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# Beyond the Floodplain: Uncovering the Spatial Spillovers of Land Price Declines after Typhoon Hagibis*

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**Abstract**

We examine how changes in flood-risk perception influence land prices by analyzing price developments in inundated and nearby areas following Typhoon Hagibis (2019), using parcel-level data, inundation maps, and an event-study approach. Our key findings indicate that land prices in inundated areas declined monotonically after the flood, falling 10% after five years. Furthermore, a distance-decay effect is observed, with non-inundated plots within 100 meters of the flood boundary declining by 5%, whereas effects disappear beyond 800 meters. Price declines differ inside and outside official hazard zones, with larger spillover effects in unaffected areas outside the zones. To clarify the mechanism, we extend the Bayesian belief-updating framework of Bakkensen and Barrage (2022) to account for variations in flood-risk perception arising from temporal lags, proximity to the affected area, and hazard-zone designation. Simulation results based on the model show that three factors explain price changes: delayed adjustment of risk perceptions after the flood, reduced impact of flood risk perceptions with distance from the disaster area, and pre-flood incorporation of flood risk into prices within hazard map zones.

**JEL classification:** D83, Q54, R30

**Keywords:** Flood Risk, Land Prices, Risk Capitalization

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# 1 Introduction

Climate change is fundamentally reshaping the global structure of risks associated with residential and business activities, as evidenced by the increasingly frequent and severe catastrophic flooding events. Global annual losses from riverine floods have reached $388 billion, with the number of flood events since 2000 increasing by 134% compared to the preceding two decades (UNDRR, 2025). These disasters impose multifaceted stresses on local economies, causing direct physical damage to human life and health, as well as to tangible household and firm fixed assets, and to critical regional infrastructure such as bridges and roads. Furthermore, beyond the immediate and direct damage (direct effects), floods may also lead to declines in local economic activity in affected regions (indirect effects). The effects may extend beyond property values affected by physical damage to the disruption of financial intermediation activities, as housing and commercial collateral values are affected. This can result in a contraction of credit supply and an increase in borrowing costs.

Theoretically, land prices are determined as the expected discounted present value of the future returns or utility derived from the use of the land. When land is exposed to flood risk, however, its price must also account for the net expected loss, defined as the product of the probability of future flooding and the anticipated damage or disutility from flooding. Within this framework, land prices may fluctuate as perceptions of the future probability of flooding or of the anticipated returns and benefits from the land change. The changes in the probability of flooding that matter for land prices are the changes in the subjective risk perceptions of market participants, including landowners, which do not necessarily align with objective probabilities of flooding and are known to be subject to revision due to specific events, such as the occurrence of a flood (e.g., Kousky, 2010; Gallagher, 2014).[1]

This paper first provides an empirical investigation of the impact of Typhoon Hagibis—a catastrophic flood event—on land prices, with a specific focus on the spatio-temporal dynamics. Building on these findings, we develop a theoretical framework that explicitly integrates flood-risk beliefs and examines the conditions under which the belief-formation process allows the model to replicate the observed spatio-temporal patterns of land price depreciation following flood events.

To estimate the impacts of floods, we focus on Typhoon Hagibis, which severely affected ex-

[1] The decline in regional economic activity triggered by natural disasters may reduce the actual returns or amenities derived from the land, or the expected value of these returns and amenities, reducing prices (e.g., Deryugina et al., 2018; Boustan et al., 2020; Kocornik-Mina et al., 2020). The role of this channel is further discussed in the appendix.

tensive areas of eastern Japan in 2019, and compare land prices in the inundated areas and surrounding regions before and after the disaster. Our analysis exploits granular parcel-level data on land appraisal values (*Kōji-chika*) published annually by Japan's Ministry of Land, Infrastructure, Transport and Tourism (MLIT) and on land characteristics, such as hazard map designations and land-use zoning. Conceptually, the "*Kōji-chika*" represents the "fair market value of land under normal conditions," evaluated based on the assumption that the land is vacant, excluding the value of any structures or atypical transaction conditions. This unique methodology helps minimize confounding effects arising from physical damage to buildings when assessing changes in land value. Furthermore, by using parcel-level data together with detailed location-based information, such as hazard map designations and land-use zoning, we can precisely estimate the impacts of flooding, depending on ex-ante flood risks and land-use.[2]

The findings of our empirical analysis can be summarized in three primary observations. First, land directly affected by flooding experienced a sustained, gradual price decline of approximately 10% over the five years following the flood event. Second, there were significant negative spillover effects, where land prices within 100 meters of the flood boundary decreased by approximately 5%, although this impact dissipated beyond a distance of 800 meters from the flood boundary. Third, the impact of hazard map designations was significant: properties located outside the flood boundary exhibited substantial price declines, particularly for those within 600 meters of the flood boundary. This trend was particularly pronounced in residential areas, whereas the impact on commercial land prices was relatively limited.

Given the nature of the land price data used in our analysis, the observed changes in post-flood land prices—whether in flooded or non-flooded areas—are not reflective of the physical damage to buildings in these areas. Instead, they are better understood as capturing shifts in market participants' subjective perceptions regarding the benefits and revenues associated with owning the land. Specifically, they reflect changes in subjective beliefs about future flood risk at the transaction sites, in the anticipated impact of flooding on the magnitude of economic activity in the affected areas, and in the expected costs of future flood mitigation measures arising from the recent flooding.

To rationalize these empirical patterns, we extend the Bakkensen and Barrage (2022) sorting model of risk-heterogeneous agents in two key dimensions. First, we endogenize belief formation through adaptive learning, in which stochastic flood events trigger gradual information acquisition

[2] Shertzer et al. (2018) explains the crucial role of zoning on economic activity in the USA. See also Hino and Burke (2021) for a discussion of the differences between commercial and residential buyers in real estate transactions.

rather than instantaneous updates. This captures the persistent post-disaster learning behavior observed following Typhoon Hagibis. Second, we allow the information signal strength to vary with locational attributes. By incorporating spatial decay and site-specific characteristics (e.g., hazard map status or land use), we account for heterogeneous magnitudes and speeds of belief revisions across locations.

Our simulations identify three mechanisms essential to replicating the observed post-flood land price dynamics: (i) temporal frictions in information dissemination, (ii) spatial frictions in information diffusion, and (iii) pre-flood risk capitalization via hazard map designations. First, temporal frictions are necessary to match the gradual, multi-year price decline observed in the data. A frictionless benchmark would yield a counterfactual instantaneous drop to a new equilibrium. Second, spatial frictions govern the observed localized spillovers. While a frictionless information environment implies uniform price drops regardless of distance and prohibitive frictions preclude spillovers entirely, the data support an intermediate case of geographically decaying impacts. Third, the role of prior capitalization is evident from heterogeneous responses across hazard zones. Specifically, the larger spillovers observed outside hazard zones suggest that these areas had lower ex-ante risk pricing. Ultimately, the empirical patterns—larger direct impacts within hazard zones but greater spillovers outside—reflect the interplay between spatial decay and the degree of pre-flood risk capitalization.

**Literature Review** This study contributes to three strands of literature. In addition to the following literature review, Section 4.5 presents a quantitative comparison between the empirical findings obtained in this study and the existing literature. The first strand examines the effects of flooding on land or property prices. This field has accumulated substantial empirical evidence (Hallstrom and Smith, 2005; Bin and Landry, 2013; Zhang, 2016; Beltrán et al., 2018; Ortega and Taşpinar, 2018; McCoy and Zhao, 2018; Sheldon and Zhan, 2019; Cohen et al., 2021; Hennighausen and Suter, 2020; Gruhl et al., 2025).[3] While most studies analyze price declines for damaged properties, some also examine spillover effects to surrounding areas as a function of distance from flooded locations (Pommeranz and Steininger, 2020). Additionally, much of the existing research focuses on specific cities or regions, such as New York or Louisiana, thereby limiting external validity, whereas this study examines multiple cities across Japan. This geographical diversity enables us to identify the effects of flooding by zoning, hazard map designation, and distance

[3] Contat et al. (2024) provides a comprehensive review of this literature.

from the inundated area. In particular, data covering broad inundated areas allow us to assess the "spatial decay" of flood risk capitalization by estimating price effects at fine-grained intervals along the inundation perimeter. By exploiting this boundary-discontinuity-style variation, we can rigorously examine the mechanism in a broader neighborhood spillover.

Second, this paper contributes to the literature on the impact of natural disasters on economic activity. Natural disasters change economic activity both in the short and long term, affecting, for example, firm profits (Kruttli et al., 2025), employment (Barattieri et al., 2023), GDP (Cavallo et al., 2013), out-migration (Boustan et al., 2020), and income (Roth Tran and Wilson, 2025). These impacts arise not only from reduced productive capacity due to damage to tangible fixed assets but also from changes in economic agents' perceptions of risk following natural disasters, which can alter households' and firms' decisions in the affected regions and their surrounding areas. Land prices may reflect all of these effects, though changes in economic activity are likely to vary by factors such as whether the land is used for commercial or residential purposes.[4] Given this, in our empirical exercises, we conduct analyses for residential and commercial areas separately, and in the Appendix, we theoretically study the relationship between changes in economic activity and land price changes following flood events. Related literature includes Bernstein et al. (2019), which shows that only sophisticated buyers in the residential market appropriately discount flood risk in property valuations. While a significant portion of the existing literature focuses on residential markets, evidence on commercial real estate remains relatively scarce. For example, Addoum et al. (2023) analyzes the impact of Hurricane Sandy on commercial real estate transactions before and after the disaster. Coulson et al. (2020) examines how industrial diversity in commercial districts affects property prices, and Meltzer et al. (2021) reports that locally-based retail establishments were more vulnerable to the effects of Hurricane Sandy.

The third strand includes studies about flood risk perception, in particular how individuals perceive and respond to flood risks (Gallagher, 2014; Baldauf et al., 2020; Gibson and Mullins, 2020; Bakkensen and Barrage, 2022; Wagner, 2022; Le, 2024). Specifically, Gallagher (2014) examines the role of behavioral factors in shaping flood insurance demand, whereas Baldauf et al. (2020) examines the influence of geographic and socioeconomic factors on flood risk awareness. Gibson and Mullins (2020) examines the psychological drivers of individual responses to flood risk and highlights the importance of risk communication in shaping perceptions. Bakkensen and Barrage

[4] The feedback mechanism between land prices and economic activity when land is used as collateral has been explored in detail in a number of theoretical studies, such as Kiyotaki and Moore (1997).

(2022) develops a model that links individual risk perceptions to the demand for flood insurance, emphasizing the role of local environmental and policy factors. Wagner (2022) complements this work by documenting low willingness to pay for flood insurance and attributing part of the wedge between willingness to pay and expected costs to risk misperception. Le (2024) examines the use of microdata to analyze the heterogeneity of flood risk perceptions across different population segments.

The remainder of this paper is organized as follows. Section 2 describes the data sources and how these data are combined. Section 3 presents the empirical model. Section 4 reports the empirical findings. Section 5 develops a theoretical model and discusses specific features of the model needed to account for empirical observations. Section 6 concludes.

## 2 Data

This section describes the data sources and the sample construction. Section 2.1 defines the treatment and control groups based on flood exposure. Section 2.2 describes the land price data from the Official land prices. Section 2.3 explains the hazard map designations. Section 2.4 presents summary statistics.

In our empirical section, we aim to examine how changes in flood-risk beliefs following a natural disaster are capitalized into land prices using granular inundation maps associated with the impacts of Typhoon Hagibis. Typhoon Hagibis serves as a relevant quasi-experimental setting for several compelling reasons. First, it was a landmark meteorological event that brought widespread torrential rainfall to eastern Japan, spanning multiple prefectures. As a result, the disaster affected a large geographic area characterized by high socioeconomic and geographic heterogeneity.[5] The characteristics of our data set facilitate deriving general implications from the empirical results. Existing studies often assess flood impacts by examining a single event in a specific metropolitan area. For example, Ortega and Taşpinar (2018) and Gibson and Mullins (2020) examine the effects of Hurricane Sandy on the real estate market in New York City. However, because New York City is a unique global metropolis with distinct features, these findings may be limited in their gener-

[5] Total rainfall from October 10 to 13 reached 1,000 mm in Hakone, Kanagawa Prefecture, with 17 other locations across eastern Japan exceeding 500 mm. The disaster resulted in 91 fatalities, 3,273 residential buildings destroyed, 63,743 partially damaged buildings, and 29,556 inundated buildings (Cabinet Office of Japan, White Paper on Disaster Management 2020, in Japanese, available at https://www.bousai.go.jp/kaigirep/hakusho/r02/honbun/0b_1s_01_03.html, accessed January 2, 2026). Insured losses totaled approximately 475.1 billion yen, making it one of the costliest natural disasters in Japanese insurance history (General Insurance Rating Organization of Japan, Flood Damage Prevention Report, in Japanese, available at https://www.giroj.or.jp/publication/accident_prevention_report/pdf/flood.pdf, accessed January 2, 2026).

alizability to other contexts. In contrast, as the spatial impact of Typhoon Hagibis spans multiple prefectures with diverse regional conditions, controlling for regional characteristics such as land use and whether areas fall within or outside hazard map zones can help capture less context-specific impacts, offering broader applicability of the findings.

Second, our access to confidential, high-resolution inundation maps enables unprecedented spatial granularity. This precision enables us to identify the "spatial decay" of flood-risk capitalization by estimating price effects at fine-grained intervals along the inundation perimeter. By exploiting this boundary-discontinuity-style variation, we can isolate the direct impact of physical flooding from broader neighborhood spillovers.[6]

## 2.1 Treatment and Control Groups

Panel A of Figure 1 illustrates the spatial distribution of municipalities inundated during Typhoon Hagibis (dark blue) alongside their contiguous counterparts (light blue). The affected regions span a broad geographic corridor of approximately 300 kilometers, extending from central to northern Japan. Panel B provides a granular visualization of Koriyama City in Fukushima Prefecture —one of the most severely impacted areas—where the Abukuma River breached its levees. This map disentangles fluvial flooding (dark blue) from pluvial flooding (light blue), which are overlaid with official hazard map designations (gray) and assessed land price points (yellow).[7] This spatial alignment allows for a precise matching between localized flood exposure and high-frequency land value assessments.

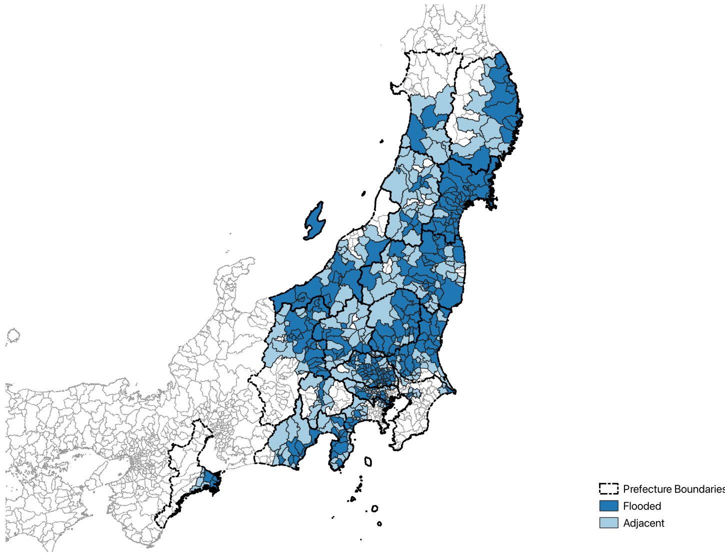
We use disaggregated administrative data on inundated areas from the Ministry of Land, Infrastructure, Transport, and Tourism (MLIT). Under the statutory Statistical Survey on Floods Damage, municipalities are required to report the number of inundated structures and to prepare flood extent maps. While these administrative records categorize the causal mechanisms of flooding—distinguishing between fluvial, pluvial, coastal, and landslide-induced events—they lack systematic information on inundation depth.

To ensure spatial comprehensiveness, we supplement these municipal records with flood-extent maps produced by the Geospatial Information Authority of Japan (GSI), which derive inundation

6 The maps further distinguish between fluvial (riverine) and pluvial (surface water) flooding mechanisms, allowing us to examine whether markets differentiate between distinct types of hydrological risks. These granular features of our empirical setting also yield novel insights into the heterogeneous pricing of disaster risk. Appendix Section D presents results disaggregated by flood type (fluvial vs. pluvial), documenting heterogeneous capitalization patterns across distinct hydrological risk mechanisms.

7 The hazard map reflects the administrative designations in effect at the time of Typhoon Hagibis. These maps have since been revised. We discuss the empirical implications of these information updates in Appendix B.

Panel A. Flooded and Adjacent Municipalities




Panel B. An Example of Flooding from Typhoon Hagibis (Koriyama City, Fukushima)

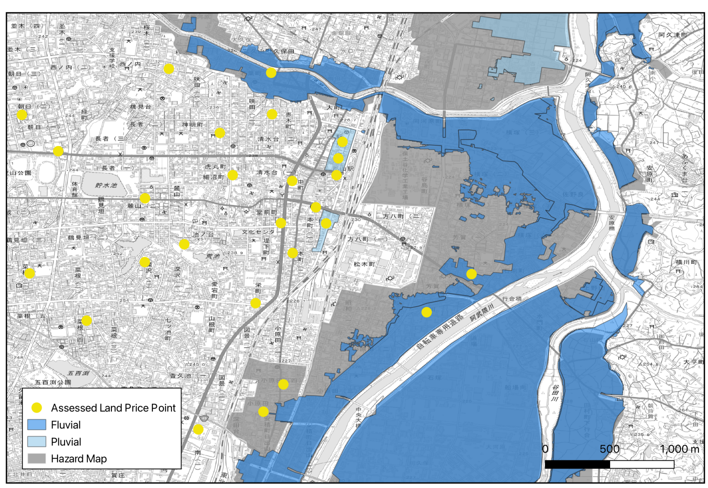



Figure 1: Geographic Distribution of Floods from Typhoon Hagibis

*Notes:* Panel A delineates the municipalities inundated during Typhoon Hagibis (2019) alongside their contiguous, non-flooded counterparts within the same prefecture. To accurately identify flooded jurisdictions, we rely on inundation-area maps synthesized from local government Flood Statistics and flood-extent spatial data provided by the Geospatial Information Authority of Japan (GSI). In our empirical framework, land prices in these adjacent municipalities serve as the counterfactual control group. Panel B illustrates a granular example of fluvial and pluvial flooding in the vicinity of Koriyama City, Fukushima Prefecture. Here, dark blue regions denote fluvial flooding, light blue areas indicate pluvial flooding, and gray shading indicates high-risk zones on official hazard maps.

boundaries by integrating satellite imagery with high-resolution digital elevation models.[8] Although the GSI data include estimated depths, we use them solely to refine the flood-extent delineation for two reasons. First, municipal field surveys may be subject to idiosyncratic measurement errors. Second, GSI depth estimates are only available for a non-random subset of affected regions. We define the final inundated area as the union of these two data sources, adopting the maximum observed extent to minimize under-reporting bias.

