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Cashing in on others' misfortune: Institutional investments in China's commercial property market in times of flooding crisis

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ABSTRACT

Flooding disasters have extensively disrupted productive activities, causing market uncertainties. However, how these uncertainties affect institutional investors' strategies in the commercial property market remains an underexplored question. To address the question, we provide a novel perspective by classifying flooding events into seasonal and climate change-induced (CCI) floods. Specifically, we conduct a spatial quasi-natural experiment to examine the treatment effect of seasonal and CCI floods on the commercial property market in Chinese cities from 2010 to 2018. We find that flooding disasters create a discount effect on property prices, which lures investors to flock into the market. However, institutional investors perform more cautiously in properties within CCI floodplains relative to counterparts within seasonal floodplains. In addition, local institutional investors benefit from higher discount premiums more than non-local institutional investors in floodplain markets, though this advantage diminishes in CCI floodplain markets. Our findings provide valuable implications for investors' decision-making in flood-prone cities. Policymakers are encouraged to promote market information transparency and resilience-building initiatives to mitigate the adverse effects of flooding events on local economies.

1. Introduction

The World Bank (2020) estimated that flooding events globally accounted for an astonishing economic loss of 651 billion US dollars between 2000 and 2019. China, the second largest economy in the world, is acutely susceptible to such events, suffering an annual economic loss of more than 19.2 billion dollars from 1984 to 2018, accounting for 54 % of the country's total economic loss from all-natural disasters (World Bank, 2020). China's urban agglomerations in coastal areas and the Yangtze River Basin, which are the most economically developed regions, are particularly exposed to flooding risk (see Fig. 1).[1] The conventional research focus has been on quantifying direct physical damage to affected assets, along with associated health and insurance costs (Benson & Clay, 2004; Cavallo et al., 2013; Cavallo & Noy, 2011; Kates et al., 2006). However, few attentions have been drawn on unravelling the potential for investment premium and arbitrage interests derived from post-disaster interventions (e.g., green gentrification and infrastructure improvements) from a perspective of institutional investors (Kim et al., 2020; Kim & Wu, 2022). This evolving dynamic has reshaped institutional investors' risk perceptions towards property markets, necessitating a reassessment of their investment strategies.

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[1] The focus of this study is on mainland China. The dataset excludes Hong Kong, Macao and Taiwan due to their distinct legal, financial, and regulatory environment, which differ significantly from the rest of China in terms of property transactions and flood risk management.

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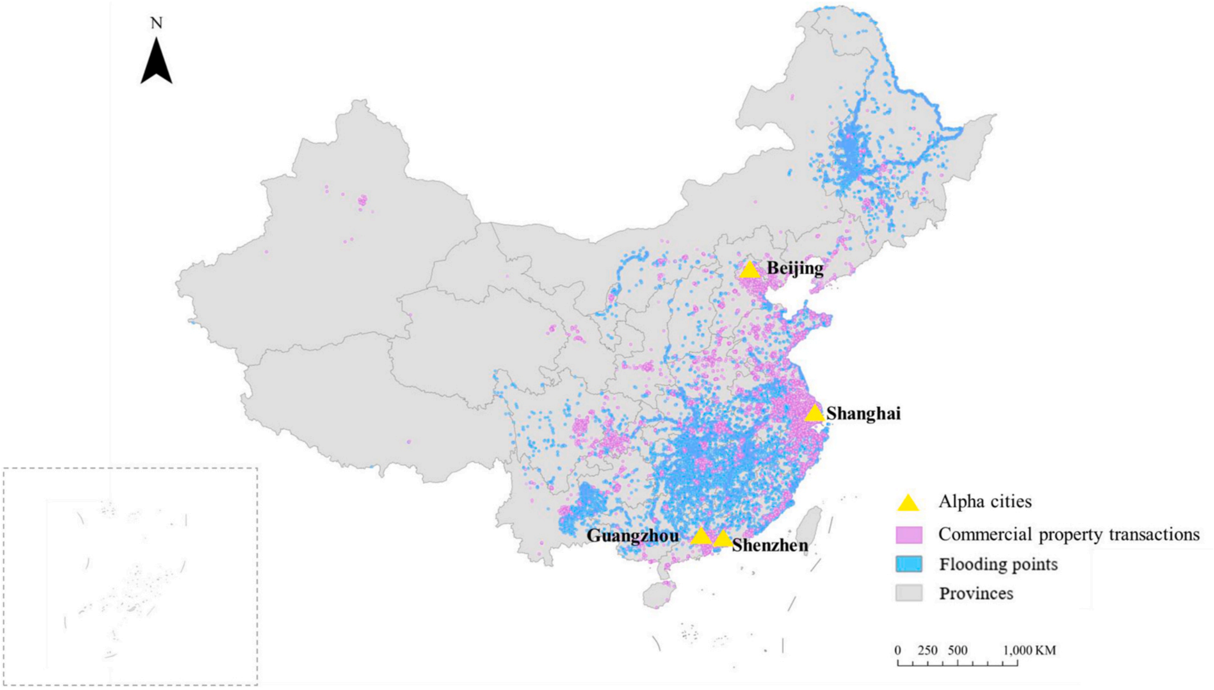

Fig. 1. The geographical distribution of flooding points and property transactions in China.

We thus ask, "How do institutional investors leverage flooding and market information to capitalise on flooding events in urban China?" This article addresses this question by examining the investment decisions of institutional investors in China's commercial property market in the aftermath of flooding events. Practically, the investment decisions are reflected in the realised transaction prices and trading volumes in the commercial real estate market, which reflects institutional investors' revealed preferences under varying flood-risk conditions. In addition, post-flood assessments by the World Bank and China's Ministry of Emergency Management suggest that in major urban floods, the majority of commercial properties suffer partial damage such as inundation of lower floors, electrical systems, and interior fittings, with complete structural destruction being rare and confined to low-lying industrial or warehouse facilities. Importantly, China's national building codes require elevated ground floors and basic flood-proofing in designated high-risk zones, but their enforcement varies widely across regions and between historically seasonal versus emerging CCI floodplains. The lack of harmonised flood-specific codes, combined with uneven drainage capacity, leaves many properties in old urban centers exposed to repetitive seasonal inundation. Our analysis does not directly quantify these engineering factors due to the absence of parcel-level building-code or damage-severity data, but these contextual differences help explain heterogeneous investor risk perceptions across flood types.

Commercial real estate (CRE) investment concerns the acquisition of properties intended for business uses, including retail, industrial, rental housing and offices. Former studies have concentrated on investigating the effect of flooding risk on urban residential property market (Hino & Burke, 2021; Hummel et al., 2021; Lamond et al., 2010; Zhang, 2016), leaving a notable research gap in the commercial property market, particularly in rapidly urbanizing China (Fisher & Rutledge, 2021; Holtermans et al., 2023). In contrast with individual households' residential property transactions, commercial property transactions are typically conducted by institutional investors to manage portfolio assets and create rental streams. The most salient difference between residential and commercial property markets lies in the extent of information asymmetry in respective markets. The information on residential properties is relatively transparent because of small lump sums and high market liquidity (Cvijanović et al., 2022; Geltner & Van De Minne, 2017). By contrast, commercial property markets, especially in China, are characterised by restricted access to data that are available primarily to professional investors specialised in evaluating complex proprietary attributes and calculating risk-adjusted returns (Newell et al., 2009, 2023; Pain et al., 2023). In addition, the market positioning of institutional investors can significantly influence commercial property bidding outcomes (Chinloy et al., 2013). Given these distinct characteristics, institutional investors are expected to exhibit distinct behavioural patterns during the time window of flooding disasters than homeowners (Liu et al., 2024). Despite the importance of institutional investors in China's commercial property market, their behavioural patterns associated with flooding events have yet to be explored.

This article fills the research void by examining investors' risk perceptions from the following three perspectives. First, investors' decisions in floodplain commercial properties are modelled based on real option theory, where acquisitions act as option costs, enabling them to monitor post-flood recovery, government responses and market dynamics. Favourable conditions allow investors to exercise options by selling at a premium or redeveloping for higher yields, while protracted recovery permits divestment, limiting losses to the initial cost. Second, the cost of real options is contingent on the transparency of market information. Instead of assuming the homogeneity of flooding impacts, we distinguish between CCI and seasonal floods to examine their respective impacts on investors' behavioural patterns. This provides nuanced insights into how institutional actors recalibrate risk assessments and real option valuations in response to flood-specific characteristics. Third, the complexity of commercial property information and tenant management demand investors' expertise and market familiarity with the localised business characteristics. Aligned with information asymmetry theory, local investors' information advantage can be translated into a higher discount in transacted prices and timely market entry (Akerlof, 1978; Barberis et al., 2001; Grossman & Stiglitz, 1980; Huberman, 2001), while non-local investors, hindered by tacit knowledge gaps, often overbid or delay.

Methodologically, we employ a semi-natural experiment approach, namely the spatial Difference-in-Difference (DiD) model, to tease out the causal impact of flooding events on China's commercial property market. We retrieved remote sensing data of flooding areas from the Global Flood Database (GFD) and utilised the spatial buffering method to identify flood-affected properties as the treatment group. Commercial property transaction data were acquired from Morgan Stanley Capital International (MSCI). The flooding data and property data were crossmatched, resulting in a repeated cross-section dataset covering 63,384 commercial property transactions from 2010 to 2018 across 81 Chinese cities (see Fig. 1). The flooding events are classified as CCI and seasonal floods based on China Hydrological Information Annual Reports (HIAR). Lastly, to validate the causality of model results, parallel trend analysis and placebo tests are implemented.

This article establishes a novel combined theoretical framework drawing on real options and information asymmetry theories to unveil the rationality boundary of institutional investors in response to regional flooding risks. Empirically, the article advances understanding of informational cascades concerning environmental risks in the commercial property market by dichotomizing flood types (CCI vs. seasonal) and investor categories (local vs. non-local), thereby revealing how spatial informational disparities shape market behaviour. Additionally, by shifting the analytical lens from residential to commercial property markets, it offers novel insights into urban economic recovery dynamics, which have been underexplored in existing literature. Practically, since China's developed cities, which are the country's biggest concentrations of commercial activity, property and skilled workforce, are confronted with significant flooding risk exposure, the research is highly relevant for governments to facilitate economic recoveries by hedging investors' risk perceptions.

Our findings reveal that flooding events trigger significant commercial property devaluation in affected regions, with seasonal floods exerting disproportionately severe price discounts. Local investors, leveraging asymmetric informational advantages and market familiarity, capitalise on these discounts to secure higher risk-adjusted returns. The remaining sections of this article are structured as follows. The second section reviews former studies concerning the impact of natural disasters on the property market and formulates hypotheses under the integrated theoretical framework. The third section elaborates on the data processing, variables, and specification of the DiD model. The fourth section presents the main model findings, parallel trend analysis, placebo test, and mechanism test. The final section concludes with a discussion of the substantive results and directions for further research.

2. Literature and hypothesis: price discount, risk perception, and information asymmetry

A growing body of literature highlights the heightened vulnerability of property assets to natural hazards exacerbated by climate change, urging investors to integrate associated risks in decision-making processes (Contat et al., 2024; Hallstrom & Smith, 2005; Kang et al., 2024; Kim et al., 2020; Zheng et al., 2014). Among these hazards, flooding events pose acute threats to commercial property values due to their direct and indirect consequences (Meltzer et al., 2021). First, direct physical damage, the most immediate and visible consequence of flooding, undermines building structures, electrical systems, and critical infrastructure, necessitating costly repairs and causing operational paralysis (Benson & Clay, 2004; Kousky, 2014). Although fine granule-level data on structural damage are unavailable, existing reports suggest that most flood-related losses arise from partial inundation rather than structural collapse. This distinction, together with heterogeneous local drainage systems and zoning enforcement, is likely to influence both the depth of price discounts and the pace of market recovery following different types of floods. Industrial facilities and retail centers are particularly vulnerable, as complex repairs and supply chain interdependencies often prolong recovery periods (Webb et al., 2002). An extended recovery period further erodes commercial property value by depressing rental income and deterring tenants (Alok et al., 2020; Bin & Landry, 2013). Indirect financial risks are amplified in China's institutional context, where the absence of flood-specific insurance schemes shifts nearly all post-disaster repair costs onto investors. Unlike developed countries with risk transfer mechanisms (e.g., flood insurance), China's property markets lack institutional buffers to mitigate financial uncertainty (Lamond et al., 2010). This unmitigated exposure suppresses property values by inflating operational risks and destabilizing long-term cash flow projections. Accordingly, we postulate:

H1a. Commercial properties within floodplains will experience significant devaluation following flooding events.

While properties situated in floodplains experience a devaluation risk, the flooding risk also encourages landowners and governments to invest in infrastructure and structural enhancements to mitigate flood damage, potentially offsetting the devaluation effect (Kim et al., 2020). For instance, Kousky's (2010) study on the impact of the 1993 Missouri and Mississippi River floods found no significant devaluation within 100-year floodplains, where seasonal hydrological patterns and historical data enable predictable risk delineation. This suggests that anticipated risks, coupled with adaptive measures, may attenuate observable devaluation effects (Bin & Landry, 2013; Blöschl et al., 2020; Kousky, 2014). However, CCI floods, driven by shifting precipitation, sea-level rise, and storm intensification, defy historical models, creating novel uncertainties in regions lacking formal flood zones (Hirabayashi et al., 2013; Kay et al., 2009; Milly et al., 2002). Consequently, CCI floodplains incur higher investor skepticism and risk premiums due to unpredictable damage potential. This is particularly evident in coastal cities in China, where urban development and business agglomeration have intensified, and the wetland area is projected to be further reduced, surpassing the protective capacity of infrastructure designed in accordance with historical flood benchmarks (Peng et al., 2017; Zong et al., 2025). Accordingly, the first hypothesis is extended as:

H1b. Investors demand higher discounts for commercial properties within CCI floodplains.

