7-2020

Impacts of green infrastructure on flood risk perceptions in Hong Kong

Seung Kyum KIM

Paul JOOSE

Mia M. BENNETT

Terry VAN GEVELT
Singapore Management University, tvangevelt@smu.edu.sg

Citation

KIM, Seung Kyum; JOOSE, Paul; BENNETT, Mia M.; and VAN GEVELT, Terry. Impacts of green infrastructure on flood risk perceptions in Hong Kong. (2020). *Climatic Change*. 162, (162), 2277-2299.
Available at: https://ink.library.smu.edu.sg/cis_research/49

Climatic Change (2020) 162:2277–2299
https://doi.org/10.1007/s10584-020-02803-5

Impacts of green infrastructure on flood risk perceptions in Hong Kong

Seung Kyum Kim[1] · Paul Joosse[2] · Mia M. Bennett[3] · Terry van Gevelt[4,5]

Received: 20 February 2020 / Accepted: 19 July 2020/ Published online: 30 July 2020

Abstract
To better address climate unpredictability, green infrastructure is increasingly deployed alongside gray infrastructure as an alternative strategy for flood risk mitigation. Previous research has not clearly distinguished the flood-mitigation effects of green infrastructure at the local scale due to its complex range of functions including socioeconomic benefits, ecosystem services, and amenity value. Using data on 3768 housing sales from 2009 to 2019 in Hong Kong, we employ a difference-in-differences framework to examine the effect of green infrastructure on perceptions of flood risk mitigation, with housing prices as a proxy for risk perception. We find a positive effect of green infrastructure on the value of nearby housing. The effect does not exist in apartment units on higher floors, however. This vertical discrepancy further suggests that the observed pricing effects are due to green infrastructure's capacity to reduce perceptions of flood risk. By contrast, properties near conventional gray infrastructure show no evidence of such effects. The results thus provide quantitative evidence that supports the ongoing shift toward green infrastructure as a form of climate change adaptation.

Keywords Green infrastructure · Flood mitigation · Climate change adaptation · Difference-in-differences · Hong Kong · Coastal cities

✉ Seung Kyum Kim
skim1@hku.hk

1 Faculty of Social Science, University of Hong Kong, 7. 02C, Jockey Club Tower, Centennial Campus, Pok Fu Lam, Hong Kong SAR

2 Department of Sociology, University of Hong Kong, Pok Fu Lam, Hong Kong SAR

3 Department of Geography and School of Modern Languages and Cultures (China Studies Programme), University of Hong Kong, Pok Fu Lam, Hong Kong SAR

4 Department of Politics and Public Administration, University of Hong Kong, Pok Fu Lam, Hong Kong SAR

5 Department of Civil Engineering, University of Hong Kong, Pok Fu Lam, Hong Kong SAR

1 Introduction

As coastal urban populations rise and climate change accelerates, the risks of flooding in the world's coastal cities are increasing (Buurman and Babovic 2016). Urban expansion reduces water-permeable surfaces and increases the prevalence of gray infrastructure, thereby increasing flood risk. Consequently, cities are compelled to build more drainage infrastructure in order to manage concentrated stormwater runoff (Kim et al. 2017). A representative case of a city facing chronic flood risk is Hong Kong, which is subtropical, coastal, and comprised of many low-lying areas. The metropolis of 7.4 million people exemplifies the difficulties associated with flood-mitigation strategies in coastal cities. Despite the government's continued efforts to reduce flooding over the past two decades (Environment Bureau 2015), massive floods have occurred repeatedly in conjunction with a series of mature tropical cyclones over the last 10 years (Lau 2019). In 1 day in June 2008, a torrential downpour caused 162 floods (Aerts et al. 2012). One source of the challenges with flood mitigation is that the increased intensity of flooding due to climate change is surpassing the capacities of previous preventative measures. Another is that the reactive nature of gray infrastructural adaptation measures means they are poorly suited for effectively reducing flood risk (Santoro et al. 2019). The former problem defies easy solution, since we cannot precisely estimate unforeseen extreme weather. The latter problem, however, may be mitigated by improving and diversifying adaptive measures, whether through emergency preparation (e.g., early warning systems) or, promisingly, as we will analyze, green infrastructure (Chambwera et al. 2014).

A recent wave of studies examines resilience-based infrastructure design paradigms—particularly green infrastructure—rather than solely relying on conventional risk-based approaches (Denjean et al. 2017; Park et al. 2011). Although conventional risk-based approaches such as advanced climate modeling, weather forecasting, and risk analysis of historical data can be useful, single pieces of infrastructure based on such models often do not account for the interdependency of complex urban systems (Kim et al. 2017; Park et al. 2011). In addition, optimal adaptations vary over time with urban growth (e.g., the expansion of impervious surfaces associated with urban sprawl will require larger drainage systems). Furthermore, since adaptation measures have ancillary effects (co-benefits or co-costs), strategies that can maximize the net positive effects of adaptation are desirable in the decision-making stage (Chambwera et al. 2014). Many studies therefore determine green infrastructure to be a viable adaptation strategy since it provides other benefits such as ecosystem services, lower maintenance costs, and esthetic pleasure (Costanza et al. 2008; Demuzere et al. 2014; European Commission 2013). Few studies, however, empirically explore the actual flood risk–reduction effects of green infrastructure in dense urban settings. This research gap partly owes to the difficulty of separating the interdependency effects in functions (Chambwera et al. 2014) and scales (Benedict and McMahon 2002; Weber et al. 2006).

In an effort to close this gap and identify such interdependency effects, we employ the difference-in-differences (DiD) approach to estimate changes in flood risk perception that are inherently reflected in people's economic decisions with respect to housing choice. We use a total of 13,824 housing sales data to estimate the pricing effect of green infrastructure projects, comparing sales prices before and after the projects' completion dates and between areas nearer and farther away from these projects. Although this study does not indicate the extent to which elements of green infrastructure contribute to actual threats or risk perceptions, it sheds light on the risk-reduction function and capacity of green infrastructure in urban residential markets that stand to be affected by future climate uncertainties.

Our paper obtains empirical evidence in three ways. First, the study focuses on the neighborhood-scale effect of green infrastructure on coastal housing markets. Second, rather than examining the multivalued functions of green infrastructure, our analysis explores its risk perception effects using vertical proximity factors among residential units in multi-story residential buildings. Third, differing from the conventional hedonic method used in previous studies, this paper employs the DiD method as an identification strategy.

2 Green infrastructure and flood mitigation

As flood risk mitigation shifts beyond risk-based approaches and toward more resilience-based, comprehensive strategies (Lennon et al. 2014; Mei et al. 2018), green infrastructure is gaining popularity, especially in cities. Green measures for flood management like permeable paved surfaces, vegetated drainage ditches, and stormwater retention ponds offer a number of benefits that gray infrastructure, such as sea walls and levees, does not. As a result, policymakers are spotlighting green infrastructure as an additional and possibly more robust source of resilience against flood risks (Denjean et al. 2017; Lennon et al. 2014; Park et al. 2011). Hesitancy about green infrastructure remains, however, among urban planners due to concerns over its performance and public acceptability (Thorne et al. 2018). Indeed, support for conventional gray infrastructure projects persists despite evident failures. On September 16, 2018, for instance, a tropical cyclone called Typhoon Mangkhut hit Hong Kong. This "super typhoon"—the strongest in the city's recorded history—led officials to raise the highest Signal level, No. 10, for 10 h.[1] In the storm's wake, a sea wall collapsed in the seaside neighborhood of Sai Kung, expelling sewage offshore. Despite this failure, the government continues to invest in conventional storm defense systems such as new floating breakwaters.

As the above incident illustrates, gray infrastructure's efficacy relies on the fact that it is designed to be "fail-safe." It promises *not* to fail based on probabilistic extrapolations of historical data (Kim et al. 2017; Santoro et al. 2019). One problem with this approach is that failures of gray infrastructure, should they occur, are likely to be catastrophic as attested by the collapse of the levees and flood walls surrounding New Orleans during the Hurricane Katrina in 2005 (Park et al. 2011). A second problem is that this retrospective strategy may be increasingly unable to cope with future climate extremes. In light of these issues, green infrastructure is a promising option for flood risk mitigation thanks to its "safe-to-fail" characteristics (Kim et al. 2017). In other words, solutions such as mangroves and retention ponds avoid the additional risks that levees or sea walls introduce due to their potential for catastrophic failure. Green infrastructure is also multi-functional, providing positive net socioeconomic and environmental benefits such as CO_2 sequestration and improved health (Demuzere et al. 2014; Nordman et al. 2018). It can also be integrated with existing gray infrastructure to reduce impacts from excessive precipitation, floods, and storm surges (Hill 2015).