Our primary treatment group comprises land price observations located within the identified inundation perimeters. The control group comprises land price points within municipalities adjacent to the flooded jurisdictions (indicated in light blue in Panel A of Figure 1). These adjacent municipalities serve as a plausible counterfactual for two reasons. First, they share similar unobserved geographic and economic fundamentals with the affected areas. Second, they provide a unique setting to isolate the role of information salience. While residents in flooded municipalities are continuously exposed to recovery-related news via local media and municipal gazettes, those in neighboring jurisdictions are less likely to encounter such intensive exposure to post-disaster information.[9]

## 2.2 Land Price

We obtain land price data from the National Land Numerical Information database. Our primary source is the Official land prices (*Kōji-chika*), Japan's official land valuation system overseen by the MLIT. Annually, the Land Appraisal Committee publishes assessed values for designated benchmark sites as of January 1. These sites are selected to be representative of their respective local markets in terms of land use, environment, and physical characteristics. The reported figures represent "normal prices"—the values expected in arm's-length transactions under typical market conditions. Each site is evaluated by at least two independent, licensed real estate appraisers, primarily using the sales comparison approach. The final valuations are determined following a formal review by the Committee.[10]

We employ the Official land prices for several key reasons. First, a defining feature of this system is that all sites are appraised as vacant land (*sarachi*), irrespective of any existing structures. This

[8] Available at `https://www.gsi.go.jp/BOUSAI/R1.taihuu19gou.html` (accessed January 2, 2026). GSI notes potential classification errors, where some inundated areas may be omitted, and certain dry areas may be misidentified as flooded.

[9] We further examine potential heterogeneous effects by partitioning the sample into affected and non-affected municipalities. These results are reported in Appendix Section C.

[10] While this institutional framework aims to ensure objectivity, it is worth noting that appraisers' risk perceptions may shift following major flood events, potentially incorporating subjective bias into post-disaster valuations.

approach ensures that assessed values reflect the highest and best use of the land, effectively isolating the land's intrinsic value from building-specific attributes such as building age, construction type, or depreciation. Crucially, this allows us to disentangle changes in risk perception from physical capital damage, providing a cleaner identification of how flood-risk beliefs, rather than structural impairment, drive price adjustments. Second, because the same benchmark sites are appraised annually, the data form repeated observations. This structure allows us to control for time-invariant parcel heterogeneity by including parcel fixed effects.[11] Third, the data set offers a high degree of transparency and objectivity. While actual transaction data in Japan are subject to privacy-related access restrictions, the *Kōji-chika* is publicly available. Fourth, these valuations carry substantial economic weight in practice. Financial institutions frequently rely on these official assessments rather than volatile transaction prices for collateral valuation.[12]

### 2.3 Hazard Maps

Under the Flood Control Act and the Basic Act on Disaster Management, the national and prefectural governments designate and publish flood inundation warning area maps (hazard maps) for rivers where flooding poses a significant risk to the economy or human life. These maps delineate areas projected to be inundated under the design rainfall—the precipitation level used in local flood control planning—which varies across river systems. The projected inundation data are sourced from the National Land Numerical Information database.[13] We utilize the 2012 version (ver. 1.1) of this data set, as it was the most current information available to the public and authorities at the onset of Typhoon Hagibis. It is important to distinguish between fluvial (riverine) and pluvial (inland) flooding. While the analyzed hazard maps focus on fluvial flooding, pluvial flooding, which occurs when heavy rainfall exceeds the capacity of sewer systems and drainage channels, was not systematically mapped until the 2021 legislative reforms. Consequently, comprehensive pluvial hazard maps did not exist at the time of the typhoon. Nevertheless, empirical evidence suggests that certain properties within the designated fluvial hazard zones were affected by pluvial flooding

[11] Although our land-parcel fixed effects absorb all time-invariant characteristics by construction, the dataset also records granular attributes-such as distance to the nearest station, zoning designations, and floor-area ratios, which we exploit in heterogeneity and subgroup analyses in our empirical analysis.

[12] Koide et al. (2022) shows that among the most commonly used methods for real estate collateral valuation, one third of regional banks rely on *Kōji-chika*, and another one third use roadside land values, which are administrative land valuations published by National Tax Agency. This underscores the practical relevance of officially assessed land prices, as they serve as a transparent and uniform benchmark for financial institutions to consistently reflect disaster risk in collateral valuation and lending decisions.

[13] Available at https://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-A31a-2024.html (accessed January 2, 2026).

during the event.

## 2.4 Summary Statistics

Table 1 presents the pre-disaster summary statistics across our sample groups. Column (1) reports statistics for properties directly inundated during the event, while Columns (2) and (3) provide benchmarks for non-inundated properties within flooded municipalities and the control group in neighboring non-flooded municipalities.

Systematic differences are observed across these groups, reflecting the inherent geographical and economic characteristics of flood-prone areas. Inundated properties exhibit substantially lower land prices ($51,000$ yen/$m^2$) compared to their counterparts in flooded ($151,000$ yen) and control municipalities ($265,000$ yen). Pre-disaster price trends also show some divergence: inundated areas experienced an annual growth rate of 0.11%, whereas other groups grew at approximately 1%. Furthermore, inundated properties are characterized by smaller average lot sizes (336 $m^2$ versus approximately 750 $m^2$ in surrounding areas), higher hazard map coverage (55%), and lower population density.

While these baseline imbalances might initially suggest potential violations of the parallel trends assumption, they do not necessarily invalidate our Difference-in-Differences (DiD) framework. First, the observed disparities are largely cross-sectional and time-invariant and are effectively absorbed by the inclusion of property-level or municipality-level fixed effects. Second, to formally address concerns regarding differential trajectories, we employ an event-study specification to verify that pre-treatment trends were stable prior to the shock. Third, we demonstrate that key time-varying covariates, such as distance to the nearest railway station and working-age population ratios, are well-balanced across groups, suggesting that the fundamental economic drivers of land value during the sample period are comparable. Furthermore, as detailed in Appendix B, our results remain qualitatively and statistically consistent across various robustness checks, confirming that the baseline findings are not driven by these initial differences.

Appendix Table A1 presents summary statistics separately for parcels located inside and outside designated hazard zones, providing the descriptive context for the heterogeneity analyses that follow. A notable pattern emerges in the composition of land use: among inundated parcels, commercial properties account for only 14% of those within hazard zones, compared to 33% of those outside hazard zones. This disparity suggests that commercial activities may be disproportionately concentrated in areas explicitly flagged as low-risk. While this pattern is less pronounced in non-

Table 1: Summary Statistics

| Variable | Treatment (1) | Within Flooded Cities (2) | Control (3) |
|---|---|---|---|
| Price (1000 JPY) | 51 | 151 | 265 |
| | (62) | (265) | (895) |
| Price Change 2018–2019 (%) | 0.11 | 0.99 | 0.93 |
| | (1.57) | (3.04) | (2.78) |
| Area (sqm) | 336 | 778 | 735 |
| | (272) | (8021) | (5680) |
| Dist. to Station (m) | 1973 | 2030 | 1958 |
| | (2557) | (2477) | (2623) |
| Hazard Map Incl. | 0.55 | 0.26 | 0.23 |
| Floor Area Ratio | 230.74 | 205.91 | 209.91 |
| | (104.28) | (104.50) | (120.69) |
| Building Coverage Ratio | 64.84 | 61.03 | 60.61 |
| | (9.66) | (10.78) | (12.00) |
| Commercial % | 22.1 | 17.3 | 19.5 |
| Residential % | 52.6 | 65.1 | 64.2 |
| Industrial % | 6.3 | 7.0 | 6.3 |
| Adjustment Area % | 18.9 | 10.7 | 10.0 |
| Neighborhood population (250m grid) | 289.27 | 470.37 | 557.57 |
| | (240.57) | (392.39) | (452.94) |
| Working-age ratio (250m grid) | 0.58 | 0.61 | 0.61 |
| | (0.08) | (0.09) | (0.08) |
| Properties | 95 | 3549 | 2910 |
| No. of Cities | 30 | 232 | 213 |

*Notes:* Summary statistics are computed as of January 1, 2019, prior to Typhoon Hagibis. The treatment group consists of properties directly exposed to flooding. The Flooded Cities group includes properties in cities affected by flooding but not directly exposed to it. The control group comprises properties in non-flooded cities near flood-affected municipalities. Values in parentheses report standard deviations. Land use categories are expressed as percentages of each group.

inundated and control municipalities, the observed correlation should be interpreted with caution due to potential endogeneity. Specifically, this distribution likely reflects the historical trajectory of urban development in Japan: prime commercial districts have traditionally been concentrated in central urban cores, where flood control infrastructure was established earlier and to a higher technical standard, thereby reducing their likelihood of being classified as hazardous under contemporary hazard designations. Crucially, however, these systematic baseline differences do not bias our primary empirical strategy. Since our main specification utilizes parcel-level fixed effects, any such time-invariant locational sorting or historical infrastructure advantages are effectively absorbed. We therefore present these patterns as relevant descriptive context for understanding the landscape of risk exposure, rather than as a causal claim regarding land-use sorting.

# 3 Empirical Model

This section details our empirical strategy for identifying the causal impact of Typhoon Hagibis on land market dynamics. While an extensive body of literature has documented the direct capitalization of flood risk into property values (Atreya and Ferreira, 2014; Bin and Landry, 2013; Ortega and Taşpinar, 2018; Gibson and Mullins, 2020), analysis of spillover effects has often relied on frameworks that may not fully capture the underlying spatial dependencies (McCoy and Zhao, 2018; Pommeranz and Steininger, 2020; Cohen et al., 2021). To address these methodological challenges, we adopt a potential outcomes framework that explicitly accounts for interference across units (Aronow and Samii, 2017; Vazquez-Bare, 2023), building on recent advancements in the empirical application of this methodology (Butts, 2023; Ortega et al., 2025). Specifically, we embed this framework within an event-study design to trace the temporal evolution of both impacts at inundated sites and spillover effects in surrounding sites.

$$\log(p_{ic\tau}) = \sum_{\substack{\tau=-5 \\ \tau\neq-1}}^{5} \left[\beta_\tau \cdot Flood_i \times \mathbf{1}[\tau] + \gamma_\tau \cdot S_i(1 - Flood_i) \times \mathbf{1}[\tau]\right] + \alpha_i + \nu_c + \delta_\tau + \epsilon_{ic\tau}. \quad (1)$$

In this specification, $p_{ic\tau}$ denotes the assessed value of parcel $i$ in municipality $c$ at event time $\tau$, where $\tau = 0$ corresponds to the 2020 assessment. Given that Typhoon Hagibis made landfall in October 2019 and land prices are appraised as of January 1 each year, the 2020 values constitute the first post-treatment observations. The treatment status is captured by two indicators: $Flood_i$ is a dummy variable equal to one if parcel $i$ was directly inundated, while $S_i$ is a spatial spillover indicator equal to one if any inundated area exists within a specified radius (e.g., 100 meters) of a non-flooded parcel. The term $\mathbf{1}[\tau]$ represents a vector of event-time dummies.

Following the standard convention in event study designs (Miller, 2023), we normalize the coefficients by designating $\tau = -1$ (the 2019 assessment) as the reference period. As the final pre-treatment observation, this baseline enables a clean comparison with post-shock dynamics. The pre-treatment coefficients ($\beta_\tau$ and $\gamma_\tau$ for $\tau < -1$) provide a formal test of the parallel trends assumption. Under a valid identification strategy, these estimates should be statistically indistinguishable from zero, confirming the absence of systematic divergence in price trajectories prior to the exogenous shock.

For our baseline specification, we define spatial spillovers as parcels located within a 100-meter radius of the inundated area but are not themselves inundated. This threshold is informed by the existing literature. For instance, McCoy and Zhao (2018) uses buffers of 250 feet (76 meters) and 500 feet (152 meters), while Ortega et al. (2025) examines spillover effects within New York City blocks containing flooded properties. While we adopt the 100-meter buffer as our primary benchmark, we also explore the degree of spillover effects using wider cumulative distance thresholds (e.g., 200m and 300m). We deliberately avoid non-overlapping distance bins (e.g., $[100, 200]$ or $[200, 300]$) to maintain sufficient statistical power, as the number of observations within such narrow spatial increments becomes too small for robust inference.

To isolate the causal impact of the typhoon, our specification includes three fixed effects. The parcel fixed effect, $\alpha_i$, effectively purges bias arising from all time-invariant property characteristics, such as site-specific amenities, lot size, and localized neighborhood endowments. The municipality fixed effect, $\nu_c$, absorbs systematic cross-sectional heterogeneity, including variations in local fiscal policies, public service quality, and regional economic cycles. Furthermore, the year fixed effect, $\delta_t$, captures aggregate temporal shocks and macroeconomic fluctuations that uniformly affect the housing market across the study area.

The idiosyncratic error term is denoted by $\epsilon_{ict}$. Our primary coefficients of interest, $\beta_t$ and $\gamma_t$, identify the time-varying direct and spatial spillover effects of the inundation event.

A critical challenge in this empirical setting is the potential for complex error dependencies. As established by Bertrand et al. (2004), failure to account for serial correlation in difference-in-differences designs can lead to severely downward-biased standard errors and spurious significance. Moreover, land prices often exhibit spatial correlation within administrative units and common shocks within specific time periods. To ensure the validity of our statistical inference, we employ a two-way clustering strategy by municipality and year, following the framework developed by Cameron et al. (2011). This approach allows for arbitrary correlation of the error term within municipalities over time and across municipalities within a given year. By relaxing the restrictive independence assumption, this robust clustering method yields more reliable standard errors, mitigating the risk of overstating the precision of our estimates in the presence of multi-dimensional dependencies.

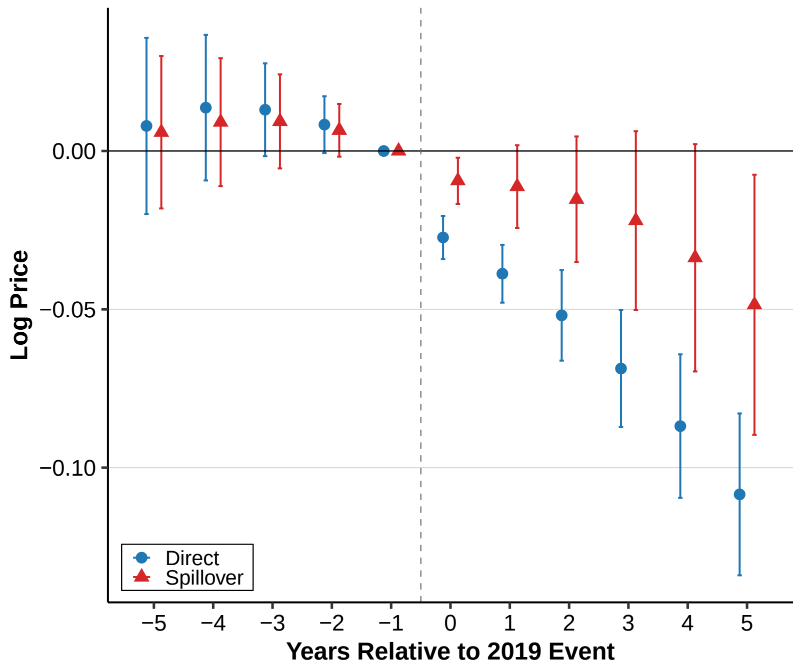



Figure 2: Baseline Results

*Notes:* This figure presents event study estimates of the effects of flood risk on parcel prices. The reference year is 2019. Error bars represent 95% confidence intervals with standard errors clustered at the city-year level.

# 4 Results

This section details our empirical findings. We begin by establishing the baseline estimates in Section 4.1, before extending the analysis to examine potential spillover effects in Section 4.2. To uncover the underlying drivers of these effects, Sections 4.3 and 4.4 explore how the impact varies across hazard map designations and zoning classifications. We conclude by discussing the broader economic implications in Section 4.5. A variety of robustness checks, including falsification tests, Synthetic Difference-in-Differences estimation, and controls for concurrent policy shifts, are reported in Appendix B.

## 4.1 Baseline

Figure 2 plots the event study coefficients characterizing the dynamic impact of flood exposure on parcel prices. The estimation follows Equation (1), with 2019 serving as the omitted reference year. Capped vertical bars denote 95% confidence intervals based on standard errors clustered at the municipality-by-year level. For the spillover analysis, $S_i$ denotes the set of parcels within a 100-meter buffer of the inundated area.

Several salient features emerge from the empirical analysis. First, the estimated coefficients for the pre-treatment periods are statistically indistinguishable from zero, providing evidence in support of the parallel trends assumption. Second, for directly affected parcels, we observe a significant and persistent price depreciation immediately following the flood event. The magnitude of this effect intensifies over time, reaching approximately 10 log points by the end of the sample period. While one might ex ante expect a discrete price jump, the observed gradual capitalization is consistent with the institutional framework of official price assessments. Since these assessments isolate land value by excluding physical structures, building-specific damages are not capitalized, leading to the delayed adjustment in land prices. Third, we find evidence of localized externalities: parcels within the 100-meter spillover zone, excluding directly affected parcels, experience a decline of roughly 5 log points, with significant effects manifesting in the first and fifth years after the event.

Table 2 evaluates the sensitivity of our baseline results to alternative fixed effects and clustering structures. A comparison between Columns (1) and (2) indicates that the inclusion of municipality fixed effects leaves the point estimates qualitatively unchanged. However, these specifications yield some statistically significant coefficients in the pre-event period, suggesting potential violations of the identifying assumption. Crucially, these pre-event discrepancies are highly sensitive to the choice of standard error formulation. Column (3) implements clustering at the municipality level, which generally inflates the standard errors and renders the pre-trends less significant. Column (4) presents our preferred specification, employing two-way events clustering by municipality and year. Under this more rigorous framework, the parallel trends assumption appears fundamentally satisfied, as the coefficients for the pre-event periods are statistically indistinguishable from zero. To further mitigate concerns about potential violations of the parallel trends assumption, Appendix B conducts a series of robustness checks on our baseline findings. Specifically, we conduct falsification tests and implement the Synthetic Difference-in-Differences (SDID) estimator to account for potential unobserved heterogeneity in trends. These alternative methodologies consistently yield results that reinforce our main findings, confirming that the observed price depreciation is not driven by pre-existing idiosyncratic trends. Collectively, these tests lend further credence to a causal interpretation of our estimates.