Regardless of devaluation risks, it is found that flooding events paradoxically stimulate transaction volume within floodplains (Addoum et al., 2024; Bernstein et al., 2019; Cohen et al., 2021). By drawing on real options theory, in uncertain environments, investors possess flexible decision-making rights, namely "options", that allow them to delay, expand, or abandon investments until conditions become clearer (Pindyck, 1991). Investors weigh the option to delay purchase against the potential gains from acquiring undervalued assets, with the flexibility to either redevelop, sell, or repurpose properties depending on subsequent recovery trajectories. In other words, investors facing an uncertain future after a flood event are not locked into a single outcome but can adapt their strategies as the situation evolves (Dixit & Pindyck, 1994). Likewise, if post-flood recovery proceeds favourably, investors may exercise the option by redeveloping and leasing the property for enhanced returns in the affected regions, thereby boosting transaction volumes (Kim et al., 2020); if not, they can decide to sell or repurpose the property, in effect allowing the real option to expire. Thus, temporary price declines after a flood event attract risk-tolerant investors who anticipate recovery-driven appreciation, government subsidies, or resilience upgrades (Atreya et al., 2013; Atreya & Ferreira, 2015; Bin & Landry, 2013; Cohen et al., 2021), which grants them real options to purchase according to dynamic market conditions. Accordingly, we propose the second hypothesis as:

H2a. Flooding crises will stimulate the transaction volume of commercial properties within floodplains.

Yet, the cost of real options might be affected by the transparency of market information at the time of property acquisition. Former studies assume that flooding events are homogenous and generate universal impacts on property values. However, this assumption is increasingly challenged by evidence showing variability in the impacts of different types of flooding events (Kousky, 2010; Ortega & Taș;pınar, 2018). Increased media coverage makes climate change-related events more salient, influencing investors' perceptions of flooding impacts. Thus, the enhanced transaction volume may be unevenly distributed in seasonal and CCI floodplains. Institutional investors can modify their risk perception based on evolving climate models of seasonal flood damage, but it is difficult for them to assess CCI flood damage. In the context of seasonal floodplains, where flood damage is more predictable, investors are more confident in exercising their options. Conversely, due to the greater uncertainty and destructive potential associated with CCI floods, investors are inclined to postpone investment options until associated risks are resolved. Thus, we extend the second hypothesis as follows:

H2b. Seasonal floodplains experience stronger transaction surges than CCI floodplains.

By drawing on the information asymmetry theory, the impacts of flood events are further mediated by information asymmetry embedded in commercial property markets (Akerlof, 1978). Information asymmetry arises when one party in a transaction possesses superior information to the other, leading to strategic advantages in decision-making and resource allocation (Coval & Moskowitz, 1999). In the context of commercial property markets, this asymmetry is particularly pronounced due to the complexity of proprietary data, tenant profiles, and localised market dynamics (Broxterman & Zhou, 2023; Ling et al., 2018). Flood events exacerbate this complexity by introducing additional layers of uncertainty, such as flood aetiology, recovery timelines, and potential regulatory shifts (Kousky, 2010; Ortega & Taș;pınar, 2018). Local investors, by virtue of their proximity and embeddedness in the market, possess superior access to tacit knowledge, such as historical flood patterns, local government responses, and community resilience, that non-local investors lack. This informational advantage enables local investors to make more informed and timely decisions, particularly in the aftermath of flood events when market conditions are volatile and uncertain. While non-local investors are less equipped to assess the true value of flood-affected properties, leading to overestimated bids or conservative behaviour (Alok et al., 2020; Li & Chau, 2024). Accordingly, we postulate:

H3a. Local institutional investors secure higher discounts on commercial properties in floodplains.

In addition to localised business resources, local investors possess a significant informational advantage when it comes to the tacit specifics of flooding events. Likewise, local investors can obtain timely and accurate information on whether incumbent floods are seasonal hydrological phenomena or caused by systematic climate change. Meanwhile, local investors can take advantage of their experiences in historical floods to anticipate market reactions and economic resilience to incumbent floods. Consequently, they can enter the market promptly, particularly targeting properties within seasonal floodplains where investment risks are manageable. By contrast, non-local investors, due to their lack of local market familiarity and reliance on third-party reports, may not fully capture procurement-relevant nuances of the local property market and economic recovery prospects following a flooding event. This disadvantage may result in less competitive or overestimated price bids, leading to more conservative behaviour and exhibit strong loss aversion to entering the market (Li & Chau, 2024; Nanda & Ross, 2012). This informational disadvantage renders non-local investors less competitive in bidding for undervalued commercial properties within seasonal floodplains. Accordingly, we extend the third hypothesis as follows:

H3b. Local investors disproportionately acquire seasonal floodplain properties, outperforming non-local counterparts.

In China's commercial property market, underdeveloped risk mitigation systems, sparse flood insurance, and fragmented data are more likely to amplify CCI-related devaluation (H1a–b) and speculative transactions (H2a–b). Concurrently, China's unique guanxi networks entrench local investors' dominance (H3a–b), as tacit knowledge of recovery programs and flood nuances enables opportunistic acquisitions. Overall, the hypothesised relationships (H1a–b, H2 a–b and H3a–b) collectively explain how flood risks translate into price discounts, risk perception, and information asymmetry mechanisms in China's commercial property markets.

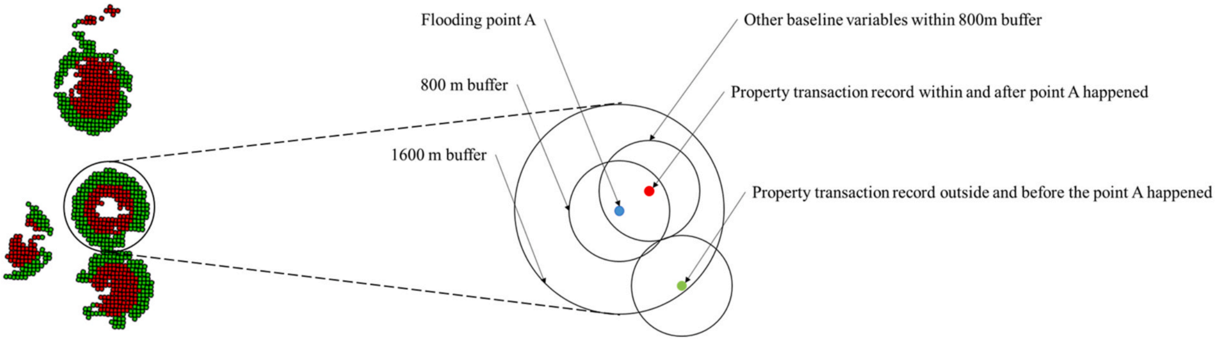

Fig. 2. The buffer method for distinguishing treatment and control groups (note: the blue node indicates the centroid of flooding event; the red node represents a treated observation; the green node represents a control observation).

3. Data and methods

3.1. Flooding data

China's floodplain maps are derived from the GFD, which uses satellite imagery with a 250-m resolution to estimate flood extent and population exposure from 2010 to 2018. To detect surface water, the GFD applies Otsu-optimised thresholds for spectral bands-short-wave infrared, near-infrared, and red (bands 7, 2, and 1). These bands are captured by the Moderate-Resolution Imaging Spectroradiometer (MODIS) instrument, a multispectral optical sensor on NASA's Terra and Aqua satellites. The results were validated against higher-resolution (30-m) Landsat imagery, focusing on the day of maximum flooding for 30,638 points. This validation achieved a mean accuracy of 83 % for empirically derived thresholds and 80 % for Otsu-optimised thresholds. The advantage of these satellite-based observations lies in their ability to reduce the uncertainty inherent in earlier models that relied on limited observational data (Tellman et al., 2021).

Next, we conducted a spatial matching analysis by integrating the flood points with rainfall, hydrological, and ice conditions from the HIAR. To classify flood events, we developed a lexicon-and-sentence-based methodology. CCI floods are identified by sentences, such as "exceeded the warning threshold across all monitored sections", "the peak historical flood for the season/timeframe", and "flood exceeding historical maxima" in HIAR narratives. Flood events are categorised as seasonal ones when reporters use terms such as "seasonal", "consistent with past years", and "routine". Our analysis excluded ambiguous cases to focus on clearly distinguishable flood types, ensuring methodological rigor. The HIAR data are derived from the annual comprehensive data of national hydrological departments, as well as meteorological and groundwater data from authoritative ministries and commissions. Flood classifications were validated against rainfall and hydrological observatory detection data, with regional runoff calculations incorporating inputs from 3,000 river hydrological stations nationwide. This multi-source triangulation underpins the robustness of our flood typology and spatial matching framework.

3.2. Real estate data

Commercial property data were sourced from MSCI, a data vendor that compiles deed transaction records and property tax roll information. We extracted commercial property transactions from 2010 to 2018 to align with the period of the flood data. The dataset provides comprehensive details on proprietary attributes, including property locations, types, age, floor area, transacted price, deal time, and method of payment. The data were meticulously cleaned by removing abnormal deals (e.g., multiple parcel sales and foreclosures) and deals lacking critical information (e.g., transaction price and date). Next, property transactions were geocoded and crossmatched with the floodplain maps. As shown in Fig. 2, floodplains are defined as an 800-m buffer zone surrounding a flood point (roughly equivalent to 200 ha). The buffering radius is determined based on the average population density and the average number of individuals exposed to flooding events in China between 2010 and 2018. Specifically, the flooding events resulted in an average of 3,856,880 exposed persons per event (GFD). The national average population density in China is 146.03 persons per square kilometer (World Bank, 2022). Based on this density, the estimated flood-affected land area is approximately 2,641,156 ha, with around 200 ha per flooding point. Geometrically, 200 ha equate to a circular area with a radius of 798 m (πR^2), which we rounded to 800 m for practicality. Commercial properties situated within the buffering radius that had been transacted after a flood event were included in the treatment group. The control group comprises commercial properties that are situated beyond the 800-m radius but within a 1600-m radius surrounding a flood point, since the impact area is constrained to a radius of 1,600 m, as no recorded flooding event has resulted in an exposed population exceeding this threshold (see Fig. 2). To account for locational attributes influencing prices, we measure transportation accessibility and green space availability within an 800-m radius of each property.[2] These metrics were

[2] Urban residents generally share similar neighbourhood amenities within a 15-min walking radius (around 800 m) (Perry, 2015; Wei et al., 2024; Zhang et al., 2023).

Table 1
Variable description.

Variable	Description	Max	Min	Std. Deviation
Near	Near is a dummy variable, which is equal to 1 if property is situated within floodplains, and is equal to 0 if property is situated outside of floodplains but within the secondary buffer	1.000	0.000	0.500
Post	Post is a categorical indicator variable, equals 0, if the transaction occurs in the 3-month period before the flood event (pre-flood period); equals 1, if the transaction occurs in the 1st quarter (0–3 months) after the flood event; equals 2, if the transaction occurs in the 2nd quarter (4–6 months) after the flood event, equals 3, if the transaction occurs in the 3rd quarter (7–9 months) after the flood event.	3.000	0.000	1.154
Flooding history	Flooding history is a dummy variable, indicating whether the buffer has been affected by flooding event(s) in the previous year, otherwise 0	1.000	0.000	0.492
Square feet	Total area of the commercial property in square feet	12800.000	2048.497	4269.209
Building age	Calculated as the difference between the transaction year and the year the building was constructed	83.000	0.000	3.168
Transportation	The sum of neighboring transportation hubs, such as metro stations, bus routes, and major roads.	10.000	0.000	4.332
Green space	The total area of parks or green spaces near a property.	39.000	0.000	7.988

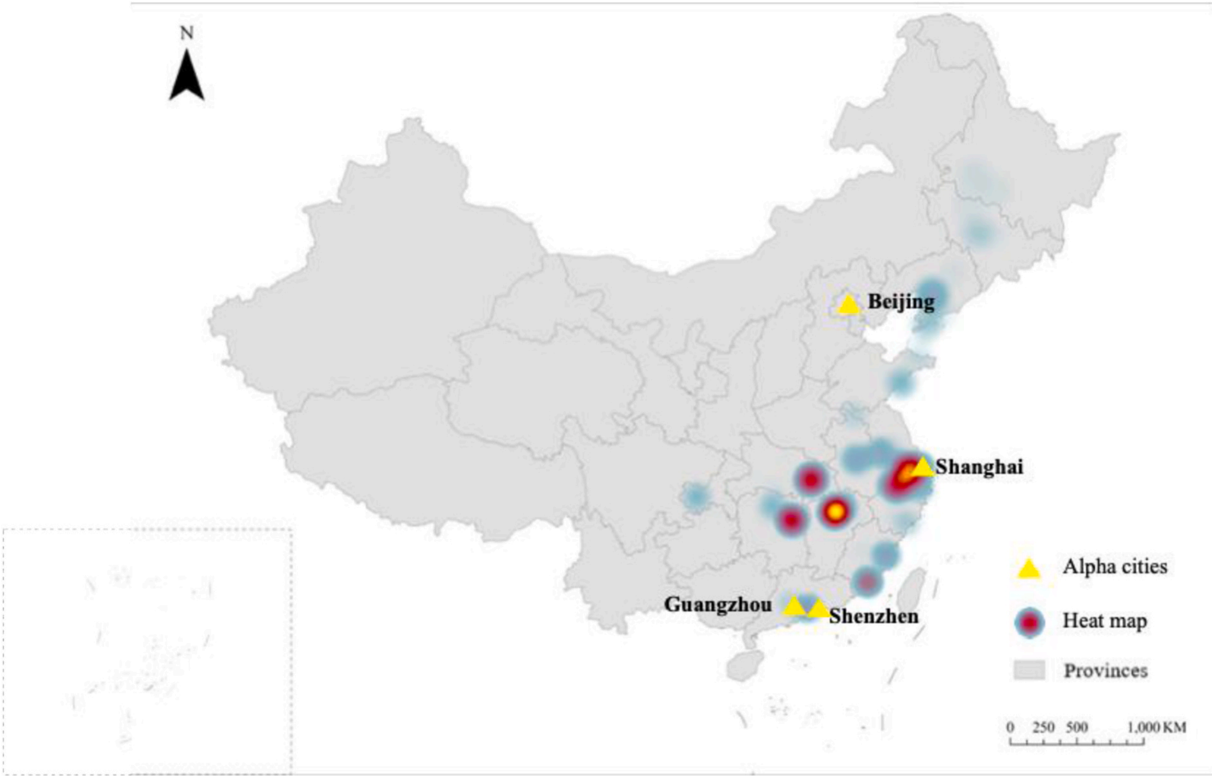

Fig. 3(a). Post-seasonal flood transaction prices.

integrated into our baseline model alongside property-specific variables, including square footage, building age, transportation access, and the area of neighboring green spaces. The variable descriptions are presented in Table 1. Last, we identified the geographic location of investors by parsing company names and cross-referencing them with Qichacha, a public enterprise information platform. Local investors were defined as those headquartered within the same city as the transacted property; non-local investors operated outside these jurisdictions. Considering some non-local institutional investors may access local information through branches or local partnerships, we identify the institutional investors that are listed in stock markets in our sample and categorise them as local investors. It is found that there are only 8 transactions involving listed investors, which is less likely to cause the headquarter bias.

