neighborhood park sold 8.5% more than a house greater than far away (Espey & Owusu-Edusei, 2001). Also, Larson & Perrings (2013) found that a larger size of parks (e.g., >250 acres) positively affected housing prices. Troy and Grove (2008) found that with a 1% increase in distance, housing sale prices decreased by 2.2% or proximity to parks positively affected housing sale prices when the crime was below a certain threshold.

In contrast, three of six studies showed that parks negatively impacted housing sale prices (Kashian et al., 2018; Larson & Perrings, 2013; Troy & Grove, 2008). Kashian et al. (2018) found that adjacent to the park decreased housing value by $ 39,995 (14.54%) and suggested that distance away from parks were preferred. Larson & Perrings (2013) addressed that a smaller size of the park (e.g., <250 acres) negatively affected housing prices. In addition, proximity to parks negatively affected housing sale prices when the crime exceeds a certain threshold (Troy & Grove, 2008).

These findings indicate that studies only on parks had more positive effects than negative effects on housing prices.

Rainwater Tanks. Rainwater tanks, also known as rainwater harvesting systems, were increasing globally by reducing stormwater runoff (Zhang et al., 2015). Among twenty-three studies, a study showed that rainwater tanks positively affected housing sale prices (Zhang et al., 2015). Authors found that a premium of up to AU$18,000 was built into the sale prices of houses with rainwater tanks installed.

More than One BMPs. Out of 23 articles, eight articles (34.7%) include more than one BMPs. Each article included two or three BMPs in their article.

Trees + Parks. Among twenty-three studies, two literature (8.7%) studied a combination of trees and parks for the economic effects on housing sale prices (Boslett, 2012; Franco & Macdonald, 2018). Both studies found that trees and parks positively affected housing sale prices (Boslett, 2012; Franco & Macdonald, 2018). Boslett (2012) found that increased tree canopy coverages between 100-m and 150-m buffer increased the housing sale prices. The relative size of the tree canopy within a square kilometer increased by 0.20% of dwelling prices, or approximately €400 per dwelling (Franco & Macdonald, 2018). They also found that proximity to smaller parks capitalized on dwelling prices.

In contrast, both studies also negatively affected housing sale prices (Boslett, 2012; Franco & Macdonald, 2018). Boslett (2012) found that increasing tree canopy coverages within a 25-m buffer decreased housing sale prices. The author also found that proximity to community parks and neighborhood parks decreased housing sale prices. Franco & Macdonald (2018) found that proximity to the largest park negatively affected housing sale prices.

Trees + Retention Basins + Parks. Among twenty-three studies, three literature (13.0%) studied a combination of trees, retention basins, and parks for the economic effects on housing sale prices (Jia & Zhang, 2021; Sander et al., 2010; Saphores & Li, 2011).

All three studies addressed that combining trees, retention basins, and parks positively affected housing sale prices (Jia & Zhang, 2021; Sander et al., 2010; Saphores & Li, 2011). Jia & Zhang (2021) found that visible green plants positively affected housing sale prices. They also found that with every 1% increase in the size of the parks, the economic benefits increased between 2.9% and 3.0%. Sander et al. (2010) found that with every 10% increase in tree canopy coverage within a 100-m donut parcel increased the housing sale price by $1,371 (0.48%) and within a 250-m donut parcel increased the housing sale prices by $836 (0.29%). The authors also found that proximity to lakes increased housing sale prices. Saphores and Li (2011) found that additional neighborhood trees increased the value of the property by over 97%. They also found that proximity to national/state parks increased the value of property and far distance from the lakes decreased the property's value.

In contrast, two studies negatively affected housing sale prices (Jia & Zhang, 2021; Saphores & Li, 2011). Jia and Zhang (2021) found that increased distances from all kinds of green infrastructures (e.g., trees and lakes) increased housing sale prices by 5.4%, 4.9%, 2.7%, and 3.2%, respectively.

Another study found that increased tree canopy coverages within a 25 m buffer decreased the housing sale prices or increased parcel trees decreased the value of almost $40 of the properties (Saphores & Li, 2011). They also found that neighborhood parks negatively affected the property value.

A study found no relationship between tree canopy coverage and housing sale prices beyond 250-m and no effects of parks on housing prices (Sander et al., 2020).

Trees + Green Street Facilities. Among twenty-three studies, a study (4.3%) addressed the economic effects of combining trees and green street facilities (Netusil et al., 2014). They found both positive and no effects on a property's sale price. The property's sale price increased by $18, 707 as 10 percent point increase in tree canopy coverages near the closet green street facilities. They also found that proximity to green street facility increased the property sale prices by $0.30. However, the characteristics of green street facilities (e.g., size, proportion of the facility covered by tree canopy) did not significantly affect the sale price of the property.

Detention Basins + Retention Basins. Among twenty-three studies, a study (4.3%) addressed the economic effects of a combination of detention basins and retention basins (Sohn et al., 2020). They found positive, negative, and no effects on housing prices. Every 100 m (500 m) distance closer to the retention pond by Network distance analysis, housing sale prices increased by 1.4% (6.6%). The author also found that the view of the retention pond increased property values by 2.7%.

In contrast, every 100 m (500 m) distance closer to the retention pond by Euclidean distance analysis, housing sale prices decreased by 0.5% (2.7%). They also found that distances close to detention basins decreased housing sale prices. Every 100 m (500 m) distance closer to the detention pond, housing sale prices decreased by 0.3% (1.4%). Meanwhile, there was no evidence that existed between the distance and the view of detention pond (Sohn et al., 2020).

Detention Basins +Rain Gardens +Bio-retentions. Among twenty-three studies, a study (4.3%) addressed no significant evidence of the economic effects of a combination of detention basins, rain gardens, and bio-retention on housing prices (Hoover et al., 2020).

2.5 Discussion

Although research on the economic effects of stormwater BMPs on housing prices is limited, implementation of BMPs is critical since the need for flood control increases with the NPDES permit programs. While the hydrological functions of BMPs have been examined thoroughly, current debates remain on whether different designs, operations, or measurements of stormwater BMPs can provide extra economic benefits to housing prices. Our prominent findings of this review can be summarized various effects (e.g., positive, negative, and no relationships) of stormwater BMPs on housing prices. Relatedly, further research could be developed by following our suggestions.

Given our study results, findings suggested that studies with trees had more positive effects than negative effects on housing prices. Interestingly, distance was the major factor that affected the economic effects of tree canopy coverage on housing prices. Studies showed that distances (e.g., <10 m, 10-50 m, <30.5 m, <100 m, 100-150 m, <250 m, and <1 km^2) of tree canopy coverage from houses had positive impacts (Appendix A). However, distances (e.g., <25 m buffer and .25 miles) of tree canopy coverage from houses had negative or no impact beyond 250 m. Even though various distances had no patterns of economic effects of tree, such evidence might be explained by several possibilities. The positive effects of tree canopy coverages might be affected by the heterogeneity characteristics of surroundings, such as street trees, the presence of gardens, and access to nearby green spaces or parks. These surrounding amenities may reflect a preference for shading and the aesthetic environment they offer or different types of trees (e.g., Hawthrone trees) and vegetation compositions might positively affect housing prices (Donovan & Butry, 2010).

Meanwhile, studies with distances negatively affected trees on housing prices might be due to negative externalities, such as blocking views, causing diseases, or damaging pavement and housing structures if trees were nearby houses (Bolitzer & Netusil, 2000). Another possibility is that homeowners might not prefer planting trees in their properties due to maintenance cost. Yet, they might want to take advantage of tree canopy coverages from outside their properties, such as the beauty of streetscape and recreational and ecological benefits. Practically, three studies used street trees/ tree planting in public areas, but near their houses and addressed that street trees/ tree planting affected housing prices positively (Donovan & Butry, 2010; Li, 2019; Overwater, 2020).

Evidence of detention basins showed that studies found positive, negative, and no effects on housing prices. Distances and locations of detention basins affect housing prices. The results of distance have positive (every 10 m far away), negative (every 100 m and 500 m closer), and no impacts (beyond 274 m) on housing prices. Even though no patterns of distance were found, this might be due to several possibilities. It might be difficult to generalize the results because the number of studies of detention basins is relatively small and each study used different sizes and conditions of detention basins. Another point of our findings was that locations of detention basins were important for housing prices. For example, detention basins within parks had positive effects on housing prices. These might be due to the interactions with surrounding environmental characteristics and parks. Park designs might overcome the negative effects of detention basins by providing recreation facilities or different types of BMPs, such as rain gardens and trees, offer aesthetic values (e.g., view), composition of greenness and ecosystem functions, which positively affect the housing prices. In contrast, detention basins outside parks had negative effects on housing prices. These might be because detention basins outside parks needed more attention to manage the condition from maintenance.

Evidence of retention basins showed that studies found positive, negative, and no effects on housing prices. Distance and age of retention basins affect housing prices. The positive aspects of retention basins might be due to the benefits of permanent pools. Lake or pond collects the stormwater and allows for biological interactions, while dry ponds, a short-term water storage, disturb sufficient settlement of sand particles and prevent the removal of soluble contaminants (Hares & Ward, 1999; Søberg et al., 2016). In addition, nearby areas of well-maintained retention ponds generated value for community by offering a pleasant environment and diverse services (Irwin et al., 2017) or manufactured lakes were integrated with landscape design to produce the aesthetic view. Another interesting point of our finding is that different types of distance measurements (Euclidean distance vs Street Network distance) provided the reversed economic effects of retention basins on housing prices (Sohn et al., 2020). Although Euclidean distance was widely used to measure the proximity to environmental amenities, recent studies on hedonic pricing methods suggested that network distance analysis was preferred since it was assumed to be the shortest-travel distance that residents decided to walk (Sohn et al., 2020) and provided a more accurate representation than a straight line (Netusil et al., 2014).

In contrast, the negative aspects of retention basins might be due to poor maintenance conditions. Poor maintenance provides unpleasant environments, such as odor, pollution, degradations, etc. In addition, basins continuously influence house prices negatively as they age. Irwin et al. (2017) found that at least seven-year-old basins estimated the total negative price capitalization of stormwater basins to be over 17%.

Evidence of parks showed that studies found positive, negative, and no effects on housing prices. Size, distance, and types of parks affect housing prices. The positive effects of parks might be because residents near parks, like natural areas, had accessibility to green spaces, leisure amenities, and aesthetic value, which improved their property value. For example, a study supported that proximity to natural areas such as ponds and streams within the large park was one of the highest positive factors for home buying in southeast Michigan (Wang et al., 2012). In contrast, the negative effects of different types of parks (e.g., neighborhood parks, community parks) might be due to various externalities, such as the condition of parks' maintenance level, lack of government budgets, and degree of amenities. Another negative effect on the property sale price of the proximity of parks might be a result of perceived or actual crime. Our findings note that parks could be a place perceived as neighborhood liabilities if crime levels rise (Troy & Grove, 2008).

Although I reviewed the economic effects of twenty-three studies on housing prices, several limitations should be developed. This systematic review relied on the PRISMA systematic approach. While the outcome of using this tool was concise and allowed searching multiple resources with various steps, using other search platforms together might include more literature. In addition, the initial literature search relies on written English, and research was conducted in any region of the world using three databases: Google Scholar, ProQuest, and EBSCOhost. Our search approach might reflect potential biases. Studies written in other languages were excluded, researchers might not include non-reported studies, ongoing research, or other resources, and there might be a potential chance of systematic bias since I checked the titles, abstracts, and full text of articles manually for the outcomes.

In addition, I investigated over 32 years of literature and the number of studies on the economic effect of BMPs on housing prices was still small. To increase the number of studies, research on other types of stormwater BMPs (e.g., permeable pavements, filtering systems, swales) or measurements (e.g., size of detention basins), enlarge the sample size and extend the scope of the economic effects of BMPs on housing prices. As well as applying other methods (e.g., cost-effective analysis and life satisfaction) could increase the statistical power of the findings or including other property value factors, such as rental prices and property tax, might be helpful to understand the capitalization of BMPs because this review focused on housing sale prices.

Poor maintenance of BMPs should be considered since those concerns have various negative economic effects associated with environmental, infrastructure, and regulatory problems (Taguchi et al., 2020). For example, an increase in basins' age negatively affects housing sale prices since the aging of basins degrades the environmental condition surrounded by BMPs, which require frequent maintenance and inspection for better performance (Kong et al., 2007) and directly affects the cost. In addition, areas surrounded by BMPs without proper maintenance might be recognized as less critical because of negative public perception.

While studies have explained the maintenance issues, only a study considered the maintenance condition of detention basins and included method (e.g., different in different) to compare before and after the installations (Irwin et al., 2017). As BMPs have negative economic effects, the advantages of the economic effect of BMPs on housing prices might be uncertain, and long-term stormwater treatment capability might be questionable.

Several suggestions are provided to overcome these limitations. The frequency of maintenance and reduction of construction costs of BMPs must be considered when the design of green infrastructures is proposed and suggestions for multiple uses of BMPs should be considered. In addition, designs, functions, and maintenance are critical. Future work will consider a more purposeful approach to green infrastructure design if BMPs function to improve water quality and generate co-benefits. This thoughtful integration of the functions of BMPs with multiple uses, such as recreational use, might change the public perception of stormwater green infrastructure. Therefore, understanding BMPs factors (e.g., maintenance characteristics and perceptions) that affect the household's evaluation is necessary for improving the design and management of stormwater BMPs. Further, future literature might need to include variables which are associated with the condition of maintenance to estimate a better model than the current results. Data for maintenance variables is also important since current research mainly focused on the quantitative method, not including qualitative method.

2.6 Conclusion

This review study addressed several questions: What kinds of stormwater BMPs have been studied that affect housing prices over 32 years? Second, how do BMPs affect housing prices economically? Third, to generate an agenda for further study based on the evidence from this assessment, what are the other factors that contribute to boosting the economic effects of BMPs on housing prices and improving the limitations?

Based on the twenty-three literatures summarized here, fifteen literature (65.2%) studied single types of BMPs (e.g., trees, detention basins, parks) and eight literatures (34.8%) studied with more than one type of BMPs (e.g., trees + parks and detention basins + retention basins) over 32 years. Our robust findings address that BMPs show positive (n = 19, 82.6%), negative (n = 12, 52.2%), and no relationship (n = 6, 26.1%) on housing prices. Overall, our findings recommend that BMPs have more substantially positive than negative economic impacts on housing prices and provide several suggestions to develop the limitations of the current literature.

There are several strategies for enhancing the economic effects of BMPs in current literature. A range of factors should be measured together since BMPs are affected by size, age, conditions, locations (e.g., within parks), and the level of maintenance simultaneously. Strategies for well-maintained BMPs might be an attractive factor that encourages residents to live nearby and increase the property value. Further, advanced policies and supportive programs can develop the initial phase of designs, maintain multiple functions, and avoid the depreciation of housing construction of BMPs. Such considerations generate residents to install BMPs that positively impact their property value. Above all, experts, landscape architects, economists, planners, and governments from multidisciplinary fields need their collaboration to generate long-term value for communities, serving environmental, social, and economic benefits.

Chapter 3: The Economic effects of stormwater Best Management Practices (BMPs) on Housing Sale Prices in Washington, D.C.

3.1 Introduction

Stormwater runoff poses various environmental risks as urbanization progresses and precipitation intensity rises. During intense rainfall, increased runoff speed alters water volume and velocity, carrying pollutants that harm ecosystems and property (Braden & Johnston, 2004; National Research Council, 2009). As awareness of stormwater management grows, structural solutions like trees, detention basins, and retention basins become crucial for mitigating runoff issues, addressing environmental concerns, and promoting sustainable development (Arnold & Gibbons, 1996).

The integration of stormwater best management practices (BMPs) into green infrastructure has gained attention in the past two decades (Fletcher et al., 2015). Following the adoption of the National Pollutant Discharge Elimination System (NPDES) permit program by the U.S. Environmental Protection Agency (EPA) in the early 1990s, regulations were established for managing water runoff from municipalities, construction sites, and industrial facilities nationwide (Department of Energy and the Environment, 2022). In Washington, D.C., stormwater management regulations have been in place since 1988, aiming to reduce pollution through BMPs capable of directing, retaining, and absorbing stormwater (Department of Energy and the Environment, 2022).

While many studies have examined the physical and biological impacts of stormwater BMPs (Steinnes, 1992), research on their economic effects on housing prices has been limited.

This study addresses two key questions: Do stormwater BMPs positively influence housing prices? How do the proximity and quantity of structural BMPs impact housing sale prices?