Table 2: Baseline Event Study Estimates

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Panel A: Direct Effects* | | | | |
| Year 2015 | 0.008 | 0.008 | 0.008 | 0.008 |
| | (0.008) | (0.008) | (0.022) | (0.014) |
| Year 2016 | 0.014** | 0.014** | 0.014 | 0.014 |
| | (0.005) | (0.005) | (0.013) | (0.012) |
| Year 2017 | 0.013*** | 0.013*** | 0.013* | 0.013 |
| | (0.003) | (0.003) | (0.008) | (0.007) |
| Year 2018 | 0.008*** | 0.008*** | 0.008** | 0.008* |
| | (0.002) | (0.002) | (0.003) | (0.005) |
| Year 2019 | [Reference] | | | |
| Year 2020 | −0.027*** | −0.027*** | −0.027*** | −0.027*** |
| | (0.003) | (0.003) | (0.005) | (0.003) |
| Year 2021 | −0.039*** | −0.039*** | −0.039*** | −0.039*** |
| | (0.005) | (0.005) | (0.007) | (0.005) |
| Year 2022 | −0.052*** | −0.052*** | −0.052*** | −0.052*** |
| | (0.007) | (0.007) | (0.009) | (0.007) |
| Year 2023 | −0.069*** | −0.069*** | −0.069*** | −0.069*** |
| | (0.009) | (0.009) | (0.011) | (0.009) |
| Year 2024 | −0.087*** | −0.087*** | −0.087*** | −0.087*** |
| | (0.011) | (0.011) | (0.014) | (0.012) |
| Year 2025 | −0.108*** | −0.108*** | −0.108*** | −0.108*** |
| | (0.013) | (0.013) | (0.017) | (0.013) |
| *Panel B: Spillover Effects* | | | | |
| Year 2015 | 0.006 | 0.006 | 0.006 | 0.006 |
| | (0.010) | (0.010) | (0.015) | (0.012) |
| Year 2016 | 0.009 | 0.009 | 0.009 | 0.009 |
| | (0.008) | (0.008) | (0.011) | (0.010) |
| Year 2017 | 0.009* | 0.009* | 0.009 | 0.009 |
| | (0.005) | (0.005) | (0.007) | (0.008) |
| Year 2018 | 0.007*** | 0.007*** | 0.007* | 0.007 |
| | (0.003) | (0.003) | (0.003) | (0.004) |
| Year 2019 | [Reference] | | | |
| Year 2020 | −0.009*** | −0.009*** | −0.009** | −0.009** |
| | (0.003) | (0.003) | (0.004) | (0.004) |
| Year 2021 | −0.011*** | −0.011*** | −0.011* | −0.011 |
| | (0.004) | (0.004) | (0.007) | (0.007) |
| Year 2022 | −0.015*** | −0.015*** | −0.015 | −0.015 |
| | (0.006) | (0.006) | (0.010) | (0.010) |
| Year 2023 | −0.022*** | −0.022*** | −0.022 | −0.022 |
| | (0.008) | (0.008) | (0.014) | (0.014) |
| Year 2024 | −0.034*** | −0.034*** | −0.034* | −0.034* |
| | (0.011) | (0.011) | (0.019) | (0.018) |
| Year 2025 | −0.049*** | −0.049*** | −0.049* | −0.049** |
| | (0.014) | (0.015) | (0.025) | (0.021) |
| Property FE | Yes | Yes | Yes | Yes |
| Municipality FE | No | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Clustering | None | None | City | City + Year |
| Observations | 72,094 | 72,094 | 72,094 | 72,094 |
| $R^2$ | 0.997 | 0.997 | 0.997 | 0.997 |

*Notes:* This table reports event study estimates from Equation (1). The dependent variable is the log of land price. Panel A shows coefficients for properties directly exposed to flooding. Panel B shows coefficients for non-flooded properties within 100 meters of the inundation boundary. The reference year is 2019, the period immediately preceding Typhoon Hagibis. Columns vary by fixed effects and clustering: Column (1) includes property and year fixed effects with no clustering; Column (2) adds municipality fixed effects; Column (3) clusters standard errors by municipality; Column (4) clusters by both municipality and year. Column (4) is our preferred specification. Standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

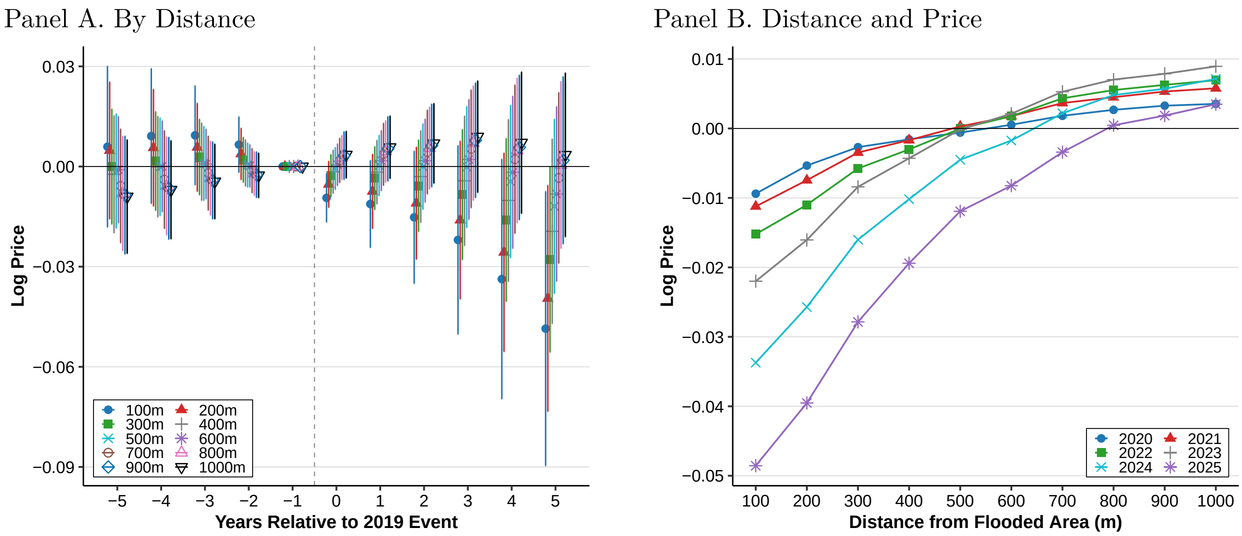



Figure 3: Spillover Effects on Parcel Values

*Notes:* This figure illustrates the event-study estimates characterizing the geographical spillovers of flood events. We report the estimated coefficients $\gamma_\tau$ from Equation (1) across two distinct dimensions. Panel A presents the temporal evolution of spillover effects, where the treatment group is defined as non-flooded parcels situated within specified buffer distances from the inundated area. Panel B displays the spatial gradient of the impact, plotting the coefficients for each post-disaster year against the distance from the flood boundary on the horizontal axis. To ensure a valid counterfactual, the control group comprises parcels in neighboring municipalities that did not experience flooding during the sample period. The reference year is 2019. Capped vertical bars denote 95% confidence intervals, with standard errors clustered at the city-year level to account for potential spatial and temporal correlations.

## 4.2 Spillover Effects

Figure 3 presents the estimated spillover effects, denoted by $\gamma_t$ in Equation (1). Panel A displays the event-study estimates with the temporal dimension on the horizontal axis, examining how proximity to inundated areas affects the pricing of non-inundated parcels within specified buffer distances. To illustrate the precision of our estimates, we plot both the point estimates and their corresponding standard errors. The coefficients for the pre-event periods are statistically indistinguishable from zero, supporting the validity of the parallel trends assumption. Notably, for parcels within the 300-meter buffer, we observe a significant price depreciation that becomes statistically significant five years after the initial shock.

Panel B illustrates the spatial decay of the impact by plotting the coefficients for each post-event year (2020–2025) against the distance from the flood boundary. For clarity of exposition, confidence intervals are suppressed in this panel. The results reveal that parcels within 400 meters of inundated areas exhibit persistent price declines throughout the post-event period. Of note is the temporal

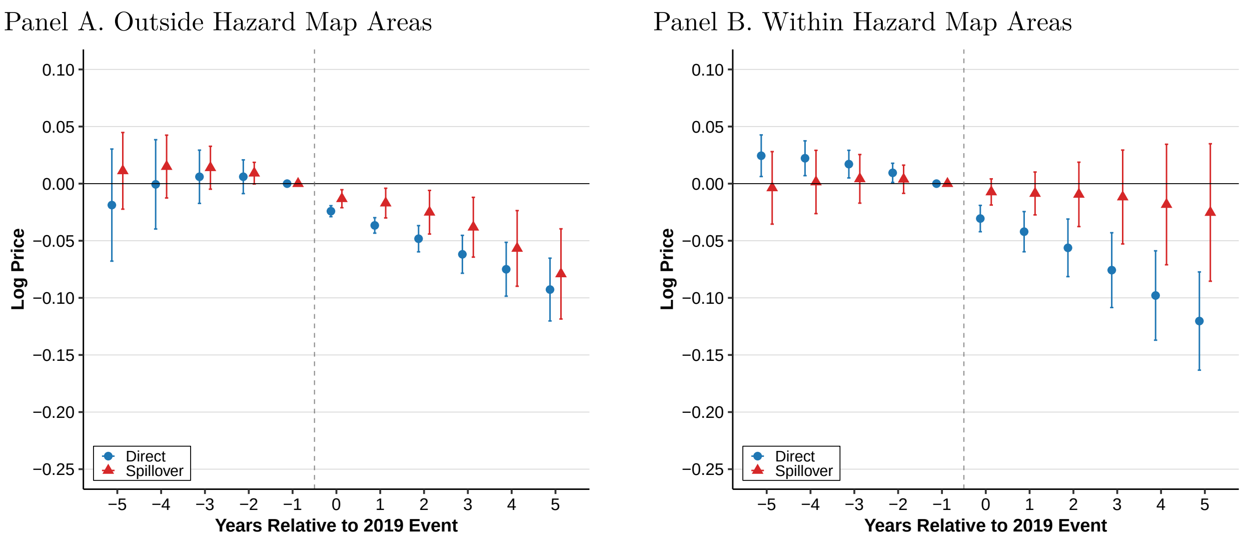



Figure 4: Heterogeneous Effects by Hazard Maps

*Notes:* This figure presents event-study estimates of the impact of the 2019 flood event, estimated separately for parcels located inside and outside designated flood hazard maps. The reference year is 2019. Error bars represent 95% confidence intervals, with standard errors clustered at the city-year level.

intensification of this effect: the price depreciation becomes markedly more pronounced four to five years after the flood event. This gradual, slow response suggests that the capitalization of flood risk spans both physical space and time, possibly reflecting relocation adjustment costs faced by households and firms or the time required for updated risk perceptions to be fully incorporated into market transactions. More broadly, negative price effects extend to distances of up to 800 meters, whereas parcels beyond this threshold show no decline and even exhibit marginal increases. Although not statistically significant, this latter pattern is consistent with potential replacement demand as households relocate to areas perceived as safer.

## 4.3 Hazard Maps

The heterogeneity in land price responses between parcels located within and outside hazard map zones could provide critical insights into the role of updating beliefs regarding flood risks. For example, if households with different risk perceptions or flood-related concerns choose their residential locations based on their attributes and perceived risk, then differences in land price changes following a flood event could be interpreted as reflecting variations in household concerns and risk awareness. Indeed, existing research has reported that risk perceptions can vary across households (e.g., Gallagher, 2014; Bakkensen and Barrage, 2022). Another plausible mechanism is that flood risks may already be priced into the value of land within hazard map zones. If this is the

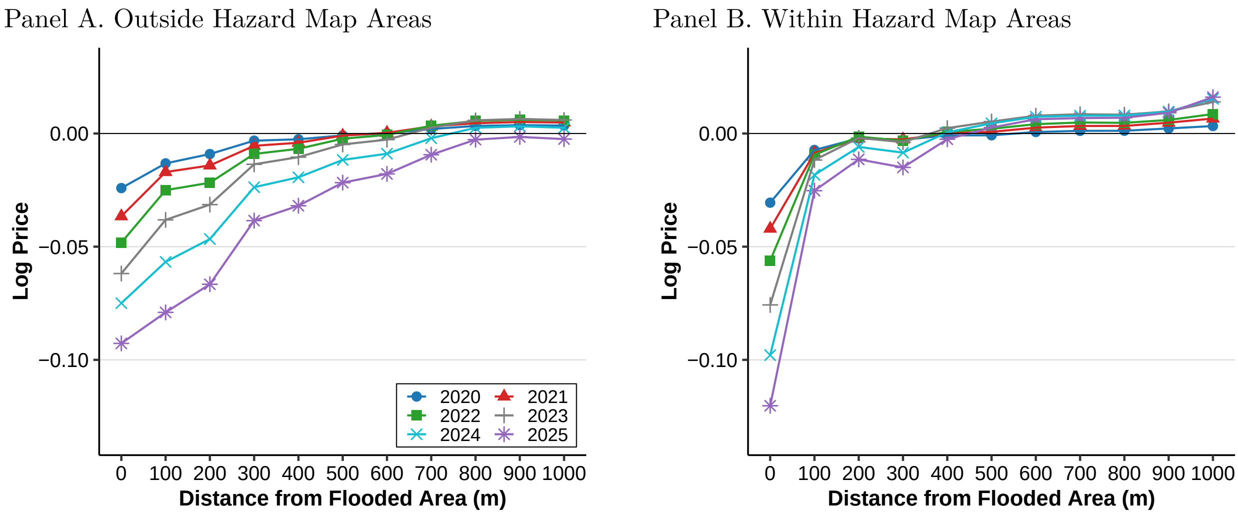



Figure 5: Spillover Effects by Distance from Flooded Area

*Notes:* This figure shows the estimated spillover effects on log parcel prices as a function of distance from the inundated areas. Panel A reports results for parcels situated outside hazard map areas, while Panel B presents estimates for parcels within hazard map areas. The reference year is 2019.

case, even if flood risk perceptions rise to the same level across areas, the magnitude of land price changes could be greater in areas where flood risks were not previously priced in (e.g., Hallstrom and Smith, 2005; Bin and Landry, 2013).

Figure 4 presents the event study estimates for these two subsamples. Panel A (outside hazard zones) shows significant and comparable price depreciations for both directly inundated parcels and those in the spillover group. This suggests substantial upward revisions in risk beliefs for these areas. In contrast, Panel B (inside hazard zones) shows a distinct pattern: while the price decline for directly affected parcels is markedly larger than that observed in Panel A, spillover effects are statistically negligible, suggesting that revisions of risk beliefs are confined to affected properties.

Figure 5 further explores these dynamics by plotting the distance gradient of the flood impact for each subgroup. Comparing Panels A and B, one can observe that parcels outside hazard map zones exhibit larger price declines at equivalent distances, with the magnitude of depreciation intensifying over time. The only exception is affected parcels, where price declines are larger inside the hazard map.

## 4.4 Zoning

We also explore the heterogeneous effects across land-use categories. The comparison between residential and commercial parcels provides a quasi-experimental setting to examine how poten-

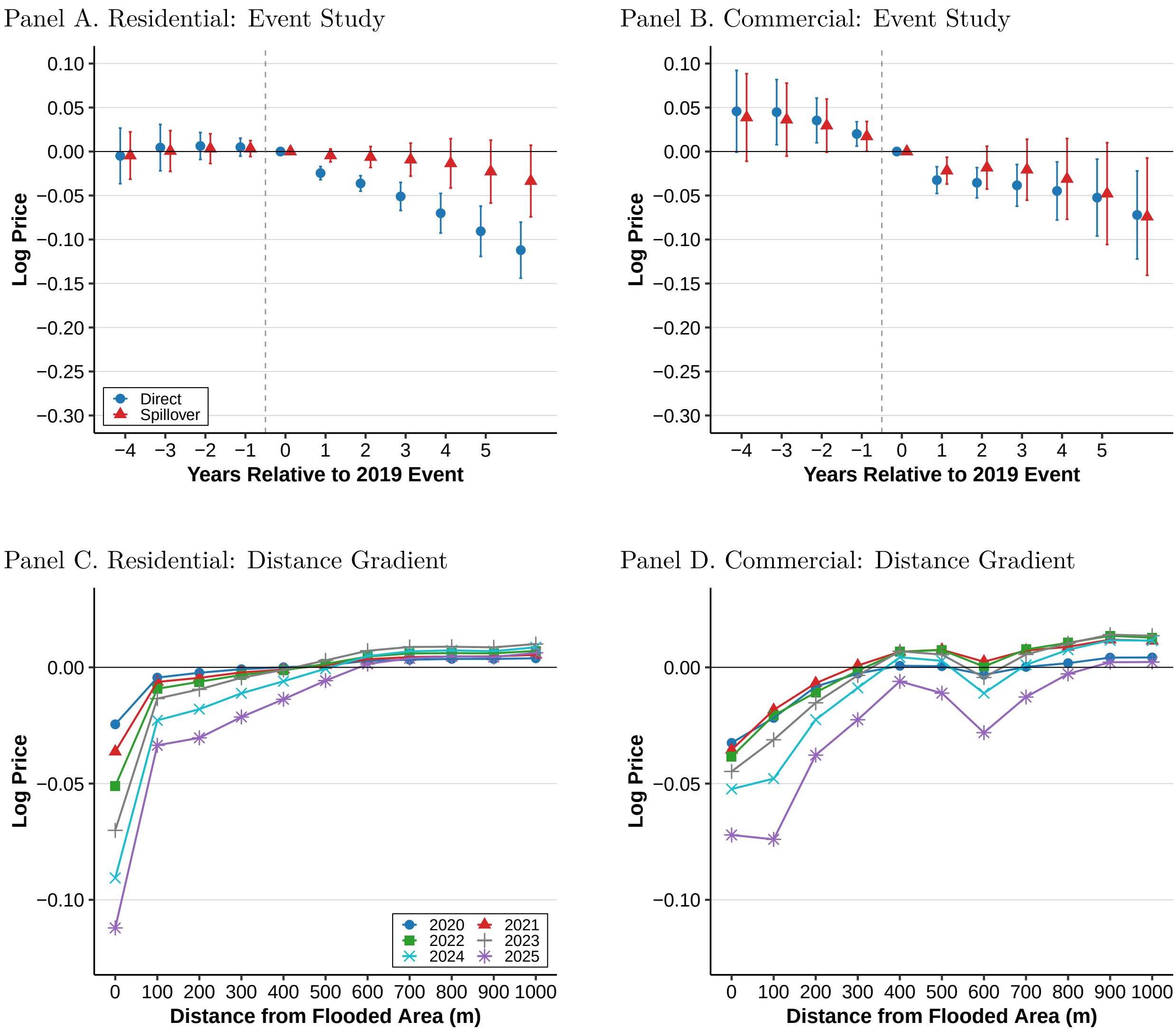



Figure 6: Heterogeneous Effects by Land Use Zone

*Notes:* This figure illustrates the heterogeneous impacts of flood exposure across different land-use categories. Panels A and B present event study estimates from Equation 1 for residential and commercial parcels, respectively, distinguishing between parcels directly inundated (Direct, $\beta_\tau$) and those within a proximity of 100 meters (Spillover, $\gamma_\tau$). Panels C and D plot the estimated spatial gradients against the distance from the inundated area for each post-event year (2020–2025), where a distance of zero denotes directly inundated parcels. The reference year is 2019. Error bars indicate 95% confidence intervals based on standard errors clustered by city and year.

tially different degrees of risk awareness and market sophistication influence market participants' belief updating. Hino and Burke (2021) suggests that commercial buyers, who are typically more sophisticated and experienced in real estate transactions, are more likely to have incorporated flood risks into property valuations ex ante.

Figure 6 illustrates the event study estimates for land prices, with Panels A and B presenting results for residential and commercial parcels. Correspondingly, Panels C and D plot the spatial gradients of land price changes in affected and neighboring parcels following the flood event. Several key findings emerge from these results. First, the direct impact of inundation on commercial parcels is significantly smaller than on residential parcels. This aligns with the discussion by Hino and Burke (2021), which suggests that commercial buyers may have partially capitalized flood risk into property values prior to the event. As a result, the flood event generates a smaller update in risk perceptions, leading to moderate changes in land prices.