To provide a clearer descriptive picture of the data prior to the regression analysis, we present spatial heat-map distributions of the two outcome variables, transaction prices and transaction volumes, disaggregated by floodplain type (seasonal vs CCI) and by investor type (local vs non-local). As shown in Fig. 3, both prices and volumes of seasonal flood transactions are highly concentrated in eastern and central river-basin cities, most notably in Jiangxi, Hunan, and the lower Yangtze River delta, where recurrent monsoon flooding coincides with commercial property markets. By contrast, CCI flood transactions are spatially concentrated in the Pearl River Delta and

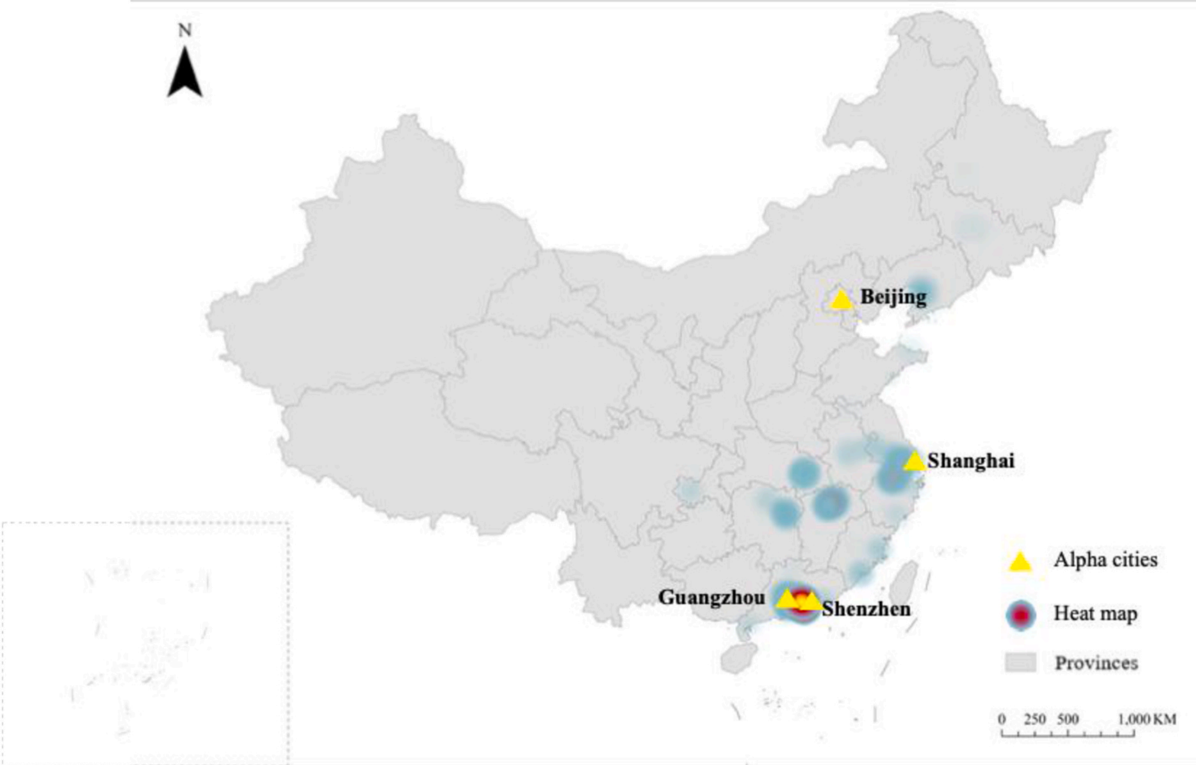

Fig. 3(b). Post-CCI flood transaction prices.

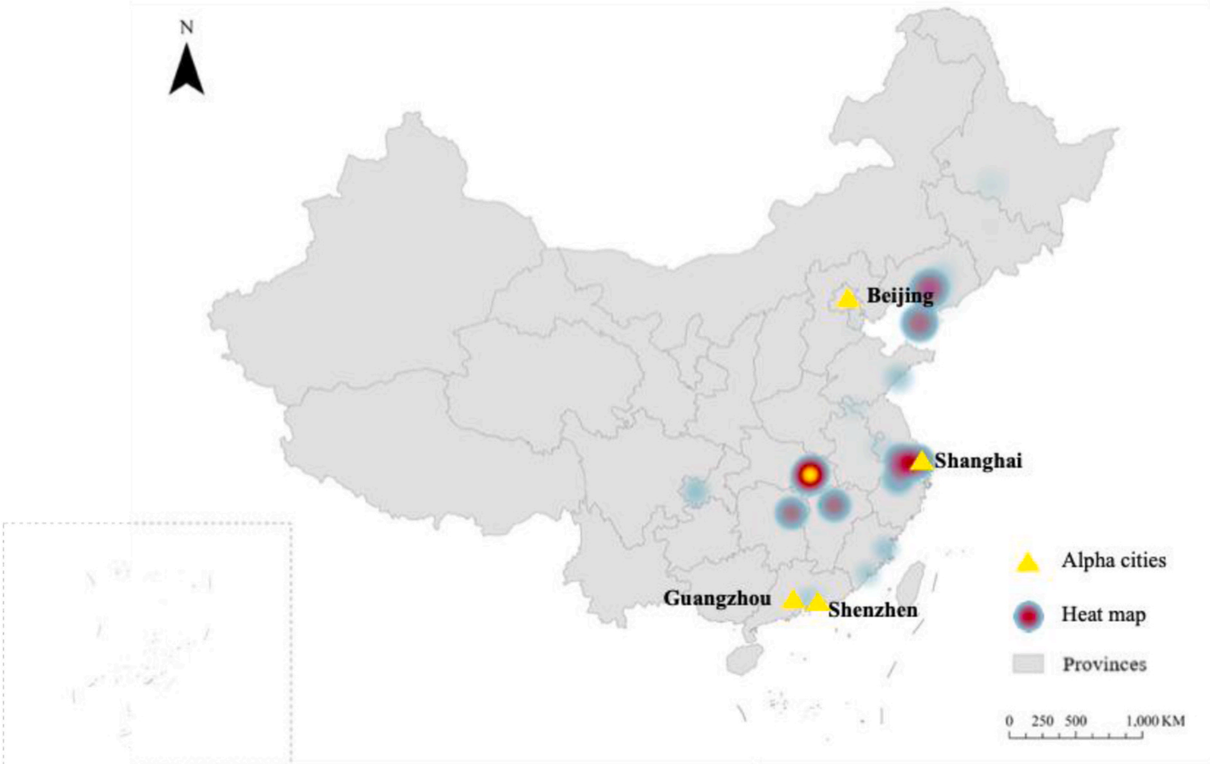

Fig. 3(c). Post-seasonal flood transaction volumes.

Fig. 3(d). Post-CCI flood transaction volumes.

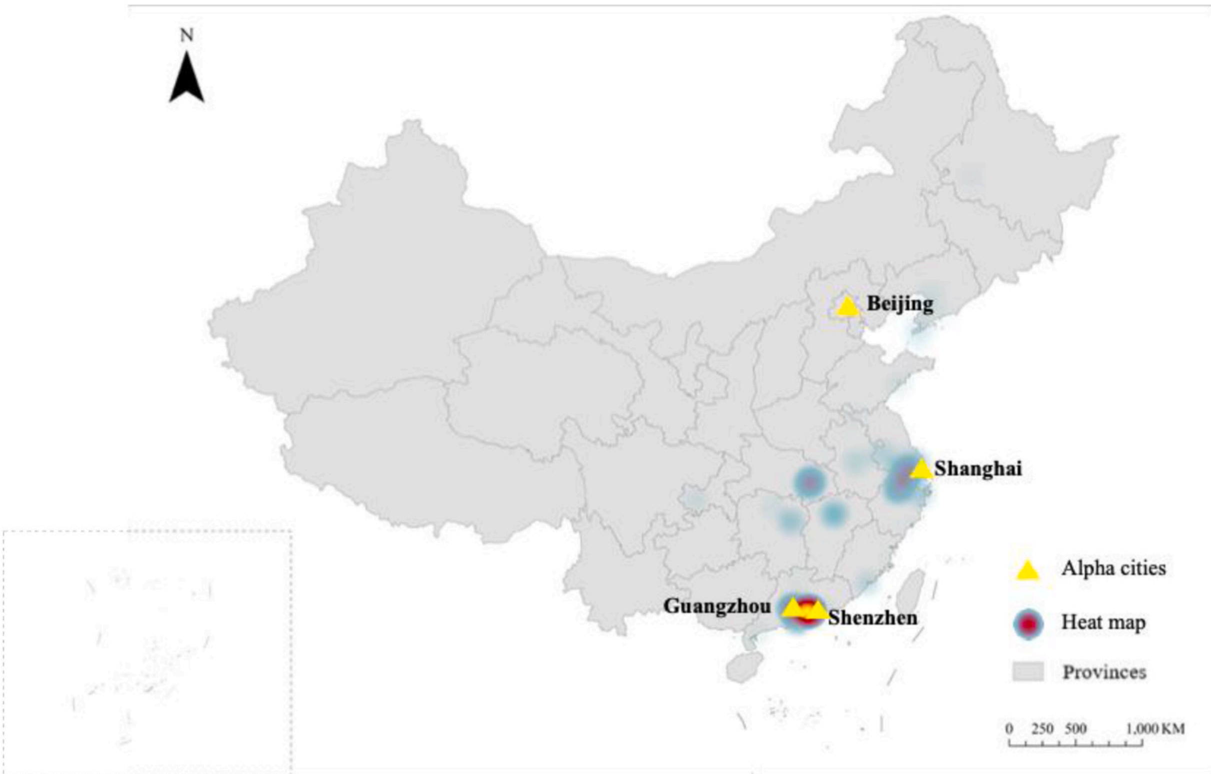

Fig. 4(a). Post-flood local investor transaction prices.

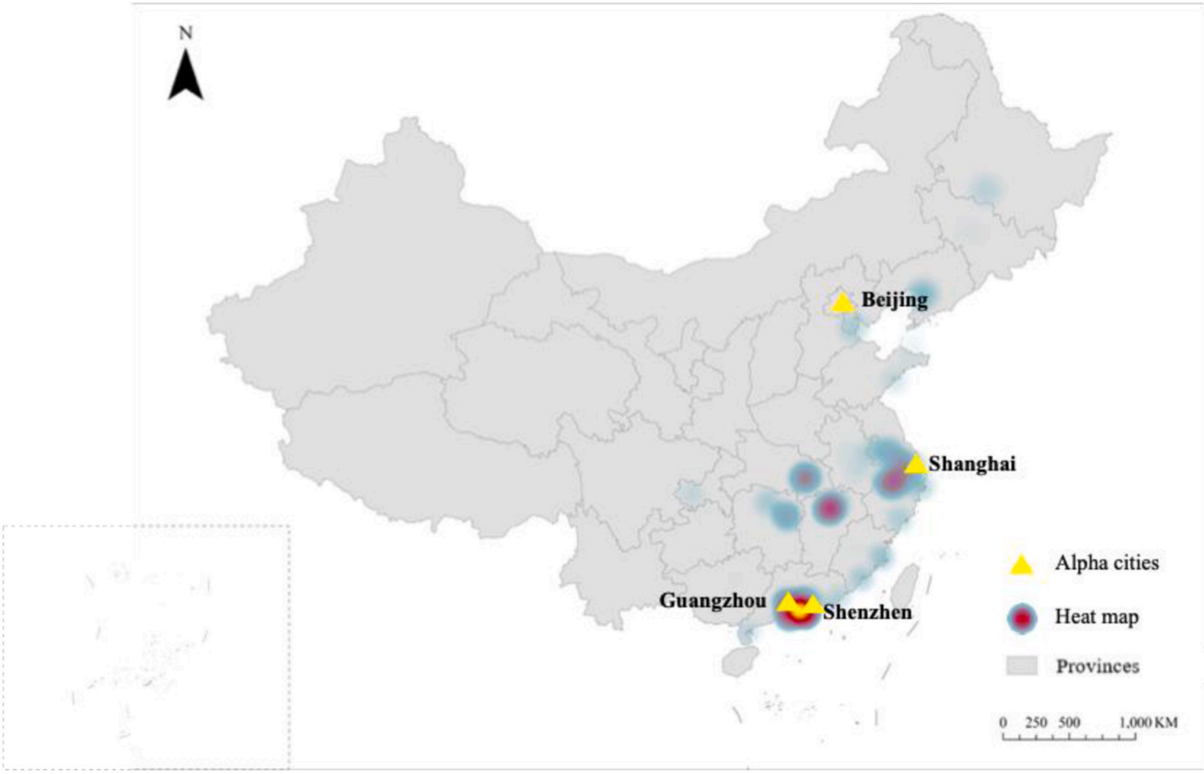

Fig. 4(b). Post-flood non-local investor transaction prices.