Over the past decade, many studies have examined concepts and applications of green infrastructure (Barnhill and Smardon 2012; Lennon et al. 2014; Thomas and Littlewood 2010; Wright 2011). Several studies focus on hazard-reduction functions, which have both

[1] The Hong Kong tropical cyclone warning system consists of Signals 1 (standby), 3 (strong wind), 8 (gale or storm), 9 (increasing gale or storm), and 10 (hurricane). Signal 8 is issued when a sustained wind speed ranges from 63 to 87 km/h. Signal 9 is issued when wind speed ranges from 88 to 117 km/h. Signal 10, the highest level in the warning system, indicates persistent hurricane-forced winds exceeding 117 km/h.

environmental and economic dimensions. For example, wetlands have been shown to reduce flood damages by 54–78% (Watson et al. 2016). Beyond just providing storm protection, green infrastructure is also self-maintaining and can host ecosystem services that vertical levees are unable to provide (Costanza et al. 2008) while also attenuating stormwater runoff (Liu et al. 2014). China's national "Sponge City Program," which relies on green infrastructure, has also been shown to effectively mitigate floods, though it does not eliminate them completely (Mei et al. 2018). Green infrastructure can improve insurance value by reducing the costs of gray infrastructure while decreasing vulnerability and costs of adaptation to climate change (Green et al. 2016), and it can also reduce the number of insurance claims compared with conventional stormwater systems (Sörensen and Emilsson 2019).

Despite such benefits, the uptake of green infrastructure in flood management projects remains low relative to gray infrastructure (Derkzen et al. 2017; Jaffe 2010; Thorne et al. 2018). Many flood management professionals and decision-makers still perceive scientific uncertainties in the hydrologic service delivery of green infrastructure (Chambwera et al. 2014; Sussams et al. 2015; Thorne et al. 2018). Part of this problem with valuation is related to green infrastructure's cross-boundary and multi-scalar nature (Carter et al. 2018). Interventions such as planting trees may reduce the threat of flooding downstream, for example, but provide few tangible benefits at the intervention site (Jackson et al. 2008). Another issue is that willingness to pay for flood mitigation is mediated by micro-cultural variations in risk perception (Derkzen et al. 2017; Harclerode et al. 2016; Santoro et al. 2019), which itself is shaped and constrained by awareness of local weather patterns (Lo and Jim 2015). To identify the economic benefits, if any, of green infrastructure initiatives, our study examines four relevant sites in Hong Kong, a city in which policymakers are considering both green and gray options to mitigate floods.

3 Institutional setting and empirical approach

Since extreme rainfall is an unpredictable phenomenon, proving whether flood protection projects can actually protect against extreme flooding within a short period of time is almost impossible. As empirical evidence suggests, however, interventions consisting of physical infrastructure can at the very least lessen *perceptions* of flood risks (Barnhill and Smardon 2012; Harclerode et al. 2016; Santoro et al. 2019). This, in turn, has its own ancillary consequences for well-being. Thus, we conceive of risk perception as a valid medium for investigating the efficacy of green infrastructure in flood-prevention projects.

To overcome the subjective nature of risk perception (Ludy and Kondolf 2012), we employ property market values as a proxy for measuring risk perception changes. As many studies demonstrate, perceived risk can be capitalized into housing prices by altering people's willingness to pay for risk reduction (Bin and Landry 2013; Hallstrom and Smith 2005; Nyce et al. 2015). A hedonic pricing model has commonly been used to infer economic values for nonmarket effects (Denant-Boemont and Hammiche 2019). Omitted variable bias and misspecification, however, can bias coefficients in hedonic pricing models (List and Uhlig 2017). Recent reviews of the modern econometric methods thus recommend using DiD models to avert these biases (Kuminoff et al. 2010).

Even with the DiD approach employed in this study, ambiguity remains as to whether the causal effect on housing prices owes to changes in risk perception or other environmental benefits that green infrastructure provides. The regressor containing such multivalued functions can be endogenous, but adding those omitted variables problematically also leads to multicollinearity. Thus, to identify the effect of risk perception from the multivalued functions of green infrastructure, we test another treatment variable: vertical distance between residential units in multi-story residential buildings. The general logic behind this approach is that such distances represent diminishing exposure to the risk associated with flooding. We adapt this strategy to the context of Hong Kong, but rather than looking at vertical distance from either the sea level or surrounding bodies of water, as other studies have done (Boinas et al. 2016; Keenan et al. 2018), we use vertical distance to a ground-level "blackspot," or flood risk area, as defined by the Hong Kong Drainage Services Department (DSD) based on previous records of flooding. Accordingly, we construct the following two hypotheses: (1) if flood-prevention infrastructure (whether gray or green) decreases perceptions of flood risks, price appreciation will be realized in homes located at lower floors, and (2) if other environmental benefits such as ecosystem services, lower maintenance costs, and esthetic pleasure from green infrastructure influence the housing market, price increases will be realized in homes located on both higher and lower floors.

3.1 Project sites

With a large portion of the city consisting of densely populated, low-lying areas, Hong Kong faces chronic flood risk. The city's weather patterns exacerbate this risk, with three quarters of average annual rainfall concentrated into the tropical cyclone season (May through October) (Chan 2018). Residential areas on higher ground are also not immune from flood threats caused by intense precipitation (Aerts et al. 2012).

Hong Kong's flood mitigation systems for the urban drainage trunk and its branches were initially designed based on 200-year and 50-year return periods of flooding (the estimated recurrence intervals) (Beckers et al. 2012). Yet, high-density urban development coupled with climate change has reduced these systems' capacities, and they are now only able to protect 1-in-10-year floods (DSD 2004). When intense precipitation and storm surges occur in areas with inadequate drainage capacity, flood damage can double (Aerts et al. 2012; Beckers et al. 2012). The combination of these two phenomena into "perfect storm" scenarios has caused substantial coastal and inland flooding, to which the Hong Kong DSD has responded with several flood-prevention initiatives (Chan et al. 2018).

Since 2009, four local flood prevention projects have been completed (Fig. 1, Table 1). The first site—the Fuk Man Road Nullah improvement project in Sai Kung—was completed in May 2012. The project involves the construction of 4000 m^2 of permeable surface to improve stormwater drain-off by decking over an existing open nullah (ravine). The second project, completed in January 2014, is the reconstruction of Kai Tak Nullah—a major channelized water course in East Kowloon—from Po Kong Village Road to Tung Kwong Road. This project is classified as a gray infrastructural project consisting of a 100-m-long twin-cell box culvert with a widened 200-m section of abutted local road that is meant to alleviate flooding risk in the Wong Tai Sin area. The third project, completed in October 2017, is an underground stormwater storage tank constructed with a permeable surface cover in the neighborhood of Happy Valley. This project has both green and gray infrastructural components and enables the storage of 60,000 m^3 of stormwater. The most recently completed project, a green infrastructural development, was finished in November 2017. This project restored a 500-m-long section of the Kai Tak Nullah into a green river corridor (DSD 2019b). Through these projects, along with other flood-prevention programs such as flood-pumping schemes and city-wide drainage

Fig. 1 Project site locations. Illustration by authors. Mapping source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community

tunnel installation, about 70% of flooding "blackspots" have been removed since 2010 (DSD 2019a).

We expect that flood prevention projects serve to ease perceived flood risk, which will be reflected in higher housing prices (Belanger and Bourdeau-Brien 2018; Rajapaksa et al. 2017), particularly near the project sites.[2] We further hypothesize that since flooding is the perceived threat, effects will vary by vertical distance in high-rise apartments and by types of project (e.g., gray versus green infrastructure).

3.2 Methods

To test these effects empirically, we adopt the DiD approach. We estimate the following model:

$$y_{ibt} = \alpha_0 + \alpha_1(\text{near}_i \times \text{completion}_t) + \alpha_2 \cdot \chi_{it} + \gamma_b + \eta_t + \varepsilon_{ict} \quad (1)$$

where y_{ibt} is the log of housing sales price of property i in tertiary planning units b on time t. The housing sales prices are adjusted to 2019 prices using the relevant monthly consumer price index and are the seasonal index–adjusted prices. near_i is a dummy variable, is equal to 1 if property i is near to a flood-prevention project, and is equal to 0 otherwise; $completion_t$ is an indicator variable, equal to 1 for all housing sales after a project is completed, and a value of zero before a new project is completed; the vector of covariates χ_{it} includes housing structural and locational variables, project attributes (i.e., project size and linear distance), and the occurrence of past floods. γ_b is building fixed effects; η_t is year and month of year fixed effects; and ε_{ibt} is the error term.