Focusing on spillover effects, as shown in Panel C, the magnitude of the land price decline diminishes sharply with distance from the affected parcel in residential areas. On the other hand, as depicted in Panel D, commercial parcels show significant price declines even at greater distances from the affected site. One possible explanation for this pattern is that commercial buyers may be more proactive in gathering information on flood risks. This heightened risk awareness may lead to reductions in land prices even for parcels located farther from the directly affected areas.[14]

Figure 7 shows the impulse responses categorized by whether the parcels are located inside or outside the hazard map and by land use type (residential or commercial). Several key patterns emerge from this figure.[15] Panel A (Residential Land, Outside Hazard Map) exhibits the largest price declines among the four groups, both in terms of direct effects and spillover effects caused by the flood event. Geographic decay is also relatively limited, as shown by the fact that even at a distance of around 600 meters, price declines are still observed in 2025. In contrast, in Panel B (Commercial Land, Outside Hazard Map), the price declines are generally smaller in magnitude. However, as in Panel A, price declines can still be observed at distances of up to 500 meters from the inundated area.

Within hazard map zones, a different dynamic emerges. In particular, there is a sharper geo-

[14] An alternative interpretation relates to the COVID-19 pandemic. Rosenthal et al. (2022) reports that commercial rent gradients fell by roughly 15% in U.S. transit-oriented cities following the pandemic. Similarly, in Japan, commercial land prices in metropolitan areas experienced sharper declines than residential prices during the pandemic (see `https://www.mlit.go.jp/totikensangyo/totikensangyo_fr4_000432.html`, in Japanese; accessed January 25, 2026). However, the timing and spatial patterns in Panel B, which specifically isolate post-flood price movements, suggest that our estimates are not primarily driven by pandemic-related shocks.

[15] Estimates with full confidence intervals for all sub-samples are available upon request.

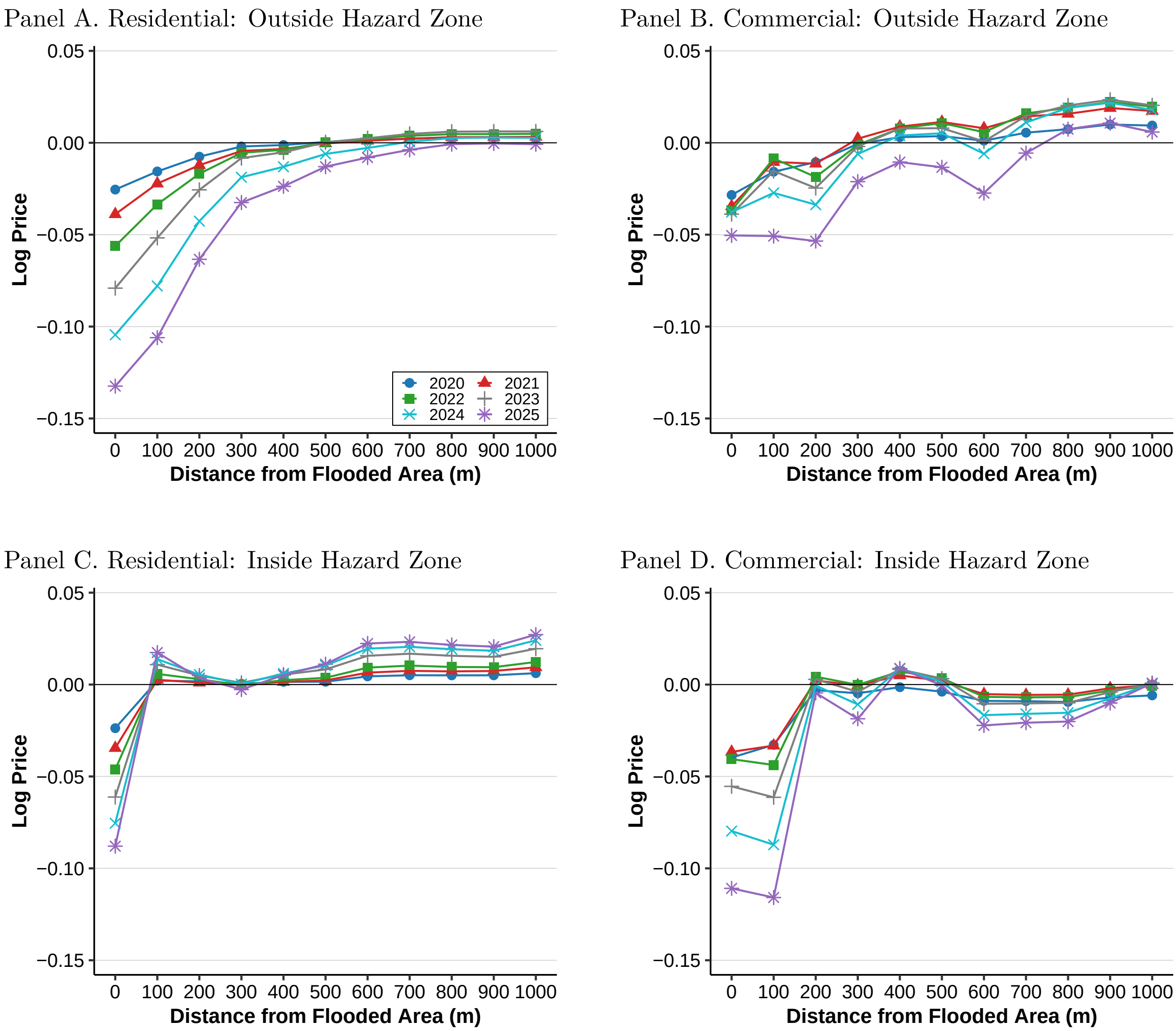



Figure 7: Spillover Effects by Distance: Land Use and Hazard Map Status

*Notes:* This Figure characterizes the spatial gradients of flood-induced land price adjustments, decomposed by land-use category and ex-ante hazard map designation. Each curve traces the estimated impact on log parcel prices for specific post-event years (2020–2025) as a function of distance from the inundation boundary. Panels A and B present results for residential and commercial parcels located outside designated hazard map zones. Conversely, Panels C and D display the corresponding estimates for residential and commercial parcels situated within hazard map zones. A distance of zero on the horizontal axis denotes parcels that were directly inundated during the 2019 event. The omitted reference period is 2019.

graphic decay relative to areas outside the hazard map boundaries (Panels C and D). In both Panel C (Residential Land, Inside Hazard Map) and Panel D (Commercial Land, Inside Hazard Map), a sharp, highly localized price decline is observed at or near the inundated parcel. However, the price impact quickly diminishes to negligible levels as the distance from the affected area increases.

From a theoretical perspective, it is not straightforward to determine which of the two areas, i.e., inside or outside hazard map zones, should experience greater land price declines following a flood. Suppose that the objective probability of flooding outside the hazard map is zero, and the subjective probability of flooding among market participants is aligned with this. In such a case, changes in the subjective probability of flooding following the flood event might occur only within the hazard map zone but not outside it. Conversely, if the objective probability of flooding within the hazard map is fully incorporated into parcel prices in the area, whereas the subjective probability of flooding outside the hazard map is significantly affected by the event, we might observe notable price declines outside the hazard map, with limited declines within it.

Our estimation results indicate that, for unaffected parcels, land price declines are generally larger outside hazard map zones in both residential and commercial areas. However, at inundated sites, the results are mixed: residential parcels outside the hazard map exhibit more pronounced price declines than those within the hazard map, whereas for commercial parcels, the opposite holds. This indicates a complex interplay of factors, including differences in objective flood probabilities between areas inside and outside the hazard map, varying degrees to which subjective flood risks have already been capitalized into land prices, and the geographic decay within which risk perceptions are reflected in prices.

## 4.5 Discussion

### 4.5.1 Comparison with Existing Literature

A substantial body of literature examines the capitalization of flood risk following major inundation events. Early empirical contributions typically employ a quasi-experimental framework that compares property values within and outside designated hazard zones, although hazard map designations do not necessarily coincide with actual flood exposure. Estimates from this approach range from roughly 6% to 32% (Hallstrom and Smith, 2005; Bin and Landry, 2013; Atreya et al., 2013), with varying degrees of persistence.

More recent studies utilize high-resolution inundation maps, a setting that closely parallels our identification of direct effects. Atreya and Ferreira (2014) re-evaluates Atreya et al. (2013) using actual inundation footprints and finds even more pronounced discounts for directly impacted properties.[16] Ortega and Taşpinar (2018) identifies persistent price declines of 17%–22% for flooded properties. In contrast, Gibson and Mullins (2020) finds that direct inundation from Hurricane Sandy had a negligible impact on prices in New York City, while redesignation into new hazard zones led to a significant 11% decline, suggesting that information shocks, rather than physical exposure, can dominate the price response.

Our baseline estimates indicate a 10% decline after five years. Since appraised land values exclude the value of damaged structures, this estimate is largely purged of the direct physical damage channel and instead reflects the capitalization of updated beliefs about flood risk and associated economic disruptions. That a 10% discount reaches roughly half to two-thirds of the total post-flood capitalization documented in Ortega and Taşpinar (2018) and Atreya and Ferreira (2014) —both of which include unobserved damage costs—suggests that belief updating and economic disruption are primary drivers of post-flood price declines. Gibson and Mullins (2020) reinforces this interpretation: their significant 11% decline is attributable entirely to hazard zone redesignation, an information shock analogous to risk updating.

This motivates a closer examination of the spillover channel. Our baseline estimates identify a 5% decline in parcel values within 100 meters of flooded areas five years after the event. Empirical evidence on such indirect effects is less extensive, but several studies provide benchmarks. Pommeranz and Steininger (2020) identifies an indirect effect of −6.5% in Dresden, Cohen et al. (2021) finds a 6%–7% price decline per additional mile from the inundation boundary after Hurricane Sandy, and Ortega et al. (2025) reports a 13% decline for properties on the same block as flooded structures.[17] Despite these contributions, estimated magnitudes exhibit considerable variation across institutional contexts.

Our estimated spillover effects are more conservative than those reported above, likely reflecting heterogeneity in study design: our reliance on appraised land values that exclude structural depreciation, the use of *Kōji-chika* assessments that reflect potential use as cleared sites, and regional heterogeneity in recovery costs, risk perceptions, and post-disaster population sorting.

[16] McCoy and Walsh (2018) documents a similar phenomenon for wildfires, though the effects appear to dissipate within two years.

[17] Atreya and Ferreira (2014) and McCoy and Zhao (2018) also examine indirect effects within hazard zones, finding heterogeneous responses.

### 4.5.2 SUTVA and Spillovers

Our empirical framework explicitly incorporates spatial spillovers to identify treatment externalities, documenting significant price depreciations both at inundation sites and in their immediate vicinity. By formally modeling and estimating spillover effects, we relax the no-interference component of SUTVA, ensuring that our causal estimates account for cross-unit dependencies.

When specifications ignore potential interference, the choice of control group becomes a critical determinant of estimated treatment effects. The divergent findings of Busso et al. (2013) and Neumark and Kolko (2010) on U.S. place-based policies exemplify this concern. Busso et al. (2013) compares Empowerment Zones with geographically distant areas that rejected applicants and reports substantial poverty reduction, whereas Neumark and Kolko (2010) uses a narrow buffer within 1,000 feet of California's Enterprise Zone boundaries as the counterfactual and finds null employment effects. The contrasting results can be largely attributed to the geographic proximity of the control groups: distant controls are less susceptible to spillovers, while adjacent control rings are likely contaminated, biasing estimates toward zero.

The literature offers two primary strategies to address spatial spillovers: treating them as a nuisance by identifying control groups insulated from externalities, or explicitly modeling the structure of interference to estimate both direct and spillover effects. We adopt the latter approach, as the policy importance of disaster-induced risk spillovers warrants treating them as estimable parameters rather than confounding factors.

We operationalize our estimation using the partial interference framework of Hudgens and Halloran (2008), which allows for interference within clusters—defined here as municipalities—while assuming independence across them. We identify direct effects at inundated sites and spillover effects in proximate non-flooded areas within the same municipality, using non-inundated parcels in adjacent municipalities as a counterfactual. This identification is supported by the observed distance decay of price impacts, and any residual negative externalities spilling over into control municipalities would make our estimates a conservative lower bound.

### 4.5.3 Mechanism

In this section, we discuss the potential mechanisms that may explain the observed decline in land prices following flooding.

**Economic activity** Theoretically, flood-related land price discounts depend on both the perceived probability of future inundation and the expected returns from land ownership. We therefore evaluate factors that shift these expectations, including local economic disruptions, fluctuations in insurance premiums, revised risk perceptions, and the effectiveness of post-flood government interventions. A permanent decline in local economic activity may diminish the dividends of land ownership, thereby depressing prices. However, directly identifying shifts in land returns requires granular data—such as housing sales or business value-added—which are seldom available at the same spatial scale as our price data. Therefore, in this context, we use census population data at a 125-meter grid scale as a proxy for housing demand and business activity in the affected areas.[18] Specifically, we link each evaluation point to the grid cell in which it is located and examine the changes in total population and the ratio of the working-age population (ages 15 to 64) over the five-year period from October 2015 (before Typhoon Hagibis) to October 2020 (after Typhoon Hagibis).[19]

Table 3 presents the results of analyzing population changes in the region over a five-year period surrounding the flood event using the Difference-in-Differences (DiD) method. The analysis is conducted for the entire area overall as well as the areas inside and outside the designated flood hazard zones, focusing on both the directly affected areas and their neighboring regions. As shown in Column (5), the population in the surrounding regions outside the designated flood hazard zones decreased statistically significantly. On the other hand, as indicated in Columns (1) and (3), there are no statistically significant population changes in either the overall region or the areas within the hazard zones, for both the affected regions and the neighboring regions. Additionally, across all specifications (Columns (2), (4), and (6)), no statistically significant changes are observed in the working-age population ratio.

The estimated population changes suggest that, at a minimum, the decline observed in areas

[18] The treatment classification follows the definitions applied at the appraisal point level. That is, rather than being based on the spatial boundaries of the grid cell itself, grid cells are classified as "Direct" or "Spillover" based on the inundation and proximity attributes of the appraisal points within them. Since the 125-meter grid cells are larger than the 100-meter spillover buffer, some grid cells assigned to the "Spillover" group may physically overlap with the inundation area. To avoid conflating spillover estimates with the effects of direct damage, we exclude observations classified as "Spillover" whose grid cells intersect the inundation polygon.

[19] For the subsample analysis based on hazard map designations, we similarly classify grid cells as either inside or outside the pre-event flood hazard zone, depending on whether the appraisal point within the grid cell lies in the designated hazard area. Changes in total population are interpreted as a proxy for shifts in local housing demand. Additionally, since household-level data on income and education are unavailable at a comparable geographic resolution, we use the working-age population ratio as a proxy for residential sorting. This proxy captures shifts in residential composition, as risk preferences and mobility costs are likely to differ between working-age and elderly populations.

Table 3: Impact of Flood Damage on Population by Hazard Map Designation

| | Overall | | Inside Hazard Zone | | Outside Hazard Zone | |
|---|---|---|---|---|---|---|
| | log(Pop.) (1) | log(Young) (2) | log(Pop.) (3) | log(Young) (4) | log(Pop.) (5) | log(Young) (6) |
| Direct × Post | −0.0302 | 0.0113 | −0.0659 | 0.0238 | 0.0066 | −0.0069 |
| | (0.0437) | (0.0280) | (0.0722) | (0.0375) | (0.0538) | (0.0427) |
| Spillover × Post | −0.0731 | 0.0018 | −0.0554 | −0.0420 | −0.0893* | 0.0296 |
| | (0.0565) | (0.0489) | (0.1106) | (0.0802) | (0.0489) | (0.0595) |
| Location FE | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 12,669 | 12,338 | 3,133 | 3,044 | 9,536 | 9,294 |
| Adj. $R^2$ | 0.958 | 0.627 | 0.956 | 0.596 | 0.957 | 0.619 |

*Notes:* This table reports difference-in-differences estimates of flood damage on population outcomes using 150-meter grid cell data from the Population Census (2015 and 2020). Columns (1)–(2) use the full sample. Columns (3)–(4) restrict to grid cells within flood hazard map designated areas. Columns (5)–(6) restrict to grid cells outside hazard map designated areas. Direct Damage indicates grid cells within flooded areas. Spillover indicates non-flooded grid cells within 100 meters of the inundation boundary in flooded municipalities. Spillover grid cells that overlap with the inundation area are excluded to ensure that spillover estimates are not conflated with direct damage effects. Standard errors clustered at city level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

outside the hazard zones may have contributed to the decrease in land values. However, while a decline in land values is confirmed both inside and outside the hazard zones as well as in the directly affected areas, statistically significant changes in population dynamics are not observed in these regions. Taking this into consideration, it is difficult to conclude that population outflow alone is the primary channel driving the decline in land prices.

**Insurance premiums** We consider whether post-disaster land price declines are driven by rising flood insurance premiums. In the U.S. context, insurance costs play a pivotal role. For instance, the surge in premiums following Hurricane Katrina significantly contributed to depreciation in land values as actuarial risks were re-capitalized. However, this channel is likely attenuated under Japan's institutional framework. Characterized by stringent regulatory oversight and a robust public-private risk-sharing mechanism, the Japanese market exhibits minimal dispersion in regional premiums (Shimamura and Managi, 2025). Furthermore, extensive state investment in flood-control infrastructure and direct subsidies stabilizes the market, rendering premium adjustments after inundation events more moderate and gradual than in market-driven systems. Such interventions effectively decouple disaster impacts from sharp increases in insurance costs. Given this institutional stability, we conclude that insurance premiums are unlikely to be the primary driver of the persistent declines in land prices observed in our sample.

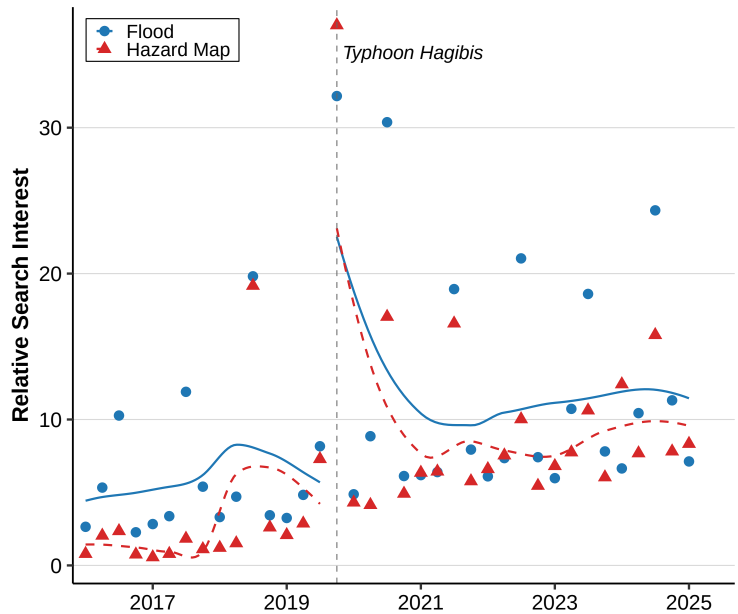



Figure 8: Flood-Related Search Trends in Japan

*Notes:* Lines show LOESS fits of quarterly average relative search interest from Google Trends for 16 prefectures affected by Typhoon Hagibis, estimated separately for the pre- and post-typhoon periods. The vertical dashed line indicates the timing of Typhoon Hagibis (October 2019).