3.2 Literature Review

Previous research indicates that stormwater BMPs can have varied economic impacts on housing prices, including positive, negative, and no effects. These studies predominantly utilize the hedonic pricing method, which allows for the breakdown of asset prices into different components such as environmental, structural, locational, and neighborhood attributes. Analysis with ArcGIS Pro tool is employed to quantify factors like percentage (e.g., tree canopy coverage), proximity/distance buffer, and count of BMPs to assess their influence on housing sale prices.

Research on the impact of trees on housing sale prices has been conducted by several scholars (Donovan & Butry, 2010; Li, 2020; Netusil et al., 2010; Sander et al., 2010; Overwater, 2020). Housing sale price increases as tree canopy coverage increases between 100 m and 150 m buffer (Donovan & Butry, 2010). The percentage coverage/number of street trees within 100ft (30.5 m) positively impacted housing prices, and street trees increased housing sale prices by an average of $8,870 (Donovan & Butry, 2010). Netusil et al. (2010) also found that increased tree canopy coverages increased per-property benefits from 7.21% to 8.21% ($149 - $528). Li (2020) found that the value of properties near tree planting locations (e.g., within 10 m buffer) increased by 1.2% in housing sale prices. A 10% increase in trees per street (per 100 m) added a 0.03% to 0.05% premium to property prices (Boslett, n.d.). This author also found that trees within 10-50 meters of the property added a 0.02%-0.05% premium to property prices. Meanwhile, housing sale prices decreased as tree canopy coverages increased within a 25 m buffer (Boslett, 2012). In addition, an increase in tree canopy coverage on the west side of Portland decreased property sale prices, or tree canopy coverage within a quarter mile of properties negatively impacted on housing sale prices (Netusil et al., 2010).

Studies of impervious surfaces contribute to housing sale prices (H. Sander et al., 2010; H. A. Sander & Haight, 2012). The mean impervious surface area in a 500 m neighborhood surrounding each property was negatively related to housing sale prices (H. Sander et al., 2010). The area of impervious land cover (26% - 51% and 51% - 76%) in the home's viewshed was negatively related to housing sale prices (H. A. Sander & Haight, 2012). In contrast, the mean area of impervious surface within 500 m of the home was positively related to housing sale prices (H. A. Sander & Haight, 2012).

Previous studies have also demonstrated the positive impacts of best management practices (BMPs) within parks on housing prices compared to those outside of parks (Lee & Li, 2009). Lee &Li (2009) revealed that proximity to BMPs inside parks was associated with decreased residential property values, with values dropping by $164.82 for every 10 m increase in distance from the BMPs. However, this effect was not significant beyond a distance of 274 m (900 ft) from the BMPs. Distance to BMPs outside of parks did not exhibit a notable effect on housing property values.

However, this effect was not significant beyond a distance of 274 m (900 ft) from the BMPs. Distance to BMPs outside of parks did not exhibit a notable effect on housing property values. The primary purpose of this study is to assess the contributions of economic effects of stormwater BMPs on housing sale prices in Washington, D.C., USA. Hedonic models were applied to analyze the statistical impact of environmental attributes while controlling for a set of housing structural, locational neighborhood, and wards variables.

3.3 Materials and Methods

3.3.1 Study Area

The study is conducted in Washington, District of Columbia (D.C.), situated in the mid-Atlantic region of the eastern United States. Covering approximately 177 square kilometers, the District comprises three distinct water bodies and is divided into eight individual wards (Figure 2). Three significant water resources—namely, the Anacostia River, Rock Creek, and Potomac River—flow into the District from neighboring jurisdictions. The Potomac River lies to the south, the Anacostia River to the east, and Rock Creek to the north. The District's water infrastructure includes two primary wastewater collection systems: "combined" and "separate" sewers. The population of D.C. was 671,803 in 2022 with a population of 46.2% White, 45.0% Black, 4.7% Asian, and 11.7% Hispanic/Latino (U.S. Census Bureau, 2022). The District’s estimated median household income was $101,722 in 2022 in U.S. dollars (U.S. Census Bureau, 2022). The average tree canopy coverage was 37% in 2021 and the District is planning to increase tree canopy coverage up to 40% by 2032, which was linked to an annual planting target of 8600 trees/year (District of Columbia Urban Tree Plan, 2021).

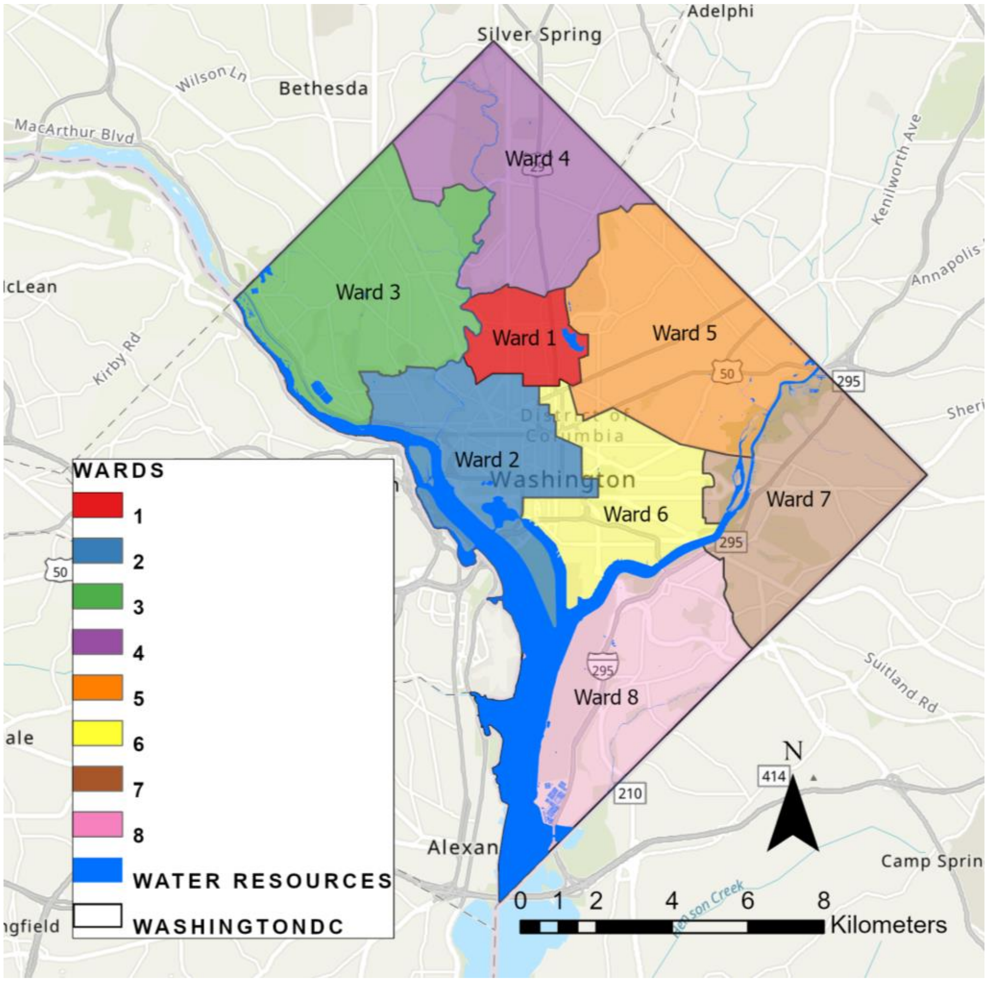

Figure 2 Study area Washington, D.C., with wards and water resources. *Note*. Map sources: Esri, HERE, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors and the GIS User Community

3.3.2 Data and Measurement

The hedonic pricing method was developed after the listwise deletion to assess the impact of stormwater BMPs on housing sale prices for each analysis. Data were processed and analyzed using Microsoft® Excel 2401, Statistical Package for the Social Sciences (SPSS®) 26.0, and ArcGIS Pro 3.2.0.

The measurements and units of dependent variables, environmental, structural, locational and neighborhood, and wards variables were shown in Table 3.

Table 3 Variables, measurement, and unit (n= 4537)

Variables	**Measurement**	**Unit**
Housing sale price (logged)	Single-family Housing sale price = logged (price)	US dollar ($)
Environmental variables		
Proximity		
House to parks with BMPs	Euclidean distance from housing parcel to parks parcel with BMPs	(m)
House to parks with no BMPs	Euclidean distance from housing parcel to parks parcel without BMPs	(m)
House to BMPs inside of parks	Euclidean distance from housing parcel to BMPs points inside of the parks	(m)
House to BMPs outside of parks	Euclidean distance from housing parcel to BMPs points outside of the parks	(m)
Count		
25 m BMPs	Number of BMPs within 25 m buffer from housing parcel	(Count)
50 m BMPs	Number of BMPs within 50 m buffer from housing parcel	(Count)
75 m BMPs	Number of BMPs within 75 m buffer from housing parcel	(Count)
100 m BMPs	Number of BMPs within 100 m buffer from housing parcel	(Count)
Landcover		
25 m tree coverage	Tree coverage within 25 m donut buffer from housing parcel	(%)
50 m tree coverage	Tree coverage within 50 m donut buffer from housing parcel	(%)
75 m tree coverage	Tree coverage within 75 m donut buffer from housing parcel	(%)
100 m tree coverage	Tree coverage within 100 m donut buffer from housing parcel	(%)
25 m impervious surfaces	Impervious surfaces within 25 m donut buffer from housing parcel	(%)
50 m impervious surfaces	Impervious surfaces within 50 m donut buffer from housing parcel	(%)
75 m impervious surfaces	Impervious surfaces within 75 m donut buffer from housing parcel	(%)
100 m impervious surfaces	Impervious surfaces within 100 m donut buffer from housing parcel	(%)
25 m impervious roads	Impervious roads within 25 m donut buffer from housing parcel	(%)
50 m impervious roads	Impervious roads within 50 m donut buffer from housing parcel	(%)
75 m impervious roads	Impervious roads within 75 m donut buffer from housing parcel	(%)
100 m impervious roads	Impervious roads within 100 m donut buffer from housing parcel	(%)
Structural variables		
Lot size	Parcel size	Logged (ft^2)
Bathroom	Number of total bathrooms	(Count)
Air conditioner	Air conditioner = 1; others = 0	(0/1)
Bedroom	Number of bedrooms	Sqrt (Count)
Building size	Gross building area in square feet	(ft^2)
Age of building	Building age	(year)
Remodeled age	Remodeled age of housing structure	(year)
Structural grade rating	=1 (lowest) to 12 (highest)	
Structural condition rating	=1 (lowest) to 6 (highest)	
Fireplaces	Fireplaces = 1; others = 0	(0/1)
Locational and neighborhood variables		
Population density	Population/Total area in square meters at census tract	
Crime	Number of reported crimes/total population at census tract	
Unemployment	Unemployment rate in census tract	(%)
Income	Median Income in census tract	US dollar ($)
Vacancy	Vacancy rate in census tract	(%)
Poverty	Poverty rate in census tract	(%)
Age	Median age of residence	(year)
Moved 2017 or later	Number of years living (tenure) 2017 or later in census tract	(%)
Moved 2015–2016	Number of years living (tenure) 2015–2016 in census tract	(%)
Moved 2010–2014	Number of years living (tenure) 2010–2014 in census tract	(%)
Moved 2000–2009	Number of years living (tenure) 2010–2009 in census tract	(%)

Moved 1990–1999	Number of years living (tenure) 1990–1999 in census tract	(%)
Moved 1989–earlier (Reference group)	=0 in all moved population categories	
Public schools	Euclidean distance from housing parcel polygon to public schools point	(m)
Grocery stores	Euclidean distance from housing parcel polygon to grocery stores point	(m)
Religious centers	Euclidean distance from housing parcel polygon to worships point	(m)
Shopping centers	Euclidean distance from housing parcel polygon to shopping centers point	(m)
U.S. Capitol	Euclidean distance from housing parcel polygon to U.S. Capitol point	(m)
Wards		
High-income ward	Median income (\$111,064–\$128,670) = 1, otherwise = 0	(0/1)
Medium-income ward	Median income (\$94,810–\$102,882) = 1, otherwise = 0	(0/1)
Low-income ward (Reference group)	Median income (\$35,245–\$71,782) = 1, otherwise = 0	(0/1)

The dependent variables utilized in the hierarchical regression models consist of the logged housing sale prices recorded between January 2017 and December 2020. These data were sourced from two distinct datasets: computer-assisted mass appraisal (CAMA) residential data and common ownership lots data available through the District's open access dataset provided by the Department of Energy & Environment (DOEE). The CAMA data provided details regarding housing sale prices and structural characteristics such as lot size, number of bathrooms, and housing dimensions. To enhance spatial analysis using ArcGIS Pro, we merged the CAMA data with the common ownership lots data, which included geographic coordinates for each housing parcel along with housing sale prices. Best management practices (BMPs) data was obtained between 2017 – 2020 from DOEE. The BMPs data include 3 types of BMPs: bioretention, rainwater harvesting, and tree planting and preservation. The data provided geographical locations, BMPs type, installation date, sur-face area of BMPs, and volume of BMPs, etc. The following indicators of BMPs data were used in this study: geographical locations and installation date of BMPs.

Initially, the dataset comprised a total sample size of n=24,084 entries. Outliers were subsequently identified and removed, and the dataset was refined to solely include single-family properties, encompassing detached, row, and semi-detached houses. Additionally, six instances of duplicate housing addresses were identified through cross-referencing with real estate websites like Zillow, Trulia, and Redfin to ensure accuracy in structural information such as the number of bedrooms and bathrooms. Following these procedures, a total of 4,537 entries remained in the dataset after implementing a listwise deletion approach.

The land cover data utilized in this study were acquired from the Chesapeake Conservancy (2022) in collaboration with the U.S. Geological Survey (USGS). Specifically, the dataset employed was the Land Use/Land Cover Data Project 2017/2018, which offered a 3-meter resolution and encompassed 54 detailed classes and 18 general classes. This dataset incorporated high-resolution satellite imagery featuring various minimum mapping units for each class, including water bodies, wetlands, tree canopy, shrubland, low vegetation, barren land, structures, impervious surfaces, impervious roads, tree canopy over structures, tree canopy over impervious surfaces, and tree canopy over impervious roads.

In this study, three key indicators derived from the land cover data were utilized: tree canopy coverage, impervious surface area, and impervious road coverage, with a minimum mapping unit (MMU) set at 9 square meters. The preparation of the land cover data involved calculating the percentage of tree canopy coverage, impervious surface area, and impervious road coverage. Subsequently, buffer analysis was conducted using ArcGIS Pro to generate buffers at distances of 25 m, 50 m, 75 m, and 100 m from the housing property parcels.

Data on parks were sourced from the Department of Energy & Environment (DOEE). The park dataset encompassed three distinct categories: national parks, parks and recreational areas, and community gardens. To assess proximity to parks and the locations of Best

Management Practices (BMPs) associated with parks, the study incorporated variables such as estimated distance from houses to parks with BMPs, parks without BMPs, BMPs located inside parks, and BMPs situated outside parks. Utilizing the BMPs and park data, the study employed Euclidean distance measurements in meters from each sold property to the nearest variable. This calculation was performed using the Near Analysis function within ArcGIS Pro. The same procedure was repeated to determine the distance from each property to the nearest park with BMPs, park without BMPs, BMPs inside parks, and BMPs outside parks. To ascertain the count of BMPs within specified buffer zones around housing property parcels, the study conducted buffer analysis and employed the spatial join tool in ArcGIS Pro. This process was repeated for buffer zones of 25 m, 50 m, 75 m, and 100 m. In the buffer analysis, the area of the housing parcel was excluded, and only the overlap buffer area (e.g., the 50 m buffer included the 25 m buffer area) was considered.

To assess the impact of land cover on housing sale prices, a buffer analysis was conducted using ArcGIS Pro. The analysis involved calculating the percentages of tree canopy coverage, impervious surfaces, impervious roads, as well as the presence of tree canopy over structures, impervious surfaces, and impervious roads. These calculations were performed at 25-meter intervals from the housing property parcel polygons. The process was repeated for buffer distances of 25 m, 50 m, 75 m, and 100 m. A maximum buffer distance of 100 m from housing parcels was chosen because areas beyond this distance were located outside the boundaries of Washington, D.C.

The structural attributes of the chosen single-family homes, including lot dimensions, building age, and the count of bathrooms and bedrooms, were obtained from the Department of

Energy & Environment (DOEE). These variables were incorporated into the statistical models to mitigate capitalization effects.