[2] For instance, if a property is at risk of flooding, market participants may expect substantial repair costs from flood damages, leading demand for lower-risk properties to rise. However, this risk does not affect the actual supply of properties at risk of flooding. The subsequent price differential between such properties thus reveals a market participant's willingness to pay for flood risk reduction.

Table 1 The list of flood-prevention projects

Project name	Location	Scope	Type	Start	Completion	Cost (HK$)
Improvement of Fuk Man Road nullah in Sai Kung	Fuk Man Road in Sai Kung	Permeability improvement, drainage improvement	Gray	Aug. 31, 2009	May 18, 2012	\$96 million
Reconstruction and rehabilitation of Kai Tak Nullah from Po Kong Village Road to Tung Kwong Road	Po Kong Village Road to Tung Kwong Road	Culvert installation, Drainage, and sewer improvement	Gray	Aug. 30, 2010	Jan. 31, 2014	\$159 million
Happy Valley underground stormwater storage scheme	Happy Valley & Wan Chai areas	Vegetated detention basin, underground stormwater storage tank	Green and gray	Sep. 30, 2012	Oct. 27, 2017	\$1066 million
Reconstruction and rehabilitation of Kai Tak Nullah from Tung Kwong Road to Prince Edward Road East	Tung Kwong Road to Prince Edward Road East	Kai Tak Nullah revitalization (green river corridor), drainage improvement	Green and gray	Dec. 30, 2013	Nov. 30, 2017	\$1200 million

Source: Drainage Services Department (DSD, 2019)

Our DiD strategy uses a full 2 years of data before and after each flood-prevention project's completion date to avoid the effects of seasonal variations in housing prices. Rain and storm events, which are the main causes of flooding, vary seasonally. Shorter-term examinations would therefore produce misleading results. The logic behind our identification strategy is straightforward, with the key assumption that before the completion of flood-prevention projects, housing sales prices near and far from project sites will display the same pricing trend. In other words, the only reason for a housing price trend change after the completion date would be the effect of the flood prevention projects.

Our coefficient of interest α_1 estimates the effect of flood prevention projects on nearby housing prices compared with the price of residential units farther away. The effects of flood prevention projects on housing prices depend crucially on the risk perception of housing market participants. If infrastructure projects increase housing demand due to properties becoming perceived as safer, then the pricing effects will be larger for areas near the projects, and α_1 is expected to be positive. Although an individual's level of risk perception will vary according to his or her own experiences with flooding, perceptions are likely clustered by influencing one another within groups (Filatova and Bin 2014; Scherer and Cho 2003), thus offsetting potential bias that may arise from the subjective nature of risk perception.

A few other estimation details are worth noting. First, since we are conducting our analysis using panel data, the observations are likely to be autocorrelated. To address this issue, we cluster standard errors by the apartment building at month levels. Second, we examine the robustness of our findings by checking for unobserved spatial proximity effects, using continuous distance to the flood risk reduction projects to replace $near_i$, as well as considering different time periods before and after project completion.

4 Data

We use data from several sources in our analysis. The owner-occupied multi-residential property sales transaction data from 2009 to 2019 was obtained from 28Hse.com. This data contains detailed housing characteristics such as gross floor area and property address. Since information on building age was not listed in the primary database, we obtained this information from other real estate agencies such as Spacious, OneDay, and Ricacorp Properties.

Since the spatial coordination of each property is excluded in the datasets, the address of each property was manually batch-geocoded in ArcGIS 10.7.1. To optimize the model's performance, outliers were excluded, such as homes smaller than 200 ft^2, homes located above the 50th floor, and inflation-adjusted prices to 2019 of less than HK$800,000 or more than HK$40 million. In light of the Hong Kong protests, which began in June 2019 and went on to dramatically impact the city's economy, we restrict our data to prior to this period. Consequently, a total of 13,824 multi-family housing units in 264 apartment buildings were analyzed.

As shown in Fig. 2, patterns of changes in the average housing sales prices varied in each neighborhood. In particular, the sale prices in Sai Kung, a low-density neighborhood not connected to the subway network with a sizeable expatriate population (Fig. 1), were well below other neighborhoods until the beginning of 2016, but then began to increase over the past 4 years (Fig. 2(1)). In contrast, as shown in the average sales prices between the Po Kong Village Road and Tung Kwong Road areas in Wong Tai Sin, patterns differ even within the same neighborhood (Fig. 2(2 and 4)). These divergent patterns signify that structural and locational factors impact housing prices, too. To account for such structural variables, we include unit square footage, year of construction, floor level, and the ground elevation of each building. Although other common variables such as number of bathrooms and bedrooms are not included in our equations due to limitations of data accessibility, these variables are substantially proportional to the unit square footage of housing stock in Hong Kong. Other variables that are commonly assessed in similar studies, such as garage size and roof type, are not applicable for the multi-family apartment samples.[3] As for locational variables, nine proximity factors that are most commonly used in similar studies are included as covariates (Table 2). Since the size of green infrastructure may have a heterogeneous impact on housing prices, the net permeable surface area of each project is considered in the regressions, too.

To establish the spatial extent of the risk perception effect of flood prevention measures on housing prices, we employ flooding blackspots in our analysis. Flooding records indicate that

[3] Overland flood insurance, which is a consideration in many contexts, is another variable that is often included in similar studies. Yet, for Hong Kong and the wider Asia Pacific, such policies are unavailable and/or unpopular (Lamond et al. 2017; Chan et al. 2018). The lack of such policies means that our study does not suffer from a systematic bias. Although some local property insurance covers water damage, this is mostly limited to pipe leakages, seepages, and drainage problems (Chan et al. 2018). Government policy does not typically support private insurers who might wish to offer this service, as there is often a lack of accurate flood risk information. Meanwhile, other private insurers estimate that risks are simply too high to offer flood premium packages.

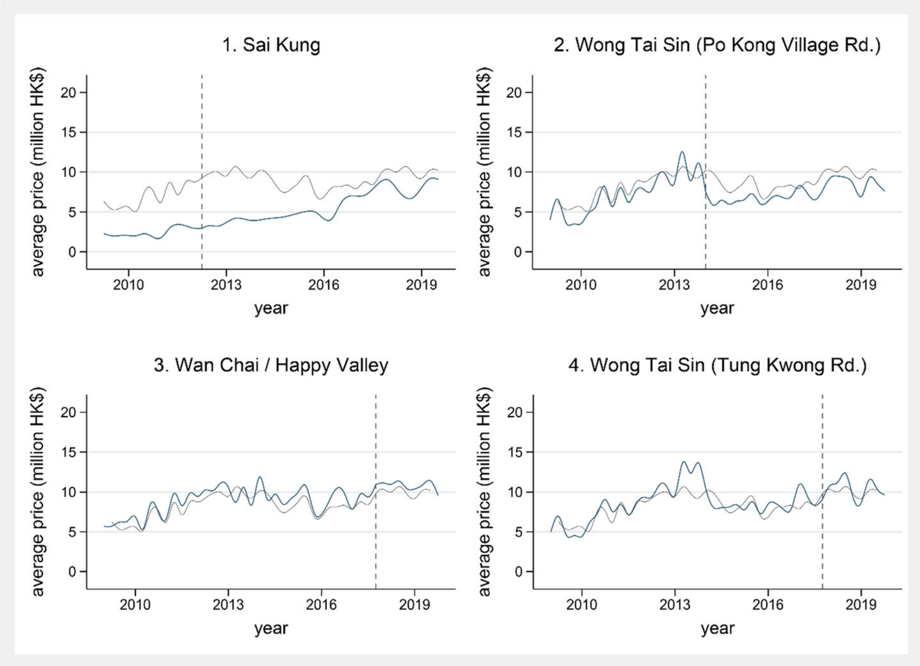

Fig. 2 Average housing sales price for each of the four project impact areas. In each subfigure, the blue line represents the quarterly average housing sales price over time for each project site. The dashed *x*-axis line indicates when the area's flood prevention project was completed. The light gray line in the background represents the quarterly average housing price trend within 560 m of the project. The price trend reflects real prices without adjustment for inflation or seasonality

within the project sites, floods have affected adjacent areas up to 10 ha around each flooding blackspot (DSD 2019a). Thus, we define the impact area for the treatment group by a 180-m buffer radius (roughly equivalent to 10 ha). For the control group, the impact area is limited to 560 m, as no flooding blackspot has ever impacted an area beyond this measure. The authors manually produced the georeferenced flood-prevention data based on DSD project information. Other necessary GIS data for locational and demographic variables were obtained from governmental sources, Hong Kong Geodata Store, and the ArcGIS Open Data community (Appendix Table 7).