**Search trends** Another salient feature of our empirical findings is the gradual, time-varying nature of the price depreciation following the flood event. One plausible channel driving this trend is the gradual elevation in flood risk perception and public awareness in the post-Typhoon Hagibis era. Figure 8 shows the relative search interest for the terms "flood" and "hazard map" from Google Trends. The quarterly averages and smoothed trend lines indicate a significant structural break around the flood event: although a transient spike occurred during the event, the post-disaster baseline for search activity gradually increased, remaining above pre-2019 levels. This persistent upward trend suggests that risk awareness did not merely revert to the historical mean but was potentially elevated by heightened media coverage and increased attention of the public.

**Infrastructure improvements** Finally, we consider the potential impact of post-disaster infrastructure improvements on land prices. For instance, new flood-mitigation facilities could reduce the perceived risk of future flooding, or improved roads could enhance the area's convenience. Ideally, it would be necessary to examine price changes near specific reconstruction project sites; however, detailed geographic coordinate data for reconstruction projects related to Typhoon Hagibis are not available. As an alternative, we utilized municipal-level disaster recovery expenditure data published by the Ministry of Internal Affairs and Communications. Specifically, we calculated the cumulative recovery expenditure per inundated property for each municipality (from FY2019 to FY2021) and divided the sample into two groups, one with higher recovery expenditures and another with lower expenditures, based on the median. The results of this analysis are reported in Appendix Table A2.

The findings show that directly affected properties experienced price declines in both groups, although the magnitude of the decline was slightly smaller in the high-recovery group (−3.6% compared to −5.9%). This is consistent with the possibility that infrastructure investments mitigated the price decline. However, the difference between the two groups was not statistically significant. Furthermore, despite classifying groups by expenditures per property, there may still be differences in the overall severity of damage, so this comparison does not clearly isolate the impact of recovery efforts.

In summary, our analysis provides no clear evidence to suggest that post-disaster infrastructure improvements were a driving force behind the observed land price effects.

Building on these discussions, while it cannot be ruled out that factors such as the decline in economic activity, including population outflows following the flood, changes in insurance premiums, and infrastructure improvement may have influenced land price changes after the flood, the nature of the available data as well as economic and institutional characteristics suggest that these factors may not have acted as the primary mechanisms. Taking these considerations into account, the following section examines, through simulations, whether changes in risk perception following the flood led to subsequent changes in land values.

# 5 Theoretical Analysis

We use a model based on the framework of Bakkensen and Barrage (2022) to discuss what characteristics of risk perception updating and information processing by market participants are necessary to explain our empirical findings.[20] Indeed, comparing the model-generated impulse responses with our empirical estimates suggests that the dynamics of land prices following Typhoon Hagibis may result from the interaction of various factors, such as adaptive learning, the spatial decay of signal intensity, and site-specific heterogeneities in the extent to which flood risks were

[20] We also consider a channel that operates through changes in returns and amenity of holding land assets that arise in sites around the inundated areas after flood events even when risk perceptions of market participants are unchanged. Our preferred interpretation is that it captures the potential impacts of economic downturns in the local community, possibly due to localized population outflows from the inundated areas. In the appendix, we conduct simulations where land price changes are driven by this channel.

incorporated into land prices prior to the flood.

Alternative frameworks highlight institutional and behavioral drivers of risk perception. Kousky (2010) emphasizes how insurance markets and policy settings modulate the speed of market adjustments to new information. From a behavioral perspective, studies such as Gibson and Mullins (2020) suggest that information shocks, ranging from inundation to map revisions, can trigger price volatility through salience or cognitive biases. In contrast to these approaches, our Bayesian framework provides a systematic formalization of the updating process, offering a tractable mapping from signal intensity to belief revision and, subsequently, to price capitalization.

### 5.1 Model Settings

Consider a housing market consisting of $k$ discrete units, of which $k_1$ are located in areas exposed to significant flood risk. Let $\xi^i$ denote the idiosyncratic flow utility associated with residing in a high-risk zone for household $i$. This term captures the net amenity value, such as riverfront views or locational convenience, that may offset the inherent disutility associated with damage from flood events. Flood damage, including damage to tangible assets, local economic activity, and disutility of affected individuals, in monetary terms, is denoted by $\delta$, while $\pi_t$ represents the subjective probability of a flood event occurring at time $t$.

In this framework, the equilibrium house price $P_t$ is determined by the present discounted value of net utility flow associated with marginal buyers, $m_t$, and can be expressed as:

$$P_t = \beta \left( e^h + \xi^{(m_t)} - \pi_t^{(m_t)} \delta + E_t^{(m_t)} \left[ P_{t+1} \right] \right), \tag{2}$$

where $\beta$ represents the discount factor, $e^h$ represents the constant flow utility derived from homeownership, and $E_t^{(m_t)}[\cdot]$ denotes the subjective expectations operator of the marginal buyer at time $t$.

We assume that flood risk perceptions are homogeneous across market participants, while the idiosyncratic flow utility associated with river-adjacent areas is independently and uniformly distributed, such that $f(\xi^i) \sim U[0, \Xi]$. In this context, $\Xi$ represents the upper bound of the flow utility a household may obtain from the amenities associated with a high-risk zone in any given period. Under the assumption of time-invariant flood risk $\pi_t$, the equilibrium land price can be derived as:

$$P_t = \frac{\beta \left( e^h + \Xi(1 - k_1) - \pi_t \delta \right)}{1 - \beta}. \tag{3}$$

Since the supply of high-risk land is fixed at $k_1$, the market-clearing condition implies that the marginal buyers are distributed at the $(1-k_1)$-th percentile of the utility distribution, which in turn implies that the amenity value facing them is $\Xi(1-k_1)$. It is important to note that land prices increase with the amenity value $\Xi$, and decrease with both the perceived subjective probability of flooding $\pi_t$ and the magnitude of expected flood damage $\delta$.

Next, we consider a change in the underlying risk environment. Bakkensen and Barrage (2022) employ a formal Bayesian learning framework to characterize the evolution of flood risk perceptions following an inundation event. In this setting, agents initially hold prior beliefs regarding the probability of flood occurrence, typically informed by historical frequencies or idiosyncratic experiences. Upon observing a flood, agents revise these beliefs by incorporating new evidence—specifically, the event's observed severity and frequency—according to Bayes' rule.

At time $t = T_1$, the objective probability of a flood increases from $\pi_1$ to $\pi_2$. Following Bakkensen and Barrage (2022), we assume that this heightened risk is gradually incorporated into market expectations. By the subsequent period $t = T_2$, all market participants' subjective risk perceptions are assumed to converge to the objective probability $\pi_2$.[21]

Under these assumptions, during the transition period $T_1 \le t < T_2$, agents revise their beliefs regarding flood risk via a recursive Bayesian updating process.

Letting $n \equiv t - T_2$, the expected price level can be analytically expressed by the following equation:[22]

$$E_{t-1}^{L}\left[P_T\right] = \sum_{j=0}^{n-1} \beta^{j+1}\left[e^h + \Xi(1-k_1) - E_{t-1}^{L}\left[\pi_T\right]\delta\right] + \frac{\beta^{n+1}\left(e^h + \Xi(1-k_1) - E_{t-1}^{L}\left[\pi_{t_2}\right]\delta\right)}{1-\beta}. \tag{4}$$

We formalize market participants' beliefs regarding the evolution of flood risk as follows. First, we impose a convergence property at $t = T_2$, such that the perceived probability of flooding for all market participants aligns with the objective probability:

$$E_t^{L}\left[\pi_{T_2}\right] = \pi_2. \tag{5}$$

Next, we characterize the expectation formation during the interim period $T_1 \le t < T_2$. Let $q_t$

[21] This informational convergence can be achieved by market participants' learning, but also facilitated by government initiatives. For example, since August 2020, the Ministry of Land, Infrastructure, Transport and Tourism has required real estate practitioners to provide formal disclosures of flood hazard map information during the "Explanation of Important Matters" (*Juyo Jiko Setsumei*) prior to any property transaction.

[22] Note that the superscript $L$ is employed to indicate that market participants' subjective assessments of flood probabilities are more optimistic than the objective probability.

denote the subjective weight that market participants assign to the state in which the flood risk has structurally increased for $t \geqq T_1$ (e.g., due to revisions of official hazard maps). These beliefs are updated endogenously upon the occurrence of a flood event, and the expected flood risk is given by the following weighted average:

$$E_t^L[\pi_T] = q_t^L \pi_2 + (1 - q_t^L)\pi_L, \tag{6}$$

where $\pi_L$ represents the lower bound of the perceived flood probability, reflecting the initial optimistic bias.

The evolution of the subjective probability $q_t$ follows a Bayesian updating process, contingent on the realization of a flood event. If a flood occurs at time $t$, the posterior belief is updated as follows:

$$(q_{t+1}^L \mid \text{Flood}_t = 1) = \Pr(\pi_2 \mid \text{Flood}_t = 1) = \frac{\pi_2 q_t^L}{\pi_2 q_t^L + \pi_L(1 - q_t^L)}, \tag{7}$$

where the denominator denotes the total probability of observing a flood at period t, taking into account that the prevailing state could be the state in which the objective risk has increased, but could also be the state in which it has remained the same. Conversely, if no flood is observed, the posterior belief is given by:

$$(q_{t+1}^L \mid \text{Flood}_t = 0) = \Pr(\pi_2 \mid \text{Flood}_t = 0) = \frac{(1 - \pi_2) q_t^L}{(1 - \pi_2) q_t^L + (1 - \pi_L)(1 - q_t^L)}. \tag{8}$$

Furthermore, we assume that information about floods in regions where individuals are not economically active can heighten their vigilance toward future flood risks in areas where they are active. Specifically, we treat floods in other regions as a form of risk vigilance that updates their beliefs about risks to their own land. (see Christiano et al. (2024) for slow learning and Marcet and Sargent (1989) for adaptive learning).

The adoption of an adaptive learning framework is considered consistent with the sustained changes in public risk awareness following major disasters. Figure 8 shows the time series of search volumes for flood-related terms "Flood" and "Hazard map" in Japan. Search volumes rose abruptly following Typhoon Hagibis in 2019 and have remained elevated for several years thereafter. This suggests that, once a major disaster occurs, the risk awareness of economic agents regarding disasters may be heightened relative to pre-disaster levels. Furthermore, it suggests that heightened risk perception could be reinforced over time through persistent information gathering by economic agents or potentially spread to a broader population.

Along these lines, we model the gradual belief-updating process, potentially through continued information acquisition, by incorporating the learning rate $\lambda$ into the framework. Specifically, once a market participant experiences and/or observes a flood, his vigilance increases, effectively setting the Bayesian target to a higher risk state (Flood = 1). This adaptive learning specification,

$$q_{t+1} = q_t + \lambda(\bar{q} - q_t) \tag{9}$$

explicitly models the gradual formation of risk perceptions, thereby enabling the progressive incorporation of flood-risk salience into land markets over time.

## 5.2 Additional Model Features

The baseline model simplifies the state space into a binary distinction–either "flood occurrence" or "no flood occurrence." However, our empirical results and documented search behavior suggest that market participants are likely to receive and process signals of varying magnitudes, possibly with more granular intensities, based on factors such as the geographic distance between their area of activity and the flood-affected location. We therefore relax the baseline settings and extend them by assuming that the signals received by market participants are continuous, $s_t$. This signal reflects variations in intensity driven by factors such as the frequency of local flooding, the density of media coverage, and the spatial proximity to affected areas.

Recall that under the binary setup, the expected flood probability was defined as:

$$\pi_t^L = q_t^L \pi_2 + (1 - q_t^L)\pi_L, \tag{10}$$

To accommodate a continuum of signals $c \in [0, 1]$, we adopt a functional form based on logit odds. Specifically, we define the transformation $f_c(A)$ as follows:

$$f_c(A) = \frac{o^{1-2c}}{1 + o^{1-2c}}, \quad \text{where } o \equiv \frac{A}{1 - A}. \tag{11}$$

This specification is mathematically convenient as it nests the following extreme cases: $f_0(A) = A$ (no flood observed), $f_1(A) = 1 - A$ (direct flood impact), and $f_{1/2}(A) = 1/2$ (informative signal).

Under this generalized transformation, the belief-updating rule for $q_{t+1}^L$, denoting the subjective weight that market participants assign to the state of high risk of flooding, is re-characterized as:

$$(q_{t+1}^L \mid \text{Signal} = c) = \frac{f_c(1-\pi_2)q_t^L}{f_c(1-\pi_2)q_t^L + f_c(1-\pi_t^L)(1-q_t^L)}. \tag{12}$$

This formulation provides a tractable and smooth mapping for all $c \in [0,1]$. By calibrating the parameter $c$, the model can distinguish between high-intensity signals—such as a household experiencing a flood firsthand or in the immediate vicinity—and low-intensity signals, such as distant flood events reported in the national media.

Recent advancements in the literature on human inference and signal strength provide strong empirical support for our continuous updating framework (Abdellaoui et al., 2025; Ambuehl and Li, 2018; Becker et al., 2025). Specifically, research indicates that agents often update their beliefs based on the perceived intensity of a signal rather than responding exclusively to binary outcomes. This leads to patterns of "partial updating" that are effectively captured by a continuous log-odds specification. For instance, the burgeoning literature on over- and under-inference from informational signals formalizes the mechanisms by which signal strength dictates the magnitude of belief adjustment (Augenblick et al., 2025). These studies emphasize the significance of intermediate belief states, demonstrating that the degree of Bayesian revision varies systematically with the salience and precision of the information provided.

We incorporate information signals via a logit-odds transformation. While various functional forms could be considered, the logit-odds specification offers several theoretical and analytical advantages. Most notably, expressing belief dynamics in terms of odds and log-odds is inherently consistent with the canonical Bayesian framework. This approach ensures that posterior beliefs remain strictly bounded in the unit interval $[0,1]$ and can be interpreted as multiplicative adjustments to prior odds, reflecting the relative strength of the signal. According to the odds form of Bayes' theorem, the posterior odds are derived by scaling the prior odds by the likelihood ratio (or the Bayes factor). Our logit-based updating framework naturally aligns with this principle.[23]

## 5.3 Simulation Parameters

We calibrate the model's structural parameters to reflect both the results of the prior research in the literature and the specific institutional context of flood risk in Japan. The annual discount

[23] The modeling of belief formation under continuous signals is well-established in the theoretical and experimental economics literature. For instance, Kieren and Weber (2025) formalizes belief updating using log-odds in environments characterized by sequential informational signals.

factor $\beta$ is set to 0.95, a standard value in the urban and macroeconomic literature. The share of the residential stock exposed to high flood risk, $k_1$, is parameterized to 0.3. This value is derived from the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) data on the *Population Living in Disaster Risk Areas by Prefecture*, which provides a granular account of demographic exposure to fluvial hazards (see also Hada and Maeda, 2020).

The flow utility from housing, $e^h$, is calibrated to yield an implicit land value of around 20 million yen. According to the 2024 Flat 35 Borrower Survey, the national average for housing-related expenditure is 38.68 million yen. Assuming a land-to-structure ratio of approximately 1:1, we set the benchmark land value at 20 million yen. The direct damage from a flood event, $\delta$, is set to 3 million yen, consistent with the mean damage reported in the 2019 Flood Damage Statistics Survey.

The amenity premium for residing in high-risk (river-adjacent) areas, $\Xi$, requires careful calibration given the significant spatial heterogeneity in hedonic estimates. While Chen et al. (2019) find that land price premia in these areas exhibit substantial dispersion—ranging from −10% to +60%—we adopt a conservative baseline following Bakkensen and Barrage (2022), who estimate a willingness-to-pay (WTP) of approximately 2% of property value for coastal amenities. Accordingly, we set $\Xi = 0.4$ million yen. However, the results remain largely unchanged regardless of variations in this parameter. The simulation horizon $n$ is fixed at 30 years.

For the flood probability parameters, we follow Bakkensen and Barrage (2022) and set the initial baseline probability $\pi_1$ to 0.01 and the post-event updated probability $\pi_2$ to 0.1. These values are consistent with MLIT's flood-map guidelines, in which "planned rainfall" events correspond to return periods of 10 to 100 years.[24] Market participants' initial subjective beliefs regarding the flood state, $\pi_0^L$, is set equal to $\pi_1$, while the prior probability that the environment has transitioned to a high-risk state, $q_0^L$, is set to 0.1 (Bakkensen and Barrage, 2022).

Finally, the learning parameter $\lambda$, which governs the speed of belief updating, is set to 0.3 in our benchmark specification. We perform sensitivity analyses over a range of $\lambda$ values to ensure the robustness of our results. While the magnitude of the land price response exhibits some variation in sensitivity to the learning rate, the qualitative dynamics of the model remain unchanged. The parameterization is summarized in Table 4.

[24] While our benchmark $\pi_2$ follows the existing literature, we also consider an alternative climate-change scenario where the updated probability is doubled to reflect the increasing frequency of extreme weather events. The qualitative implications of our model remain robust to this heightened risk profile.

Table 4: Parameter Definitions and Calibration

| Parameter | Description | Value | Source |
|---|---|---|---|
| $\beta$ | Discount factor | 0.95 | Standard |
| $k_1$ | Share of units in high flood-risk areas | 0.3 | MLIT; Hada and Maeda (2020) |
| $\Xi$ | Max amenity value in high-risk areas | 400 | Chen et al. (2019); BB (2022) |
| $\delta$ | Flood damage per event (K yen) | 3,000 | MLIT Flood Damage Stats |
| $e^h$ | Flow utility from housing | Variable | Flat 35 Borrower Survey |
| $q_0^L$ | Initial belief that risk increased | 0.1 | BB (2022) |
| $\pi_0^L$ | Initial perceived flood probability | 0.01 | BB (2022) |
| $\pi_1$ | Initial objective flood probability | 0.01 | BB (2022); MLIT |
| $\pi_2$ | Post-update flood probability | 0.1 | BB (2022); MLIT |
| $\lambda$ | Learning rate | 0.3 | — |
| $n$ | Simulation horizon (years) | 30 | — |

*Notes:* BB (2022) refers to Bakkensen and Barrage (2022). MLIT denotes the Ministry of Land, Infrastructure, Transport, and Tourism. Values in K yen represent thousands of Japanese yen.

### 5.4 Simulation Results

**Baseline** We conduct numerical simulations under the aforementioned parameterization to evaluate the model's dynamic properties. Figure 9 illustrates the baseline results over a 10-year horizon, comparing a scenario featuring a flood event at $t = 1$ against a counterfactual no-flood baseline. Panel A displays the impulse responses of land prices, normalized to 100 at $t = 0$. The results indicate that an actual flood shock triggers a persistent downward trajectory in land values. Because agents update their beliefs regarding latent flood risk gradually, the full capitalization of the shock into land prices unfolds over several periods. Notably, even in the no-flood scenario, land prices exhibit a mild secular decline as market participants progressively incorporate the scientifically assessed increase in risk into their long-run expectations of flood risks.