The locational and neighborhood characteristics of the selected single-family homes, such as population density, median income, and proximity to public schools and shopping centers, were sourced from the Department of Energy & Environment (DOEE). These variables were included in the statistical models to address capitalization effects.

The District is divided into eight wards, as provided by DOEE. These wards were grouped into three categories based on their median income ranges. The high-income ward group had a median income range of $111,064 to $128,670, the medium-income ward group ranged from $94,810 to $102,882, and the low-income ward group ranged from $35,245 to $71,782. Wards 1, 2, 3, and 6 were classified under the high-income ward group, wards 4 and 5 were categorized as medium-income wards, and wards 7 and 8 were designated as low-income wards.

3.3.3 Analytical Procedures: Hedonic Pricing Method

The valuation of residential properties poses challenges due to their diverse characteristics. The hedonic pricing method has been extensively utilized and studied in the housing market to address this issue (Kong et al., 2007). This method employs statistical techniques to estimate the contribution of individual attributes, such as housing structure and environmental amenities, to housing values (Kong et al., 2007; Malpezzi, 2002).

Established by Lancaster's theory (Lancaster, 1966), the hedonic pricing method addresses physical and other heterogeneous features (e.g., geographical location, occupancy), which can be often unobserved by homeowners (Sheppard, 1999). These factors might be considerable for homeowners when they purchase their homes. In this sense, housing sale prices are determined by a group of several factors. They consist of environmental, structural, and locational and neighborhood attributes, which is the functional form of the empirical model that can be expressed as follows:

$$\text{HP} = f\,(x_1, x_2, x_3, x_4, \cdots, x_i) \tag{3.1}$$

Where HP is the housing sale prices of individual properties and x variables indicate heterogeneous dimensions of housing characteristics. The heterogeneous characteristics can be divided into several groups, which can be expressed as follow:

$$\text{HP} = \alpha + \beta_1 S + \beta_2 L + \beta_3 E + \varepsilon \tag{3.2}$$

where P is an (n × 1) vector of housing prices; S is an (n × i) matrix of housing structure attributes; L is an (n × j) matrix of locational attributes; E is an (n × k) matrix of neighborhood environmental attributes. α is constant, and β_1, β_2, β_3 are the estimated parameter vectors, and ε is a (n × 1) vector of error terms which is normally distributed with a zero mean and constant variance.

This study employed the hierarchical regression analysis method, which effectively accounts for testing whether each set of attributes can significantly explain the variance of the dependent variable (i.e., housing sale prices) while statistically controlling the set of housing structure variables (Malpezzi, 2002). In hierarchical regression models, independent variables can be divided into small groups depending on the variables' characteristics: Environmental, Structural, Locational and Neighborhood, and Wards attributes. A proper sequence of sets of attributes is called "hierarchy". Based on previous research and the principle of hierarchical order, this study used the model with the hierarchy: (1) Environmental, (2) Structural, (3) Locational and Neighborhood, and (4) Wards. These four sets of variables were put into model cumulatively in hierarchical order.

$$\ln P_i = \alpha + \beta_1 E_i + \varepsilon_i \tag{3.3}$$

$$\ln P_i = \alpha + \beta_1 E_i + \beta_2 S_j + \varepsilon_i \tag{3.4}$$

$$\ln P_i = \alpha + \beta_1 E_i + \beta_2 S_j + \beta_3 L_k + \varepsilon_i \tag{3.5}$$

$$\ln P_i = \alpha + \beta_1 E_i + \beta_2 S_j + \beta_3 L_k + \beta_4 W_m + \varepsilon_i \tag{3.6}$$

where $\ln P_i$ is the log of the housing sale prices i; E_i is a vector of environmental variables, including proximity of house to parks with BMPs, house to parks with no BMPs, house to BMPs inside of parks, house to BMPs outside of parks, count of BMPs with 25 m, 50 m, 75 m, 100 m, tree canopy coverage with 25 m, 50 m, 75 m, 100 m, impervious surface with 25 m, 50 m, 75 m, 100 m, and impervious roads with 25 m, 50 m, 75 m, 100 m; S_j is a vector of structural variables, including lot size, total number of bathrooms, number of bedrooms, building size, building age, remodeled age, structural grading rating, structural condition rating, fire places, years of living (tenure) at the census tract, and air conditioner as a dummy; L_k is a vector of locational and structural variables, including population density, crime rate, unemployment rate, median income, vacancy, poverty rate at the census tract, median age of residence, and distance to public schools, grocery stores, religious centers, and shopping centers; W_m is a vector of wards including high, median, and low median income as dummy variables.

The coefficients to be estimated are β_1, β_2, β_3, and β_4, and ε is an error term. Therefore, housing sale prices are transformed into logs, which are interpreted as the price percentage changes resulting from one additional unit of the independent variable approximately. The R-square (R^2) of the model increases as additional independent variables are introduced in the model. The increment of R^2 prior sets was not affected by the subsequent groups of explanatory variables (Malpezzi, 2002), which can be shown as follows:

$$R^2_{\mathrm{Y \cdot ESLW}} = R^2_{\mathrm{Y \cdot E}} + R^2_{\mathrm{Y \cdot (E \cdot S)}} + R^2_{\mathrm{Y \cdot (E \cdot S \cdot L)}} + R^2_{\mathrm{Y \cdot (E \cdot S \cdot L \cdot W)}} \tag{3.7}$$

where $R^2_{\mathrm{Y \cdot ESLW}}$ is the coefficient of determination of the full model; $R^2_{\mathrm{Y \cdot E}}$ is the coefficient of determination of the model only including a set of environmental variables; $R^2_{\mathrm{Y \cdot (E \cdot S)}}$ is the increment of the coefficient of determination of the model including environmental variables and structural variables; $R^2_{\mathrm{Y \cdot (E \cdot S \cdot L)}}$ is the increment of the coefficient of determination of the model including environmental variables, structural variables, and locational and neighborhood variables. $R^2_{\mathrm{Y \cdot (E \cdot S \cdot L \cdot W)}}$ is the increment of the coefficient of determination of the model including environmental variables, structural variables, locational and neighborhood variables, and ward variables.

3.4 Results

3.4.1 Descriptive Statistics

I weighted data by ward groups to correct the under-representation issue of the low-income ward so our data can accurately represent the population before analysis. Table 4 shows the summary statistics for wards before data weighted.

Table 4 Summary statistics for wards before data weighted.

Variables	Mean	Median	Standard Deviation	Min	Max
Wards (dummy)					
High-income ward	.59	.00	.49	.00	1.00
Medium-income ward	.34	.00	.47	.00	1.00
Low-income ward (Reference group)	.07	.00	.24	.00	1.00

Table 5 provides descriptive statistics including the housing sale prices, environmental variables, structural variables, locational and neighborhood variables, and ward variables after data is weighted. I used a listwise deletion approach to exclude any missing cases to compare the results among different buffer distances.

Table 5 Summary statistics for environmental, structural, locational and neighborhood, and ward variables after data weighted (n = 4537).

Variables	Mean	Median	Standard Deviation	Min	Max
Housing sale price (2017–2020 US$)	1,105,715.38	909,384.59	881,163.58	77,000	17,750,000
Housing sale price (logged)	5.96	5.95	.24	4.90	7.20
Environmental variables					
Proximity					
House to parks with BMPs	623.13	551.94	421.02	.00	2,409.87
House to parks with no BMPs	179.24	155.31	121.86	.00	671.40
House to BMPs inside of parks	847.29	760.87	495.43	45.22	2,639.97
House to BMPs outside of parks	84.20	66.38	74.31	.00	619.98
Count					
25 m BMPs (sqrt)	.24	.00	.58	.00	4.00
50 m BMPs (sqrt)	.60	.00	.87	.00	4.58
75 m BMPs (sqrt)	.97	1.00	1.02	.00	4.90
100 m BMPs (sqrt)	1.35	1.41	1.15	.00	5.57
Landcover					
25 m tree coverage (%)	38.96	37.62	17.80	.00	96.35
50 m tree coverage (%)	37.82	36.40	16.95	.44	96.67
75 m tree coverage (%)	37.25	35.94	15.72	2.55	92.69
100 m tree coverage (%)	37.13	35.34	15.55	2.20	90.93
25 m impervious surfaces (%)	9.26	7.77	6.83	.00	54.93
50 m impervious surfaces (%)	9.49	8.29	6.59	.00	53.01
75 m impervious surfaces (%)	10.12	9.01	6.49	.08	46.83
100 m impervious surfaces (%)	10.46	9.55	6.36	.14	38.38
25 m impervious roads (%)	17.45	17.00	7.95	.00	53.76
50 m impervious roads (%)	16.59	16.37	6.92	.00	43.72
75 m impervious roads (%)	16.47	16.55	5.66	.76	38.15
100 m impervious roads (%)	16.26	16.42	5.28	1.34	35.72
Structural variables					
Lot size (lg_ft²)	8.08	8.16	.74	5.54	10.65
Bathroom (count)	3.04	3.00	1.15	.5	12.5
Air conditioner (dummy)	.93	1.00	.24	.00	1.00
Bedroom (Sqrt_count)	3.75	4.00	1.24	1.00	47.00
Building size (ft²)	1,937.17	1,696.00	928.70	528	14,12
Age of building (year)	91.94	92.00	23.82	6.00	240.00
Remodeled age (year)	11.04	7.00	12.81	.00	109.00
Structural grade rating	1.18	1.16	.22	.75	2.90

Structural condition rating	1.08	1.07	.05	.79	1.23
Fireplaces (dummy)	.11	.00	.17	.00	1.00
Locational and neighborhood variables					
Population density (%)	.51	.38	.35	.09	2.47
Crime (%)	15.24	12.00	9.94	2.00	54.00
Unemployment (%)	6.32	4.90	4.77	.20	31.6
Income (median)	123,293.79	121,176.00	55,755.94	14,413	250,00
Vacancy (%)	1.52	.00	2.50	.00	13.10
Poverty (%)	7.38	3.30	9.45	.00	63.50
Age	37.59	38.40	6.01	20.00	47.30
Moved 2017 or later (%)	10.12	9.58	5.38	.00	32.05
Moved 2015–2016 (%)	25.70	24.80	8.84	3.61	59.02
Moved 2010–2014 (%)	14.88	14.71	5.04	2.06	41.77
Moved 2000–2009 (%)	16.83	16.05	6.15	3.80	35.18
Moved 1990–1999 (%)	10.02	9.01	5.50	.00	22.44
Moved 1989–earlier (%) (Reference group)	13.70	11.96	8.78	.47	45.45
Distance to public schools (m)	494.86	428.44	296.97	23.74	1,884.71
Distance to grocery stores (m)	835.84	684.28	561.97	34.16	3,373.67
Distance to religious centers (m)	270.63	195.77	253.38	.00	1,946.87
Distance to shopping centers (m)	1,383.99	1059.76	1,129.95	43.97	5,609.40
Distance to Capitol (m)	5,980.53	5,938.30	2,633.09	526.70	11,982.89
Wards (dummy)					
High-income ward	.51	1.00	.49	.00	1.00
Medium-income ward	.25	.00	.43	.00	1.00
Low-income ward (Reference group)	.23	.00	.42	.00	1.00

Note. Moved 1989–earlier (%) is reference group; low-income ward is reference group.

Environmental variables. The mean proximity of houses to parks with BMPs was 623.13 m, while the mean proximity of houses to parks with no BMPs was 179.24 m. This indicated that the mean proximity of houses to parks with BMPs was further than the mean proximity of houses to parks with no BMP. In other words, people could easily access the parks regardless of BMPs. The mean proximity of houses to BMPs inside the parks was 847.29 m, while the mean proximity of houses to BMPs outside of parks was 84.20 m. This indicated that the mean proximity of houses to BMPs inside of parks was further than the mean proximity of houses to BMPs outside of parks, and BMPs themselves were located near housing property. The mean count of BMPs was increased from .24 to 1.35 as every 25 m buffer increased from the property. The mean percentage of tree canopy coverage consistently decreased from 38.96% to 37.13% as every 25 m buffer increased from the property. The mean percentage of impervious surfaces consistently increased from 9.26% to 10.46% as every 25 m buffer increased from the property. The mean percentage of impervious roads consistently decreased from 17.45% to 16.26% as every 25 m buffer increased from the property.

Structural variables. The mean number of bathrooms was 3.04 and the number of bedrooms was 3.75. The mean age of the building was 91.94. The oldest age of the building was 240 and the youngest age of the building was 6.

Locational and Neighborhood variables. The mean crime rate at census tract was 15.24%. The mean age of the population at census tracts was 37.59, which revealed that the residents in the District were predominantly populated with young adults. The mean distance to the U.S Capitol from property was 5,980.53 m, which was the far distance among other variables. The mean distance to religions centers was 270.63 m, which was the shortest distance among other variables.

Wards variables. Unweighted data showed that the mean high-income wards group was .59, the mean medium-income wards group was .34, and the mean low-income ward group was 0.07 (Table 4). After the data were weighted, the mean high-income ward group became 0.51, the mean medium-income ward group became 0.25, and the mean low-income ward group became 0.23 (Table 5). Our weighted data represented the proportion of each ward group better than the unweighted data.

3.4.2 Hierarchical regression model

This study uses hierarchical regression models to determine whether a set of independent variables significantly improved the hedonic models. Model 1 includes environmental variables (Table 6), model 2 includes environmental and structural variables, model 3 includes environmental, structural, and locational and neighborhood variables. I reported R-squared and R-squared changes for model 2 and model 3 to see the change of R-squared across the models (Table 7). Model 4 includes environmental, structural, locational and neighborhood, and wards variables (Table 8). The summary of the hierarchical regression model includes coefficient, significance, and R-squared in all buffers (25 m, 50 m, 75 m, and 100 m) (Table 6 and 8).

3.4.3 Model 1

Model 1 estimated the impact of the environmental variables on housing sale prices (Table 6). The model is constructed for 4,537 single-family houses after list-wise deletion in all buffers: 25 m, 50 m, 75 m, and 100 m.

Among proximity variables, proximity to house to BMPs outside of parks are significantly predicted on housing sale prices in all buffers: 25 m (β = .293, p < .001); 50 m (β = .295, p < .001); 75 m (β = .253, p < .001); and 100 m (β = .254, p < .001). This result indicates that coefficients for all buffers are positive, which is associated with an increase in housing sale prices as the proximity to house to BMPs outside of parks increased. While controlling for other covariates, a 1 unit increase in house to BMP outside park is associated with .293 unit increase in 25-m; .295 in 50-m; .253 in 75-m; and .254 in 100 m. The coefficient for proximity to house to BMPs outside of parks within 25 m - 50m increased the most from .293 to .295 (d = .002). The coefficient for proximity to house to BMPs outside of parks within 50 m – 75 m decreased the most from .295 to .253 (d = -.042).

Percent tree canopy coverages are significantly predicted on housing sale prices in buffers: 25 m (β = .089, p < .01); 50 m (β = .064, $p \leq$ .05); and 100 m (β = -.066, $p \leq$ .05). This indicates that both coefficients for 25 m and 50 m buffers are positive which means that housing sale prices increase as tree canopy coverage increases. The coefficient becomes negative and significant in 100 m buffer which indicates that housing sale prices decrease as tree canopy coverage increases. The coefficient for percent tree canopy coverages within 25 m – 100 m decreased the most from .089 to -.066 (d = -.155).

Percent impervious surfaces are significantly predicted on housing sale prices in all buffers: 25 m (β = -.047, $p \leq$.05); 50-m (β = -.080, p <.001); 75-m (β = -.094, p < .001), and 100-m (β = -.102, p < .001). The coefficient for percent impervious surfaces within 25 m – 100 m increased the most from -.047 to -.102 (d = .055). Percent impervious roads were significantly predicted on housing sale prices in buffers: 25 m (β = -.071, p < .001); 50 m (β = -.099, p < .001); 75 m (β = -.201, p < .001); and 100 m (β = -.231, p < .001). The coefficient for percent impervious roads within 25 m - 100 m increased the most from -.071 to -.231 (d = .16). The coefficients for both percent impervious surfaces and impervious roads are all negative which means that housing sale prices decreases as both percent impervious surfaces and impervious roads increases in all buffers.

The R-squared consistently increases from 25-m ($R^2 = .117$) to 75-m ($R^2 = .143$) buffers, then has the same value in 100-m buffer ($R^2 = .143$).

Table 6 A summary of regression in model 1, including environmental variables.