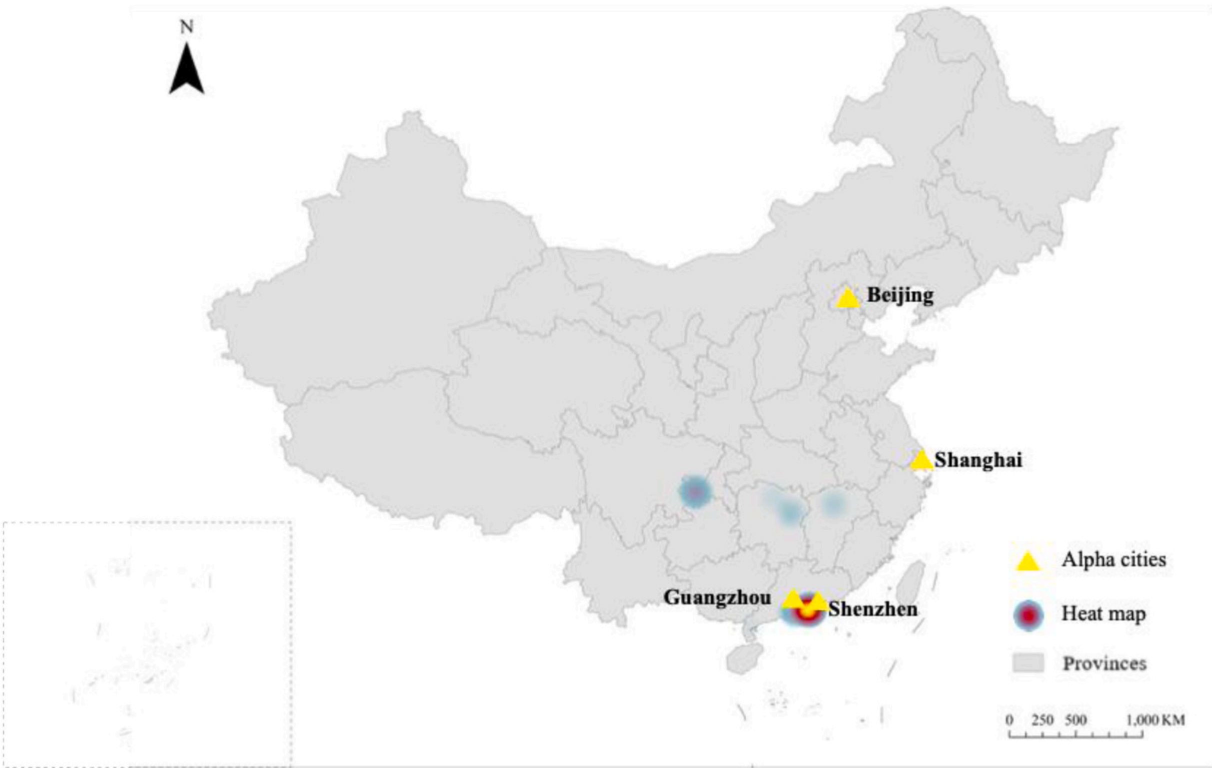

Fig. 4(c). Post-flood local investor transaction volumes.

Fig. 4(d). Post-flood non-local investor transaction volumes.

the southeast coast regions, with severe extreme-rainfall or sea-level-driven events. Importantly, the heat-maps suggest that price-intensive clusters do not always coincide with volume-intensive clusters: some flood-affected inland cities display high frequency of price outlier transactions despite smaller trading volumes, whereas southern coast cities exhibit dense post-flood trading volume with moderate prices. Fig. 4 illustrates the spatial distribution of transaction prices and volumes distinguishing local and non-local investors. Panels (a) and (c) show that local investors dominate both price- and volume-intensive clusters in southern and central cities, particularly in the Pearl River Delta and along the middle Yangtze corridor, where local knowledge of flood-risk and rebuilding prospects appears to encourage market re-entry. By contrast, non-local investors' transactions (Panels b and d) are geographically sparser and clustered in major coastal hubs, notably the Pearl River Delta.

3.3. Model specification

The DiD model identifies the causal impact of an intervention by comparing the changes in outcomes over time between a group that is exposed to the intervention and a group that is not. This approach is well-suited for our study due to its capability to control time-invariant unobserved characteristics and disentangles flood impacts from broader market trends or persistent differences between treated and control properties. By differencing outcomes across groups and time, the DiD framework mitigates endogeneity bias arising from unobserved variables that correlate with both flooding exposure and property values (e.g., latent environmental risks). To further address investor heterogeneity (e.g., divergent business models, investment strategies, and holding periods), we incorporate buffer fixed effects. These account for unobserved location-specific characteristics (e.g., micro-market dynamics) within predefined floodplain buffers, reducing concerns about omitted variable bias linked to investor behaviour (Cvijanović et al., 2022). While recent advances in DiD estimation, such as staggered DiD and synthetic controls, offer new methods to handle treatment heterogeneity and time-varying treatment effects, the spatial two-way fixed effects (TWFE) DiD model is robust to address endogeneity concerns and controlling for both time-invariant characteristics and time-varying factors (Chen et al., 2025).

Formally, our model estimates the price differences of commercial properties within the same floodplains by comparing transaction prices in the three-month pre-flood period to each of the three post-flood quarters within a rolling one-year window:

$$lnP_{i,b,t} = \alpha_0 + \alpha_1 Near_{i,b} + \sum_{j=1}^{3} \alpha_{2j}\left(Post_{i,b,t} = j\right) + \sum_{j=1}^{3} \alpha_{3j}\left(Near_{i,b} \times Post_{i,b,t} = j\right) + \alpha_4 H_{b,t-2} + \alpha_5 X_{i,t} + \gamma_b + \gamma_t + \varepsilon_{ibt} \quad (1)$$

where $lnP_{i,b,t}$ is the natural logarithm of transaction prices of property i in quarter t within the buffer b; α_0 represents the intercept or baseline effect in the model; it captures the average natural logarithm of transaction prices of commercial properties, accounting for all

Table 2
The impacts of seasonal and CCI flooding events on commercial property transaction prices.

Dependent Variable	Transacted Price	Transacted Price	Transacted Price	Transacted Price	Transacted Price	Transacted Price
Flood Type	All Floods	All Floods	Seasonal	Seasonal	CCI	CCI
Near × Post 1st quarter		−0.145*** (0.034)		−0.717*** (0.260)		−0.151*** (0.039)
Near × Post 2nd quarter		−0.360*** (0.035)		−0.654*** (0.235)		−0.022*** (0.030)
Near × Post 3rd quarter		−0.414*** (0.048)		−0.892*** (0.223)		−0.067*** (0.047)
Near	0.070*** (0.025)	0.499*** (0.030)	0.141*** (0.051)	0.786*** (0.231)	0.059*** (0.016)	0.003 (0.025)
Post 1st quarter	−0.108*** (0.026)	0.019 (0.031)	0.188** (0.083)	0.801*** (0.255)	−0.206*** (0.030)	−0.290*** (0.028)
Post 2nd quarter	−0.305*** (0.036)	0.226*** (0.034)	0.040 (0.083)	0.573*** (0.195)	−0.014 (0.025)	−0.027 (0.031)
Post 3rd quarter	0.156*** (0.038)	0.278*** (0.045)	0.039 (0.086)	0.734*** (0.208)	0.140*** (0.033)	0.106*** (0.040)
ln (Building age)	−0.022*** (0.007)	−0.021*** (0.007)	−0.334*** (0.044)	−0.333*** (0.043)	−0.011* (0.013)	−0.009* (0.013)
ln (Square feet)	0.554*** (0.005)	0.554*** (0.005)	0.786*** (0.054)	0.787*** (0.053)	0.536*** (0.008)	0.534*** (0.007)
Transportation accessibility	0.300*** (0.029)	0.294*** (0.029)	0.044* (0.021)	0.042** (0.022)	0.133*** (0.015)	0.137*** (0.015)
ln (Green space)	0.033*** (0.010)	0.032*** (0.010)	0.007* (0.001)	0.006* (0.002)	0.097** (0.018)	0.098*** (0.018)
Flooding History	−0.204*** (0.061)	−0.044 (0.036)	−0.496*** (0.067)	−0.476*** (0.078)	−0.249*** (0.095)	−0.245*** (0.094)
R^2/Pseudo R^2	0.663	0.519	0.903	0.908	0.735	0.739
Observations	55,417	55,417	29,927	29,927	25,490	25,490
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by buffer	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression estimates examining the impact of seasonal and CCI flood events on commercial property transaction prices. Columns 1 and 2 include all flood types, Columns 3 and 4 focus on seasonal floods, and Columns 5 and 6 focus exclusively on CCI floods. All specifications include control variables for building age, square feet, transportation accessibility, green space, and flooding history, and include buffer and quarter fixed effects and are clustered by buffer. Statistical significance levels are indicated as: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. *** = 0.01; ** = 0.05; * = 0.1.

Table 3
The impacts of seasonal and CCI flooding events on commercial property transaction volumes.

Dependent Variable	Transaction Volume	Transaction Volume	Transaction Volume	Transaction Volume	Transaction Volume	Transaction Volume
Flood Type	All Floods	All Floods	Seasonal	Seasonal	CCI	CCI
Near × Post 1st quarter		0.313*** (0.080)		0.472*** (0.090)		−0.084** (0.048)
Near × Post 2nd quarter		0.411*** (0.118)		0.522*** (0.132)		0.062 (0.044)
Near × Post 3rd quarter		0.483*** (0.126)		0.692*** (0.141)		−0.068*** (0.074)
Near	−0.081 (0.066)	−0.308*** (0.113)	−0.100* (0.076)	−0.393*** (0.121)	0.083* (0.060)	0.100* (0.061)
Post 1st quarter	−0.017 (0.046)	−0.156* (0.080)	−0.138*** (0.047)	−0.400*** (0.083)	−0.440*** (0.027)	0.492*** (0.026)
Post 2nd quarter	−0.174*** (0.060)	−0.051 (0.115)	0.209*** (0.068)	−0.068* (0.123)	−0.177*** (0.029)	0.136*** (0.027)
Post 3rd quarter	−0.132** (0.051)	−0.413*** (0.109)	−0.342*** (0.079)	−0.766*** (0.125)	−0.143*** (0.036)	0.184*** (0.032)
Flooding History	−0.651*** (0.108)	−0.643*** (0.103)	−0.153*** (0.057)	−0.166*** (0.056)	−0.299*** (0.069)	0.301*** (0.070)
R^2/Pseudo R^2	0.060	0.068	0.100	0.113	0.078	0.079
Observations	53,540	53,540	29,460	29,460	24,080	24,080
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by buffer	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression estimates examining the impact of seasonal and CCI flood events on commercial property transaction volumes. Columns 1 and 2 include all flood types, Columns 3 and 4 focus on seasonal floods, and Columns 5 and 6 focus on CCI floods. All models control for flooding history and include buffer and quarter fixed effects and are clustered by buffer. Statistical significance levels are indicated as: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

unobserved factors that are constant across time and buffers (floodplains and control areas) before any of the key explanatory variables are considered. $Near_{i,b}$ is a dummy variable, which is equal to 1 if property i is situated within floodplains, and is equal to 0 if property i is situated outside of floodplains but within the secondary buffer; $Post_{i,b,t}$ is a categorical indicator variable that captures the timing of

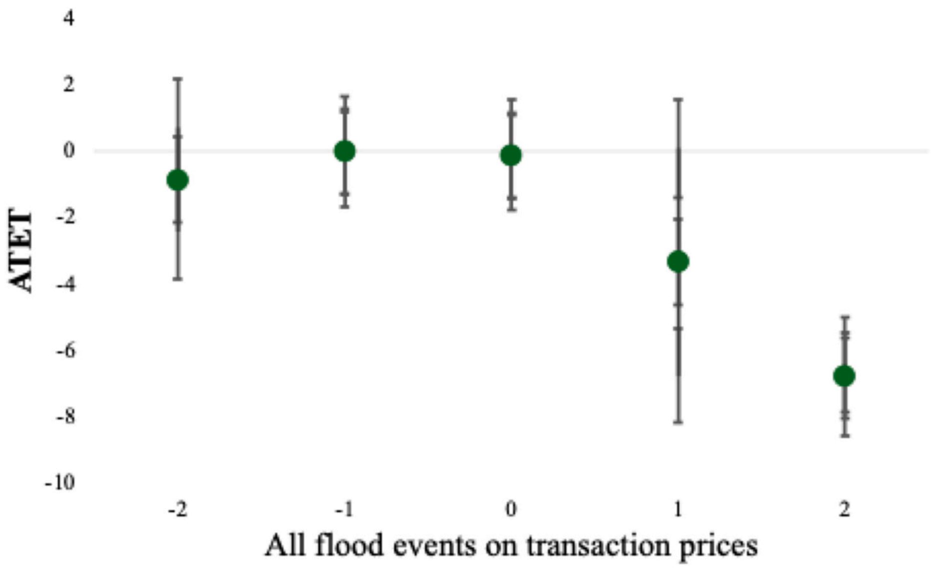

Fig. 5(a). Staggered DiD model of all flood events on commercial property transaction prices.