To separate the risk perception effect from the multivalued functions of green infrastructure, we construct dummy variables by vertical distances. Since the maximum height of storm tide–induced flooding was 8.23 m during all tropical cyclones for which Signal 8 or higher was raised between 1954 and 2018 in Hong Kong (Appendix Table 8), we consider properties to be lower-floor units (LOW, Table 2) if the apartment unit is located on the third floor or lower. This is roughly consistent with the maximum height of flooding: in the historical data, four out of 25 tropical cyclones generated tides which could have affected units on the third floor. As indirect impacts of floods such as odor pollution can be detectible even at a vertical distance of 30 m (Chen 2017), we specify higher-floor units (HIGH, Table 2) as those located on the tenth floor and above. Differentiating unit locations between lower and higher floors, rather than measuring a continuous vertical distance, controls for potential multicollinearity issues.

Table 2 Variable definitions and summary statistics ($N = 13{,}824$)

Variables	Definition	Mean	SD	Min	Max
PRICE	Housing sales price (HK$, million)	7.83	6.48	0.80	40.00
AREA	Gross floor area (square feet)	767.92	362.15	218	3350
YEAR	Year built	1992.99	16.95	1913	2017
FLOOR	Floor of building on which apartment unit is located	13.97	9.91	0	50
LOW	1 if apartment unit is located on 3rd floor or lower*	0.09	0.29	0	1
HIGH	1 if apartment unit is located on 10th floor or higher*	0.67	0.47	0	1
ELEV	Ground elevation above sea level (meter)	16.97	18.20	5.00	126.00
PARK	Distance from nearest park (meter)	115.40	68.46	8.69	371.45
SCHOOL	Distance from nearest school (meter)	115.14	63.90	10.25	418.31
MTR	Distance from nearest metro station (meter)	889.16	911.09	87.90	6034.31
SHELTER	Distance from nearest emergency shelter (meter)	2847.63	2917.59	43.00	12,287.75
COMM	Distance from nearest community building (meter)	318.28	164.72	23.10	788.56
SPORTS	Distance from nearest sports ground (meter)	1025.11	390.65	181.08	1807.39
ROAD	1 if property adjoins** a major road*	0.11	0.32	0	1
SHOPPING	Distance from nearest shopping center (meter)	2489.42	1619.66	267.65	6148.81
DISTANCE	Distance from nearest project site (meter)	347.55	171.51	8.66	640.01
GREEN	Net area of green permeable surface (hectare)	9.25	7.92	0.11	16.54
$PAST\_FLOOD_1$	1 if apartment unit was sold after the completion of a project in an area having experienced a flood in the year prior to the sale*	0.04	0.19	0	1
$PAST\_FLOOD_2$	1 if apartment unit was sold after the completion of a project in an area having experienced a flood in the 3 years prior to the sale*	0.01	0.05	0	1

*0 if otherwise

**We consider a property to adjoin a major road if it is within 30 m of its center line

5 Results

5.1 Main results: DiD estimation

We report the main estimates in Table 3. Each column reports the results from one regression using the DiD method shown in Eq. (1). Table 3 contains two major findings. First, the completion of green infrastructure projects substantially raised nearby housing prices. The results in column (1) indicate that based on the trend before project completion, housing prices near green infrastructure are higher than those located far away. Specifically, the completion of the green infrastructure projects leads to a price appreciation that is 12.6% greater than the pricing trend among far away housing units. Second, the completion of hard infrastructure projects has little effect on housing prices. The points estimated in column (2) indicate that after the completion of hard infrastructure, the difference between the before and after completion dates of nearer and farther areas is not significant at any meaningful level of statistical significance.

The results reported in the rest of the columns show that apartment units located on the third floor or lower experience a 14.3% price increase (column (3)), while price changes for apartment units located on the tenth floor or higher (column (4)) are not statistically significant. These contrasting results indicate that the pricing effects are associated with risk perception changes due to green infrastructure. Since flooding has a vertical vector (i.e., a maximum height of flooding water level), vertical distance directly affects flood risk perceptions, thereby

Table 3 Effect of flood management project on housing price nearby: DiD estimation

	(1) GREEN INFRA.	(2) GRAY INFRA.	(3) LOW FLOORS	(4) HIGH FLOORS
COMPLETION × NEAR	0.119*** (0.033)	0.019 (0.048)	0.134** (0.054)	0.036 (0.064)
Other variables	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Building fixed effects	Yes	Yes	Yes	Yes
Constant	− 20.423** (7.340)	− 1.640 (5.702)	− 41.441*** (7.328)	− 8.209 (5.815)
N	1644	2023	423	2479
Adj. R^2	0.863	0.768	0.895	0.813

Dependent variable is log(PRICE). The sample for all regressions spans 4 years: 2 years before and after each flood prevention project's completion date. Standard errors in parentheses

***$p < 0.01$

**$p < 0.05$

*$p < 0.1$

resulting in different effects between low and high floors. By contrast, other potential socio-environmental functions of green infrastructure do not rely on verticality. Typical market information such as a proximity to a park or similar urban amenity, for instance, only considers horizontal distance, leading to the same impact on both the lower and higher floors of a building (see Appendix Tables 9 and 10).

5.2 Robustness checks

To ensure that our main results are valid, we conduct seven robustness checks. First, we use *DIST*, a continuous distance variable, instead of the dummy variable *NEAR* to test whether the flood risk–reduction effect generally decreases with distance to the new flood mitigation infrastructure (Table 4). Second, we change the time period before and after project

Table 4 Effect of flood management project on nearby housing prices: continuous estimation

	(1) GREEN INFRA.	(2) GRAY INFRA.	(3) LOW FLOORS	(4) HIGH FLOORS
COMPLETION × DIST	− 0.002*** (0.001)	0.005 (0.005)	− 0.010* (0.013)	− 0.001 (0.001)
Other variables	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Building fixed effects	Yes	Yes	Yes	Yes
Constant	− 24.595*** (8.206)	− 1.982 (5.800)	− 36.902*** (6.990)	− 8.706 (5.778)
N	1644	2023	423	2479
Adj. R^2	0.862	0.767	0.893	0.812

Dependent variable is log(PRICE). The sample for all regressions spans 4 years: 2 years before and after each flood-prevention project's completion date. Standard errors in parentheses

***$p < 0.01$

**$p < 0.05$

*$p < 0.1$

completion using a 2-year window instead of a 4-year window (Table 5). Third, we conduct a placebo test to check the validity of the shorter time window, which may be biased by unobserved time-variant factors correlated with model errors (Table 6). Fourth, we perform a balance test (Appendix Table 11) to confirm that the means of the control and treatment groups are broadly the same. Fifth, we perform spatial error and spatial lag models using a spatial weight matrix to explore for spatial dependence in our data. We find no evidence of spatial dependence (Appendix Table 12). Sixth, to account for potential multicollinearity when using building fixed effects, we estimate an additional specification using tertiary planning unit fixed effects. Our results remain broadly the same (Appendix Table 9). Seventh, to test for an anticipation effect during the construction period of the projects, we conduct two placebo tests with a 2-year and 4-year windows surrounding the start date as opposed to the completion date. We find no evidence of an anticipation effect in our results (Appendix Tables 13 and 14).

5.2.1 Continuous distance

Even though we construct the treatment and control groups based on the flood prevention project impact areas around the DSD's flooding blackspots, weather unpredictability may affect the robustness of the results. Thus, we use a continuous variable *DIST* (distance to the nearest flood infrastructure—green or gray infrastructure) to test if the effect of flood risk perception generally decreases with distance to the new flood infrastructure project. Table 4 indicates that housing sale prices decrease with increased distance from green infrastructure projects (column (1)). Apartment units located on the third floor or lower show the same trend as the negative distance effect of green infrastructure projects (column (3)). The effects of gray infrastructure (column (2)) and housing units located on the tenth floor or higher (column (4)) are still insignificant. These results are thus consistent with those in our main DiD model.