Variables	**25-m**	**50-m**	**75-m**	**100-m**
Variable Intercept	5.887 ***	5.938 ***	6.109 ***	6.170 ***
Environmental variables				

Proximity				
House to Park with BMPs	.000	.009	.018	.015
House to Park no BMPs	-.013	-.015	-.017	-.020
House to BMPs inside of Park	.012	-.004	-.017	-.015
House to BMPs outside of Park	.293 ***	.295 ***	.253 ***	.254 ***
Buffer				
Count of BMPs	.010	.005	-.044 *	-.033
Landcover				
% tree canopy coverages	.089 **	.064 *	-.022	-.066 *
% impervious surfaces	-.047 *	-.080 ***	-.094 ***	-.102 ***
% impervious roads	-.071 ***	-.099 ***	-.201 ***	-.231 ***
R^2	.117	.127	.143	.143

*Note: Dependent variable: logged housing sale prices 2017 – 2020; standardized β is reported in all variables. * $p \leq .5$. ** $p < .1$. *** $p < .001$.

3.4.4 Model 2 and 3

R-squared and R-squared changes of model 2 and 3 in all buffers are shown in Table 7. The R-squared change constantly increases in all buffers across the models. Interestingly, the most drastic R-square change is in model 2 after adding structural variables in all buffers: 25 m (.609); 50 m (.601); 75 m (.585); 100 m (.583). This indicates that structural variables highly impact housing sale prices among other variables. After adding locational and neighborhood variable, the R-square change slightly increases in all buffers: 25 m (.152); 50 m (.150); 75 m (.150); 100 m (.152).

We also examined the variance inflation factors (VIF) to detect multicollinearity while running hierarchical regression models. None of the independent variables had VIF values greater than 10. All fifty-one independent variables were kept, and the variance of the dependent variable was well explained by the independent variables.

Table 7 R-squared and R-squared changes in Model 2 and 3 in 25-m, 50-m, 75-m, and 100-m buffers.

Variables	**25 m buffer**	**50m buffer**	**75 m buffer**	**100 m buffer**

	25-m	50-m	75-m	100-m
Model 2				
R^2	.726	.728	.728	.727
Change R^2	.609	.601	.585	.583
Model 3				
R^2	.878	.879	.878	.878
Change R^2	.152	.150	.150	.152

*Note. Model 2 includes environmental and structural variables. Model 3 includes environmental, structural variables, and locational and neighborhood variables.

3.4.5 Model 4

Model 4 includes environmental, structural, locational and neighborhood, and wards variables (Table 8). Proximity to house to BMPs inside of parks are significantly predicted on housing sale prices in all buffers: 25 m (β = -.041, p < .001); 50 m (β = -.040, p < .001); 75 m (β = -.041, p < .001); and 100 m (β = -.042, p < .001). The coefficient for proximity to house to BMPs inside of park are all negative, which is associated with an increase in housing sale prices as the proximity to BMPs inside of parks decreased. While controlling for other covariates, a 1 unit decrease in house to BMPs inside of park is associated with -0.041 unit increase in 25 m; -.040 in 50 m; -.041 in 75 m; and -.042 in 100 m. The coefficient for proximity to house to BMPs inside of park within 25 m – 50 m increased the most from -.041 to -.040 (d = .001). The coefficient for proximity to house to BMPs inside of parks within 25 m - 100 m decreased the most from -.041 to -.042 (d = -.001) and 75 m - 100 m from -.041 to -.042 (d = -.001).

Table 8 A summary of regression in model 4, including environmental, structural, locational and neighborhood, and wards variables.

Variables	**25-m**	**50-m**	**75-m**	**100-m**
Variable Intercept	4.150 ***	4.177 ***	4.188 ***	4.196 ***
Environmental variables				
Proximity				
House to Park with BMPs	-.005	-.006	-.004	-.003

House to Park no BMPs	.007	.007	.007	.008
House to BMPs inside of Park	-.041 ***	-.040 ***	-.041 ***	-.042 ***
House to BMPs outside of Park	.016 **	.017 **	.018 **	.017 *
Buffer				
Count of BMPs	.001	.000	-.001	-.002
Landcover				
% tree canopy coverages	-.012	-.026 **	-.010	-.010
% impervious surfaces	.013	.001	-.009	-.014
% impervious roads	-.020 **	-.029 ***	-.016 *	-.016 *
Structural variables				
Lot size (SF)_lg	.149 ***	.146 ***	.141 ***	.139 ***
Number of bathrooms	.125 ***	.125 ***	.126 ***	.126 ***
Air conditioner (dummy)	.012 *	.012 **	.011 *	.011 *
Number of bedrooms	.053 ***	.053 ***	.053 ***	.052 ***
Building size (SF)	.177 ***	.178 ***	.178 ***	.178 ***
Building age	.043 ***	.043 ***	.043 ***	.043 ***
Remodeled age	-.049 ***	-.049 ***	-.049 ***	-.049 ***
Structural grade rating	.203 ***	.201 ***	.201 ***	.201 ***
Structural condition rating	.142 ***	.142 ***	.142 ***	.142 ***
Number of fireplaces	.029 ***	.030 ***	.031 ***	.030 ***
Locational & Neighborhood				
variable				
Population density	.038 ***	.038 ***	.043 ***	.044 ***
% of Crime rate	-.028 ***	-.028 ***	-.025 ***	-.024 ***
Unemployment rate	-.049 ***	-.049 ***	-.047 ***	-.046 ***
Median income	.135 ***	.135 ***	.134 ***	.134 ***
Vacancy rate	-.007	-.006	-.006	-.005
Poverty rate	-.016	-.016	-.016	-.016
Median age of resident	.031***	.031 ***	.029 ***	.028 ***
% of Moved2017orLater	.032 ***	.032 ***	.031 ***	.030 ***
% of Moved2015_2016	.029 ***	.030 ***	.028 ***	.028 ***
% of Moved 2010_2014	-.008	-.007	-.008	-.008
% of Moved2000_2009	-.042 ***	-.041 ***	-.044 ***	-.044 ***
% of Moved1990_1999	.009	-.009	.008	.007
% of Moved1989_earlier (Reference group)				
Near distance public school	-.019 **	-.018 **	-.017 **	-.016 **
Near distance grocery store	-.025 ***	-.025 ***	-.026 ***	-.026 ***
Near distance religious center	.042 ***	.041 ***	.039 ***	.038 ***
Near distance shopping center	-.045 ***	-.045 ***	-.044 ***	-.044 ***
Near distance capitol	-.018	-.018	-.021 *	-.021 *
Wards				
Ward (High income)	.462 ***	.462 ***	.464 ***	.465 ***
Ward (Medium income)	.242 ***	.242 ***	.244 ***	.246 ***

Ward (Low income) (Reference group)				
R^2	.900	.900	.899	.899

*Note: Dependent variable: logged housing sale prices 2017 – 2020; standardized *β* is reported in all variables. * $p \leq .5$. ** $p < .01$. *** $p < .001$.

Proximity to BMPs outside of parks are significantly predicted on housing sale prices in all buffers: 25 m (β = .016, p < .01); 50 m (β = .017, p < .01); 75 m (β = .018, p < .01); and 100 m (β = 0.017, $p \leq .05$). The coefficient for proximity to house to BMPs outside of park are all positive, which is associated with an increase in housing sale prices as the proximity to BMPs outside of parks increased. While controlling for other covariates, a 1 unit increase in house to BMPs inside of park is associated with .016 unit increase in 25 m; .017 in 50 m; .018 in 75 m; and .017 in 100 m. The coefficient for proximity to house to BMPs outside of parks within 25 m - 75 m increased the most from .016 to .018 (d = .002). The coefficient for proximity to house to BMPs outside of parks within 75 m - 100 m decreased the most from .018 to .017 (d = -.001).

Percent tree canopy coverages are significantly predicted on housing sale prices in 50 m (β = -.026, p < .01) and the coefficient is negative. This indicates that housing sale prices decrease as there is an increase in tree canopy coverage within 50 m buffer from the property.

Percent impervious roads are significantly predicted on housing sale prices in 25 m (β = -.020, p < .01); 50 m (β = -.029, p < .01); 75 m (β = -.016, $p \leq .05$); 100 m (β = -.016, $p \leq .05$) and the coefficient are all negative. This indicates that housing sale prices decrease as increase in percent of impervious roads as the buffer distance increase by 75 m then the coefficient for 100 m is kept.

All the structural characteristics of the selected single-family houses such as lot size, building age, and number of bathrooms and bedrooms are statistically predicted on housing sale prices in all models. Increases in lot size and number of bedrooms are associated with higher housing sale prices. In contrast, increases in the age of remodeling of building decrease is associated with lower housing sale prices.

All the locational and neighborhood variables, except vacancy rate, poverty rate, percent move 2010-2014, percent move 1990-1999, and near distance to the U.S Capitol (25 m and 50 m), are significantly predicted on housing sale prices. Increase in population density and median income are associated with higher housing sale prices. In contrast, increases in crime rate and unemployment rate are associated with lower housing sale prices.

Both high-income and medium-income wards groups are significantly predicted on housing sale prices. Increase in both high-income and medium-income wards group are associated with higher housing sale prices.

Overall, the R-squared in model 4 increases after adding wards variables in 25 m (R^2 =.900) 50-m (R^2 =.900), 75 m (R^2 = .899), and 100 m (R^2 = .899), which improved from the previous model. Model 4 shows high performance; independent variables well-explain 89%-90% of the variances in single-family housing sale prices respectively.

3.5 Discussion

This study provides insights into how stormwater BMPs economically affect housing sale prices in Washington, D.C. The results of our hierarchical regression models indicate that proximity to houses to BMPs outside of the park is considered an unattractive option for property owners, according to models 1 and 4 (Table 6 and Table 8). This unattractiveness might be due to aging or poor maintenance of BMPs. For instance, the aging of BMPs might deteriorate surrounding areas and prevent the natural bioremediation process (Office of Technology Assessment: Washington, DC, 1991). Poor maintenance might cause concerns, such as accumulating sediment at inlet and outlet structures or increasing diseases through mosquitoes (Blecken et al., 2017; Jackson et al., 2009), which generate an unpleasant environment and alter ecosystem services (Irwin et al., 2017). Thus, people may not be willing to install BMPs adjacent to their properties, negatively affecting housing sale prices (Irwin et al., 2017; Jauregui et al., 2021).

In contrast, BMPs inside parks were an indicator of purchasing homes for property owners, according to model 4 (Table 8). This evidence indicates that the parks might affect BMPs positively, which increases the housing sale prices. Studies showed that the adjacency of the park was a critical factor that increased the property's value (Peiser, 2024), or the presence of green space positively affected the housing value (Taguchi et al., 2020). Moreover, public parks with a regular maintenance schedule could manage the ecosystems, recreational amenities, and open space preservation, which can generate value for housing prices.

The majority of prior research has highlighted the positive impact of tree canopy coverage on housing sale prices (Donovan & Butry, 2010; Netusil et al., 2010; Overwater, 2020; H. Sander et al., 2010). Various buffer distances have been employed to assess the influence of tree canopy coverage, ranging from 30.5 meters to 10 meters to a range of 10-50 meters. These findings align with these previous studies, indicating that an increase in the percentage of tree canopy coverage positively correlates with housing sale prices within 25 meter and 50 meters buffers in model 1. This trend may be attributable to the specific characteristics of Washington, D.C., as it is a densely urbanized area where properties may need to plant trees in close proximity to each other. Residents residing near areas with tree canopy coverage stand to benefit from amenities such as enhanced aesthetic value, wildlife habitat provision, and flood mitigation measures.

Meanwhile, the percent tree canopy coverage decreases housing sale prices in the 50 m buffer in model 4, which is the adverse result from model 1. This might be due to the maintenance. Trees also entail maintenance costs, such as watering, pruning, and fixing root damage, which is not an attractive investment for property owners. This factor might lead to lack of tree canopy coverage, which indicates that the current average tree canopy coverage is 37.0%, below the District's 40% tree canopy goal (Kong et al., 2007). In addition, residents might not prefer planting trees on their properties due to safety concerns (e.g., diseases).

The percent impervious surface decreases housing sale prices in all buffers in model 1. Interestingly, the percent impervious surface is not significantly predicted on housing sale prices in any buffers in model 4. This evidence might suggest that the effect of impervious surfaces is uncertain. Because previous literature found that the percentage of impervious surfaces is negative (H. A. Sander & Haight, 2012) or positive (Lee & Li, 2009) on housing sale prices.

The percent impervious roads decrease housing sale prices in all buffers in models 1 and 4. Properties close to impervious roads might be associated with more crowded conditions, pollution, noise, and other possible dis-amenities that decrease housing sale prices (H. A. Sander & Haight, 2012).

Future studies should include several considerations to overcome these current limitations. Increasing the number of BMPs inside parks could increase housing sale prices. Considering the diverse welfare effects of BMPs, social benefits might be expected by improving the surrounding landscape, recreational opportunities, and accessibility, which might encourage stakeholders and municipalities to understand the value of BMPs.

Although these results from this study area, Washington, D.C. might be difficult to generalize the economic effects of stormwater BMPs due to the size of the area, studies with a wide range of geophysical area should be included to robust their effects. Because rain gardens are an established element of water sensitive urban infrastructure in Australia, which can be used to estimate the effects of rain gardens between locations (Iftekhar et al., 2021).

Sustainable maintenance of BMPs should be developed since those concerns have negative economic effects associated with environmental, infrastructure, and regulatory problems (Pantaloni et al., 2022; Taguchi et al., 2020). Conservation of trees with proper maintenance (e.g., monitoring) is as important as tree planting. Because diverse species have different growth rates, treating their characteristics, could help achieve the District's goal and improve the ecosystem. These associations bear further study and might prevent environmental gentrification, which is linked to the monetary value of stormwater BMPs. Well-maintained conditions of the environment offer better performance and aesthetic values, which increase the public's perception of BMPs.

Considerations of systematic design of BMPs with proper maintenance are highly recommended for long-term value. Well-maintained BMPs would function properly, which decreases the maintenance cost and generates the long-term benefits for property. In addition, the proper regulatory plan should be initiated and performed for BMPs, whether their locations are inside or outside of parks.

Supportive regulations, such as BMPs regulatory building code, zoning restrictions or subsidy options regarding BMPs (e.g., tree planting). Such regulations might be used to see the economic effects of stormwater BMPs on housing sale prices before and after the installation. For example, the regulation of MS4 might be used to see the economic effects of BMPs’ after the installation, which could also encourage residents to install BMs on their properties.

The housing market fluctuates over time and is affected by other external factors, such as structural, locational, and neighborhood attributes. Using panel data helps better understand housing market trends by analyzing pre- and post-construction of BMPs while controlling for years' effects. In addition, the economic effects of BMPs might be accurate by controlling other variables, such as the view of BMPs and education level. Such external factors were ruled out in this research since there were data limitations, as our study includes only single-family houses that may feature homogeneous characteristics.

3.6 Conclusions

This research aimed to investigate the economic effects of stormwater BMPs on housing sale prices. This study addresses specific research questions: Do stormwater BMPs positively impact housing sale prices? How do proximity and number of structural BMPs affect the housing sale prices?

My robust findings conclude that the economic effects of stormwater BMPs have positive, negative, and no effects on housing sale prices. Proximity to BMPs outside of parks decreases the housing sale prices in all buffers in models 1 and 4. Meanwhile, proximity to BMPs inside parks increases the housing sale prices in all buffers in model 4. The percentage of tree canopy coverage increases the housing sale prices in 25 m and 50 m buffers in model 1. In contrast, tree canopy coverage decreases the housing sale prices in the 50 m buffer in model 4. The percentage of impervious surfaces decreases the housing sale prices in all buffers in model 1. In contrast, the percent impervious surface is not significantly predicted on housing sale prices in all buffers in model 4. The percentage of impervious roads decreased the housing sale prices in all buffers in models 1 and 4.

Therefore, these results provide incentives for property owners to consider how BMPs could benefit their communities, even though concerns remain. For this reason, sustainable strategies with sufficient regulations (e.g., management guidelines and landscaping code) can enhance green performance. Financial support (e.g., rebate program) should be improved by policymakers, landscape architects, planners, and community stakeholders for the long-term value of serving environmental, social, and economic benefits of BMPs.

Chapter 4: The comparison of economic effects of stormwater best management practices (BMPs) on housing sale prices between high-income and low-income wards in Washington, D.C.