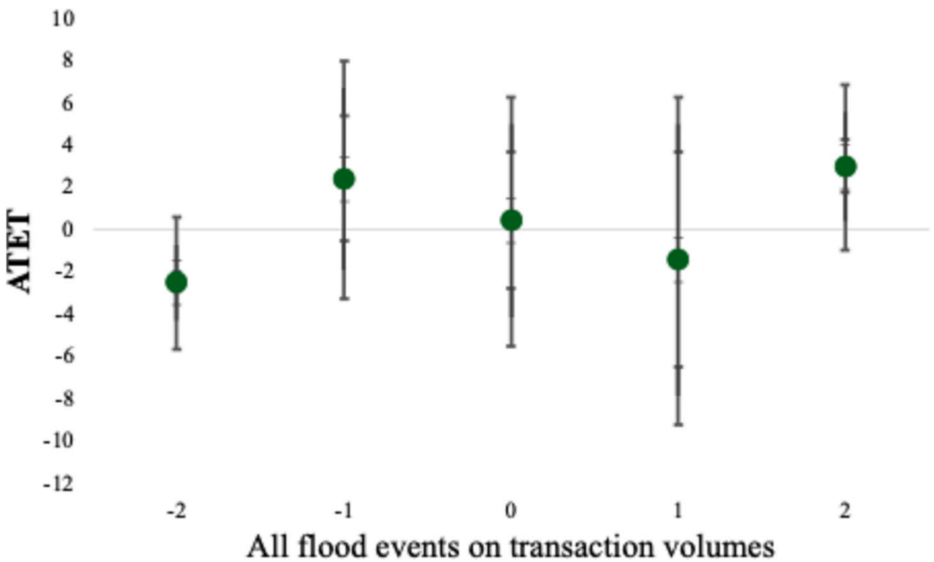

Fig. 5(b). Staggered DiD model of all flood events on commercial property transaction volumes.

property i's transaction relative to a flooding event within a rolling one-year period. Specifically, it is defined as:

$$Post_{i,b,t}\begin{cases} 0, \textit{transaction occurs in the } 3-\textit{month period before the flood event} \\ 1, \textit{transaction occurs in the } 1st \textit{ quarter } (0-3 \textit{ months}) \textit{ after the flood event} \\ 2, \textit{transaction occurs in the } 2nd \textit{ quarter } (4-6 \textit{ months}) \textit{ after the flood event} \\ 3, \textit{transaction occurs in the } 3rd \textit{ quarter } (7-9 \textit{ months}) \textit{ after the flood event} \end{cases}$$

This structure allows for a comparison of commercial property price dynamics across different post-flood quarters, using the 3-month pre-flood period as the reference category. $H_{b,t-2}$ is a dummy variable that equals 1 if buffer b experienced a flooding event in the quarter preceding the pre-flood period (i.e., two quarters before the main flooding event), and 0 otherwise. The control variable $X_{i,t}$ includes property structural and locational attributes by reference to Kim and Wu (2022), Kousky (2010), and Li and Chau (2024); γ_b denotes buffer fixed effects; γ_t denotes quarter fixed effects; and ε_{ibt} is the error term. The standard errors are clustered at the buffer level.

In addition, we examine the causal impact of flooding events on transaction volume in the commercial property markets. The model is modified as:

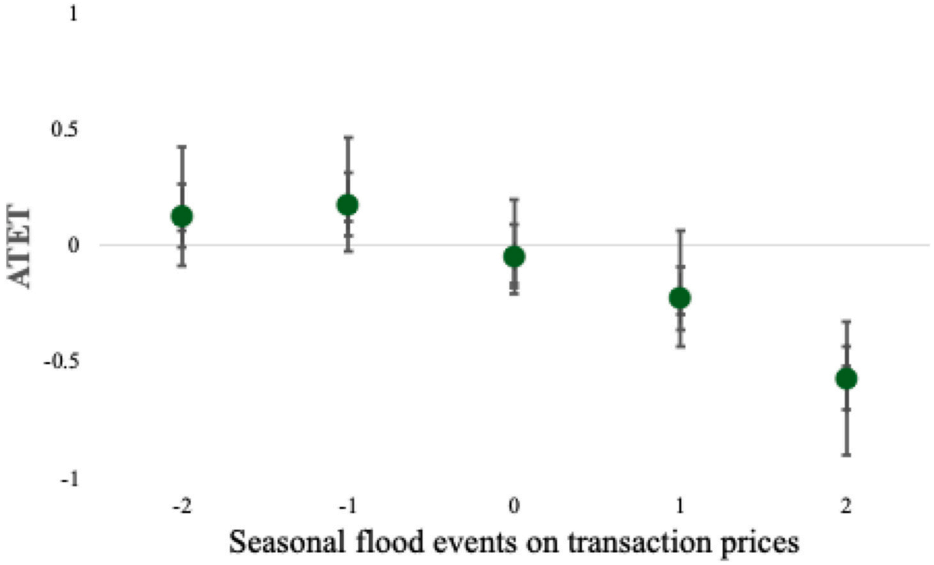

Fig. 5(c). Staggered DiD model of seasonal flood events on commercial property transaction prices.

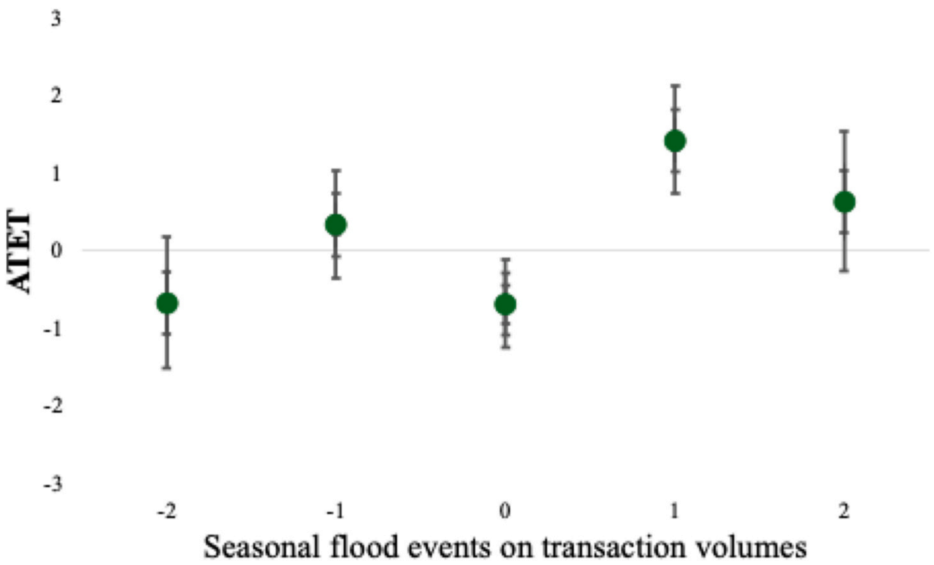

Fig. 5(d). Staggered DiD model of seasonal flood events on commercial property transaction volumes.

$$V_{b,t} = \sum_{i \in b} V_{i,b,t} = \beta_0 + \beta_1 Near_{i,b} + \sum_{j=1}^{3} \beta_{2j} \left(Post_{i,b,t} = j\right) + \sum_{j=1}^{3} \beta_{3j} \left(Near_{i,b} \times Post_{i,b,t} = j\right) + \beta_4 H_{b,t-2} + \gamma_b + \gamma_t + \varepsilon_{ibt} \tag{2}$$

where $V_{b,t} = \sum_{i \in b} V_{i,b,t}$ is the total transaction volumes of all properties i within the buffer unit b at time t; β_0 represents the expected transaction volume in the commercial property market.

4. Results

4.1. The impact of flooding events on property prices and transaction volumes

Table 2 presents the results of the DiD model to unravel the impact of flooding events on commercial property prices. Consistent with the H1a, properties within floodplains experience significant price discounts following both CCI and seasonal floods. However, the magnitude of these discounts varies: properties in seasonal floodplains see an average quarterly price decrease of 0.754 (see

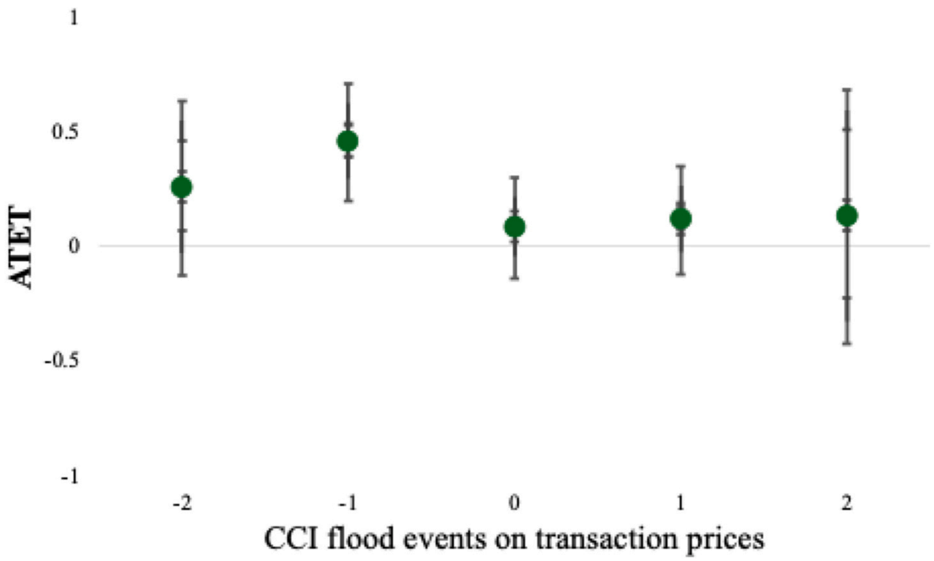

Fig. 5(e). Staggered DiD model of CCI flood events on commercial property transaction prices.

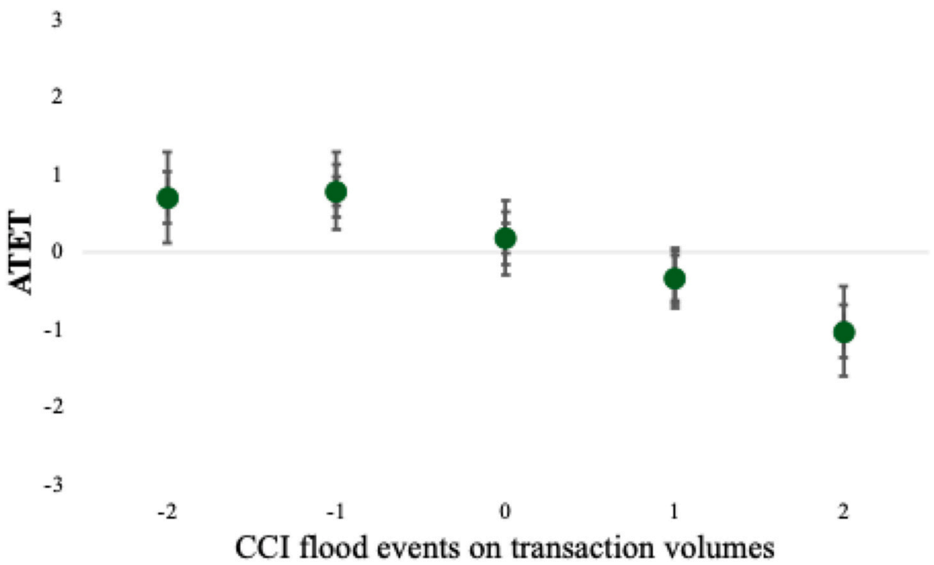

Fig. 5(f). Staggered DiD model of CCI flood events on commercial property transaction volumes.

column 5), compared to a much smaller decrease of 0.08 in CCI floodplains (see column 7). This finding contradicts H1b, which predicted greater discounts in CCI floodplains due to their higher uncertainties. This counterintuitive result suggests that sellers in CCI floodplains strategically frame climate-related floods as rare, one-off shocks during negotiations, limiting buyers' ability to leverage price reductions. In contrast, seasonal flood risks, rooted in historical data, allow institutional investors to quantify risk premiums and exploit their bargaining power. The unpredictability and ambiguous risk pricing of CCI floods deter aggressive acquisitions, as investors prioritise caution over uncertain premiums. This aligns with real options theory, where higher uncertainty increases the value of delaying investment decisions (Dixit & Pindyck, 1994).