5.2.2 Different time window: shorter-term effects

In the main results, we use a 4-year window to test for the effect of new flood infrastructure projects on housing prices. To confirm that the effect also exists in the

Table 5 Robustness check: 2-year window examination

	(1) GREEN INFRA.	(2) GRAY INFRA.	(3) LOW FLOORS	(4) HIGH FLOORS
COMPLETION × NEAR	0.055** (0.021)	− 0.037 (0.050)	0.194** (0.097)	0.024 (0.050)
Other variables	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Building fixed effects	Yes	Yes	Yes	Yes
Constant	− 19.882** (7.092)	− 1.291 (5.877)	− 25.636*** (6.406)	− 6.985 (6.561)
N	718	1208	251	1311
Adj. R^2	0.879	0.766	0.827	0.815

Dependent variable is log(PRICE). The sample for all regressions spans 2 years: 1 year before and after each flood-prevention project's completion date. Standard errors in parentheses

***$p < 0.01$

**$p < 0.05$

*$p < 0.1$

Table 6 Robustness check: 2-year window examination for placebo tests

	(1) GREEN INFRA.	(2) GRAY INFRA.	(3) LOW FLOORS	(4) HIGH FLOORS
COMPLETION × NEAR	0.004 (0.049)	0.046 (0.069)	− 0.075* (0.038)	− 0.067 (0.053)
Other variables	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Building fixed effects	Yes	Yes	Yes	Yes
Constant	− 28.957** (13.269)	− 2.411 (6.278)	− 28.799*** (7.175)	− 8.082 (6.194)
N	1120	983	326	1423
Adj. R^2	0.902	0.770	0.925	0.843

Dependent variable is log(PRICE). The sample for all regressions spans 2 years before each flood-prevention project's completion date. Standard errors in parentheses

***$p < 0.01$

**$p < 0.05$

*$p < 0.1$

short term, a 2-year window—1 year before and 1 year after completion—is adopted here, with the results shown in Table 5. In the short term, the completion of green infrastructure projects caused a 5.7% housing sales price increase compared with more distant projects. As shown in column (3), the risk perception effects of flood infrastructure are even more pronounced (a 21.4% price appreciation) in this shorter time frame after project completion. The effects of gray infrastructure (column (2)) and the effects on higher-floor units (column (4)) are still not significant in this shorter window.

5.2.3 Different time window with placebo test

Although we test different impact periods with 4-year and 2-year time windows, unobserved time-variant factors could potentially still correlate with model errors (Bajari et al. 2012). For example, individuals' economic behavior may differ during months of political and/or social unrest (such as during the Hong Kong Umbrella Protests from September to December 2014, which fall within our study period). Thus, we use the same 2-year time window in a non-impact period (a time period that should be unaffected by any anticipation of the green infrastructure's completion) as a placebo test. One time window comprises housing sales between 730 (2 years) and 365 days (1 year) prior to project completion, while the other comprises housing sales between 365 days before and on the dates of project completion. The results in Table 6 provide evidence that the flood risk perception effects on housing prices did not exist prior to project completion. The negative effect at the 10% significance level in column (3) signifies that housing units located on the third or lower floor without any flood prevention infrastructure are more exposed to flood risks, resulting in housing price depreciation. This finding further supports our main result, which demonstrates that risk perception effects of flood prevention projects are more salient for lower-floor units.

6 Discussion and conclusion

Gray infrastructure remains a popular form of flood mitigation, both in Hong Kong and worldwide. Increases in extreme weather caused by climate change, however, force reconsideration of flood mitigation strategies, including the adoption of green infrastructure as a resilience-based flood prevention measure. An increasing number of studies examine whether this trend for flood management can achieve its risk management goals. However, the multi-functional nature of green infrastructure renders its effects ambiguous, making it difficult to determine whether they derive from its risk-reduction function or other socio-environmental factors.

Our approach to evaluating the effects of green infrastructure is novel in several respects. First, this paper focuses on risk perception effects on housing prices at the local scale. Second, this study employs a different econometric approach—the DiD method—as an identification strategy. Third, we use a unique set of vertical proximity factors to address potential endogeneity issues associated with the multivalued functions of green infrastructure.

The empirical analysis of flood infrastructure projects offered here supports the hypothesis that green infrastructure projects more effectively lower perceptions of vulnerability to floods than gray infrastructure projects. The first set of findings show that housing prices increased by nearly 13% in areas proximate to green infrastructure projects in the 2 years after their completion compared with areas farther away. The estimation results, using horizontal and vertical distances as well as different event years, are summarized as follows: (1) the risk perception effect of green infrastructure on housing markets is more pronounced in the year immediately following project completion, (2) only units on lower floors (i.e., those most subject to flood risks) experience the positive effect of green infrastructure projects, and (3) there is no significant effect of gray infrastructure proximity on risk perception of flooding. Overall, the results suggest that green infrastructure has increased market stability in the face of flood risk and thus validates green infrastructure’s flood risk reduction function.

At this stage, we are unable to provide evidence for whether the specific elements of green infrastructure provide more or fewer benefits for housing prices due to the relatively small number of completed projects in our study. Hong Kong, of course, is also a rather unique case in some respects compared with other cities, especially outside of East Asia, given the propensity of high-rise residential buildings. Nevertheless, the city shares many characteristics with other coastal cities such as low-lying, densely populated areas. This commensurability means that Hong Kong, despite certain idiosyncrasies, can still serve as an important example for other coastal metropoles.

Uncertainties regarding weather extremes are increasingly challenging urban sustainability. It is therefore important to consider comprehensive approaches when determining how to improve climate change adaptation strategies. This is especially important for reducing flooding, which generates a large proportion of climate risk (Smith 2018). City planners and policymakers continue to question the value of green infrastructure (Thorne et al. 2018). We hope that our analysis of flood risk perception effects will improve stakeholders’ understanding of the budgetary and distributional aspects of flood management investment, tipping the scales in favor of going green.

Acknowledgements We are thankful to Nam Young Kwon for assistance in collecting data on housing sales transactions. We acknowledge support from the University of Hong Kong Faculty of Social Sciences Cities 2050 Research Cluster.

Appendix

Table 7 Details of supplementary GIS data (all for within Hong Kong)

Data	Description	Source and URL
District boundaries	2016 population by census (boundaries of tertiary planning units and street blocks/village clusters)	DATA.GOV.HK https://www.pland.gov.hk/open_data/tpu_sb_vc/2016BC_TPU_SB_VC.geojson
Ground elevation	Digital terrain model (DTM)	DATA.GOV.HK http://www.landsd.gov.hk/mapping/en/download/data/Whole_HK_DTM_5m.asc
Parks and open space	Country parks	Hong Kong Geodata Store https://geodata.gov.hk/gs/view-dataset?uuid=6bbc334b-cdb1-48ce-8a78-c58979327124&sidx=0
	Parks, zoos, and gardens	Hong Kong Geodata Store https://geodata.gov.hk/gs/view-dataset?uuid=5901dbab-6f89-4c41-8eec-e1f8ea9a7966&sidx=0
	Public open space	DATA.GOV.HK https://geodata.gov.hk/gs/dataset/48e12cef-cbfd-4509-9c70-7ad31250bef5
Schools	Locations of schools	ESRI China Hong Kong Ltd., DATA.GOV.HK https://services3.arcgis.com/6j1KwZfY2fZrfNMR/arcgis/rest/services/Hong_Kong_School_Location_and_Information/FeatureServer
MTR stations	Locations of MTR (subway) stations	ESRI ArcGIS Online Community http://services.arcgis.com/2ycVue24EK6qzjat/arcgis/rest/services/MTR_Stations/FeatureServer
Emergency shelters	Locations of emergency shelters	ESRI China Hong Kong Ltd. http://services1.arcgis.com/Kx7MT7XYah0yCLi4/arcgis/rest/services/Feature_EmergencyShelter/FeatureServer
Libraries	Locations of libraries	ESRI China Hong Kong Ltd. https://services3.arcgis.com/6j1KwZfY2fZrfNMR/arcgis/rest/services/Libraries_in_Hong_Kong/FeatureServer
Community centers	Locations of community halls and community centers	Hong Kong Geodata Store https://geodata.gov.hk/gs/view-dataset?uuid=ab11c2b0-8437-41d2-afe7-9f4418b817df&sidx=0
Sports grounds	Locations of sports grounds	DATA.GOV.HK http://www.lcsd.gov.hk/datagovhk/facility/facility-sg.json
Major roads	Road network (2nd generation)	DATA.GOV.HK http://static.data.gov.hk/td/road-network-v2/CENTERLINE.kmz
Shopping centers	Locations of shopping centers	DATA.GOV.HK https://services3.arcgis.com/6j1KwZfY2fZrfNMR/arcgis/rest/services/Housing_Authority_Shopping_Centres_in_Hong_Kong/FeatureServer
Cultural facilities	Locations of cultural facilities	ESRI ArcGIS Online Community https://services3.arcgis.com/6j1KwZfY2fZrfNMR/arcgis/rest/services/Museums_in_Hong_Kong/FeatureServer
Flood-prone areas	Locations of flooding blackspots	ESRI ArcGIS Online Community, DATA.GOV.HK http://www.dsd.gov.hk/datagovhk/data/flood_prevention_eng.csv