4.1 Introduction

Stormwater best management practices (BMPs) can be defined in terms of themselves environmental benefits as a green infrastructure technique which decrease the flow rate and increase the infiltration of stormwater by using vegetation, porous rocks, and engineered soil (USEPA, 2008). Typically, stormwater was treated with green and grey infrastructures across major "sewersheds" for stormwater management (Galvin & BenDor, 2023). The municipal separate stormwater sewer system (MS4) manages the outer regions of the District, which collects runoff from approximately two thirds of the area. The MS4 discharges stormwater directly into water bodies without treatment (USEPA, 2008). In contrast, the combined sewer system (CSS) manages the inner regions of the District, which collects rainwater, household sewage, and industrial wastewater in the same pipe (USEPA, 2008).

Though the placement of stormwater infrastructure can be expected to environmental benefits, such as decreasing the surface runoff rates and mitigating pollutants (e.g., biochemical oxygen demand, turbidity, heavy metals, and nitrogen (Davis et al., 2001; Mallin et al., 2009), green infrastructure can also have economic and social benefits (Benedict et al., 2002).

However, Chan & Hopkins (2017) pointed out that socioeconomic benefits of stormwater green infrastructure have received less attention in literature than studies with the effects of hydrological and ecological performance of green stormwater infrastructure. This can be linked to environmental justice which has been largely ignored by economists due to fragility of data or method in the past (Hite, 2008).

One of the major issues was addressed that green space is not always equitably distributed based on socioeconomic status (Wolch et al., 2014). Current literature indicated that the majority of green space was more likely to be located with higher economic and social standings than that of not (Chan & Hopkins, 2017). For instance, a study analyzed that tree canopy coverage in the urban area in Baltimore; Los Angeles; New York; Philadelphia; Raleigh, North Carolina; Sacramento, California; and Washington, D.C., are strongly linked to median household income and negatively correlated with race(Schwarz et al., 2015).

Given the focus on the disproportionate distribution of stormwater green infrastructure, the goal of this study is to assess the economic effects of stormwater BMPs on housing sale prices between high-income and low-income wards in Washington, D.C.

4.2 Literature Review

Previous studies showed that the economic effects of stormwater BMPs on housing sale prices play a significant role in increasing, decreasing, or having no effects on housing sale prices in Washington, D.C. (Park & Kweon, 2024). They found that the proximity of houses to BMPs inside of parks was an indicator of purchasing homes for property owners. In contrast, the proximity of houses to BMPs outside of the parks may be considered as an unattractive option for property owners.

Despite the research on the economic effects of stormwater BMPs, studies pointed out that green infrastructure might be a crucial implication for environmental justice and social equity (Kim et al., 2018). Bullard and Johnson (2009) addressed that marginalized and vulnerable communities disproportionately have limited access to environmental benefits and were exposed to greater environmental harms. A study supported that environmental justice have examined the correlation of environmental quality with underlying demographics (Banzhaf et al., 2019).

Studies showed that green infrastructure may be disproportionately distributed throughout based on socioeconomic status such as income, age, percent of minority, and education level achieved in U.S. Census block groups (Chan & Hopkins, 2017). Studies found that low-income and minority communities have less green space, both in terms of access and total area (Wolch et al., 2014). Green space was often more abundant in areas with higher economic and social standing (Berland et al., 2017; Kong et al., 2007; Schwarz et al., 2015). Other studies addressed that the quantity, quality, and accessibility of green infrastructure were poorly installed in neighborhoods with high concentration in low-income people and people of color (Dennis et al., 2020; Williams et al., 2020). Venter et al. (2020) found that high-income areas had abundant, accessible, greener and more tree canopy coverages than low-income areas. They found that high-income area with predominantly White residents have 11.7% greater tree canopy coverages, 8.9% higher vegetation greenness and 700 m closer to a public park than low-income area with predominantly Black African, Indian, and Colored. Another study demonstrated that people with the lowest income level paid more for access to green spaces than people with the highest income Shanghai (Xiao et al., 2017).

In summary, previous literature has shown that people of color or low-income communities lack green space access, tree canopy coverages and green infrastructure. Further, the distribution of such space disproportionately benefits predominantly White or high-income areas.

Although studies with green space, tree canopy coverage and green infrastructure were widely used to estimate the environmental equity to compare between high-income and low-income communities, research associated with BMPs was rarely addressed. In addition, limited studies used population, employment, criminal activity, education, and occupation to estimate the effects of structural and neighborhood and locational characteristics in low-income communities.

4.3 Methods

4.3.1 Setting

The focus of this study is to compare the economic effects of stormwater BMPs on housing sale prices between high-income ward and low-income ward groups in Washington, District of Columbia (D.C.) (Figure 3). Among eight individual wards, high-income and low-income ward groups were categorized based on the median income at Census tracts (Table 4.1). High-income ward includes ward 1,2,3, and 6 and low-income ward includes ward 7 and 8.

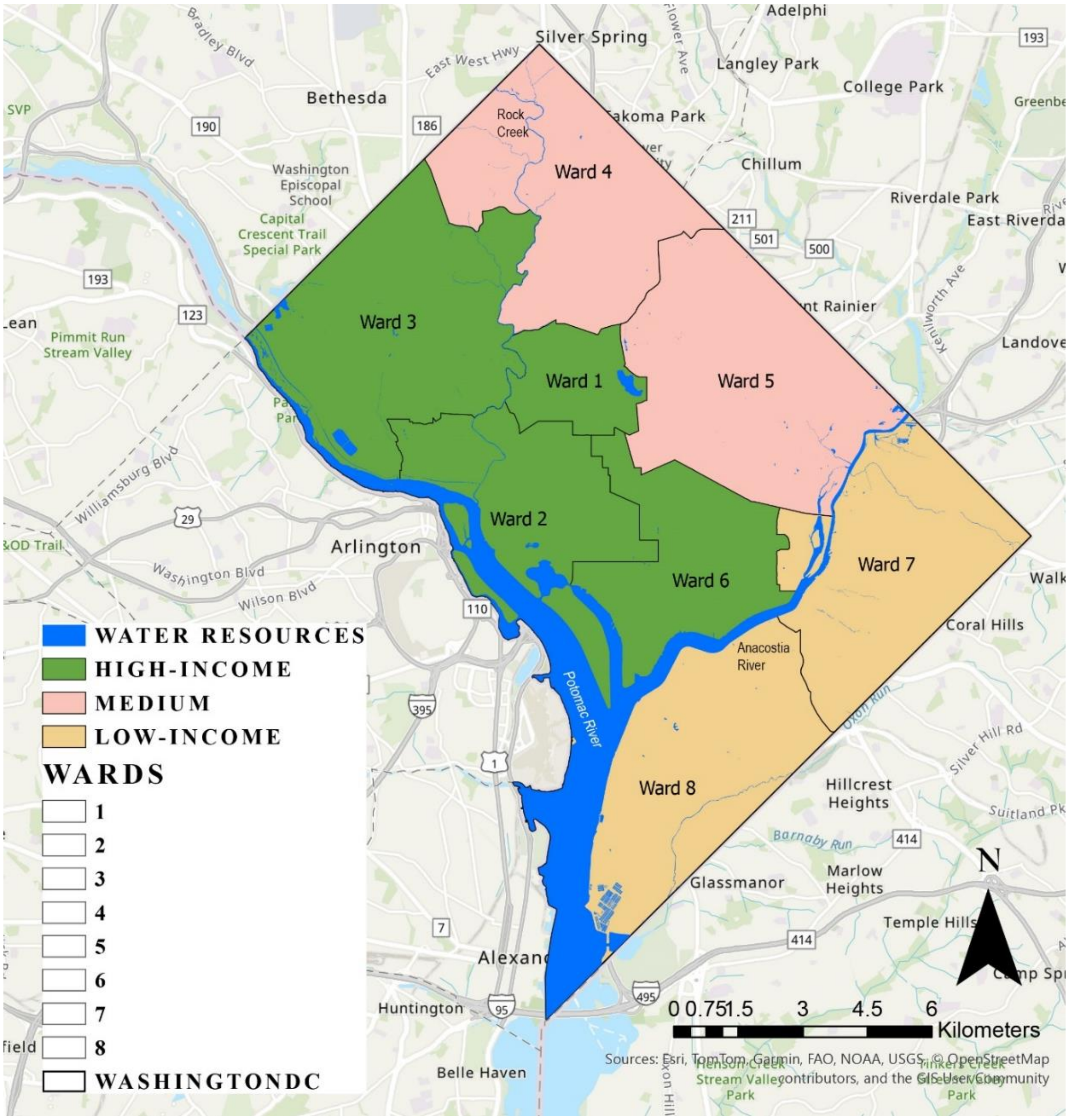

Figure 3 High, medium, and low-income wards with water resources in Washington, D.C. *Note.* Map sources: Esri, HERE, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors and the GIS User Community.

The District has an approximate area of 177 km^2. While the high-income ward has an approximate area of *71.73 km^2*, low-income ward has an approximate area of 46.61 km^2 (Table 4.1).

The District is surrounded by three water resources (e.g., Anacostia River, Rock Creek, and Potomac River). The Potomac River flows to the west side of the high-income ward, the Rock Creek flows between high-income wards 1,2, and 3. The Anacostia River flows through the west side of the low-income ward.

The population of the District was 671,803 in 2022 and the population of 46.2% White, 45.0% Black, 4.7% Asian, and 11.7% Hispanic/Latino and the District's estimated median household income was $101,722 in U.S. dollars (U.S Census Bureau, 2022). The high-income ward was predominantly White residents, and the next most populated ethnicity was either Black or Hispanic. The low-income ward was predominantly Black residents, and the next most populated ethnicity was White and Hispanic (Table 9). The median income in the high-income ward was above $100,000 and the median income in the low-income ward was below $50,000.

Table 9 Median income and race and ethnicity of eight wards in the District.

	Wards	Median income	Race and Ethnicity
High-income wards (71.73 km^2)	1	$102,882	White (45%), Black (23%), Hispanic (20%)
	2	$111,064	White (61%), Hispanic (14%), Black (11%)
	3	$128,670	White (70%), Hispanic (11%), Black (8%)
	6	$114,363	White (59%), Black (23%), Hispanic (9%)
Low-income wards (46.61 km^2)	7	$45,318	Black (83%), White (7%) Hispanic (5%)
	8	$35,245	Black (82%), White (9%) Hispanic (4%)

Note. The data of median income and race and ethnicity are from U.S. Census Bureau ACS 2017-2021.

4.3.2 Data

Data included only single-family properties, detached, row, and semi-detached houses in high-income and low-income wards in D.C. The initial sample size of the high-income ward was 5993. After identifying the outliers from the housing sale prices, which is the observation three standard deviations away from the mean in the data, 63 outliers were detected. 5930 total addresses remained in the data. The initial sample size of the low-income ward was 3566. After identifying the outliers from the housing sale prices, which is the observation three standard deviations away from the mean in the data, 3 outliers were detected. 3563 total addresses remained in the data.

The housing sale prices data obtained January 2017–December 2020 from both computer-assisted mass appraisal (CAMA)—residential data—and common ownership lots data from the District's open access dataset: Department of Energy and Environment (DOEE). Both CAMA data and common ownership lots data were combined. CAMA data included housing sale prices, and housing structural information, such as lot size, number of bathrooms, and number of kitchens. Common ownership lots data included housing sale prices with geographical locations of each housing property parcel to analyze it using ArcGIS Pro.

Best management practices data were obtained 2016–2020 from DOEE. Three different types of BMPs among 17 were included: bioretention, rainwater harvesting, and three planting and preservation. Another fourteen different types of BMPs were excluded due to lack of number of sample size. The dataset included information such as BMPs type, installation date, surface area of BMPs, volume of BMPs, and geographical locations. Park data were obtained from 2020 from DOEE.

Land cover data were obtained from the Chesapeake Conservancy (2022) in partnership with the U.S. Geological Survey (USGS). This data refers to the Land Use/Land Cover Data Project 2017/2018, which attributed to 54 detailed classes and 18 general classes with meter resolution. Each class was represented by using high-resolution satellite imagery with different minimum mapping units: water, wetlands, tree canopy, shrubland, low vegetation, barren, structures, impervious surfaces, impervious roads, tree canopy over structures, tree canopy over impervious surfaces, and tree canopy over impervious roads. The following indicators of land cover data were used in this study: tree canopy coverage, impervious surfaces, and impervious roads by drawing a nine-square-meter minimum mapping unit.

The structural characteristics of the selected single-family houses such as lot size, number of bathrooms, and number of bedrooms were provided by DOEE and specified in statistical models to control capitalization effects.

The locational and neighborhood characteristics of the selected single-family houses such as poverty rate, home ownership occupied, median income and distance to shopping centers and Capitol were provided by DOEE and specified in statistical models.

4.3.3 Variables and Measurements

Table 10 addresses the measurements and units of housing sale prices with environmental, structural, and locational and neighborhood variables. The dependent variable is logged housing sale prices and independent variables consist of environmental, structural, and neighborhood and locational variables.

Dependent variable: Housing sale prices. The dependent variable was housing sale prices. Housing sale prices in both high-income ward and low-income wards positively skewed; therefore, the data employed log-transformation to normalize the skewed features for the dataset.

Table 10 Variables, measurements, and unit for high-income and low-income wards.

Variables	Measurement	Unit
Housing sale price (logged)	Single-family Housing sale price = logged (price)	US dollar ($)
Environmental variables		

Proximity		
House to parks with BMPs	Euclidean distance from housing parcel to parks parcel with BMPs	(m)
House to parks with no BMPs	Euclidean distance from housing parcel to parks parcel without BMPs	(m)
House to BMPs inside of parks	Euclidean distance from housing parcel to BMPs points inside of the parks	(m)
House to BMPs outside of parks	Euclidean distance from housing parcel to BMPs points outside of the parks	(m)
Count		
25 m BMPs	Number of BMPs within 25 m buffer from housing parcel	(Count)
50 m BMPs	Number of BMPs within 50 m buffer from housing parcel	(Count)
75 m BMPs	Number of BMPs within 75 m buffer from housing parcel	(Count)
100 m BMPs	Number of BMPs within 100 m buffer from housing parcel	(Count)
Landcover		
25 m tree coverage	Tree coverage within 25 m donut buffer from housing parcel	(%)
50 m tree coverage	Tree coverage within 50 m donut buffer from housing parcel	(%)
75 m tree coverage	Tree coverage within 75 m donut buffer from housing parcel	(%)
100 m tree coverage	Tree coverage within 100 m donut buffer from housing parcel	(%)
25 m impervious surfaces	Impervious surfaces within 25 m donut buffer from housing parcel	(%)
50 m impervious surfaces	Impervious surfaces within 50 m donut buffer from housing parcel	(%)
75 m impervious surfaces	Impervious surfaces within 75 m donut buffer from housing parcel	(%)
100 m impervious surfaces	Impervious surfaces within 100 m donut buffer from housing parcel	(%)
25 m impervious roads	Impervious roads within 25 m donut buffer from housing parcel	(%)
50 m impervious roads	Impervious roads within 50 m donut buffer from housing parcel	(%)
75 m impervious roads	Impervious roads within 75 m donut buffer from housing parcel	(%)
100 m impervious roads	Impervious roads within 100 m donut buffer from housing parcel	(%)
Structural variables		
Lot size	Parcel size	Logged (ft^2)
Bathroom	Number of total bathrooms	(Count)
Air conditioner	Air conditioner = 1; others = 0	(0/1)
Bedroom	Number of bedrooms	Sqrt (Count)
Building size	Gross building area in square feet	(ft^2)
Age of building	Building age	(year)
Remodeled age	Remodeled age of housing structure	(year)
Structural grade rating	=1 (lowest) to 12 (highest)	
Structural condition rating	=1 (lowest) to 6 (highest)	
Fireplaces	Fireplaces = 1; others = 0	(0/1)
Locational and neighborhood variables		
Population density	Population/Total area in square meters at census tract	
Crime	Number of reported crimes/total population at census tract	
Unemployment	Unemployment rate in census tract	(%)
Income	Median Income in census tract	US dollar ($)
Vacancy	Vacancy rate in census tract	(%)
Poverty	Poverty rate in census tract	(%)
Age	Median age of residence	(year)
White	White population/Total population in high-income or low-income wards in census tract	(%)
Black or African American (Reference group)	Black or African American population/Total population in high-income or low-income wards in census tract	(%)
Hispanic or Latino	Hispanic or Latino population/Total population in high-income or low-income wards in census tract	(%)
Asian	Asian population/Total population in high-income or low-income wards in census tract	(%)
Others	Others population/Total population in high-income or low-income wards in census tract	(%)
Moved 2017 or later	Number of years living (tenure) 2017 or later in census tract	(%)
Moved 2015–2016	Number of years living (tenure) 2015–2016 in census tract	(%)
Moved 2010–2014	Number of years living (tenure) 2010–2014 in census tract	(%)
Moved 2000–2009	Number of years living (tenure) 2010–2009 in census tract	(%)
Moved 1990–1999	Number of years living (tenure) 1990–1999 in census tract	(%)

Moved 1989–earlier (Reference group)	=0 in all moved population categories	
Public schools	Euclidean distance from housing parcel polygon to public schools point	(m)
Grocery stores	Euclidean distance from housing parcel polygon to grocery stores point	(m)
Religious centers	Euclidean distance from housing parcel polygon to worships point	(m)
Shopping centers	Euclidean distance from housing parcel polygon to shopping centers point	(m)
U.S. Capitol	Euclidean distance from housing parcel polygon to U.S. Capitol point	(m)

Independent variables: Environmental, Structural, and Locational and neighborhood. Environmental variables. Parks data which consisted of three data—national parks, parks and recreation areas, and community gardens— to measure the proximity of parks and locations of BMPs from DOEE. The data estimated the proximity of houses to parks with BMPs, parks with no BMPs, BMPs inside of parks, and BMPs outside of parks variables. Beginning with the BMPs and parks data, Euclidean distance was employed in meters from each property sold to the nearest variable to calculate using the Near Analysis function in ArcGIS Pro. This process repeated for the distance from each property to the nearest parks with BMPs, parks with no BMPs, BMPs inside of parks, and BMPs outside of parks. To determine the count of BMPs, the number of BMPs within every 25 m buffer from housing property parcels was calculated by using buffer analysis and the spatial join tool in ArcGIS Pro. This process was repeated in 25 m, 50 m, 75 m, and 100 m buffer from the parcel. In the buffer analysis, I excluded the area of the housing parcel and included the overlap buffer area (e.g., 75 m buffer included 50 m buffer area).