Table 3 presents the model results investigating the impact of flooding events on transaction volume in China's commercial property market. Supporting H2a, flooding events lead to a significant increase in transaction volumes within floodplains across all three post-flood quarters. Notably, seasonal floods trigger a more immediate and pronounced surge in transactions compared to CCI floods (see columns 5 and 7), consistent with H2b. This divergence reflects investors' strategic responses to varying levels of uncertainty. In seasonal floodplains, where risks are calculable and recovery trajectories are predictable, institutional investors act swiftly to capitalise on discounted prices. Conversely, in CCI floodplains, post-flood quarters show a slight decline in transaction volumes, as investors adopt a wait-and-see approach to navigate unresolved climate uncertainties. This behaviour underscores the role of real

Table 4
The impacts of seasonal and CCI flooding events on local/non-local investors' transaction prices and volumes.

Post 1st Quarter						
Dependent Variable	Transacted Price	Transacted Price	Transacted Price	Transaction Volume	Transaction Volume	Transaction Volume
Flood Type	All Floods	Seasonal	CCI	All Floods	Seasonal	CCI
Local vs non-local	−0.196*** (0.025)	−0.433*** (0.039)	−0.202*** (0.018)	0.101*** (0.014)	0.239*** (0.028)	−0.100*** (0.012)
ln (Building age)	−0.128*** (0.026)	−0.028** (0.021)	−0.048*** (0.010)			
ln (Square feet)	0.455*** (0.012)	0.457*** (0.019)	0.538*** (0.010)			
Transportation accessibility	0.109** (0.047)	0.022*** (0.005)	−0.002 (0.055)			
ln (Green space)	0.147*** (0.028)	0.078*** (0.016)	0.053*** (0.018)			
Flooding History	−0.263*** (0.260)	−0.108* (0.056)	0.002 (0.001)	−0.225*** (0.065)	−0.226*** (0.075)	0.006 (0.002)
R^2/Pseudo R^2	0.555	0.291	0.526	0.590	0.082	0.223
Observations	6,884	3,074	3,810	4,656	2,034	2,622
Post 2nd Quarter						
Local vs non-local	−0.126*** (0.027)	−0.105*** (0.030)	−0.118*** (0.031)	0.043** (0.018)	0.012* (0.018)	−0.048** (0.017)
ln (Building age)	−0.026* (0.018)	−0.235*** (0.058)	−0.019** (0.009)			
ln (Square feet)	0.424*** (0.016)	0.670*** (0.049)	0.567*** (0.009)			
Transportation accessibility	0.193*** (0.057)	0.065*** (0.019)	0.166** (0.073)			
ln (Green space)	0.294*** (0.047)	0.162** (0.076)	0.003* (0.002)			
Flooding History	−1.941*** (0.136)	−0.351*** (0.048)	−1.585*** (0.158)	−0.069*** (0.068)	−0.308*** (0.059)	0.006 (0.004)
R^2/Pseudo R^2	0.690	0.193	0.661	0.547	0.091	0.211
Observations	8,196	4,351	3,845	4,889	2,442	2,447
Post 3rd Quarter						
Local vs non-local	−0.529*** (0.062)	−0.522*** (0.051)	−0.529*** (0.049)	0.079* (0.049)	0.242** (0.108)	−0.018* (0.046)
ln (Building age)	−0.021* (0.022)	−1.068*** (0.182)	−0.007* (0.011)			
ln (Square feet)	0.448*** (0.024)	0.646*** (0.021)	0.607*** (0.012)			
Transportation accessibility	1.408*** (0.221)	0.132*** (0.009)	0.394*** (0.096)			
ln (Green space)	0.072* (0.046)	1.085*** (0.215)	0.041** (0.019)			
Flooding History	−0.201** (0.014)	−0.217*** (0.054)	−0.003 (0.001)	−0.362* (0.210)	−0.261** (0.129)	0.018 (0.005)
R^2/Pseudo R^2	0.957	0.206	0.741	0.539	0.018	0.386
Observations	7,686	4,653	3,033	4,143	2,164	1,979
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	No	No	No	No	No	No
Cluster by buffer	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression estimates examining how seasonal and CCI flood events differentially affect transaction prices and volumes for local versus non-local investors. The table is divided into three temporal segments (Post 1st, 2nd, and 3rd Quarter), with each segment showing results for transaction prices (Columns 1–3) and transaction volumes (Columns 4–6) across all flood types, seasonal floods, and CCI floods. Price regressions (Columns 1–3) control for building age, square feet, transportation accessibility, green space, and flooding history. Volume regressions (Columns 4–6) control for flooding history. All models include buffer fixed effects and are clustered by buffer; quarter fixed effects are excluded. Statistical significance levels are indicated as: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

options theory in shaping investment timing: investors delay commitments in high-uncertainty contexts but act decisively when risks are quantifiable (McDonald & Siegel, 1986). To further test the robustness of our findings, we also conducted a staggered DiD analysis to estimate the impact of flood events on commercial property market. This staggered DiD specification accounts for differences in the timing and intensity of flood events across different properties and periods. As Fig. 5 shows, the staggered DiD model results remain consist with main findings.

In a nutshell, flooding events create discount effects on the valuation of commercial properties situated within floodplains, luring investors to enter floodplain markets. However, the timing and intensity of market entry are calibrated to the nature of the flood: investors act swiftly in seasonal floodplains but remain cautious in CCI floodplains. This aligns with Linnenluecke et al. (2012)'s emphasis on ecological discontinuities in strategic decision-making, highlighting how investors navigate environmental risks based on their predictability and severity.

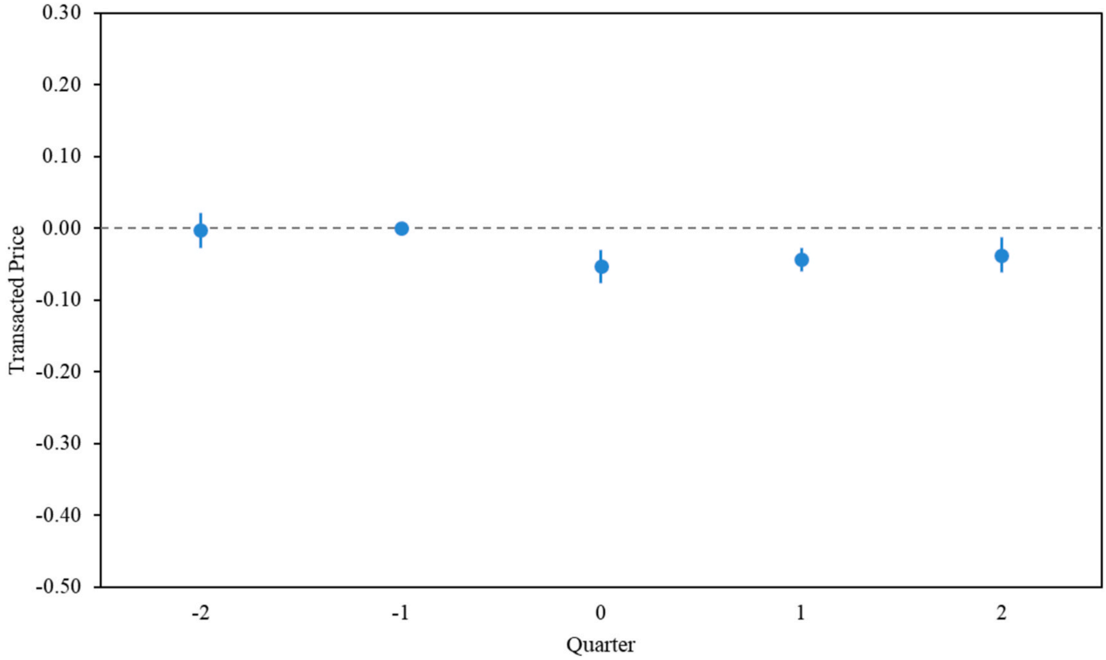

Fig. 6(a). Parallel trend test of transacted price post-all floods.

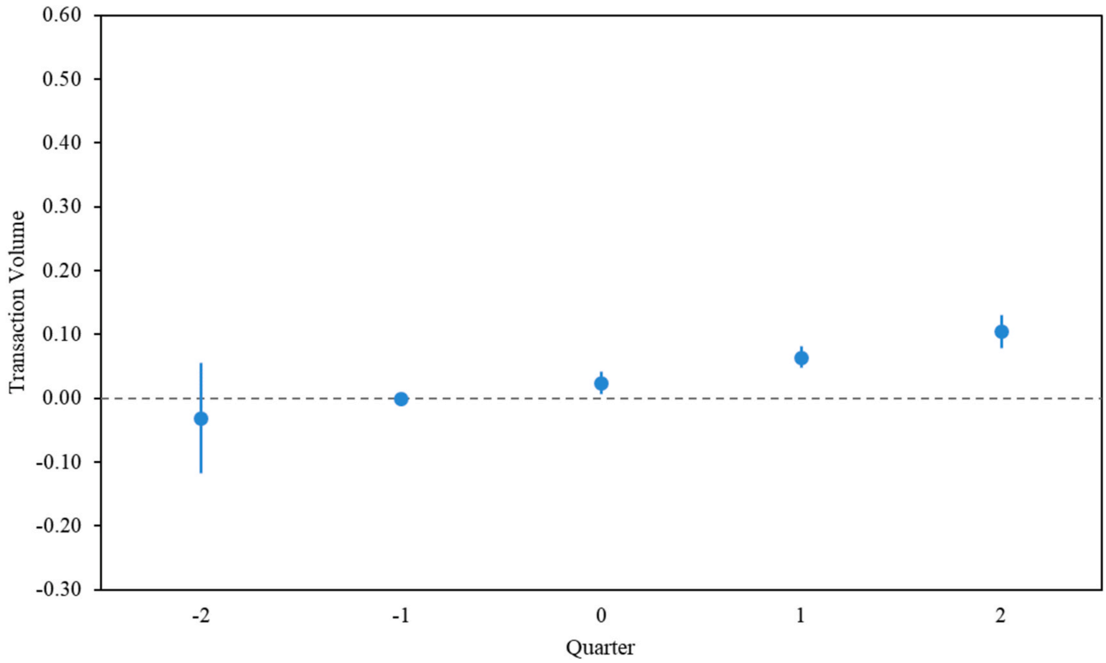

Fig. 6(b). Parallel trend test of transaction volume post-all floods.

4.2. Local versus non-local investors

Table 4 examines the divergent behavioural patterns of local and non-local investors in floodplain markets. Supporting H3a, local investors secure higher discounts on property transaction prices and enter the market more quickly than their non-local counterparts (see columns 3 and 4). Additionally, local investors disproportionately target seasonal floodplain markets (see column 6), while non-local investors focus on CCI floodplain markets (see column 7). This supports H3b and highlights the role of information asymmetry in shaping investment strategies. Specifically, local investors leverage tacit market intelligence, grounded in place-specific expertise,

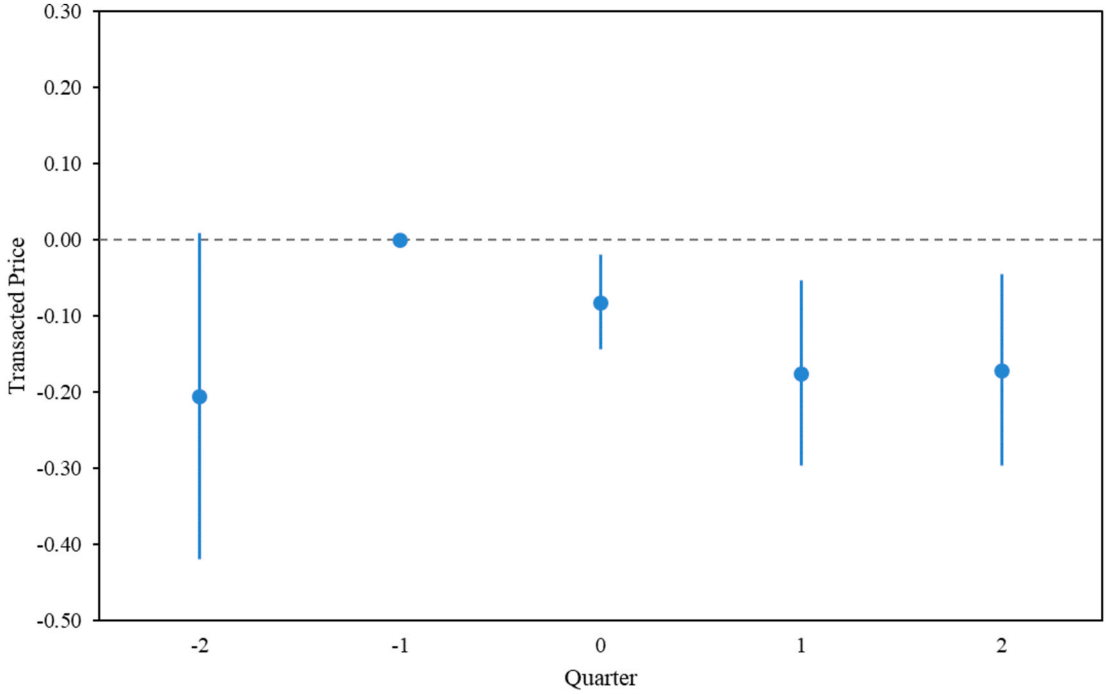

Fig. 6(c). Parallel trend test of transacted price post-seasonal floods.