Panel B isolates the flood treatment effect by plotting the percentage-point differential in land prices between the two scenarios. As shown in the baseline result, the magnitude of the land price decline generated by the simulation, approximately an 8% decline over 5 years, is roughly consistent with empirical counterparts, in which land prices decrease by around 10%. In addition, the model-generated impact of a flood event on land prices is most pronounced in the immediate aftermath, followed by a sustained decline. This persistent adjustment is again consistent with our empirical observations. These results imply that the gradual adaptation of flood risk through Bayesian learning may help explain the observed sluggish land price responses following flood events. Panel B compares land price dynamics under the baseline (belief updating with adaptive learning) with two alternatives: (i) Perfect Bayesian updates (instantaneous updates with rational expectations), Panel A. Land Price Levels

Panel B. Difference (Flood − No Flood)

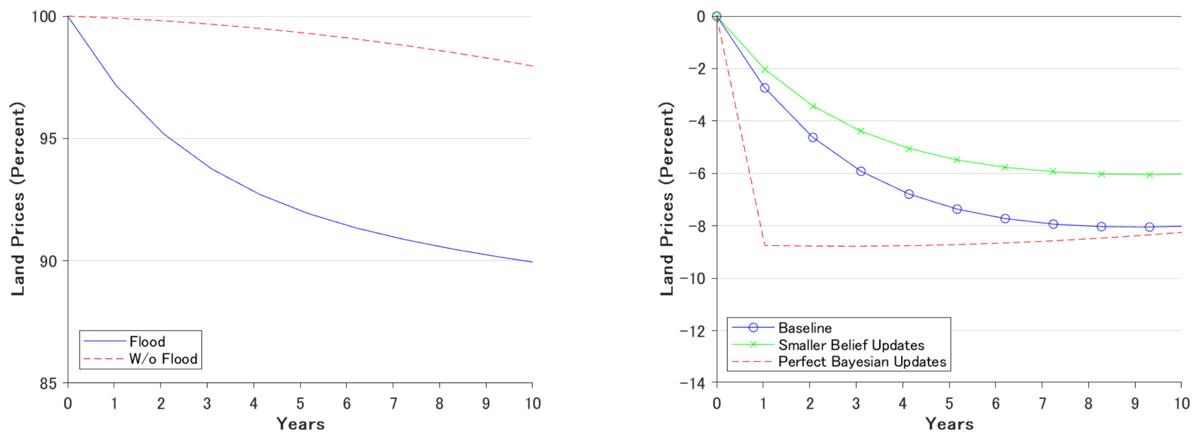



Figure 9: Baseline Simulation Results

*Notes:* This figure plots the simulated trajectory of land prices under flood risk scenarios. Panel A shows the land price indices, normalized to 100 at $t = 0$, comparing the baseline (no-flood) path with the impulse response to a flood event occurring at $t = 1$. Panel B shows the effect of the flood, defined as the percentage-point difference in land prices between the flood and no-flood scenarios. "Baseline" and "Perfect Bayesian Update" represent the land price trajectories under gradual belief revision and instantaneous rational expectations. "Smaller Belief Updates" denotes the case in which the change in the probability of flood risk before and after the flood is 0.5 percentage points smaller than in the baseline.

and (ii) Smaller Belief Updates (scenario in which the change in the subjective probability of a flood is small).[25] For areas with low objective flood risk, like those outside hazard maps, perceived flood risk may increase less after a flood compared to areas within hazard maps, which is consistent with empirical results. Conversely, in areas with past flood events and perceived risks already incorporated into land prices, additional risk adjustments due to the same flood may be mitigated. By considering cases in which the initial subjective risk belief is high, and the magnitude of updates is limited, we can analyze how differences in the responsiveness of risk-belief evaluations to flood events and the degree of prior risk incorporation into land prices influence post-flood price responses.

Under perfect Bayesian updating, as risk perceptions are revised immediately after a flood event, land prices drop sharply and remain depressed thereafter. In cases where prior risk perceptions are already high and adjustments to those beliefs are relatively limited, the magnitude of land price adjustments following a flood event is smaller compared to cases with lower initial perceived risk.

Combining these findings with Section 4, we can conclude that the observed post-flood land

[25] In this specification, we set $\pi_1$, and $\pi_0^L$ to 0.015, In the baseline simulation they are set to 0.01. However, similar results can be obtained even if the value of $\pi_2$ is changed.

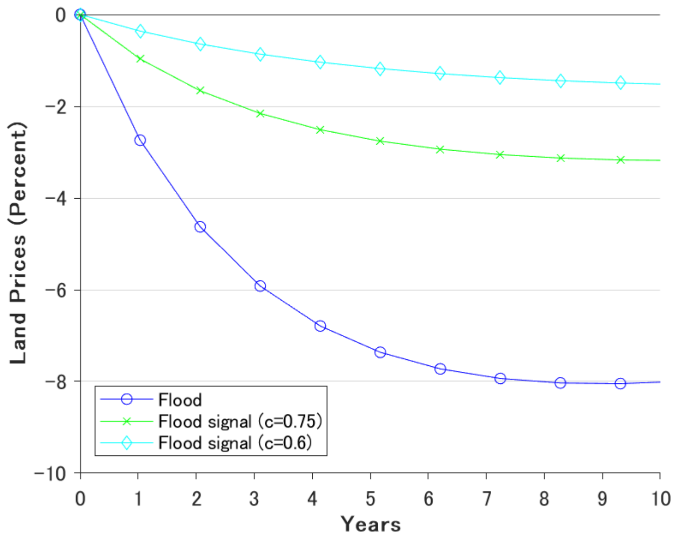



Figure 10: Signal results

*Notes:* This figure illustrates the simulated land price response to heterogeneous flood signals. The "Flood" path depicts the price trajectory in the location experiencing an inundation. In contrast, the "Flood Signal" paths represent spatial spillovers to neighboring regions, with varying signal intensities governed by the parameter $c$. These paths capture how residents in non-flooded areas revise their beliefs and subsequent valuations in response to observed proximate disasters.

price dynamics are consistent with the presence of adaptive learning, where risk belief is updated gradually over time, possibly due to a slow information gathering process. Moreover, differences in responses between areas within and outside hazard maps with respect to spillover effects may reflect variations in pre-flood risk perceptions and prior incorporation of flood risks into land prices.

**Signal intensity and spatial spillovers** Next, we simulate cases in which market participants receive flood-event signals of varying intensities. For example, we consider a case in which a flood event at a given location triggers signals of different intensities for sites A and B, depending on their geographical distance from the affected area. Admittedly, the degree of information intensity may vary not only with distance from the inundated site but also with other factors, such as land-use categorization (e.g. whether the sites are inside the designated hazard areas). To see the impact of signal intensity, we consider two levels of signal strength, 0.75 and 0.6, and compare the resulting trajectories of land prices with the baseline case of unit signal strength.

Figure 10 plots the annual differences in land prices relative to the no-flood counterfactual over a 10-year horizon. The simulation results reveal that, in areas with smaller signals, which, in

Panel A. Signal Effects (larger belief updates and lower signal)

Panel B. Signal Effects (smaller belief updates and higher signal)

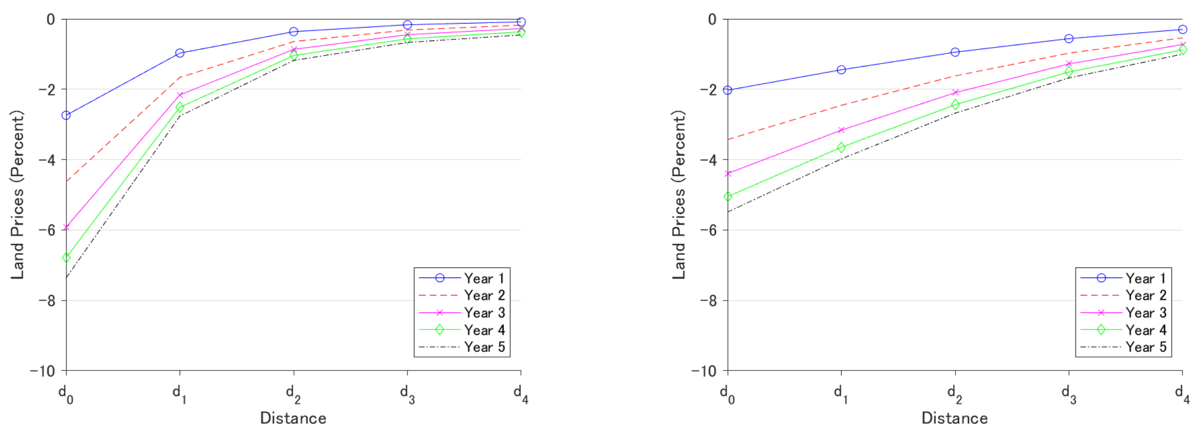



Figure 11: Land Price Responses by Distance from Flooded Area

*Notes:* This figure shows the potential spatial gradient of land price responses using settings with different values of signal. Panel A aims to represent the information-driven impact, i.e., the transmission channel through which signal transmission helps update risk perception of market participants located not only in affected areas but also in neighboring locations. Panel B shows similar simulation results with smaller belief updates and a higher signal. Here, $d_0$ represents the inundated area. $d_1$, $d_2$, $d_3$, and $d_4$ represent the distance from the inundated area with $d_1 < d_2 < d_3 < d_4$. Collectively, these panels contrast varying rates of spatial decay.

our interpretation, are adjacent non-flooded areas, declines in land prices are noticeable but less pronounced than in areas with stronger signals. Furthermore, reductions in signal strength are shown to correspond to proportionally smaller impacts on land valuations.

**Combined effects: signal intensity, pre-disaster risk perception, and distance** Finally, we study the implications of the combined effects of signal intensity, its spatial decay, and pre-disaster subjective risk perception by comparing the two cases shown in Panels A and B. Note that for simulations shown in Panel B, we assume a smaller belief update (i.e. the case where the change in the subjective probability of flooding is smaller) and higher signal intensity are assumed as compared to Panel A. One interpretation is that the location corresponding to Panel B, having already experienced flooding, has its flood risk incorporated into land prices and, being an area with relatively higher objective flood risk, receives a stronger signal compared to location A. However, alternative interpretations are also plausible, such as the possibility that location B is a region in which a larger proportion of market participants exhibit heightened risk awareness. This is consistent with the empirical results of the commercial zone, as landowners tend to exhibit higher vigilance against flood risk.[26] For simplicity, we treat spatial distance as an abstract metric, plotting the impulse responses for the disaster epicenter (distance 0) and increasingly distant locations with $d_1 < d_2 < d_3 < d_4$.

As demonstrated in the aforementioned simulation analysis, the magnitude of price declines at certain locations following a flood event tends to be smaller when the pre-flood subjective risk probability is higher or when the distance to the flood site is greater. Similarly, in areas with objectively low flood risk or where external factors make market participants less susceptible to flood signals, price declines are expected to be modest. Ultimately, the extent of land price declines in specific locations depends on the quantitative interplay of these factors.

Panel A illustrates that while land prices in directly flooded areas experience sharp declines, the spillover effects on surrounding non-flooded areas dissipate rapidly. In contrast, Panel B shows that price declines within flooded areas are more moderate, but the spillover effects are less attenuated. Even non-flooded adjacent areas further from the flood site exhibit significant price declines.

**Mapping simulations to empirical patterns** These patterns provide useful insights for explaining differences in the magnitude of land price declines between flooded and non-flooded areas, as well as between locations within and outside designated hazard map boundaries. Based on the model's results, the observation that, in commercial zones, greater price declines occurred within hazard map areas at flooded sites, while larger price declines occurred with respect to spillover effects (non-inundated area) outside hazard areas, may be explained as follows. In areas outside hazard maps, two competing forces are at play. On the one hand, the lack of, or incomplete, pre-disaster subjective risk incorporation into land prices makes prices more sensitive to changes in post-flood risk perception (the case of low pre-flood risk awareness). On the other hand, the objectively lower flood risk outside hazard maps suppresses the change in market participants' risk perception after a flood (the case of lower signal magnitude). As a result of the interaction between these two opposing factors and geographic attenuation effects, the latter factor has a greater quantitative influence in flooded areas, whereas in neighboring unaffected areas, the former factor becomes dominant.

Conversely, in residential zones, both directly flooded and neighboring areas outside hazard

[26] In this alternative specification, we set $\pi_1$, and $\pi_0^L$ to 0.015. These are the same as the parameter values used in the settings for the simulation in Figure 9, but similar results can be obtained even if the value of $\pi_2$ is changed. We also use higher signal values than in the baseline specification, with $c = 0.9, 0.8, 0.7, 0.6$ for distances $d_1, d_2, d_3$, and $d_4$. In the baseline, we use $c = 0.75, 0.6, 0.5, 0.4$ for distances $d_1, d_2, d_3$, and $d_4$.

maps experienced larger price declines than corresponding areas inside hazard maps. This suggests that even when accounting for geographic attenuation effects, the former effects (higher price sensitivity due to low pre-flood risk awareness) has a consistently greater quantitative impact than the latter in these areas.

## 6 Conclusion

This study empirically investigates the impact of flooding on land markets, not only in inundated areas but also in unaffected surrounding areas, leveraging the quasi-experimental setting created by Typhoon Hagibis, which brought catastrophic impacts to the east side of Japan in 2019, and high-resolution inundation data from that time. It then explores a potential explanation for the empirical observations using a Bayesian belief updating model of subjective risk perceptions.

Our empirical results are summarized as follows. First, land parcels directly affected by inundation exhibit a continuous decline in price following the event, reaching approximately 10% five years after the disaster. Because the land prices used in our analysis are appraisal values that exclude the value of structures, this decline is likely to reflect changes in the fundamental assessment of flood-specific risks or in the expected returns embedded in land prices. Second, spillover effects are observed in areas extending more than 100 meters beyond the inundation boundary. Property prices in this range contract by approximately 5%, with the decline in magnitude decreasing with distance. Third, there is heterogeneity in land price declines following the flood event, depending on land-use type and whether the land is designated as a hazard area. For example, in unaffected areas that were excluded from official hazard zones prior to the flood, significant and persistent price declines are observed. In contrast, again for unaffected areas, parcels within pre-existing hazard zones show little to no price reduction. Focusing on inundated areas, the relative decline in land prices between hazard and nearby non-hazard areas is larger for residential land, whereas the opposite pattern is observed for commercial land.

To better understand one potential transmission mechanism of flood events to land prices in inundated areas and unaffected areas we conduct simulation exercises using a model based on the framework of Bakkensen and Barrage (2022) by incorporating into the model additional characteristics regarding the nature of information transmission of floods, including adaptive learning, differences in signal intensity depending on the distance between the area and inundated areas, land-use categories, and whether or not the area was already designated as a hazard area.

Our simulation shows that land price dynamics following flood events are shaped by each of these factors and by their combination. Adaptive Bayesian updating, characterized by gradual recognition of risk and sustained depreciation of land values, makes land price responses more staggered following flood events, as shown in the data. Informational spillovers with spatial decay are consistent with the observation that price declines after floods are largest in affected areas and weaken with distance. Partial or full incorporation of objective flood risk is consistent with the observation that the empirical spillover effect is minor in areas outside the hazard map.

There are several caveats to our analysis. While our identification strategy successfully isolates land-value shocks from structural damage, we do not directly observe individual risk perceptions or micro-level economic transactions. Furthermore, our five-year horizon may not fully capture the transition to a long-run steady state. Finally, while the scale of Typhoon Hagibis enhances the external validity of our results, generalization to alternative institutional settings requires care. Future research incorporating survey-based expectations or linked firm-level data would further refine our understanding of how disaster-induced information and economic shocks are capitalized into urban land markets.

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# Appendix

## A Additional Tables and Figures

Table A1: Summary Statistics by Hazard Map Designation

| | Treatment | | Within Flooded Cities | | Control | |
|---|---|---|---|---|---|---|
| | Hazard | Non-Hazard | Hazard | Non-Hazard | Hazard | Non-Hazard |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Price (1000 JPY) | 49 | 54 | 147 | 153 | 172 | 293 |
| | (68) | (55) | (283) | (258) | (266) | (1009) |
| Price Change 2018–2019 (%) | -0.11 | 0.37 | 0.72 | 1.09 | 1.02 | 0.90 |
| | (1.57) | (1.54) | (2.39) | (3.24) | (2.79) | (2.78) |
| Area (sqm) | 348 | 322 | 665 | 818 | 707 | 743 |
| | (328) | (184) | (3403) | (9103) | (6383) | (5451) |
| Dist. to Station (m) | 1824 | 2152 | 1908 | 2073 | 1908 | 1973 |
| | (2219) | (2933) | (2222) | (2560) | (2291) | (2716) |
| Floor Area Ratio | 201.54 | 266.05 | 215.91 | 202.40 | 228.57 | 204.27 |
| | (60.69) | (132.42) | (95.71) | (107.22) | (113.74) | (122.18) |
| Building Coverage Ratio | 63.85 | 66.05 | 62.45 | 60.53 | 62.71 | 59.98 |
| | (8.89) | (10.50) | (8.99) | (11.31) | (9.75) | (12.54) |
| Commercial % | 13.5 | 32.6 | 16.6 | 17.5 | 19.4 | 19.5 |
| Residential % | 53.8 | 51.2 | 63.3 | 65.7 | 60.2 | 65.4 |
| Industrial % | 5.8 | 7.0 | 11.1 | 5.5 | 11.2 | 4.8 |
| Adjustment Area % | 26.9 | 9.3 | 9.0 | 11.2 | 9.2 | 10.3 |
| Neighborhood Pop. (250m grid) | 310.48 | 262.37 | 517.82 | 453.87 | 537.14 | 563.69 |
| | (292.33) | (151.07) | (446.31) | (370.48) | (434.43) | (458.26) |
| Working-age Ratio (250m grid) | 0.58 | 0.58 | 0.61 | 0.61 | 0.62 | 0.61 |
| | (0.09) | (0.07) | (0.07) | (0.10) | (0.08) | (0.08) |
| Properties | 52 | 43 | 922 | 2627 | 676 | 2234 |
| No. of Cities | 23 | 15 | 130 | 219 | 100 | 196 |

*Notes:* Summary statistics are computed as of January 1, 2019, prior to Typhoon Hagibis. Each group is further split by whether the property is located within a flood hazard map designated area (Hazard) or outside of it (Non-Hazard). The treatment group consists of properties directly exposed to flooding. The Within Flooded Cities group includes properties in flood-affected cities but not directly inundated. The control group comprises properties in non-flooded cities adjacent to flood-affected municipalities. Values in parentheses report standard deviations. Land use categories are expressed as percentages of each group.