The percentage of tree canopy coverage, percent impervious surfaces, and percent impervious roads were calculated from the land cover data for the buffer analysis in ArcGIS Pro. I calculated 25 m, 50 m, 75 m, and 100 m from the housing property parcel. To determine the effect of land cover on housing sale prices, the buffer analysis was used with ArcGIS Pro. The percentage of tree canopy coverage, impervious surfaces, impervious roads, tree canopy over structure, tree canopy over impervious surfaces, and tree canopy over impervious roads were calculated for every 25 m buffer from the housing property parcel polygon. This process was repeated in 25 m, 50 m, 75 m, and 100 m. The limit of the buffer from housing parcels was 100 m because the area beyond the 100 m buffer was outside of Washington, D.C.

Structural variables. Among ten variables, two dummy variables were converted to a dummy variable, and eight variables were numerical variables. The decision rule was if a fireplace was in the house, it was assigned a 1. All other categories were assigned a 0. The bathroom data were combined into a single, total number of bathrooms variable. The new variable was created by adding the number of full bathrooms and the number of half bathrooms multiplied by .5.

Locational and neighborhood variables. Population density per square meters at Census tract was derived by dividing the population by the total rea in square meters for each census tract. The owner-occupied indicators such as moved 2017 or later, were converted to a dummy variable. The decision rule was if a property was owner-occupied, it was assigned a 1. All other occupancy categories were assigned a 0. The distance variables such as public schools, grocery stores, and U.S. Capitol were used Euclidean distance to measure the distance from the property.

This research focused on analyzing the economic effects of stormwater BMPs on housing sale prices in high-income ward (median income range of $111,064-$128,670) and low-income ward (median income range of $35,245-$71,782) groups separately.

4.3.4 Hierarchical regression model

This study employed the hierarchical regression analysis method, which effectively accounts for testing whether each set of attributes can significantly explain the variance of the dependent variable (i.e., housing sale prices) while statistically controlling the set of housing structure variables. In hierarchical regression models, independent variables can be divided into small groups depending on the variables' characteristics: environmental, structural, locational and neighborhood attributes. A proper sequence of sets of attributes is called "hierarchy". Based on previous research and the principle of hierarchical order, this study used the model with the hierarchy: (1) environmental, (2) structural, and (3) locational and neighborhood. These three sets of variables were put into model cumulatively in hierarchical order:

$$\ln P_i = \alpha + \beta_1 E_i + \varepsilon_i \tag{4.1}$$

$$\ln P_i = \alpha + \beta_1 E_i + \beta_2 S_j + \varepsilon_i \tag{4.2}$$

$$\ln P_i = \alpha + \beta_1 E_i + \beta_2 S_j + \beta_3 L_k + \varepsilon_i, \tag{4.3}$$

Where $\ln P_i$ is the log of the housing sale prices i; E_i is a vector of environmental variables, including proximity of house to parks with BMPs, house to parks with no BMPs, house to BMPs inside of parks, house to BMPs outside of parks, count of BMPs with 25 m, 50 m, 75 m, 100 m, tree canopy coverage with 25 m, 50 m, 75 m, 100 m, impervious surface with 25 m, 50 m, 75 m, 100 m, and impervious roads with 25 m, 50 m, 75 m, 100 m; S_j is a vector of structural variables, including lot size, total number of bathrooms, number of bedrooms, building size, building age, remodeled age, structural grading rating, structural condition rating, fire places, years of living (tenure) at the census tract, and air conditioner as a dummy; L_k is a vector of locational and structural variables, including population density, crime rate, unemployment rate, median income, vacancy, poverty rate at the census tract, median age of residence, and distance to public schools, grocery stores, religious centers, and shopping centers.

The coefficients to be estimated are β_1, β_2, and β_3 ,and ε is an error term. Therefore, housing sale prices are transformed into logs, which are interpreted as the price percentage changes resulting from one additional unit of the independent variable approximately. The R-square (R^2) of the model increases as additional independent variables are introduced in the model. The increment of R^2 prior sets was not affected by the subsequent groups of explanatory variables [24], which can be shown as follows:

$$R^2{}_{\mathrm{Y\cdot ESLW}} = R^2{}_{\mathrm{Y\cdot E}} + R^2{}_{\mathrm{Y\cdot(E\cdot S)}} + R^2{}_{\mathrm{Y\cdot(E\cdot S\cdot L)}} \tag{4.4}$$

where $R^2{}_{\mathrm{Y\cdot ESLW}}$ is the coefficient of determination of the full model; $R^2{}_{\mathrm{Y\cdot E}}$ is the coefficient of determination of the model only including a set of environmental variables; $R^2{}_{\mathrm{Y\cdot(E\cdot S)}}$ is the increment of the coefficient of determination of the model including environmental variables and structural variables; $R^2{}_{\mathrm{Y\cdot(E\cdot S\cdot L)}}$ is the increment of the coefficient of determination of the model including environmental variables, structural variables, and locational and neighborhood variables.

4.4 Results

The results of this study are presented by discussing the descriptive statistics and summarizing of the results of the hierarchical hedonic regression model to compare between high-income and low-income ward groups. The inferential statistical test, two sample *t*-test, was calculated with a 95% confidence interval (CI) to determine whether there is a statistically significant between high-income and low-income ward groups. Data were processed and analyzed using Microsoft® Excel 2401, Statistical Package for the Social Sciences (SPSS®) 26.0, and ArcGIS Pro 3.2.0.

4.4.1 Descriptive statistics and two sample t-test

The descriptive statistics include the housing sale prices, environmental, structural, locational and neighborhood variables for both high-income and low-income ward groups (Table 11). I used a pairwise deletion approach to include all data available for both high-income and low-income ward groups in all buffers: 25 m, 50 m, 75 m, and 100 m. The two-sample *t*-test were examined to determine whether there is statistically significant between high-income and low-income ward groups' variables. Degree of freedom of mean difference *t*-test was reported based on Levene's Test for Equality of Variances. Four variables—25 m impervious roads (%), age of buildings (year), structural condition ratings, and distance to shopping centers (m)—were assumed equal variances. All other variables were not assumed equal variances.

Table 11 Descriptive statistics and mean difference *t*-test between high-income and low-income ward groups.

	High-Income Ward (n = 5930)		**Low-Income Ward** (n = 3563)		
Variables	Mean (SD)	Median	Mean (SD)	Median	Mean difference *t*-value
Housing sale price (2017–2020 US$)	1,211,868.15 (661,305.51)	1,019,750.00	381,940.53 (121,237.27)	371,000.00	94.19 ***
Housing sale price (logged)	6.03 (.19)	6.00	5.55 (.14)	5.56	135.21 ***
Environmental variables					
Proximity					
House to parks with BMPs	607.81 (415.45)	521.56	500.83 (318.51)	469.21	14.10 ***
House to parks with no BMPs	152.58 (98.27)	135.10	225.85 (152.77)	198.79	-25.62 ***
House to BMPs inside of parks	793.34 (495.72)	702.63	779.91 (390.94)	762.20	1.464
House to BMPs outside of parks	92.78 (79.35)	75.55	83.59 (69.06)	68.38	5.93 ***
Count					
25 m BMPs (sqrt)	.17 (.46)	.00	.24 (.59)	.00	-5.50 ***

50 m BMPs (sqrt)	.47 (.73)	.00	.58 (.89)	.00	-6.30 ***
75 m BMPs (sqrt)	.79 (.90)	.00	.94 (1.05)	1.00	-7.15 ***
100 m BMPs (sqrt)	1.14 (1.01)	1.00	1.31 (1.17)	1.41	-7.10 ***
Landcover					
25 m tree coverage (%)	33.22 (18.09)	31.07	30.17 (16.82)	29.15	8.29 ***
50 m tree coverage (%)	32.15 (17.23)	29.45	29.31 (15.22)	28.22	8.36 ***
75 m tree coverage (%)	31.59 (16.23)	28.87	28.99 (13.08)	27.72	8.58 ***
100 m tree coverage (%)	31.35 (16.00)	28.95	29.17 (12.68)	27.65	7.33 ***
25 m impervious surfaces (%)	11.93 (8.47)	10.61	12.45 (7.84)	10.89	-3.05 **
50 m impervious surfaces (%)	12.13 (7.95)	11.27	12.58 (7.02)	11.27	-2.91**
75 m impervious surfaces (%)	12.83 (7.63)	12.50	13.37 (6.54)	12.23	-3.69 ***
100 m impervious surfaces (%)	13.20 (7.46)	12.87	13.74 (6.32)	12.71	-3.74 ***
25 m impervious roads (%)	18.24 (8.42)	17.72	20.10 (8.26)	19.07	-10.50 ***
50 m impervious roads (%)	17.83 (7.29)	17.56	18.47 (6.77)	18.28	-4.30 ***
75 m impervious roads (%)	17.79 (6.08)	17.83	18.11 (5.23)	17.89	-2.64 **
100 m impervious roads (%)	17.74 (5.94)	17.71	17.65 (4.87)	17.44	.771
Structural variables					
Lot size (lg_ft²)	7.66 (.76)	7.49	7.86 (.53)	7.82	-14.93 ***
Bathroom (count)	2.89 (1.25)	2.50	2.20 (.84)	2.00	32.06 ***
Air conditioner (dummy)	.87 (.33)	1.00	.86 (.34)	1.00	1.702
Bedroom (Sqrt_count)	1.84 (.29)	1.73	1.73 (.22)	1.73	20.12 ***
Building size (ft²)	1,895.81 (944.48)	1,606.00	1,268.06 (426.00)	1,188.00	44.29 ***
Age of building (year)	93.53 (31.20)	98.00	65.65 (30.24)	74.00	42.62 ***
Remodeled age (year)	12.71 (12.44)	10.00	5.20 (9.01)	2.00	28.10 ***
Structural grade rating	1.20 (.22)	1.16	1.02 (.04)	1.00	61.48 ***
Structural condition rating	1.08 (.06)	1.07	1.07 (.06)	1.07	2.49 *
Fireplaces (dummy)	.13 (.19)	.00	.05 (.13)	.00	10.16 ***

Locational and neighborhood variables					
Population density (%)	.71 (.42)	.65	0.51 (0.21)	.49	30.63 ***
Crime (%)	16.66 (11.67)	13.00	14.02 (5.45)	13.00	14.88 ***
Unemployment (%)	4.24 (3.31)	3.50	14.99 (5.54)	13.80	-105.04 ***
Income (median)	144,988.92 (40,119.57)	147,431.00	45,535.58 (17,280.43)	39,492.00	167.07 ***
Vacancy (%)	.90 (1.76)	.00	2.47 (2.94)	2.40	-28.94 ***
Poverty (%)	4.31 (7.21)	1.20	23.45 (11.13)	24.00	-91.72 ***
Age	35.44 (6.16)	34.70	34.35 (4.82)	33.30	9.53 ***
White (%)	63.52 (16.08)	68.67	2.88 (3.89)	1.79	277.538 ***
Black or African American (%)	17.24 (15.87)	10.34	91.84 (5.95)	94.30	-326.275 ***
Hispanic or Latino (%)	10.61 (6.45)	8.45	2.85 (2.41)	2.15	83.424 ***
Asian (%)	5.17 (2.48)	5.56	0.54 (1.52)	.00	112.554 ***
Others (%)	3.33 (1.33)	3.00	1.65 (1.36)	1.22	58.752 ***
Moved 2017 or later (%)	12.58 (5.10)	11.21	7.80 (5.55)	7.05	41.90 ***
Moved 2015–2016 (%)	30.18 (8.43)	29.75	25.73 (7.46)	26.13	26.77 ***
Moved 2010–2014 (%)	14.27 (4.50)	13.53	17.08 (6.66)	16.23	-22.33 ***
Moved 2000–2009 (%)	16.73 (6.11)	15.15	18.68 (6.21)	17.59	-14.89 ***
Moved 1990–1999 (%)	7.95 (5.03)	7.77	7.86 (4.20)	7.28	.995
Moved 1989–earlier (%) (Reference group)	9.34 (5.35)	9.11	12.30 (9.23)	11.25	-17.45 ***
Distance to public schools (m)	448.90 (305.26)	369.02	413.66 (218.84)	373.98	6.52 ***
Distance to grocery stores (m)	557.62 (330.09)	484.09	1,454.90 (720.83)	1,381.56	-70.03 ***
Distance to religious centers (m)	259.70 (219.82)	188.52	222.39 (162.87)	187.92	9.45 ***
Distance to shopping centers (m)	932.47 (546.09)	801.22	1,065.61 (503.03)	1,017.98	-11.85 ***
Distance to Capitol (m)	4,936.396 (2,928.12)	4,674.42	5,694.30 (1,332.03)	5,836.93	-17.19 ***

Note. SD refers to Standard deviation. * $p \leq .05$, ** $p < .01$, *** $p < .001$.

The total sample of single-family housing in the high-income ward was 5930 and the low-income ward was 3563 (Table 11). The mean housing sale prices in the high-income ward was $1,211,868.15 and in low-income ward was $381,940.53. The result of *t*-test showed that there was a significant difference in the mean housing sale prices between high-income (t (6600) = 94.197, $p < .001$).

Environmental Variables. All the environmental variables, except the proximity of houses to BMPs inside of parks and percent of impervious roads in 100 m, were statistically significant difference between high-income and low-income ward groups.

The mean proximity of houses to parks with BMPs was 607.81 m in the high-income ward and 500.83 m in the low-income ward. The result of *t*-test showed that there was a significant difference in the mean proximity of houses to parks with BMP between high-income and low-income wards (t (8952) = 14.11, $p < .001$). This indicated that the mean proximity of houses to parks with BMPs in the high-income ward was significantly further than that of the low-income ward. The mean proximity of houses to parks with no BMPs was 152.58 m in the high-income ward and 225.85 m in the low-income ward. The result of *t*-test showed that there was a significant difference in the mean proximity of houses to parks with no BMPs between high-income and low-income wards (t (5349) =-25.62, $p < .001$). This indicated that the mean proximity of houses to parks with no BMPs in high-income ward was significantly closer than that of the low-income. The mean houses to BMPs outside of parks in the high-income ward was 92.78 m in the high-income ward and 83.59 m in the low-income ward. The result of *t*-test showed that there was a significant difference in the mean houses to BMPs outside of parks between high-income and low-income wards (t (8309) =5.93, $p < .001$). This indicated that the mean proximity of houses to BMPs outside of parks in the high-income ward was significantly further than that of the low-income ward. The mean count of BMPs in the low-income ward was statistically higher than that of the high-income ward in all buffers. The result of *t*-test showed that there was a significant difference in the mean count of BMP between high-income and low-income wards (t (6190) =-5.50, $p < .001$) in 25 m buffer.