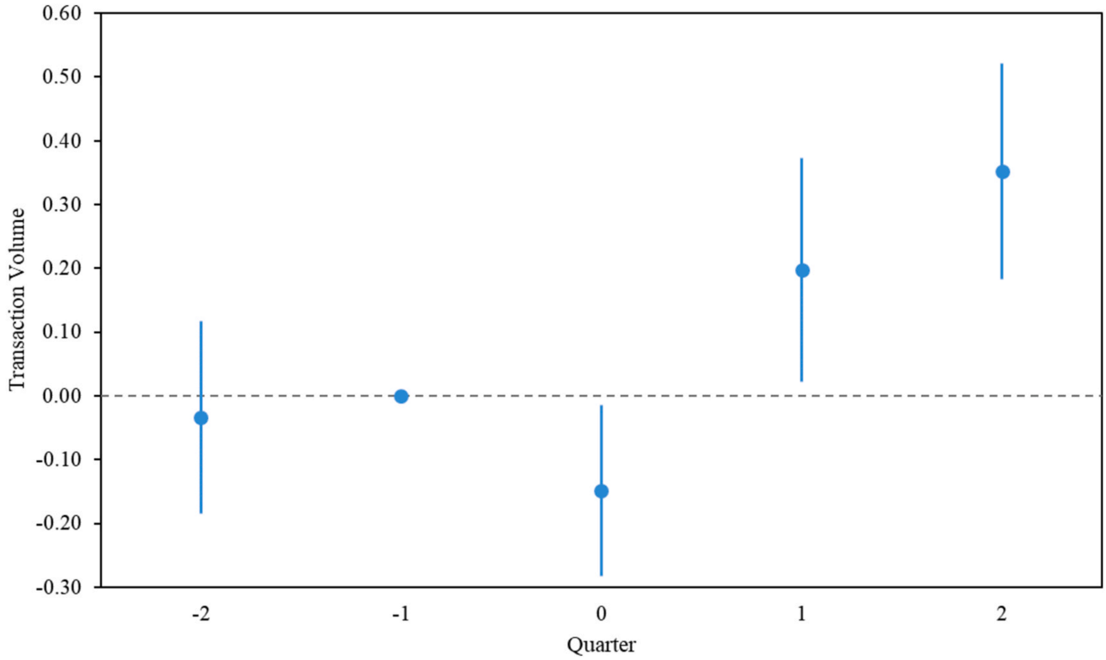

Fig. 6(d). Parallel trend test of transaction volume post-seasonal floods.

historical flood data, and guanxi networks, to exploit seasonal flood opportunities. In contrast, non-local investors, lacking localised insights, adopt portfolio-level strategies for CCI floodplains, where long-term holding periods mitigate unpredictable climate risks. Paradoxically, local investors exhibit caution in CCI floodplain markets, as climate uncertainties erode the value of place-based knowledge, while non-local actors prioritise diversification over localised precision.

Overall, local investors retain a distinct informational edge in acquiring commercial properties within floodplain markets, particularly in regions prone to recurrent seasonal floods. However, this advantage erodes in CCI floodplain markets, where the

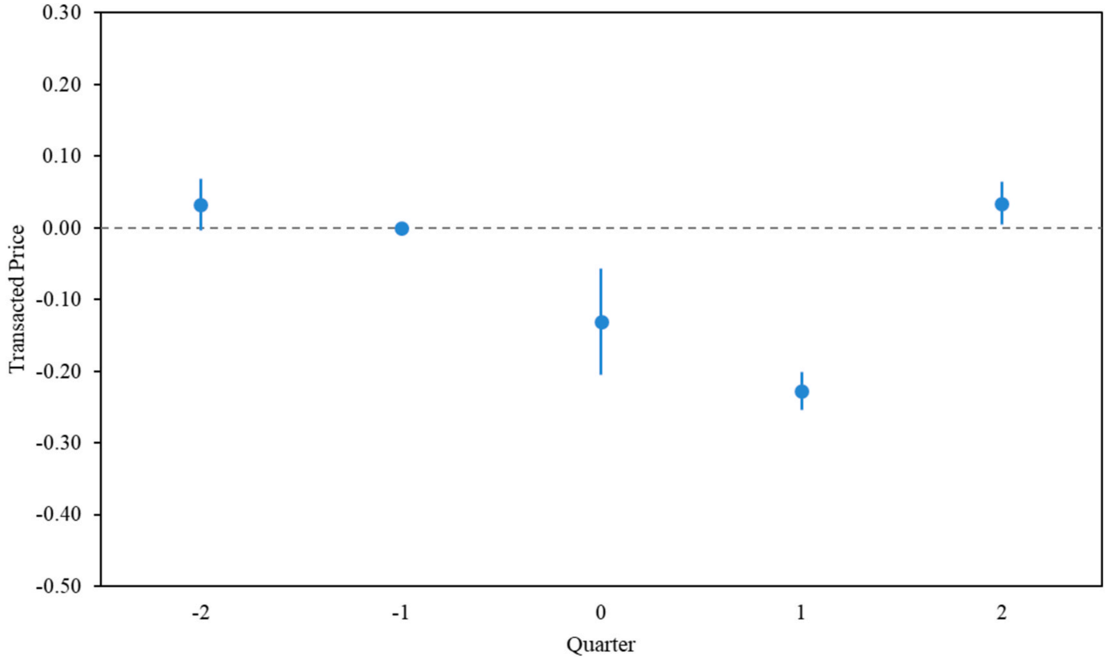

Fig. 6(e). Parallel trend test of transacted price post-seasonal floods.

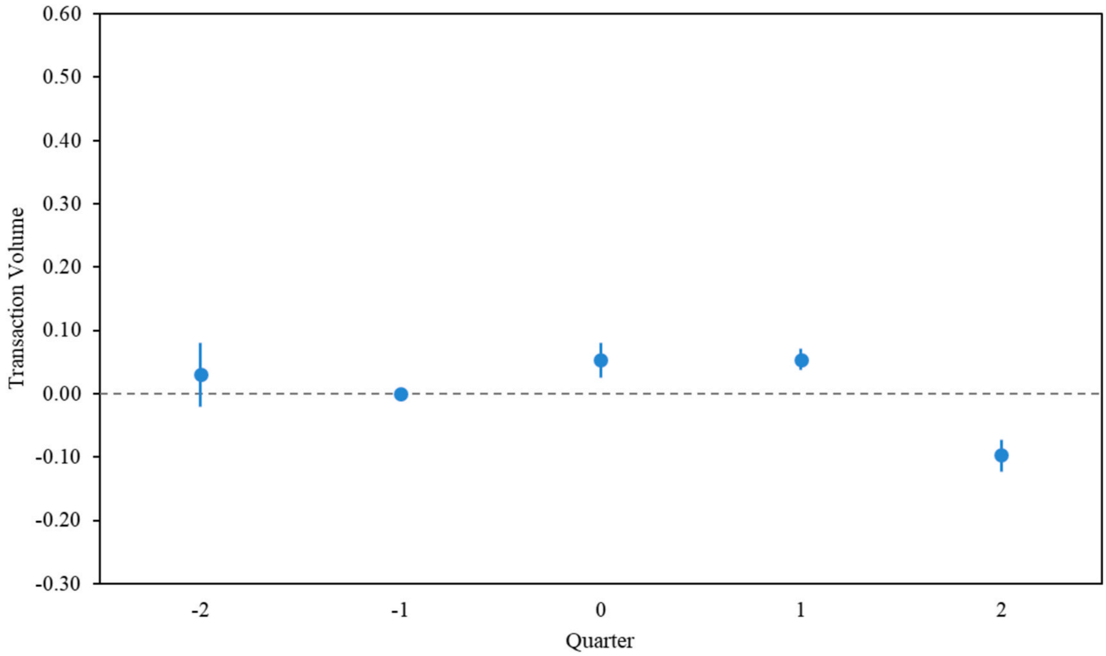

Fig. 6(f). Parallel trend test of transaction volume post-CCI floods.

inherent unpredictability and systemic complexity of CCI floods neutralise the utility of place-specific insights. The diminished efficacy of localised knowledge underscores that informational asymmetries are contingent upon the predictability of environmental risks: in contexts of escalating climatic uncertainty, even embedded actors struggle to reconcile short-term gains with long-term ecological volatility.

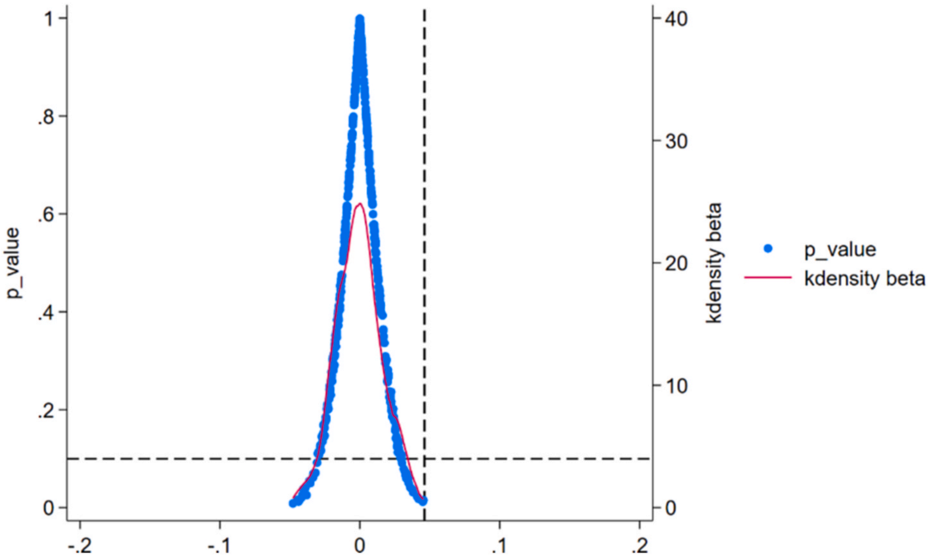

Fig. 7(a). Placebo test of transacted price post-all floods.

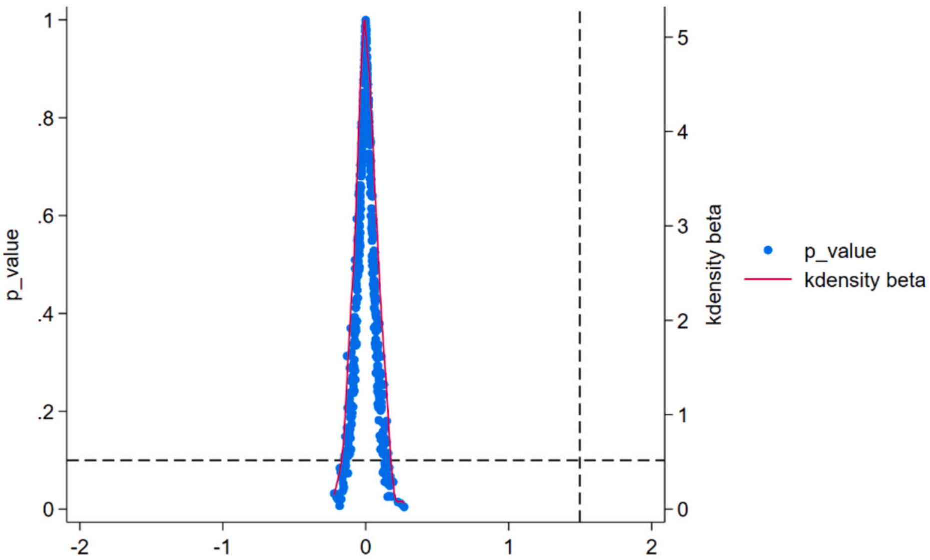

Fig. 7(b). Placebo test of transaction volume post-all floods.

4.3. Model validity tests

To ensure the validity of our results, a parallel trend analysis and a counterfactual placebo test were conducted. Fig. 6 illustrates that pre-flood trends for the treatment and control groups are statistically indistinguishable, confirming that pre-existing trends did not confound our results. This affirms that the observed post-flood differences in property prices and transaction volumes are attributable to the flooding events themselves rather than pre-existing trends or periodic fluctuations. In addition, we further implemented a placebo test by randomly assigning flood exposure timing and locations across our sample, generating 1,000 simulated datasets. Fig. 7 shows that the estimated coefficients from these iterations are centered around zero and follow a normal distribution, with the vast majority being statistically insignificant. This confirms that our baseline results are unlikely to arise from spurious correlations or model misspecification.

4.4. Mechanism tests and robustness checks

The results in Table 5 explore the interplay between transaction prices and volumes in floodplain markets, providing insights into

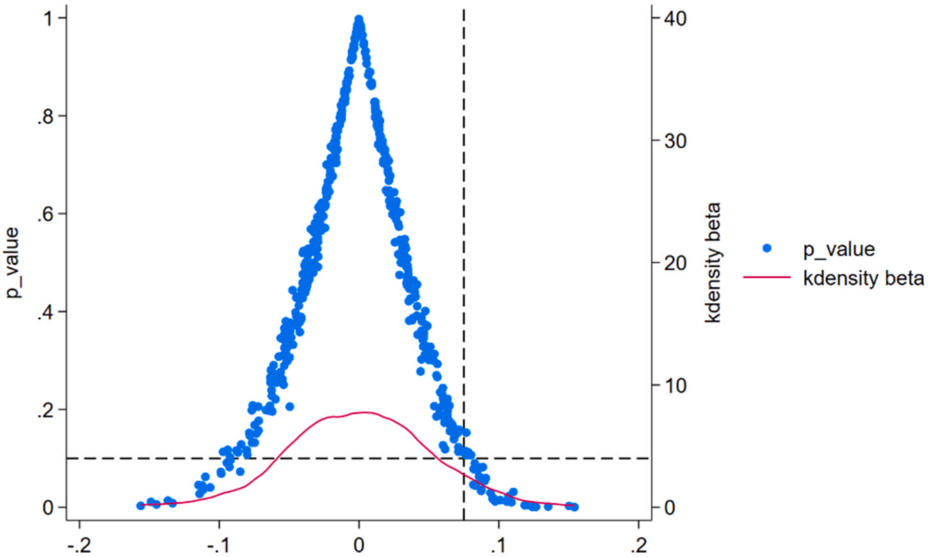

Fig. 7(c). Placebo test of transacted price post-seasonal floods.