Table A2: Disaster Recovery Expenditure and Land Prices

| | (1)<br>High Recovery | (2)<br>Low Recovery |
|---|---|---|
| *Panel A: Municipality Characteristics* | | |
| Number of municipalities | 88 | 148 |
| Mean inundated properties | 0.8 | 0.2 |
| Mean cumulative recovery (million yen) | 1248 | 56 |
| Mean recovery per inundated property (1000 yen) | 394436 | 5620 |
| *Panel B: Direct Damage (Inundated)* | | |
| Post × Inundated | −0.036 * | −0.059 ** |
| | (0.017) | (0.022) |
| *Panel C: Spillover (Non-Inundated in Flooded City)* | | |
| Post × Spillover | −0.013 | −0.010 |
| | (0.017) | (0.032) |
| Observations | 9,361 | 62,733 |
| $R^2$ | 0.992 | 0.997 |
| Property FE | Yes | Yes |
| Municipality FE | Yes | Yes |
| Year FE | Yes | Yes |
| Cluster | City+Year | City+Year |

*Notes:* This table examines whether municipal disaster recovery expenditure attenuates land price declines after Typhoon Hagibis (October 2019). Municipalities are split by whether cumulative recovery spending per inundated property (FY2019–2021) exceeds the median among flooded municipalities, conditioning on damage severity. Panel A reports municipality-level characteristics for each group. Panels B and C report difference-in-differences estimates where Post is an indicator for years after 2020. Recovery expenditure data are from the Ministry of Internal Affairs and Communications. Standard errors clustered by municipality and year in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

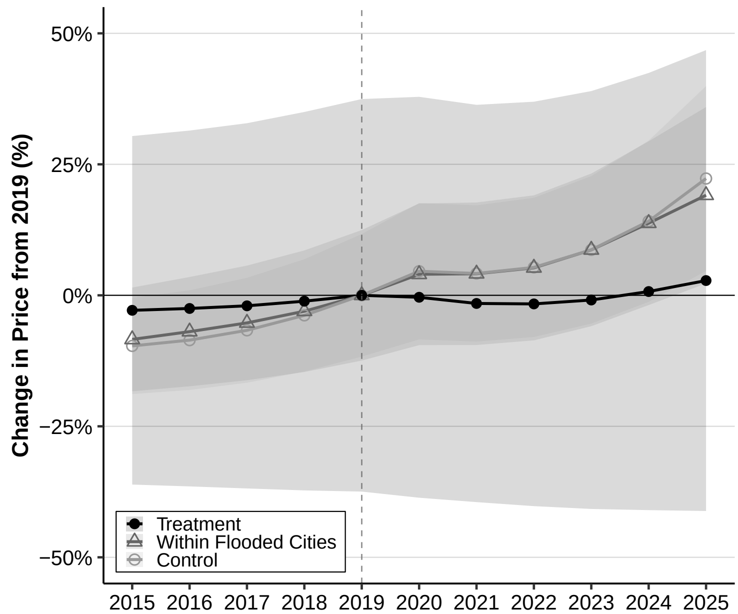


Figure A1: Land Parcel Prices Trends

*Notes:* This figure shows the trends in officially assessed land parcel prices, normalized to 2019. Parcel prices are assessed as of January 1 each year. Data for 2019 thus correspond to the period before Typhoon Hagibis made landfall in October 2019. The treatment group consists of parcels directly exposed to flooding. The Flooded Cities group includes parcels in affected municipalities that are not directly flooded. The control group comprises parcels in adjacent municipalities that are not flooded. Shaded areas represent 95% confidence intervals.

## B Robustness

This section scrutinizes the internal validity of our baseline estimates through a variety of supplementary analyses. First, we implement a falsification test to establish that our results are not artifacts of pre-existing differential trends between flooded and non-flooded areas. Second, to address potential concerns regarding imbalances in pre-treatment price levels and time-varying unobservables, we employ the Synthetic Difference-in-Differences (SDID) estimator. This framework enhances the comparability of our treatment and control groups by reweighting units to satisfy the parallel trends assumption more robustly. Finally, we investigate whether our findings are confounded by concurrent policy shifts or historical context. Specifically, we account for the designation of residential inducement zones and the publication of updated hazard maps, both of which could independently shift property valuations. We also evaluate the extent to which prior flood experience shapes the market's response to recent inundation events.

**Falsification Test** A primary identification challenge is the potential for unobserved heterogeneity between flooded and non-flooded areas. If such latent differences exist, the post-disaster price dynamics we document might reflect inherent disparities in sample composition or pre-existing trends rather than the causal impact of the flooding itself.

To mitigate this concern, we perform a falsification test using the pre-treatment period. Specifically, we restrict our sample to years prior to the 2019 flood and impose a hypothetical disaster in 2017, re-estimating our baseline specification under this placebo regime. If the baseline results were merely capturing fundamental differences between the treatment and control groups, we would expect to see statistically significant coefficients following this pseudo-event.

Figure B1 reports the results of this exercise. We find no evidence of statistically significant effects following the hypothetical disaster. Moreover, the point estimates are negligible in magnitude—standing in sharp contrast to the substantial effects observed in our main analysis. This null result reinforces the validity of our identification strategy, suggesting that our primary findings are not driven by pre-existing idiosyncratic differences across areas.

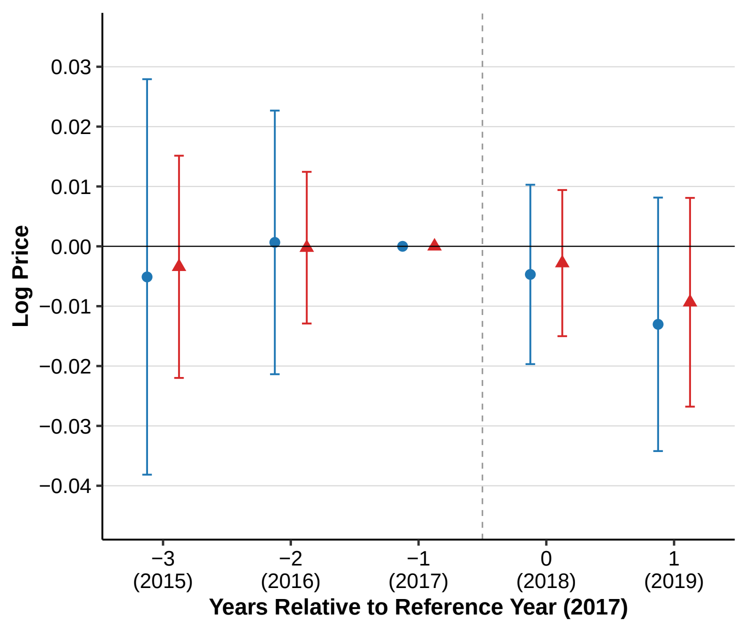


Figure B1: Falsification Test

*Notes:* This figure presents a falsification test using pre-treatment periods only (2015–2019). The reference year is 2017. Error bars represent 95% confidence intervals with standard errors clustered at the city-year level.

**Synthetic Difference-in-Differences** Table 1 reveals discernible disparities in mean pre-disaster price levels and trends between the treatment and control groups. Furthermore, while the point estimates for the treatment group in Figure A1 remain within the confidence intervals of the control group, the limited sample size of the treated units leads to wider intervals that may obscure underlying heterogeneity. Although the baseline event study detects no statistically significant pre-treatment divergence, these differences in observed characteristics pose a potential threat to the internal validity of our estimates.

To address this concern, we employ the Synthetic Difference-in-Differences (SDID) estimator developed by Arkhangelsky et al. (2021). SDID enhances the standard DID framework by incorporating unit-specific weights to balance pre-treatment levels and time weights to align trends, ensuring a more robust comparison even with a small number of treated units. This approach offers a methodological advantage over related strategies. For instance, propensity score methods typically require larger samples to achieve covariate balance (see Gibson and Mullins, 2020), whereas the conventional Synthetic Control Method (SCM) focuses on level matching but does not explicitly account for differential trends (Abadie, 2021).

We execute two separate SDID specifications to isolate direct effects and spillover effects, using properties in adjacent municipalities as the control donor pool.[27] Following Arkhangelsky et al. (2021), we derive estimates by optimizing unit and time weights. To maintain consistency with our baseline specification, we first partial out city fixed effects from the outcome variable and apply the SDID procedure to the residuals. For inference, we utilize the jackknife variance estimator, as it is computationally more tractable than the bootstrap while remaining conservative and exact in this context.

Table B1 presents the SDID estimates across various dimensions of heterogeneity. Panel A reports the direct effects on inundated parcels. The aggregate estimate indicates a statistically significant 5.2% decline in property values. Consistent with our baseline event study, the price response is more pronounced for parcels located outside designated hazard map zones (5.9%) compared to those within such zones (5.1%). Regarding land use, we find a significant 6.1% depreciation in residential prices. While the estimate for commercial properties is smaller and lacks statistical

[27] Specifically, we employ the following two specifications. For direct effects:

$$\log(p_{ict}) = \sum_{\substack{t=2015 \\ t\neq 2019}}^{2025} [\beta_t \cdot Flood_i \times Year_t] + \alpha_i + \nu_c + \delta_t + \epsilon_{ict}. \tag{B1}$$

For spillover effects:

$$\log(p_{ict}) = \sum_{\substack{t=2015 \\ t\neq 2019}}^{2025} [\gamma_t \cdot S_i(1 - Flood_i) \times Year_t] + \alpha_i + \nu_c + \delta_t + \epsilon_{ict}. \tag{B2}$$

significance, this likely reflects attenuated statistical power due to limited sample size rather than a genuine absence of an economic effect.

Panel B examines spillover effects as a function of distance from the inundated areas. The overall estimates reveal significant negative externalities extending up to 300 meters, with the magnitude of the effect decaying monotonically as distance increases. A key finding emerges when partitioning the sample by hazard map status: parcels outside designated zones exhibit significant spillover effects up to 500 meters, whereas those within hazard zones show no discernible impact at any distance. This pattern aligns with a residential sorting mechanism, suggesting that individuals with lower risk sensitivity tend to locate within designated hazard zones. Consequently, while direct inundation necessitates a price adjustment, the mere proximity to flooded parcels may not trigger a significant revaluation among these relatively risk-tolerant agents.

The comparison between the standard DID and SDID estimates in Columns (1) and (2) is informative. For direct effects, both estimators yield qualitatively similar results, with the DID point estimate of 7.0% being somewhat larger than the SDID estimate of 5.2%. For spillover effects, however, the two approaches diverge markedly: the standard DID estimates are uniformly statistically insignificant across all distances, whereas the SDID identifies significant negative spillovers extending up to 300 meters. This divergence is driven primarily by differences in precision rather than in point estimates. Under standard DID, all control units receive equal weight regardless of their comparability to the treated group, thereby introducing residual variation from poorly matched donors and inflating standard errors. The SDID estimator addresses this by constructing a synthetic control that reweights donor units to match the pre-treatment outcome trajectory of the treated group, thereby providing a more credible counterfactual and substantially improving estimation precision.

Table B1: Synthetic Difference-in-Differences Estimates

| | | Synthetic DID | | | | |
|---|---|---|---|---|---|---|
| | | | Hazard Map | | Land Use | |
| | DID | Overall | Inside | Outside | Resid. | Comm. |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Direct* | | | | | | |
| Estimate | −0.070*** | −0.052*** | −0.051*** | −0.059*** | −0.061*** | −0.013 |
| | (0.021) | (0.008) | (0.011) | (0.013) | (0.012) | (0.013) |
| *Panel B: Spillover* | | | | | | |
| 100m | −0.028 | −0.015* | −0.011 | −0.026** | −0.013 | −0.008 |
| | (0.023) | (0.008) | (0.011) | (0.011) | (0.010) | (0.024) |
| 200m | −0.019 | −0.012** | −0.006 | −0.021*** | −0.012 | −0.007 |
| | (0.021) | (0.006) | (0.008) | (0.008) | (0.007) | (0.017) |
| 300m | −0.010 | −0.009* | −0.004 | −0.015** | −0.007 | −0.008 |
| | (0.019) | (0.005) | (0.007) | (0.007) | (0.006) | (0.015) |
| 400m | −0.005 | −0.006 | 0.000 | −0.013** | −0.004 | −0.004 |
| | (0.019) | (0.004) | (0.006) | (0.006) | (0.005) | (0.013) |
| 500m | −0.001 | −0.003 | 0.004 | −0.009* | −0.000 | −0.004 |
| | (0.019) | (0.004) | (0.005) | (0.005) | (0.004) | (0.012) |
| 600m | 0.001 | −0.001 | 0.006 | −0.007 | 0.002 | −0.004 |
| | (0.018) | (0.003) | (0.005) | (0.005) | (0.004) | (0.011) |
| 700m | 0.006 | −0.001 | 0.005 | −0.006 | 0.002 | −0.002 |
| | (0.019) | (0.003) | (0.005) | (0.004) | (0.004) | (0.010) |
| 800m | 0.008 | −0.000 | 0.005 | −0.005 | 0.002 | −0.001 |
| | (0.018) | (0.003) | (0.005) | (0.004) | (0.003) | (0.009) |
| 900m | 0.009 | 0.000 | 0.007 | −0.005 | 0.002 | 0.000 |
| | (0.019) | (0.003) | (0.005) | (0.004) | (0.003) | (0.009) |
| 1000m | 0.010 | 0.001 | 0.008* | −0.005 | 0.003 | 0.001 |
| | (0.018) | (0.003) | (0.004) | (0.004) | (0.003) | (0.008) |

*Notes:* Column (1) reports standard DID estimates with two-way (city, year) clustered standard errors and parcel, year, and city fixed effects for the overall sample. Columns (2)–(6) report Synthetic DID estimates with jackknife standard errors. Panel A: directly flooded properties. Panel B: spillover effects by distance from flooded areas. * p<0.1, ** p<0.05, *** p<0.01.

**Confounding Policy** A potential threat to our identification strategy is the presence of concurrent policy interventions that may independently influence land values. If post-disaster urban planning decisions are correlated with flood-affected areas, our baseline estimates could be biased by these non-flood-related factors.

A primary candidate for such confounding is the *Act on Special Measures Concerning Urban Reconstruction*, amended in 2014. Under this framework, municipalities develop Location Normalization Plans (LNP) to promote "compact city" structures by designating Residential Inducement Zones (RIZ). The designation of an RIZ typically exerts upward pressure on land prices, as these zones are prioritized for public investment, infrastructure development, and administrative incentives. Conversely, areas included in a LNP but excluded from the RIZ may experience relative price stagnation or decline due to the lack of these benefits. If flooded parcels were systematically excluded from these inducement zones in the post-disaster planning phase, our baseline results might conflate the causal impact of the flood with the negative signaling effect of policy exclusion.

To disentangle these effects, we augment our baseline model by explicitly controlling for the policy status of each parcel. Specifically, we estimate the following specification:

$$\begin{aligned}\log(p_{ict}) = &\sum_{\substack{t=2015 \\ t\neq 2019}}^{2025} [\beta_t \cdot Flood_i \times Year_t + \gamma_t \cdot S_i(1 - Flood_i) \times Year_t] \\ &+ \sum_{\substack{t=2015 \\ t\neq 2020}}^{2025} \theta_t \cdot PostPolicy_i \times Year_t + \alpha_i + \nu_c + \delta_t + \epsilon_{ict},\end{aligned} \tag{B3}$$

where $PostPolicy_i = \mathbf{1}\{$ parcel $i$ is within an LNP area designated after October 2019, but outside the RIZ $\}$. The reference year for flood effects ($\beta_t$, $\gamma_t$) is set to 2019, while the reference year for the policy effect ($\theta_t$) is 2020, aligning with the timing of the plan formulations in our sample municipalities.

Figure B2 compares the coefficients from this augmented model with our baseline estimates. The results are virtually identical, suggesting that the observed price depreciation is driven primarily by the flood event itself rather than by the institutional shifts in urban planning designations.

**Hazard Map Updates** Another potential confounding factor is the institutional signaling effect of hazard map updates. A growing body of literature suggests that formal revisions to flood risk maps can induce significant property value adjustments by updating market expectations, even in the absence of a disaster event (e.g., Gibson and Mullins, 2020; Pollack et al., 2023). In the wake

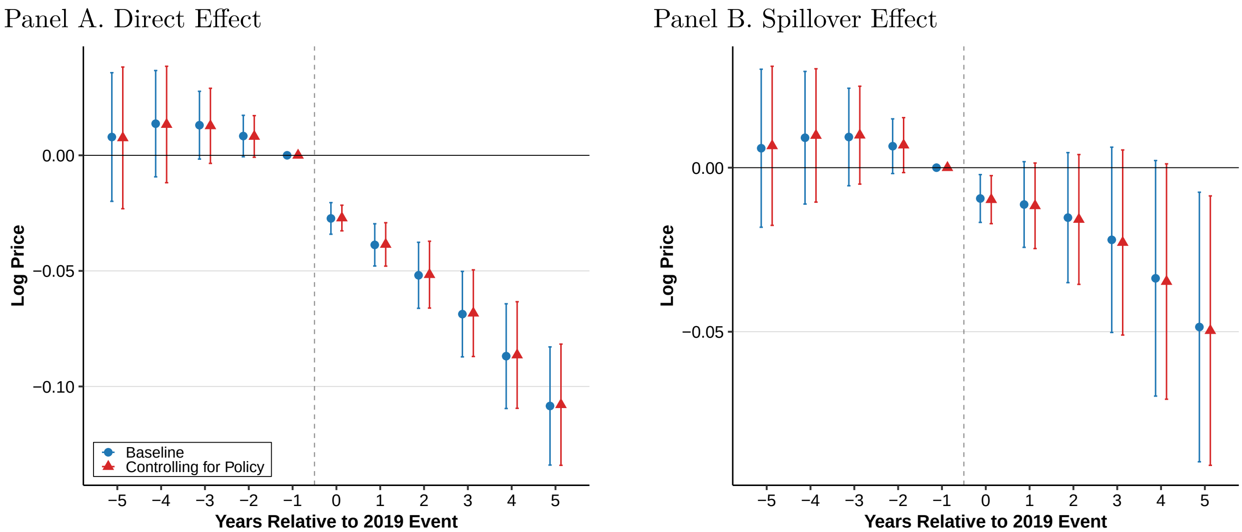


Figure B2: Robustness Check: Controlling for Post-Typhoon Urban Planning Designations
*Notes:* This figure compares baseline event study estimates with estimates controlling for areas designated outside residential inducement zones after Typhoon Hagibis. The similarity between baseline and policy-controlled estimates suggests that the estimated flood effects are not driven by post-disaster urban planning policy changes.

of Typhoon Hagibis, many municipalities updated their hazard maps in fiscal year 2020 to reflect revised inundation assumptions. This raises a crucial identification concern: if flooded parcels were disproportionately transitioned from "outside" to "inside" hazard zones during these revisions, our baseline estimates might conflate the direct impact of the flood experience with the signaling effect of a new institutional designation as a high-risk area.

To isolate the causal effect of the flood itself from these mapping updates, we utilize the National Land Numerical Information database to identify parcels that underwent a change in their hazard status. Specifically, we compare the fiscal year 2020 hazard maps (Version 2.1) with the earlier 2012 versions (Version 1.1) across seven prefectures where updated GIS data are available: Iwate, Yamagata, Tochigi, Gunma, Kanagawa, Yamanashi, and Shizuoka. We then augment our baseline specification by explicitly controlling for properties that were newly designated as being within a hazard zone.