The mean percentage of tree canopy coverage was statistically higher in the high-income ward than that of the low-income ward in all buffers. For example, the result of *t*-test showed that there was a significant difference in the mean percentage of tree canopy coverage between high-income and low-income wards (t (7926) =8.29, $p < .001$) in 25 m buffer.

The mean percentage of impervious surfaces was statistically higher in low-income ward than that of high-income. For example, the result of *t*-test showed that there was a significant difference in the mean percentage of impervious surfaces between high-income and low-income wards (t (7954) =-3.05, $p < .001$) in 25 m buffer.

The mean percentage of impervious roads is higher in low-income ward than that of the high-income ward in 25 m, 50 m, and 75 m. For example, the result of *t*-test showed that there was a significant difference in the mean percentage of impervious roads between high-income and low-income wards (t (7607) =-10.55, $p < .001$) in 25 m buffer.

Structural Variables. All the variables, except air conditioner, are statistically significant difference between high-income and low-income ward groups.

The mean number of bathrooms was statistically higher in the high-income ward than in the low-income ward. The result of *t*-test showed that there was a significant difference in the mean number of bathrooms between high-income and low-income wards (t (9364) =32.06, p

< .001) in 25 m buffer. The mean age of the building was statistically higher in the high-income ward than in the low-income ward. The result of *t*-test showed that there was a significant difference in the mean age of the building between high-income and low-income wards (t (7674) =42.96, $p < .001$) in 25 m buffer.

Locational and Neighborhood Variables. All the variables, except percent moved 1990-1999, are statistically significant difference between high-income and low-income ward groups.

The mean unemployment rate at the census tract was statistically higher in the low-income ward than that of high-income ward. The result of *t*-test showed that there was a significant difference in the mean unemployment rate between high-income and low-income wards (t (5113) =-105.04, $p < .001$).

4.4.2 Hierarchical regression models in high-income and low-income wards

This study uses hierarchical regression models in high-income and low-income ward groups to determine whether a set of independent variables significantly improved the hedonic models. Two model 1s include environmental variables (Table 12), two model 2s include environmental and structural variables. Table 13 reported R-squared and R-squared changes for model 2s to see the change of R-squared across the models. Two model 3s include environmental, structural, and locational and neighborhood variables (Table 14). The summary of the hierarchical regression model includes coefficient, significance, and R-squared in 25 m, 50 m, 75 m, and 100 m buffers.

Model 1. Two model 1s estimated the impact of the environmental variables on housing sale prices for high-income and low-income wards (Table 12).

Environmental Variables. Variables in high-income ward were significantly predicted on housing sale prices in buffers. In contrast, none of the environmental variables in the low-income ward were significantly predicted on housing sale prices in all buffers.

Among proximity variables, the proximity of houses to parks with BMPs is significantly predicted on housing sale prices in all buffers in high income ward: 25 m (β = .114, p < .01); 50 m (β = .109, p < .01); 75 m (β = .110, p < .01); 100m (β = .098, p < .01) (Table 4.4). While controlling for other covariates, a 1 unit increase in the proximity of houses to parks with BMPs is associated with .114 unit increase in 25m; .109 in 50 m; .110 in 75 m; and .098 in 100 m. The proximity of houses to parks no BMPs is significantly predicted on housing sale prices in all buffers in high income ward: 25 m (β = .044, $p \leq$ .05). While controlling for other covariates, a 1 unit increase in the proximity of houses to parks no BMPs is associated with .044 unit increase in 50m.

Table 12 A summary of regression in model 1, including environmental variables in high-income and low-income wards.

	High-income ward				Low-income ward			
Variables	25 m	50 m	75 m	100 m	25 m	50 m	75 m	100 m
Variable intercept	5.834 ***	5.921 ***	5.994 ***	6.029 ***	5.562 ***	5.569 ***	5.541 ***	5.533 ***
Environmental variables								
Proximity								
House to Parks with BMPs	.114 **	.109 **	.110 **	.098 **	.068	.069	.068	.067
House to Parks no BMPs	.044 *	.029	.024	.022	-.073	-.071	-.073	-.070
House to BMPs inside of Parks	-.112 **	-.135 ***	-.173 ***	-.175 ***	-.104	-.107	-.110	-.110
House to BMPs outside of Parks	.229 ***	.238 ***	.206 ***	.192 ***	-.051	-.067	-.054	-.046
Buffer								
Count of BMPs	.033	.053 **	.028	.018	.061	.021	.036	.047
Landcover								
% tree canopy coverage	.378 ***	.318 ***	.307 ***	.292 ***	.039	.034	.061	.068
% impervious surfaces	-.018	-.085 **	-.100 **	-.111 ***	.015	.012	.033	.034
% impervious roads	.014	-.073 **	-.138 ***	-.161 ***	.055	.045	.052	.047
R^2	.212	.245	.282	.295	.024	.021	.021	.022

Note. Dependent variable: logged housing sale prices 2017 – 2020; standardized β is reported in all variables. * $p \leq .05$, ** $p < .01$, *** $p < .001$.

The proximity of houses to BMPs inside of parks is significantly predicted on housing sale prices in all buffers in high-income ward: 25 m (β = -.112, p < .01); 50 m (β = -.135, p < .001); 75 m (β = -.173, p < .001); 100m (β = -.175, p < .001) (Table 4.4). The coefficient for the proximity of houses to BMPs inside of parks is all negative in high income ward. This means that while controlling for other covariates, a 1 unit decrease in the proximity of houses to BMPs inside of parks is associated with -.112 unit increase in 25m; -.135 in 50 m; -.173 in 75 m; and -.175 in 100 m.

The proximity of houses to BMPs outside of parks is significantly predicted on housing sale prices in all buffers in high-income ward: 25 m (β = .229, p < .001); 50 m (β = .238, p < .001); 75 m (β = .206, p < .001); 100m (β = .192, p < .001). The coefficient for the proximity of houses to BMPs outside of parks is all positive, which means that while controlling for other covariates, a 1 unit increase in the proximity of houses to BMPs outside of parks is associated with .229 unit increase in 25m; .238 in 50 m; .206 in 75 m; and .192 in 100 m.

The count of BMPs is significantly predicted on housing sale prices in 50 m (β = .053, p < .01) in high-income ward, which is associated with an increase in housing sale prices as the count of BMPs increase.

Percent tree canopy coverage is significantly predicted on housing sale prices in all buffers in in high-income ward: 25 m (β = .378, p < .001); 50 m (β = .318, p < .001); 75 m (β = .3607 p < .001); and 100 m (β = .292, p < .001). This indicates that while controlling for other covariates, a 1 unit increase in the percentage of tree canopy coverage is associated with .378 unit increase in 25 m; .318 in 50 m; .307 in 75 m; and .292 in 100 m.

Percent impervious surface is significantly predicted on housing sale prices in high-income ward 50 m (β = -.085, p < .01); 75 m (β = -.100, p < .01); and 100 m (β = -.111, p < .001). This indicates that while controlling for other covariates, a 1 unit increase in the percentage of impervious surface is associated with -.085 unit increase in 50 m; -.100 in 75 m; -.111 in 100 m.

Percent impervious roads is significantly predicted on housing sale prices in high-income ward 50 m (β = -.073, p < .01); 75 m (β = -.138, p < .001); and 100 m (β = -.161, p < .001). This indicates that while controlling for other covariates, a 1 unit increase in the percentage of impervious surface is associated with -.073 unit increase in 50 m; -.138 in 75 m; -.161 in 100 m.

Overall, the R-squared values for 25 m (R^2= .212), 50 m (R^2= .245),75 m (R^2= .282), and 100 m (R^2= .295) are given in high income ward and 25 m (R^2= .024), 50 m (R^2= .021), 75 m (R^2= .021), and 100 m (R^2= .022) in low income ward (Table 3.4). Two model 1s show high performance; independent variables well-explain 29% (high-income ward) and 2% (low-income ward) of the variance in single-family housing sale prices, respectively.

Model 2. R-squared and R-squared changes of two Model 2s estimated the impact of the environmental and structural variables on housing sale prices for high-income and low-income wards (Table 13).

Table 13 *R*-squared and *R*-squared changes in Model 2 in 25 m, 50 m, 75 m, and 100 m buffers in high-income and low-income wards.

	High-income ward				**Low-income ward**			
	25 m	50 m	75 m	100 m	25 m	50 m	75 m	100 m
Model 2	4.390***	4.469 ***	4.512 ***	4.536 ***	4.112 ***	4.087 ***	4.006 ***	3.957 ***
R^2	.800	.802	.802	.803	.398	.400	.404	.408
Change R^2	.588	.557	.521	.508	.374	.379	.383	.386

Note. Model 2 includes environmental and structural variables. *** p < .001.

Interestingly, the most drastic R-square change is in model 2s after adding structural variables in all buffers: 25-m (.588); 50-m (.557); 75-m (.521); and 100-m (.508) in high-income ward and 25-m (.374); 50-m (.379); 75-m (.383); 100-m (.386) in low-income ward. This indicates that structural variables highly impact housing sale prices among other variables.

I also examined the variance inflation factors (VIF) to detect multicollinearity while running hierarchical regression models. None of the independent variables had VIF values greater than 10. All fifty-one independent variables were kept, and the variance of the dependent variable was well explained by the independent variables.

Model 3. Two model 3s include environmental, structural, and locational and neighborhood variables in high-income and low-income wards (Table 14).

Environmental Variables. Variables in high-income ward were significantly predicted on housing sale prices in buffers. In contrast, some of variables in structural and neighborhood and locational variables in the low-income ward were significantly predicted on housing sale prices in all buffers.

Among proximity variables, the proximity of houses to parks with BMPs was significantly predicted on housing sale prices in all buffers in high-income ward: 25 m ($\beta = .056$, $p < .01$); 50 m ($\beta = .057$, $p < .01$); 75 m ($\beta = .065$, $p < .01$); 100 m ($\beta = .064$, $p < .01$). The coefficient for the proximity of houses to park with BMPs are all positive, which means that while controlling for other covariates, a 1 unit increase in the proximity of houses to BMPs inside of parks is associated with a .056 unit increase in 25 m; .057 in 50 m; .065 in 75m; and .064 in 100 m.

Table 14 A summary of regression in model 3, including environmental, structural, locational and neighborhood variables in high-income and low-income wards.

	High-income ward				Low-income ward			
Variables	25 m	50 m	75 m	100 m	25 m	50 m	75 m	100 m
Variable intercept	4.403 ***	4.455 ***	4.486 ***	4.497 ***	4.063 ***	4.036 ***	3.988 ***	3.963 ***
Environmental variables								
Proximity								
House to Parks with BMPs	.056 **	.057 **	.065 **	.064 **	-.048	-.045	-.038	-.036
House to Parks no BMPs	.001	-.001	-.001	-.001	-.009	-.009	-.017	-.021
House to BMPs inside of Parks	-.095 ***	-.097 ***	-.106 ***	-.107 ***	.003	.000	-.011	-.016
House to BMPs outside of Parks	.035 ***	.043 ***	.040 ***	.037 **	-.014	-.026	-.012	.001
Buffer								
Count of BMPs	-.011	.003	.000	-.005	.013	-.010	.011	.029
Landcover								
% tree canopy coverage	-.007	-.020	-.013	-.020	-.013	.000	.039	.057
% impervious surfaces	-.031 *	-.060 ***	-.076 ***	-.087 ***	.003	.017	.035	.046
% impervious roads	-.044 ***	-.051 ***	-.055 ***	-.058 ***	.012	.032	.074	.089
Structural variables								
Lot size	.245 ***	.231 ***	.229 ***	.228 ***	.118 *	.016 *	.125 *	.127 *
Number of bathrooms	.157 ***	.159 ***	.159 ***	.160 ***	.256 ***	.011 ***	.259 ***	.261
Air conditioner (dummy)	.047 ***	.048 ***	.046 ***	.046 ***	.069	.022	.069	.069
Number of bedrooms	.079 ***	.078 ***	.077 ***	.074 ***	.077	.038	.075	.076
Building size	.228 ***	.229 ***	.227 ***	.228 ***	.145 *	.000 *	.145 *	.142 *
Building age	.069 ***	.065 ***	.062 ***	.061 ***	.096	.000	.089	.086
Remodeled age	-.025 **	-.025 **	-.026 **	-.026 **	-.125 *	.001 *	-.125 *	-.123 *
Structural grade rating	.248 ***	.246 ***	.243 ***	.242 ***	.069	.196	.071	.070
Structural condition rating	.198 ***	.196 ***	.196 ***	.197 ***	.280 ***	.124 ***	.280 ***	.282 ***
Number of fireplaces	.074 ***	.076 ***	.075 ***	.074 ***	.032	.056	.031	.033
Locational and neighborhood variables								
Population density	.036 **	.034 *	.038 **	.038 **	.098	.041	.098	.096
Crime rate	-.023	-.020	-.014	-.011	.109	.002	.107	.104
Unemployment rate	-.078 ***	-.076 ***	-.074 ***	-.070 ***	-.019	.002	-.018	-.017
Median income	.031	.032	.035	.033	.242 *	.000 *	.235 *	.233 *
Vacancy rate	.012	.015	.019 *	.020 *	.022	.003	.019	.016

Poverty rate	-.039 **	-.037 **	-.034 *	-.034 *	.080	.001	.081	.077
Age	.036 **	.033 **	.029 **	.027 **	.012	.002	.016	.014
Moved 2017 or later	-.007	-.004	-.002	.000	-.041	.001	-.043	-.043
Moved 2015–2016	.012	.015	.016	.019	.046	.002	.039	.037
Moved 2010–2014	-.030 **	-.027 **	-.026 **	-.026 **	-.013	.001	-.022	-.023
Moved 2000–2009	-.063 ***	-.060 ***	-.063 ***	-.061 ***	.063	.002	.056	.054
Moved 1990–1999	.058 ***	.055 ***	.053 ***	.051	.098	.041	.098	.096
Moved 1989–earlier (Reference group)								
Distance to public schools	-.020	-.021	-.021	-.021	-.010	.000	-.013	-.016
Distance to grocery stores	-.029 **	-.030 **	-.034 **	-.035 **	.022	.000	.021	.023
Distance to religious centers	-.013	-.015	-.022	-.025 *	-.022	.000	-.014	-.011
Distance to shopping centers	.004	.004	.007	.007	-.046	.000	-.046	-.049
Distance to Capitol	-.085 ***	-.087 ***	-.093 ***	-.092 ***	-.187 *	.000 *	-.176 *	-.172 *
R^2	.824	.825	.826	.826	.481	.481	.483	.484

Note. Dependent variable: logged housing sale prices 2017 – 2020; standardized β is reported in all variables. * $p \leq .05$, ** $p < .01$, *** $p < .001$.

The proximity of houses to BMPs inside of parks was significantly predicted on housing sale prices in all buffers in high-income ward: 25 m (β = -.095, p < .001); 50 m (β = -.097, p < .001); 75 m (β = -.106, p < .001); 100m (β = -.107, p < .001). The coefficient for the proximity of houses to BMPs inside of parks is all negative, which means that while controlling for other covariates, a 1 unit decrease in the proximity hose to BMPs inside of parks is associated with a -.095 in 25 m; -.097 in 50 m; -.106 in 75 m; and -.107 in 100 m.

The proximity of houses to BMPs outside of parks was significantly predicted on housing sale prices in all buffers in high-income ward: 25 m (β = .035, p < .001); 50 m (β = .043, p < .001); 75 m (β = .040, p < .001); 100 m (β = .037, p < .001). The coefficient for the proximity of houses to BMPs outside of parks are all positive, which means that while controlling for other covariates, a 1 unit increase in the proximity of houses to BMPs inside of parks is associated with a .035 unit increase in 25 m; .043 in 50 m; .040 in 75m; and .037 in 100 m.

Percent impervious surfaces was significantly predicted on housing sale prices in high-income ward in 25 m (β = -.031, $p \leq .05$); 50 m (β = -.060, p < .001); 75 m (β = -.076, p < .001); 100m (β = -.087, p < .001). This means that a 1 unit increase in the percent impervious surfaces is associated with a -.031 unit decrease in 25 m; -.060 in 50 m; -.076 in 75 m; -.087 in 100 m.