Table 8 Mature tropical cyclones with Signal 8 or higher between 1954 and 2018 in Hong Kong

Year	Month	Name	Highest signal hoisted	Maximum astronomical tide (m)	Maximum storm surge (m)	Maximum storm tide (m)	Station
1954	8	Ida	9	3.18	1.68	4.86	North Point
1954	7	Pamela	9	2.83	1.16	3.99	North Point
1957	9	Gloria	10	3.08	1.34	4.42	North Point
1960	6	Mary	10	2.77	1.10	3.87	North Point
1961	5	Alice	10	2.59	0.55	3.14	North Point
1962	9	Wanda	10	5.03	3.20	8.23	Tai Po Kau
1964	8	Ida	9	3.63	2.16	5.79	Tai Po Kau
1964	9	Ruby	10	3.54	2.96	6.50	Tai Po Kau
1964	10	Dot	10	2.65	0.58	3.23	North Point
1965	7	Freda	8	2.99	1.01	4.00	North Point
1968	8	Shirley	10	2.85	1.78	4.63	Tai Po Kau
1971	7	Lucy	8	2.91	1.40	4.31	Tai Po Kau
1971	8	Rose	10	2.56	0.64	3.20	North Point
1978	8	Elaine	8	2.90	1.15	4.05	Tai Po Kau
1979	8	Hope	10	4.33	3.23	7.56	Tai Po Kau
1989	7	Gordon	8	3.31	1.36	4.67	Tai Po Kau
1993	6	Koryn	8	3.01	1.46	4.47	Tai Po Kau
1997	8	Victor	9	2.76	1.01	3.77	Quarry Bay
1999	9	York	10	2.39	0.74	3.13	Quarry Bay
2001	7	Utor	8	3.47	1.35	4.82	Tai Po Kau
2003	7	Imbudo	8	2.75	1.02	3.77	Quarry Bay
2008	9	Hagupit	8	3.77	1.77	5.54	Tai Po Kau
2012	7	Vicente	10	3.09	1.47	4.56	Tai Po Kau

Table 8 (continued)

Year	Month	Name	Highest signal hoisted	Maximum astronomical tide (m)	Maximum storm surge (m)	Maximum storm tide (m)	Station
2017	8	Hato	10	3.57	1.18	4.75	Quarry Bay
2018	9	Mangkhut	10	3.88	2.35	6.23	Quarry Bay

Storm tide is the combination of storm surge and astronomical tide

Sources: Storm surge records in Hong Kong during the passage of tropical cyclones (Hong Kong Observatory 2019); Maximum storm surge and sea level recorded in Hong Kong during the passage of tropical cyclones between 1954 and 2015 (Lau 2016); A brief history of Hong Kong typhoons (Cheung 2017)

Table 9 Full set of DiD estimation (combined model)

	(1)	(2)	(3)
AREA	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)
YEAR	0.010*** (0.002)	0.010*** (0.001)	0.010*** (0.001)
FLOOR	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
ELEV	0.002 (0.001)	0.001 (0.001)	0.002*** (0.001)
PARK	− 0.034** (0.016)	− 0.030** (0.013)	− 0.034** (0.013)
SCHOOL	− 0.029** (0.013)	− 0.030* (0.016)	− 0.029* (0.016)
MTR	− 0.087*** (0.026)	− 0.087** (0.036)	− 0.086 (0.056)
SHELTER	0.012 (0.068)	0.042 (0.032)	0.013 (0.028)
COMMUNITY	− 0.023*** (0.009)	− 0.023*** (0.006)	− 0.023*** (0.006)
SPORTS	− 0.016 (0.013)	− 0.017 (0.013)	− 0.016 (0.013)
ROAD	− 0.009 (0.010)	− 0.009** (0.004)	− 0.009** (0.004)
SHOPPING	− 0.064** (0.032)	− 0.063* (0.038)	− 0.065* (0.038)
DISTANCE	0.007 (0.012)	0.007 (0.005)	0.007 (0.005)
GREEN_AREA	− 0.001 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)
PAST_FLOOD (1-year)	0.085*** (0.032)	0.083** (0.036)	–
PAST_FLOOD (3-year)	–	–	− 0.087 (0.087)
GREEN_NEAR	− 0.014 (0.038)	− 0.014 (0.031)	− 0.015 (0.031)
GREEN_COMPLETION	− 0.022 (0.057)	− 0.018 (0.062)	− 0.075 (0.062)
GREEN_NEAR × GREEN_COMPLETION	0.125*** (0.031)	0.127*** (0.031)	0.126*** (0.031)
GRAY_NEAR	0.116* (0.065)	0.087** (0.039)	0.119*** (0.037)
GRAY_COMPLETION	0.049* (0.028)	0.049** (0.022)	0.049** (0.022)
GRAY_NEAR × GRAY_COMPLETION	0.042 (0.056)	0.045 (0.052)	0.039 (0.052)
LOW_FLOOR	− 0.047** (0.022)	− 0.050* (0.027)	− 0.048* (0.027)
COMPLETION	− 0.067*** (0.024)	− 0.070** (0.029)	− 0.068** (0.029)
LOW_FLOOR × COMPLETION	0.067*** (0.026)	0.067** (0.032)	0.068** (0.032)
HIGH_FLOOR	− 0.008 (0.017)	− 0.008 (0.019)	− 0.009 (0.019)
HIGH_FLOOR × COMPLETION	− 0.008 (0.022)	− 0.007 (0.024)	− 0.008 (0.024)
Time dummies	Yes	Yes	Yes
Space fixed effects	Building	Tertiary planning units	Tertiary planning units
Constant	− 5.213 (4.877)	− 5.037*** (1.456)	− 5.221*** (1.468)
N	3768	3768	3768
Adj. R^2	0.812	0.812	0.812

Dependent variable is log(PRICE). The sample for all regressions spans 4 years: 2 years before and after each flood-prevention project's completion date. Standard errors in parentheses

***$p < 0.01$

**$p < 0.05$

*$p < 0.1$

Table 10 Full set of DiD estimation (separate models)

	(1) GREEN*	(2) GRAY**	(3) LOW FLOORS	(4) HIGH FLOORS
AREA	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)
YEAR	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)
FLOOR	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
ELEV	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
PARK	− 0.036** (0.016)	− 0.034** (0.016)	− 0.035** (0.016)	− 0.034** (0.016)
SCHOOL	− 0.027** (0.013)	− 0.025* (0.013)	− 0.026* (0.013)	− 0.025* (0.013)
MTR	− 0.080*** (0.025)	− 0.086*** (0.027)	− 0.088*** (0.028)	− 0.089*** (0.027)
SHELTER	0.044 (0.063)	0.013 (0.069)	0.041 (0.062)	0.040 (0.062)
COMMUNITY	− 0.023** (0.009)	− 0.023** (0.009)	− 0.022** (0.009)	− 0.023** (0.009)
SPORTS	− 0.017 (0.013)	− 0.015 (0.013)	− 0.016 (0.013)	− 0.016 (0.013)
ROAD	− 0.010 (0.010)	− 0.010 (0.011)	− 0.010 (0.011)	− 0.010 (0.011)
SHOPPING	− 0.062* (0.033)	− 0.062* (0.032)	− 0.061* (0.033)	− 0.062* (0.033)
DISTANCE	0.001 (0.012)	0.003 (0.010)	− 0.004 (0.099)	− 0.001 (0.010)
GREEN_AREA	− 0.001 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)
PAST_FLOOD	0.096*** (0.032)	0.091*** (0.032)	0.098*** (0.032)	0.097*** (0.032)
NEAR	− 0.024 (0.038)	0.106 (0.065)	− 0.013 (0.028)	− 0.018 (0.016)
COMPLETION	0.007 (0.039)	0.023 (0.038)	0.045* (0.026)	0.017 (0.041)
COMPLETION × NEAR	0.126*** (0.030)	0.043 (0.058)	0.047** (0.024)	0.005 (0.019)
Constant	− 5.054 (4.889)	− 5.448 (4.894)	− 5.263 (4.898)	− 5.321 (4.911)
N	3768	3768	3768	3768
Adj. R^2	0.811	0.811	0.810	0.810