Figure B3 summarizes these results. We observe that the point estimates for flooded parcels are slightly attenuated compared to the baseline, suggesting that a portion of the observed price decline indeed reflects the institutional information shock of being newly incorporated into a hazard zone. However, this policy-induced effect accounts for only a limited fraction of the total price depreciation. The overall estimates for both direct and spillover effects remain substantially negative

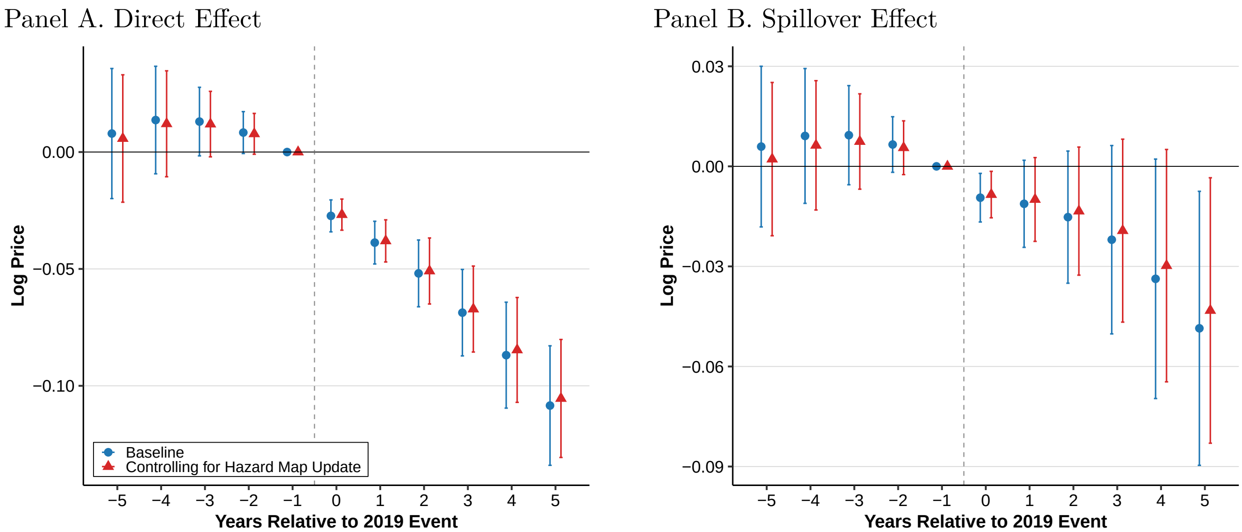


Figure B3: Event Study Estimates: Controlling for Hazard Map Update

*Notes:* The figure shows event study estimates comparing the baseline specification (circles) with a specification controlling for hazard map updates (triangles). The vertical dashed line indicates Typhoon Hagibis (October 2019). Error bars represent 95% confidence intervals based on standard errors clustered at the city-year level.

and statistically significant, reinforcing the conclusion that the physical realization of the flood and the subsequent market revaluation of risk are the primary drivers of our results. In short, while formal remapping contributes to property value adjustments, it does not fundamentally diminish the magnitude or the robustness of our core findings.

**Prior Flood Experience** A critical question in the literature on natural disasters is whether past experiences shape current risk perceptions and, consequently, land prices. Building on the findings of Koide et al. (2022) and Furukawa and Suzuki (2026), who document that flood risk is more likely to be capitalized into Japanese land prices in areas with frequent inundation, we investigate whether prior belief updating influences the marginal impact of the 2019 typhoon. Specifically, in high-frequency areas, risk may already be reflected in the baseline valuation.

To test this channel, we focus on the September 2015 Kanto-Tohoku Heavy Rainfall, which caused a catastrophic levee breach along the Kinugawa River. If this major event had already induced a significant downward revision of risk beliefs in the affected regions, the incremental price response to Typhoon Hagibis in 2019 might be more muted compared to areas with no recent disaster history. While an ideal test would involve a formal subgroup analysis, our sample contains only a limited number of properties (2 direct and 4 spillover) within the most severely affected

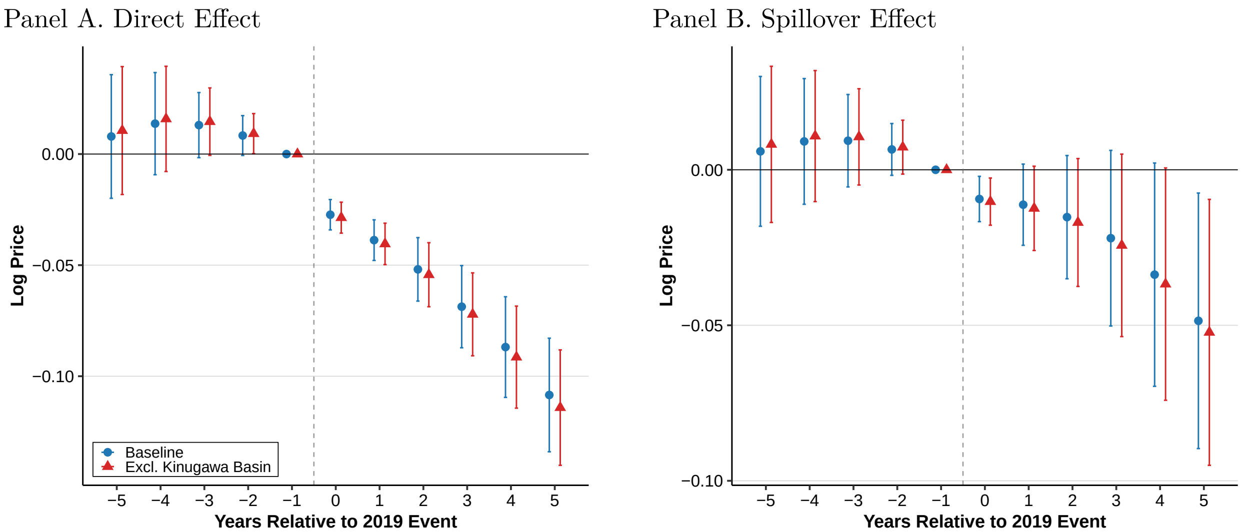


Figure B4: Robustness Check: Excluding Kinugawa River Basin

*Notes:* This figure compares the baseline estimates with those excluding municipalities in the Kinugawa River basin, which experienced major flooding in September 2015. Panel A shows direct effects on flooded properties; Panel B shows spillover effects on nearby properties within 100m of flooded areas. The baseline sample includes 6,554 properties, while the restricted sample excludes 365 properties (2 directly flooded, 4 spillover, and 359 not directly affected by Typhoon Hagibis) located in the Kinugawa River basin. The reference year is 2019. Error bars represent 95% confidence intervals with standard errors clustered at the city-year level.

Kinugawa basin municipalities. Given this constraint on statistical power, we compare our baseline estimates with those obtained by excluding the Kinugawa basin sample.

Figure B4 presents the results. The overall price patterns remain qualitatively consistent between the two specifications, and the differences in point estimates are not statistically significant. However, excluding the Kinugawa basin yields slightly larger effect magnitudes—approximately 5% larger for the direct effect by 2025 (−0.114 vs. −0.108). While we interpret these results with caution due to the limited sample size, the pattern is directionally consistent with our hypothesis: the 2015 Kinugawa flood likely triggered prior belief updating, thereby attenuating the subsequent price adjustment in 2019. This suggests that while prior experience does matter for risk capitalization, its quantitative impact on the 2019 price dynamics, while detectable, remains secondary to the magnitude of the Typhoon Hagibis disaster itself.

## C Spillover within Flooded Municipality

We examine whether the entire municipality affected by flooding experiences spillovers. Specifically, we define spillover effects as the impact on parcels outside the inundated areas within those

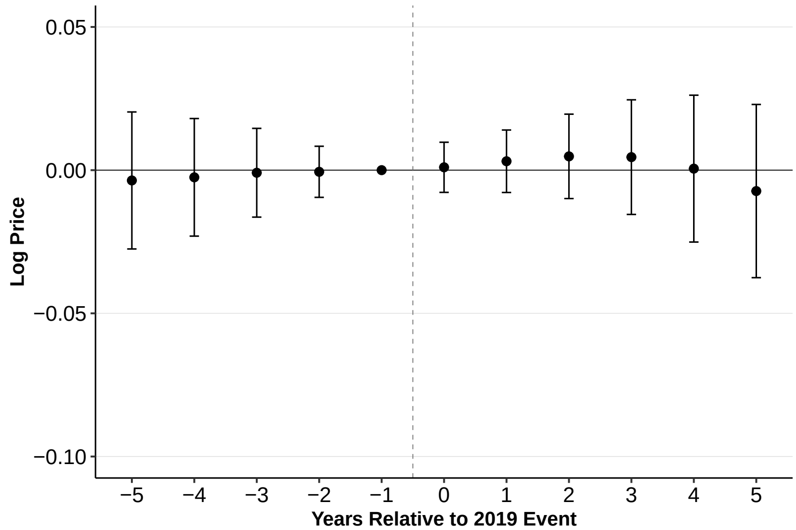


Figure C1: Spillover Effects within Flooded Municipalities

*Notes:* This figure presents event study estimates of spillovers within inundated municipalities. The reference year is 2019. Error bars represent 95% confidence intervals with standard errors clustered at the city-year level.

municipalities. The control group consists of land parcels in municipalities adjacent to the flooded ones. Figure C1 presents the results of this event study. When the sample includes all parcels within the flooded municipalities (excluding those directly inundated), we find no significant decrease in land prices, suggesting that the negative impact does not extend to the entire municipality.

## D Fluvial and Pluvial Floods

The appropriate countermeasures vary by flood type: reinforcing river embankments for fluvial flooding versus strengthening sewage drainage facilities for pluvial flooding. Therefore, analyzing the impacts of each type of flood separately is important. However, empirical analysis distinguishing between pluvial and fluvial floods remains limited. In our dataset, some municipality-collected data classify the cause of inundation as either fluvial or pluvial, enabling us to leverage these categories in our analysis. Specifically, we extend the baseline specification to incorporate flood types as follows:

$$\log(p_{ict}) = \sum_{F \in Floodtypes} \left[ \sum_{\substack{t=2015 \\ t \neq 2019}}^{2025} \left[ \beta_{t,F} \cdot Flood_{i,F} \times Year_t + \gamma_{t,F} \cdot S_{i,F}(1 - Flood_{i,F}) \times Year_t \right] \right] \\ + \alpha_i + \nu_c + \delta_t + \epsilon_{ict} \tag{D1}$$

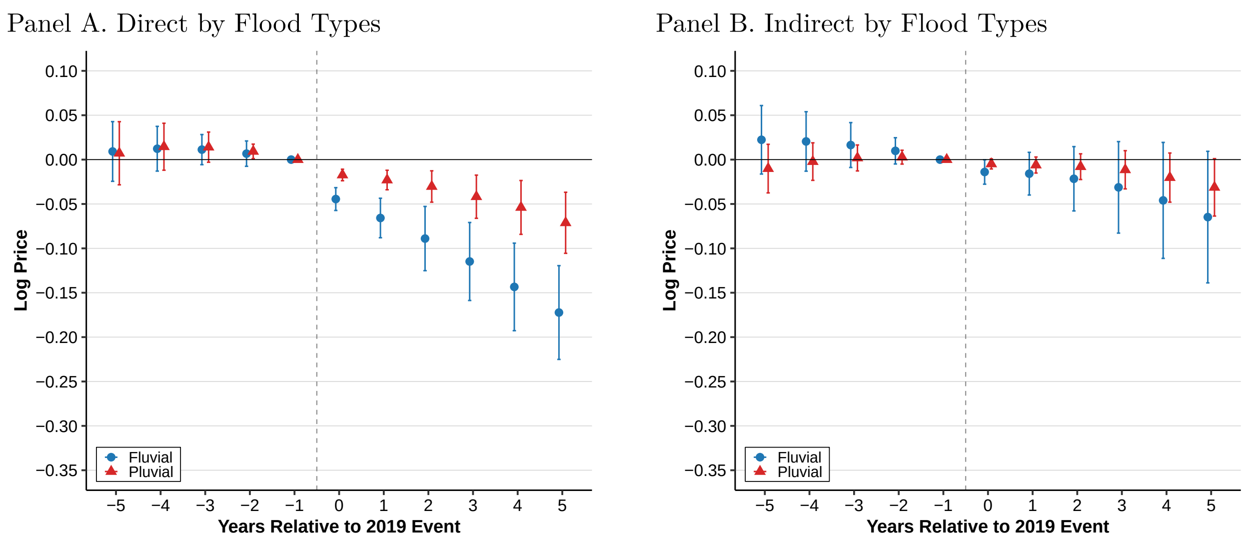


Figure D1: Heterogeneous Effects by Flood Pattern

*Notes:* This figure presents event study estimates of the spillover effects of realized flood risk on parcel prices. We report $\beta_{t,F}$ and $\gamma_{t,F}$ in Equation (D1). The reference year is 2019. Error bars represent 95% confidence intervals with standard errors clustered at the city-year level.

We consider two flood types: pluvial and fluvial. Panel A reports the direct effects $\beta_{t,F}$. The results indicate that fluvial flooding has a greater impact than pluvial flooding. Both types, however, exhibit persistent effects. Panel B reports the spillover effects $\gamma_{t,F}$. Although the point estimates suggest a declining trend for both flood types, with fluvial flooding showing a somewhat larger magnitude, neither estimate is statistically significant.

## E Incorporating Economic Activity in the Model

After a flood, local economic activity may decline due to various reasons, such as population outflows or the relocation of economic hubs. As a result, even if there is no change in the risk perception of market participants themselves, it is possible that their living environment or working environment may deteriorate exogenously from their perspective. We therefore model the utility degradation that arises from such contractions in local economic activity. $a_t$ represents the losses of local amenity value. This framework encompasses scenarios where exogenous shocks—such as flood-induced inundation—precipitate a demographic exodus that erodes the welfare of the remaining residents. Such out-migration generates negative utility to neighbors by weakening social networks, deteriorating non-traded local services, and diminishing the productivity gains associated with agglomeration economies.[28]

While our theoretical framework is primarily centered on household welfare, these can be rather salient in commercial districts. The evolution of the welfare degradation parameter, $a_t$, is governed by the temporal trajectory of population outflows and the sensitivity of market participants to the receding economic density. For tractability in our simulation exercise, we assume that utility declines monotonically under sustained demographic contraction. Specifically, the contemporaneous amenity value at time $t$ is defined as:

$$e_t^h = e_0^h - a_t. \tag{E1}$$

The cumulative utility loss follows a recursive law of motion:

$$a_t = a_0 e^{-\rho_d t} + a_{t-1}, \tag{E2}$$

where $a_0$ captures the impact magnitude at the shock's onset and $\rho_d > 0$ denotes the rate of temporal decay. Under this specification, while the marginal welfare impact of the disaster diminishes exponentially, the aggregate effect accrues recursively over time.[29] We also conduct a simulation with an alternative simple formulation, where this $a_t$ diminishes linearly with distance.

Finally, we incorporate spatial externalities. We assume that the scale of residential and business relocations generates spatial spillover effects that decay exponentially with distance from the affected areas. Specifically, the welfare impact at distance $d$ can be described as

$$a_{t,d} = a_t e^{-\tau_d d}. \tag{E3}$$

Moreover, as an alternative specification, following standard gravity-based assumptions, the welfare impact at a distance $d$ from the shock's origin is subject to distance decay, parameterized by $\omega > 0$:

$$e_{t,z}^h = e_0^h - \frac{a_t}{\omega d}. \tag{E4}$$

This corresponds to the case where the spillover effects decay linearly.

[28] Some prior literature demonstrates that exogenous shocks trigger persistent out-migration, which subsequently erodes the local tax base and undermines the provision of public and private amenities (Glaeser and Gyourko, 2005; Hornbeck, 2012). These studies highlight how such demographic shifts can result in long-term welfare scars by disrupting local social capital and labor market equilibrium (Boustan et al., 2020; Roth Tran and Wilson, 2025).

[29] Following Krugman (1991) and Tabuchi (1998), we model transportation costs using the iceberg formulation with exponential decay in distance, which implies that only a fraction of shipped goods arrive at the destination. This mechanism affects market access and product variety, thereby shaping spatial patterns of agglomeration and welfare.

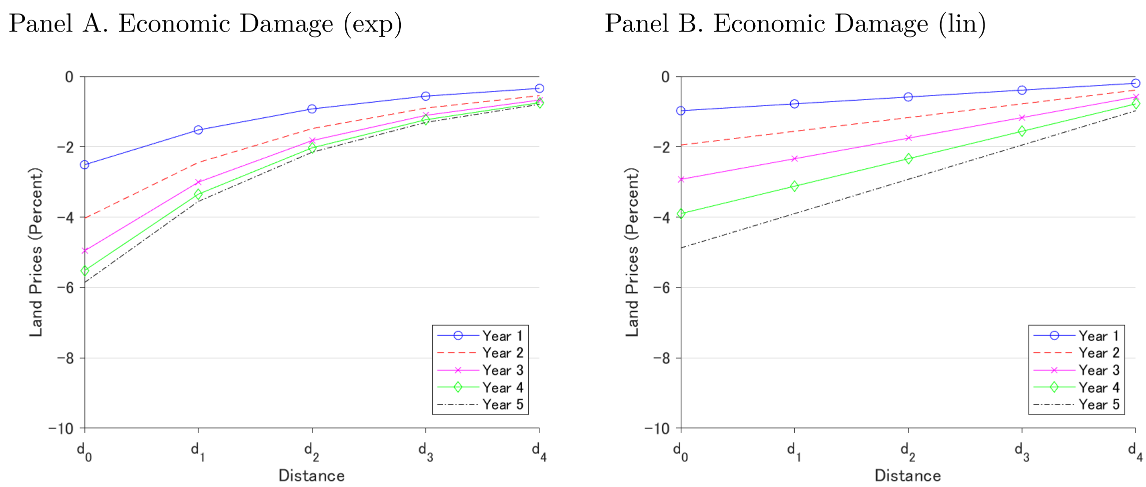


Figure E1: Land Price Responses by Distance in the case of Economic Damage

*Notes:* This figure shows the potential spatial gradient of land price responses using different signal values. Panel A shows the simulation results with a downturn in local economic activities of different sizes. Panel B presents an alternative formulation with linear decay in the impact of the downturn of local economic activity. Here, $d_0$ represents the inundated area and $d_1$, $d_2$, $d_3$, and $d_4$ represent the distance from the inundated area with $d_1 < d_2 < d_3 < d_4$. Collectively, these panels contrast the varying rates of spatial decay across distinct transmission channels.

Figure E1 presents the response functions for a decline in the scale of local economic activity. [30] We study the implications of the spatial-temporal propagation of flood events to land price responses. Endogenous economic externalities (exp) are explored in Panel A, and endogenous economic externalities (lin) are explored in Panel B of Figure E1.[31] If the reduction in utility associated with economic stagnation decreases exponentially, the decline in land prices becomes more prolonged as denoted by "exp," and if it decreases linearly, it is denoted as "lin."

The effects of economic channels also attenuate with distance; the price decline remains more persistent at greater distances compared to the informational channel. Especially, in the linear case, the magnitude of price decline attenuation is small, suggesting that floods also tend to affect land prices in relatively distant places.

[30] For the parameters used in the simulation, the utility decline due to population outflow in inundated areas ($a_0$) is set at 2,000 K yen, and the parameter governing the persistence of population outflows following a flood ($\rho_d$) is assigned a value of 0.5.

[31] For simplicity, our simulation assumes that decay over time and space in terms of the size of signals and of economic losses follows the same functional form. Specifically, when the decay with respect to distance from the inundated area is exponential, the time decay is also modeled as exponential. Similarly, when the decay with respect to distance is linear, the time decay is assumed to follow a linear trajectory as well.