Percent impervious roads was significantly predicted on housing sale prices in high-income ward in 25 m (β = -.044, p < .001); 50 m (β = -.051, p < .001); 75 m (β = -.055, p < .001); 100m (β = -.058, p < .001). This means that a 1 unit increase in the percent impervious surfaces is associated with a -.044 unit decrease in 25 m; -.051 in 50 m; -.055 in 75 m; -.058 in 100 m.

Structural Variables. All the structural variables were significantly predicted on housing sale prices in high-income ward. Increases in structural grade and condition ratings, building size and property lot size were associated with higher housing sale prices. In contrast, the increase in number lot size, number of bathrooms, and building size are associated with higher housing sale prices in all buffers in low-income ward.

Locational and neighborhood Variables. Variables in locational and neighborhood variables were significantly predicted on housing sale prices. The decrease in unemployment rate, moved 1990-1999, and proximity to Capitol were associated with higher housing sale prices in all buffers in high-income ward. In contrast, the increase in median income and proximity to Capitol were associated with higher housing sale prices in all buffers in low-income ward.

Overall, the R-squared values for 25 m (R^2= 0.842), 50 m (R^2= 0.825),75 m (R^2= 0.826), and 100 m (R^2= 0.826) are given in high income ward and 25 m (R^2= 0.481), 50 m (R^2= 0.481),75 m (R^2= 0.483), and 100 m (R^2= 0.484) in low income ward (Table 14). Two model 3s show high performance; independent variables well-explain 82% (high-income ward) and 48% (low-income ward) of the variance in single-family housing sale prices, respectively.

4.5 Discussion

Our findings of this study provided insights into how stormwater BMPs economically affect housing sale prices in high-income and low-income wards in Washington, D.C. The results of our hierarchical regression analysis address that the environmental attributes may be considered purchasing home ownership for high-income ward according to model 1 and model 3 but not in low-income ward (Table 12 and Table 14).

The proximity of houses to BMPs inside of the parks and may be considered as an attractive option for purchasing houses. This fact can be addressed that there might be a positive effect of parks. A study supported the idea that the presence of green space positively affected the housing value (Peiser, 2024) Because neighborhood or regional level of parks might be operated by municipalities or government, and such systematic management keeps a better condition of BMPs (Peiser, 2024; Taguchi et al., 2020).

In contrast, the proximity of houses to BMPs outside of parks might be an unattractive option. This might be due to aging or poor maintenance of BMPs. The aging of infrastructure without proper maintenance might have a high chance of deteriorating of infrastructure as well as poor maintenance causes accumulating sediment at inlet and outlet structures, which increase diseases through mosquitoes (Blecken et al., 2017; Jackson et al., 2009).

Percent tree canopy coverage might be considered as an attractive option for purchasing houses for high-income ward, according to model 1 (Table 12). This finding can be supported by a majority of previous studies which addressed that high-income area had much percent of tree canopy coverage that that of low-income areas (Dennis et al., 2020; Liu et al., 2017; Venter et al., 2020; Williams et al., 2020).

Interestingly, this study found no relationship between environmental variables and housing sale prices in low-income wards in model 1 and 3 (Table 12 and Table 14). This result can be explained that the proximity of houses to stormwater BMPs, percent tree canopy coverage, impervious surfaces and impervious roads might not be considerable factors for low-income communities for purchasing homes. Further, there might be no positive effects of parks with or without BMPs for low-income communities.

In addition, there was a huge gap of *R*-squared value between high-income and low-income wards. Model 1 showed that there was approximately 26% difference between high-income and low-income wards. Model 3 showed that there was approximately 34% difference between high-income and low-income wards. This result might be due to variables. Previous literature indicates that school quality or population variables were used to estimate the socio-economic effects of low-income communities, which this study did not include due to the violation of VIFs. Another possibility might be that hedonic pricing method might not be a proper method to compare between high-income and low-income wards.

This study has several highlights on the economic effects of stormwater BMPs between high-income and low-income wards on housing sale prices in the District. The disproportionate effects of stormwater BMPs might be linked to environmental justice in the District. Even though green space strategies provide benefits, such as increasing aesthetic view and decreasing crime rate, low-income neighborhoods and people of color communities had disproportionately distribution of such advantages than high-income neighborhood (Wolch et al., 2014).

In addition, such disproportionate distribution of green space and infrastructure may have paradoxical results (Wolch et al., 2014). Environmental injustice can be associated with green gentrification which can cause increasing housing costs and property values (Wolch et al., 2014). This phenomenon is a critical since housing prices is a significant factor in the real estate market and linked to socio-economic development in nearby neighborhood (Owusu-Ansah, 2011). New York's High Line is perhaps the most famous example of green gentrification (Wolch et al., 2014). New York City Economic Development Corporation (2011) found that although there was a deep recession, nearby property values of New York's High Line had increased 103%. Another example found that after the state-led restoration project of the Cheonggye-cheon Waterway in

Seoul, the property value has increased. Such problems can be dealt with by landscape designers, planners, and government sectors.

4.6 Conclusion

This research aimed to compare the economic effects of stormwater BMPs on housing sale prices between high-income and low-income wards in Washington, D.C. This study addresses how environmental, structural, neighborhood and locational variables hierarchically affect housing sale prices in high-income and low-income wards (Table 12 and Table 14).

The robust findings of this study conclude that environmental variables (e.g., proximity of houses to parks with BMPs, house to BMPs inside of parks, and house to BMPs outside of parks, impervious surfaces, and impervious roads) can be attractive factors for purchasing homes, according to model 1 and model 3 in high-income ward. In contrast, there was no evidence of the economic effects of environmental variables on housing sale prices in low-income ward. All structural variables in the high-income ward were statistically significant on housing sale prices. In contrast, limited structural variables in low-income ward were statistically significant on housing sale prices. Several locational and neighborhood variables (e.g., population density, unemployment rate, and poverty rate) in the high-income ward were statistically significant on housing sale prices. In contrast, limited variables in the low-income ward (e.g., median income and distance to Capitol) were statistically significant on housing sale prices.

Therefore, these results contribute to property owners to consider how environmental, structural and neighborhood and locational variables could be beneficial between high-income and low-income communities. However, such disproportionate economic effects of factors concern remain. The intervention of green gentrification should be considered between local government and disparate community groups by supporting financial incentives for homeownership or having an equity project for existing residents to improve their communities. This could change the neighborhood composition which is associated with the availability of stormwater BMPs as well as the involvement of these efforts from landscape architects, urban planners, stakeholders, and government is essential to accelerate the strategies to fair distribution and effects of stormwater BMPs on housing sale prices.

Appendices

Appendix A. Findings of literature studies that include BMPs (32 years).

Author/ Year	Location	Housing type	Method	Types of BMPs: Trees	Detention basins	Retention basins	Parks	Others	Measure	D.V	Key Findings
				Trees (n = 4)							
Donovan & Butry (2010)	Portland, OR USA	Single-family houses (n= 2,608)	Hedonic pricing	Street trees (+)					• Count • Buffer distance • Proximity	Housing sale price	• Number/ percent coverage within 100ft (30.5-m) of the house were positively significant • Street trees ↑ housing sale prices by an average of $8,870
Netusil et al. (2010)	Portland, OR USA	Single- family residential properties (n= 30,015)	Hedonic pricing	Trees (+, -)					• Buffer distance • Percent coverage • Proximity	Housing sale prices	• ↑ tree canopy up to 16.80%/ 97.36% in SW/NW Portland, property sale price ↓ • Negative impact of tree canopy within ¼ miles of property • ↑ tree canopy covers from 7.21% - 8.21% increase per-property benefits from $149 to $528
Li (2019)	NYC, NY USA	All homes (Single/ Two/ Three-family, Condo, and Mixed-use) (n= 297,412)	Difference in difference hedonic pricing	Street tree plantings (+)					Buffer distance	Housing prices	• Properties near street tree planting (10-m buffer) ↑ property values by 1.2% • On average, the value of properties on streets with street tree planting would be $6,309 more expensive
Overwater (2020)	Amsterdam, Germany	Single-family home (n= 100,503)	Hedonic pricing	Street trees (+)					• Count • Distance	Property price	• ↑ 10% of trees per street (per 100m) adds a 0.03% to 0.05% premium on property prices

									• Trees within 10-50 meters of a property ↑ 0.02% to 0.05% premium to property prices
Detention basins (n = 1)									
Lee & Li, (2009)	College Station, TX USA	Single-family home (n= 760, from two subdivisions)	Hedonic pricing	• Uni-use detention basins • Multi-use detention basins (+, -, x)			• Distance • View	Residential property value	• Every 10-m (33ft) distance ↑ from the detention basins within parks, housing sale prices ↓ by $164.82 • No effects beyond 274-m (900-ft) • Residential properties within view of the uni-use detention basins less expensive than others
Retention basins (n = 3)									
Irwin, et al. (2017)	Baltimore, MD USA	Detached single-family house (n= 90,948)	• Hedonic pricing • Spatial regression		Stormwater retention basins (-)		• Age • Proximity	Sale price	• Distance to stormwater retention basins ↑, housing sale prices ↓ by $28,185 - $30,579 (13% - 14%) • Age of basin ↑, sale price ↓
Natarajan et al. (2018)	Australia	Surrounding houses (n= 469)	Hedonic pricing		Lake (+)		Proximity	Property price	• Every 100-m distance ↓ to the lake, ↑ housing sale prices by AU $17.33 for each meter • Over 70% of respondents – lake positively impact property prices
Jauregui et al. (2021)	Fresno County, CA USA	Houses (n= 13,451)	Hedonic pricing		Stormwater retention basins (-, x)		• Distance • View	House price	• Properties close to the basin sell at a discount relative to properties farther away • Home buyers pay premium prices to be located closer to a basin in construction • ↑ age basin, ↓ housing price • No significant effect on houses with view to the stormwater basins
Parks (n = 6)									
Espey & Owusu-Edusei (2001)	Greenville, SC USA	Single-family residential properties (n= 4,153)	Hedonic pricing			Urban parks (+)	• Distance • Size	Property value	• House within 1500 feet of any park sells for 6.5% more than house greater than 1500 feet • House within 1500 feet of smaller neighborhood park sells for 8.5% more than house greater than far away
Crompton (2004)	Dallas-Fort Worth, TX USA	Single-family residential	Hedonic pricing			Fourteen neighborhood parks	Distance	Property value	• Homes adjacent to parks received an approximate price premium of 22% relative to properties a half-mail away

		properties (n=3,200)				(+)				
Troy & Grove (2008)	Baltimore, MD USA	Single-family residential properties (n= 15,600)	Hedonic pricing			Urban parks (+, -)		• Distance • Proximity	Property sale price	• As 1% ↑ in distance, housing sale price ↓ by 2.2% • Proximity to park positively/negatively affect housing sale prices as the crime below/exceed a certain threshold
Cebula (2009)	Savannah, GA USA	Single-family residential properties (n=2,888)	Hedonic pricing			Parks (+)		• Distance • Proximity	Housing prices	• Home adjacent to park ↑, housing sale pries ↑ approximately by 14%
Larson & Perrings (2013)	Phoenix, AZ USA	Single-family residential properties (n= 46,600)	Hedonic pricing			Parks (+, -)		• Distance • Size	Housing prices	• Smaller park (<250 acres) negatively affect housing price • Larger park (>250 acres) positively affect housing price
Kashian et al., (2018)	Muskego, WI USA	Single-family residential properties (n= 6,938)	Hedonic pricing			Parks (-)		Distance	Housing value	• Adjacent to a park ↓ housing value $39,985 (14.54%) • Distance away from park was preferred
					Rainwater Tanks (n = 1)					
Zhang et al., (2015)	Perth, Western Australia	Single-family home (n= 77,234)	Hedonic pricing				Rainwater Tanks (+)	Count (dummy)	sale price	• A premium of up to AU $18,000 built into the sale prices of houses with tanks installed
					More than one BMPs (n = 8)					
Sander et al. (2010)	Minneapolis, MN USA	Single-family (n= 9,992)	• Hedonic pricing Spatial simultaneous autoregression (SAR) error model	Trees (+, x)	Lake (+)	Parks (x)		• Percent coverage • Buffer distance (Euclidean) • Proximity • Area	Home sale price	• A 10% ↑ tree canopy coverage within a 100-m donut parcel, average housing sale prices ↑ by $1,371 (0.48%). • A 10% ↑ tree canopy coverage within a 250-m donut parcel, average housing sale prices ↑ by $836 (0.29+%). • No contribute to sale price from tree cover beyond 250-m • Positive neighborhood externalities from tree cover • Proximity to lake, home sale prices ↑ • No housing sale price ↑ from proximity to large parks

Saphores & Li. (2011)	Los Angeles, CA USA	Single-family detached homes (n= 20,660)	• Hedonic pricing • Geographically weighted regression • Cliff-Ord	Urban trees (+, -)		Lake (+)	Neighbor hood parks (-) National/s tate parks (+)		• Percent coverage • Buffer distance • Proximity	House market price	• Marginal ↑ in percent tree cover within 25-m buffer of the parcel, negative impact on sale price • ↑ parcel trees ↓ the value of almost 40% of the properties • Additional neighborhood trees slightly ↑ the value of over 97% of the properties • Proximity ↑, national/state parks and lakes ↑ value of property, except neighborhood parks
Boslett (2012)	Syracuse, NY USA	Single-family residential property (n= 6,637)	• Hedonic pricing	Urban trees (+, -)			Communi ty parks (-) Neighbor hood parks (-)		• Buffer distance (Euclidean) • Height/ Percent coverage • Proximity	Property price	• ↑ percent tree cover within 25-m, sale price ↓ • ↑ percent tree cover within 100-150-m, sale price ↑ • Proximity to community park and neighborhood park, ↓ housing sale price • Surrounding tree cover effect on sale price
Netusil et al. (2014)	Portland, OR USA	Single-family residential properties (n= 29,712)	• Hedonic pricing • Spatial regression	Trees (+)				Green street facility (sidewalk bioswale, corner curb extension, curb extension, grassy bioswale) (+, x)	• Abundance • Buffer distance (Euclidean/ street network) • Characteristics • Percent coverage • Proximity	Housing property sale price	• ↑ 10 percentage point of tree coverage at the closest green street facility, ↑ property's sale price by $18, 707 • Near green street facility ↑ property's sale price by $0.30/ $0.20 (direct effect/ indirect effect) • No relationship between characteristics of facilities (e.g., area, age) and property sale price
Franco & Macdonald (2018)	Lisbon, Portugal	Two-bedroom apartments (n= 11,617)	• Hedonic pricing • Remote sensing	Trees (+)			Neighbor hood parks (+, -)		• Buffer distance • Percent • Coverage • Proximity • Size	Residential price	• The relative size of the tree canopy with km^2 ↑ dwelling prices by 0.20% (€400 per dwelling) • Dwelling prices capitalize on proximity to smaller parks • Negative impact with proximity to the largest parks
Hoover et al. (2020)	Omaha, NE USA	Single-family home (n= 25,472)	• Hedonic analysis • Repeat-sale		Detention ponds (x)			• Bio-retentions • Rain gardens (x)	• Buffer distances	Residential property sales	• No statistically significant relationships between housing values and green infrastructure
Sohn et al. (2020)	Houston, TX USA	Single-family house (n= 1,650)	• Hedonic pricing • Spatial regression		Detention ponds (-, x)	Retention ponds (+, -)			• Distance (Network & Euclidean) • View	Housing market value	• Housing price ↓ by 0.3% for every 100-m (or 1.4% for every 500-m) of network distance ↓ to the detention ponds • No significant impact on property values with Euclidean distance and view to detention pond • Housing prices ↑ by 1.4% for every 100-m (6.6% for every 500-m) of network distance ↓ to the retention pond

											• Housing prices ↓ by 0.5% for every 100-m (or 2.7% for every 500-m) of Euclidean distance ↓ to the retention pond • View of the border of the retention pond ↑ property’s value by 2.7%
Jia & Zhang (2021)	Wuhan, China	Single-family home (n= 1,031)	• Hedonic pricing • Multiscale geographically weighted regression	Trees (+, -)		Lakes (-)	Parks (+)	• Natural areas • Agricultural fields • Green buffers	• Buffer distance • Size • Vision	Sale price	• Every 1% in size of park ↑, the economic benefits ↑ between 2.9% and 3.0% • Housing sale prices ↑ by 5.4%, 4.9%, 2.7%, and 3.2% when the distance to all kinds of green and blue infrastructures ↑ by 1%, respectively • Visible green plants positively affect house prices

Note. Marks indicate positive (+), negative (-), and no relationship (×) impacts of BMPs on housing price.

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