Dependent variable is log(PRICE). The sample for all regressions spans 4 years: 2 years before and after each flood-prevention project's completion date. Standard errors in parentheses

***$p < 0.01$

**$p < 0.05$

*$p < 0.1$

Table 11 Balance test

Variables	Mean (control)	Mean (treatment)	Differences	Two-sample t test $\Pr(\lvert T\rvert>\lvert t\rvert)$
AREA	752.296	754.046	1.751	0.392
YEAR	1990.637	1990.801	0.164	0.254
FLOOR	13.239	13.315	0.076	0.170
LOW	0.067	0.069	0.002	0.128
HIGH	0.687	0.686	− 0.001	0.124
ELEV	17.394	17.324	− 0.070	0.247
PARK	103.262	104.136	0.874	0.177
SCHOOL	120.983	120.395	− 0.589	0.003
MTR	771.085	769.892	− 1.193	0.780
SHELTER	2642.739	2675.615	32.876	0.057
COMMUNITY	292.909	293.797	0.888	0.251
SPORTS	1088.036	1087.254	− 0.782	0.599
ROAD	0.058	0.059	0.001	0.575
SHOPPING	2331.522	2316.059	− 15.463	0.215
DISTANCE	359.038	357.076	− 1.963	0.146
GREEN_AREA	9.211	9.125	− 0.085	0.122
$PAST\_FLOOD_1$	0.005	0.006	0.001	0.198
$PAST\_FLOOD_2$	0.012	0.011	− 0.001	0.484

This table provides the mean values for the control and treatment groups for the control variables. The final column provides respective p values using a two-sample t test

Table 12 Spatial regression models

	(1) OLS	(2) OLS (RS*)	(3) Spatial error	(4) Spatial lag
AREA	0.012*** (0.001)	0.013*** (0.001)	0.012*** (0.001)	0.012*** (0.001)
YEAR	0.010*** (0.002)	0.012*** (0.002)	0.013*** (0.001)	0.013*** (0.001)
FLOOR	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
ELEV	0.002 (0.001)	− 0.008 (0.151)	0.008 (0.001)	0.010 (0.071)
PARK	− 0.035** (0.016)	− 0.046** (0.022)	− 0.008*** (0.071)	− 0.008*** (0.002)
SCHOOL	− 0.024* (0.013)	− 0.034** (0.017)	0.001 (0.002)	0.000 (0.002)
MTR	− 0.088*** (0.027)	− 0.073** (0.035)	− 0.078*** (0.018)	− 0.078*** (0.018)
SHELTER	0.042 (0.062)	− 0.003 (0.070)	− 0.001*** (0.001)	− 0.001*** (0.001)
COMM	− 0.022** (0.009)	− 0.045* (0.023)	0.003 (0.003)	0.003 (0.003)
SPORTS	− 0.016 (0.013)	− 0.043 (0.026)	− 0.027 (0.026)	− 0.027 (0.026)
ROAD	− 0.010 (0.011)	− 0.011 (0.009)	− 0.005 (0.004)	− 0.005 (0.004)
SHOPPING	− 0.062* (0.033)	− 0.061* (0.036)	0.080** (0.034)	0.080** (0.034)
DISTANCE	− 0.001 (0.010)	0.001 (0.012)	− 0.030*** (0.007)	− 0.030*** (0.007)
GREEN_AREA	− 0.001 (0.001)	− 0.001 (0.002)	− 0.003 (0.002)	− 0.003 (0.002)
$PAST\_FLOOD_1$	0.099*** (0.032)	0.084*** (0.027)	0.013 (0.034)	0.013 (0.034)
Constant	− 5.054 (4.889)	− 5.448 (4.894)	− 5.263 (4.898)	− 5.321 (4.911)
Rho (ρ)				− 0.002 (0.003)
Lambda (λ)			0.003 (0.005)	
Sigma (σ)			0.338*** (0.007)	0.338*** (0.007)
N	3768	1132	1132	1132
Adj. R^2	0.810	0.825		

Column (2) is a random sample (30%) of column (1). Columns (3) and (4) use the same sample as column (2). Standard errors are clustered at the building level by year and month (in parentheses). Dependent variable is log(PRICE)

***$p < 0.01$

**$p < 0.05$

*$p < 0.1$

Table 13 Robustness check: 2-year window examination of construction start dates for placebo tests

	(1) GREEN INFRA.	(2) GRAY INFRA.	(3) LOW FLOORS	(4) HIGH FLOORS
COMPLETION × NEAR	− 0.054 (0.035)	− 0.037 (0.053)	− 0.006 (0.039)	0.035 (0.034)
Other variables	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Building fixed effects	Yes	Yes	Yes	Yes
Constant	3.199 (9.744)	− 3.445 (4.389)	− 19.084*** (5.356)	− 7.181* (4.169)
N	2064	1843	613	2662
Adj. R^2	0.940	0.912	0.956	0.929

Dependent variable is log(PRICE). The sample for all regressions spans 2 years: 1 year before and after each flood-prevention project's start date. Standard errors in parentheses

***$p < 0.01$

**$p < 0.05$

*$p < 0.1$

Table 14 Robustness check: 4-year window examination of construction start dates for placebo tests

	(1) GREEN INFRA.	(2) GRAY INFRA.	(3) LOW FLOORS	(4) HIGH FLOORS
COMPLETION × NEAR	− 0.016 (0.028)	− 0.043 (0.055)	0.0613 (0.043)	− 0.028 (0.031)
Other variables	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Building fixed effects	Yes	Yes	Yes	Yes
Constant	4.179 (9.633)	− 11.519** (4.556)	− 11.480 (6.942)	− 14.919*** (4.490)
N	3830	3683	1103	5133
Adj. R^2	0.938	0.877	0.961	0.899

Dependent variable is log(PRICE). The sample for all regressions spans 4 years: 2 years before and after each flood-prevention project's start date. Standard errors in parentheses

***$p < 0.01$

**$p < 0.05$

*$p < 0.1$

References

Aerts J, Botzen W, Bowman M, Dircke P, Ward P (2012) Climate adaptation and flood risk in coastal cities. Earthscan, New York

Bajari P, Fruehwirth JC, Timmins C (2012) A rational expectations approach to hedonic price regressions with time-varying unobserved product attributes: the price of pollution. Am Econ Rev 102:1898–1926

Barnhill K, Smardon R (2012) Gaining ground: green infrastructure attitudes and perceptions from stakeholders in Syracuse, New York. Environ Pract 14:6–16

Beckers J, Diermanse F, Verwey A, Tse M, Kan F, Yiu C (2012) Design of flood protection in Hong Kong. In: Klijn F, Schweckendiek T (eds) Comprehensive flood risk management: research for policy and practice. Taylor & Francis, London, p 37

Belanger P, Bourdeau-Brien M (2018) The impact of flood risk on the price of residential properties: the case of England. Hous Stud 33:876–901

Benedict MA, McMahon ET (2002) Green infrastructure: smart conservation for the 21st century. Renew Resour J 20:12–17

Bin O, Landry CE (2013) Changes in implicit flood risk premiums: empirical evidence from the housing market. J Environ Econ Manag 65:361–376

Boinas R, Guimarães AS, Delgado JM (2016) Rising damp in Portuguese cultural heritage–a flood risk map. Struct Surv 34:43–56

Buurman J, Babovic V (2016) Adaptation pathways and real options analysis: an approach to deep uncertainty in climate change adaptation policies. Polic Soc 35:137–150

Carter JG, Handley J, Butlin T, Gill S (2018) Adapting cities to climate change–exploring the flood risk management role of green infrastructure landscapes. J Environ Plan Manag 61:1535–1552

Chambwera MA, Heal G, Dubeux C, Hallegatte S, Leclerc L, Markandya A, McCarl B, Mechler R, Neumann J (2014) Economics of adaptation. Climate change 2014: impacts, adaptation, and vulnerability. Cambridge University Press, Cambridge, pp 945–977

Chan F, Chuah CJ, Ziegler A, Dąbrowski M, Varis O (2018) Towards resilient flood risk management for Asian coastal cities: lessons learned from Hong Kong and Singapore. J Clean Prod 187:576–589

Chan W (2018) Super typhoon Mangkhut is a flood threat for Hong Kong, but climate change will bring a lot worse. South China Morning Post. https://www.scmp.com/comment/letters/article/2164227/super-typhoon-mangkhut-flood-threat-hong-kong-climate-change-will. Accessed 13 December 2019

Chen WY (2017) Environmental externalities of urban river pollution and restoration: a hedonic analysis in Guangzhou (China). Landsc Urban Plan 157:170–179

Cheung E (2017) A brief history of Hong Kong typhoons. South China Morning Post. https://www.scmp.com/news/hong-kong/healthenvironment/article/2107903/brief-history-hong-kong-typhoons. Accessed 11 Nov 2019

Costanza R, Pérez-Maqueo O, Martinez ML, Sutton P, Anderson SJ, Mulder K (2008) The value of coastal wetlands for hurricane protection. AMBIO: A Journal of the Human Environment 37:241–249
Demuzere M, Orru K, Heidrich O, Olazabal E, Geneletti D, Orru H, Bhave A, Mittal N, Feliu E, Faehnle M (2014) Mitigating and adapting to climate change: multi-functional and multi-scale assessment of green urban infrastructure. J Environ Manag 146:107–115
Denant-Boemont L, Hammiche S (2019) Economic measurement of environmental costs for transportation activity. in Faulin J, Grasman S, Juan A, Hirsch P (eds.) Sustainable transportation and smart logistics. Elsevier, Amsterdam, pp. 153–167
Denjean B, Altamirano MA, Graveline N, Giordano R, Van Der Keur P, Moncoulon D, Weinberg J, Costa MM, Kozinc Z, Mulligan M (2017) Natural assurance scheme: a level playing field framework for green-grey infrastructure development. Environ Res 159:24–38
Derkzen ML, van Teeffelen AJ, Verburg PH (2017) Green infrastructure for urban climate adaptation: how do residents' views on climate impacts and green infrastructure shape adaptation preferences? Landsc Urban Plan 157:106–130
DSD (2004) Drainage improvement in Sai Kung–design and construction: final executive summary for the EIA report. in Environmental Protection Department (ed.). Hong Kong Drainage Services Department, Hong Kong
DSD (2019a) Flooding blackspots. Hong Kong Drainage Services Department, Hong Kong
DSD (2019b) List of flood prevention projects. Hong Kong Drainage Services Department, Hong Kong
Environment Bureau (2015) Hong Kong climate change report 2015. Hong Kong Environment Bureau, Hong Kong
European Commission (2013) Building a green infrastructure for Europe. European Union, Luxembourg
Filatova T, Bin O (2014) Changing climate, changing behavior: adaptive economic behavior and housing markets responses to flood risks. Advances in social simulation. Springer, Berlin, pp. 249–258
Green TL, Kronenberg J, Andersson E, Elmqvist T, Gomez-Baggethun E (2016) Insurance value of green infrastructure in and around cities. Ecosystems 19:1051–1063
Hallstrom DG, Smith VK (2005) Market responses to hurricanes. J Environ Econ Manag 50:541–561
Harclerode MA, Lal P, Vedwan N, Wolde B, Miller ME (2016) Evaluation of the role of risk perception in stakeholder engagement to prevent lead exposure in an urban setting. J Environ Manag 184:132–142
Hill K (2015) Coastal infrastructure: a typology for the next century of adaptation to sea-level rise. Front Ecol Environ 13:468–476
Hong Kong Observatory (2019) Storm surge records in Hong Kong during the passage of tropical cyclones. https://www.weather.gov.hk/en/wservice/tsheet/pms/stormsurgedb.htm. Accessed 13 Oct 2019
Jackson B, Wheater H, McIntyre N, Chell J, Francis O, Frogbrook Z, Marshall M, Reynolds B, Solloway I (2008) The impact of upland land management on flooding: insights from a multiscale experimental and modelling programme. J Flood Risk Manag 1:71–80
Jaffe M (2010) Environmental reviews & case studies: reflections on green infrastructure economics. Environ Pract 12:357–365
Keenan JM, Hill T, Gumber A (2018) Climate gentrification: from theory to empiricism in Miami-Dade County, Florida. Environ Res Lett 13:054001
Kim Y, Eisenberg DA, Bondank EN, Chester MV, Mascaro G, Underwood BS (2017) Fail-safe and safe-to-fail adaptation: decision-making for urban flooding under climate change. Clim Chang 145:397–412
Kuminoff NV, Parmeter CF, Pope JC (2010) Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities? J Environ Econ Manag 60:145–160
Lamond J, Bhattacharya-Mis N, Chan FKS, Kreibich H, Montz B, Proverbs D, Wilkinson S (2017) Flood risk mitigation and commercial property advice: an international comparison. Royal Institution of Chartered Surveyors, London, UK
Lau D (2016) Development of an Operational Storm Surge Prediction System for a Coastal City – Hong Kong Experience. Hong Kong Observatory, Typhoon Committee Roving Seminar 2016. http://www.typhooncommittee.org/docs/roving_seminar/2016/2016_C1.pdf. Accessed 15 Dec 2019
Lau D (2019) Report on sea level observing activities in Hong Kong, China
Lennon M, Scott M, O'Neill E (2014) Urban design and adapting to flood risk: the role of green infrastructure. J Urban Des 19:745–758
List J, Uhlig H (2017) The past, present, and future of economics: a celebration of the 125-year anniversary of the JPE and of Chicago economics introduction. Univ. Chicago Press, Chicago
Liu W, Chen W, Peng C (2014) Assessing the effectiveness of green infrastructures on urban flooding reduction: a community scale study. Ecol Model 291:6–14
Lo AY, Jim CY (2015) Come rain or shine? Public expectation on local weather change and differential effects on climate change attitude. Public Underst Sci 24:928–942

Ludy J, Kondolf GM (2012) Flood risk perception in lands “protected” by 100-year levees. Nat Hazards 61:829–842

Mei C, Liu J, Wang H, Yang Z, Ding X, Shao W (2018) Integrated assessments of green infrastructure for flood mitigation to support robust decision-making for sponge city construction in an urbanized watershed. Sci Total Environ 639:1394–1407

Nordman EE, Isely E, Isely P, Denning R (2018) Benefit-cost analysis of stormwater green infrastructure practices for grand rapids, Michigan, USA. J Clean Prod 200:501–510

Nyce C, Dumm RE, Sirmans GS, Smersh G (2015) The capitalization of insurance premiums in house prices. J Risk Insur 82:891–919

Park J, Seager TP, Rao PSC (2011) Lessons in risk-versus resilience-based design and management. Integr Environ Assess Manag 7:396–399

Rajapaksa D, Zhu M, Lee B, Hoang V-N, Wilson C, Managi S (2017) The impact of flood dynamics on property values. Land Use Policy 69:317–325

Santoro S, Pluchinotta I, Pagano A, Pengal P, Cokan B, Giordano R (2019) Assessing stakeholders’ risk perception to promote nature based solutions as flood protection strategies: the case of the Glinščica river (Slovenia). Sci Total Environ 655:188–201

Scherer CW, Cho H (2003) A social network contagion theory of risk perception. Risk Anal 23:261–267

Smith A (2018) 2017 U.S. billion-dollar weather and climate disasters: a historic year in context. https://www.climate.gov/news-features/blogs/beyond-data/2017-us-billion-dollar-weather-and-climate-disasters-historic-year. Accessed October 26, 2019

Sörensen J, Emilsson T (2019) Evaluating flood risk reduction by urban blue-green infrastructure using insurance data. J Water Resour Plan Manag 145:04018099

Sussams L, Sheate W, Eales R (2015) Green infrastructure as a climate change adaptation policy intervention: muddying the waters or clearing a path to a more secure future? J Environ Manag 147:184–193

Thomas K, Littlewood S (2010) From green belts to green infrastructure? The evolution of a new concept in the emerging soft governance of spatial strategies. Plan Pract Res 25:203–222

Thorne CR, Lawson EC, Ozawa C, Hamlin SL, Smith LA (2018) Overcoming uncertainty and barriers to adoption of blue-green infrastructure for urban flood risk management. J Flood Risk Manag 11:S960–S972

Watson KB, Ricketts T, Galford G, Polasky S, O'Niel-Dunne J (2016) Quantifying flood mitigation services: the economic value of Otter Creek wetlands and floodplains to Middlebury, VT. Ecol Econ 130:16–24

Weber T, Sloan A, Wolf J (2006) Maryland’s green infrastructure assessment: development of a comprehensive approach to land conservation. Landsc Urban Plan 77:94–110

Wright H (2011) Understanding green infrastructure: the development of a contested concept in England. Local Environ 16:1003–1019