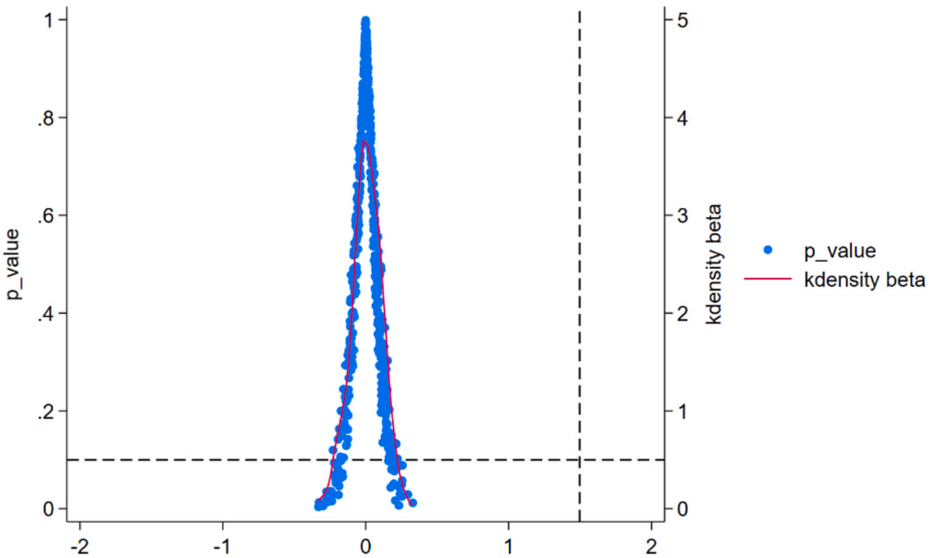

Fig. 7(d). Placebo test of transaction volume post-seasonal floods.

the underlying mechanisms that drive investor behaviour in response to flood risks. The negative association between post-flood price trends and transaction volume trends, unravelling the mechanism interlinking H1a and H2a (see column 2). In seasonal floodplains, calculable risks allow investors to interpret price discounts as signals to act swiftly, driving transaction surges (see column 5). While in CCI floodplains, the muted transaction response underscores the challenges of non-stationary uncertainties (see column 8). This validates the divergence in risk premiums between seasonal and CCI floodplains, interlinking H1b and H2b. In addition, the disproportionate increase in transaction volumes by local investors, particularly after seasonal floods (see columns 3 and 6), highlights the role of information asymmetry (H3a, H3b). It implies that local investors leverage business resources to identify and act on mispriced assets, boosting transaction volume as a result (Bayer et al., 2011; Pope, 2008). This advantage diminishes in CCI floodplains (see column 9), where climate uncertainty neutralises spatial embeddedness. This mechanism underscores the contingent nature of informational asymmetries.

Last, commercial property transactions are characterised by high-value, intricate negotiations, due diligence processes, and significant legal and financial considerations, which necessitate the involvement of professional services (e.g., appraisal, brokerage, and legal services). Thus, risk perception towards flooding events can be mediated by the quality of local specialised business services. Meanwhile, the business networks of specialised business services are important to reduce transaction costs and information

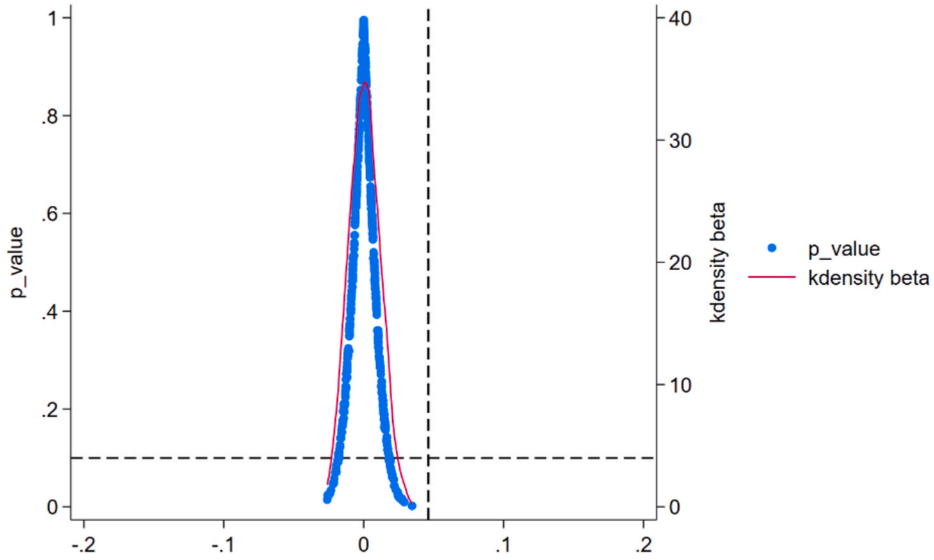

Fig. 7(e). Placebo test of transacted price post-CCI floods.

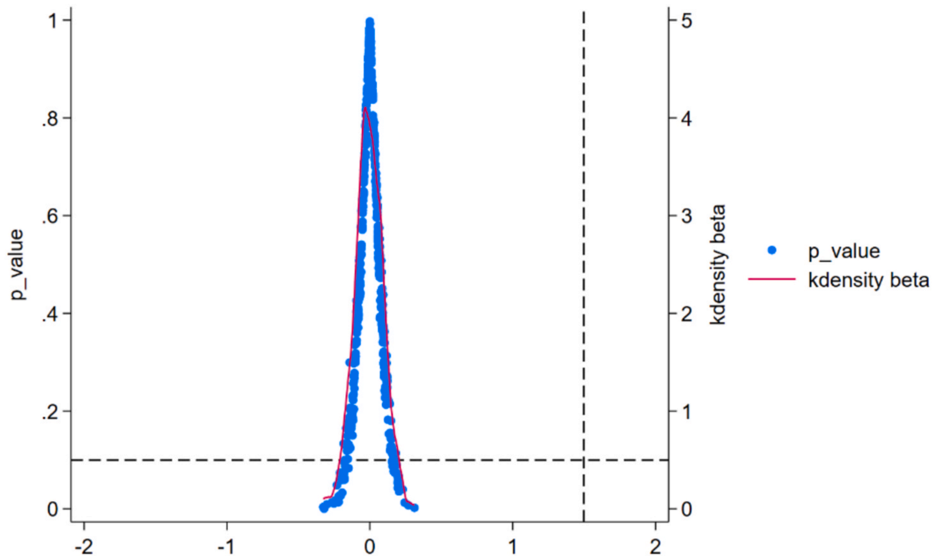

Fig. 7(f). Placebo test of transaction volume post-CCI floods.

asymmetries under the context of China's state-oriented economy (Shi et al., 2022). To address this concern, we conducted a robustness check using Globalization and World City Research Network (GaWC) rankings, which classify cities by their development status of advanced business service.[3] The GaWC framework, specifically its top-tier "Alpha" classifications (e.g., Alpha++, Alpha+, Alpha), identifies world cities that function as pivotal nodes in global economic network. These Alpha cities such as Beijing, Shanghai, and Guangzhou are distinguished by their dense agglomeration of multinational firms and advanced producer services (APS) firms (e.g., finance, law, and consultancy). Beyond market size, these Alpha cities excel in deep connectivity and capacity to command global capital and information flows. For Chinese cities ranked as global service hubs, flood impacts on prices and transaction volumes remain consistent with baseline results, albeit with attenuated coefficient magnitudes (See Table 6 Panel A and 7 Panel A). Moreover, it is found that local investors' advantage is still eminent, even in these high-service agglomerations (see Table 8 Panel A). It suggests that while professional intermediaries enhance information transparency and risk appraisal for non-local investors, local actors exploit

[3] The GaWC data rank world cities based on their development level of advanced producer service companies including accountancy, advertising, banking/finance, consultancy, legal and realtor services (Pain et al., 2024).

Table 5
The impacts of commercial property price trends on transaction volume trends during seasonal and CCI flooding events.

Post 1st Quarter									
Dependent Variable	Transaction Volume Trends			Transaction Volume Trends			Transaction Volume Trends		
Flood Type	All Floods			Seasonal			CCI		
Investor Origin	All	Local	Non-local	All	Local	Non-local	All	Local	Non-local
Property price trend	−0.878**	−0.989***	−0.842***	−0.368***	−0.327**	−0.019*	−0.297*	−0.172*	−0.107
	(0.923)	(0.759)	(0.666)	(0.271)	(0.066)	(0.007)	(0.248)	(0.268)	(0.164)
Flooding History	0.274	0.059	0.080	0.009	0.009	0.023	0.028	0.022	0.026
	(0.298)	(0.594)	(0.098)	(0.006)	(0.004)	(0.016)	(0.021)	(0.016)	(0.020)
R^2/Pseudo R^2	0.075	0.107	0.127	0.055	0.071	0.011	0.015	0.029	0.016
Observations	4,308	2,646	1,662	1,963	981	982	2,345	1,174	1,171
Post 2nd Quarter									
Property price trend	−0.304*	−0.407*	−0.285**	−0.611***	−0.714***	−0.439**	−0.249*	−0.143*	−0.069
	(0.077)	(0.020)	(0.353)	(0.036)	(0.073)	(0.296)	(0.223)	(0.265)	(0.070)
Flooding History	0.058	0.578	0.978	0.882	0.820	0.844	0.555	0.197	0.113
	(0.164)	(0.027)	(0.867)	(0.708)	(0.703)	(0.691)	(0.196)	(0.149)	(0.108)
R^2/Pseudo R^2	0.109	0.032	0.179	0.132	0.289	0.046	0.120	0.213	0.087
Observations	4,059	2,153	1,906	2,383	1,323	1,060	1,676	831	845
Post 3rd Quarter									
Property price trend	−0.627**	−0.744***	−0.090***	−0.608**	−0.917**	−0.484*	−0.126*	−0.125*	−0.594
	(0.497)	(0.089)	(0.418)	(0.058)	(0.913)	(0.342)	(0.294)	(0.097)	(0.077)
Flooding History	0.706	0.190	0.026	0.023	0.025	−0.064	0.035	0.173	0.124
	(0.361)	(0.039)	(0.021)	(0.015)	(0.024)	(0.063)	(0.021)	(0.142)	(0.126)
R^2/Pseudo R^2	0.024	0.023	0.199	0.134	0.023	0.074	0.027	0.017	0.036
Observations	4,278	2,154	2,124	2,407	1,320	1,087	1,871	834	1,037
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	No	No	No	No	No	No	No	No	No
Cluster by buffer	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression estimates analyzing the effect of commercial property price trends on transaction volume trends during seasonal and CCI flooding events. The analysis is segmented by post-flood quarter (1st, 2nd, and 3rd) and examines all investors collectively, as well as local and non-local institutional investors separately. All specifications control for flooding history and include buffer fixed effects with standard errors clustered by buffer; quarter fixed effects are excluded. Statistical significance levels are indicated as: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

structural embeddedness, tacit knowledge of recovery trajectories and localised business networks to dominate procurement negotiations.

Additionally, to examine the regional heterogeneities, we conducted the sub-sample analysis for non-business service centers for robustness check. These cities are not listed in the GaWC rankings due to their less developed business service sectors, which are mostly distributed to smaller and industrial cities in China. It is found that compared with business service centers, non-business service centers experience higher price discounts post-flood events (see Table 6 Panel B) but lower transaction volumes at the significance level (see Table 7 Panel B). Moreover, local investors are relatively passive to purchase the post-flood properties (see Table 8 Panel B). This suggests that non-business service centers exhibit lower disaster resilience and limited post-disaster recovery capacity, undermining investor confidence in speculative opportunities. Furthermore, flood disasters may exacerbate downward pressure on housing prices in these regions, puncturing real estate bubbles and dampening market activity.

Overall, by integrating real options and information asymmetry theories, this study advances our understanding of how environmental risks and localised knowledge shape market outcomes, offering investment insights into China's commercial property market.

5. Conclusion and policy implications

This article addresses the fundamental question of how institutional investors perceive flooding risk in their decision-making processes, with a particular focus on commercial property transactions involving intricate proprietary and financial information. By focusing on institutional actors, rational, informationally sophisticated decision-makers, we isolate the causal mechanisms linking flood risks to asset pricing and market liquidity, circumventing the sentiment-driven noise pervasive in residential markets. The main findings identified are: first, flooding leads to significant price discounts in both seasonal and CCI floodplains, with greater discounts in seasonal floodplains, as seasonal flood risks allow investors to quantify and exploit risk premiums; second, transaction volumes surge

Table 6
The impacts of seasonal and CCI flooding events on commercial property prices in business and non-business service centers.

Panel A: Business service centers						
Dependent Variable	Transacted Price	Transacted Price	Transacted Price	Transacted Price	Transacted Price	Transacted Price
Flood Type	All Floods	All Floods	Seasonal	Seasonal	CCI	CCI
Near × Post 1st quarter		−0.001* (0.039)		−0.280* (0.259)		−0.107*** (0.039)
Near × Post 2nd quarter		−0.115*** (0.037)		−1.364*** (0.259)		−0.038* (0.037)
Near × Post 3rd quarter		−0.058* (0.044)		−1.507*** (0.240)		−0.059** (0.030)
Near	0.140*** (0.016)	0.181*** (0.024)	0.267*** (0.064)	1.495*** (0.258)	0.043*** (0.014)	−0.007 (0.018)
Post 1st quarter	0.005 (0.020)	0.004 (0.030)	0.032 (0.109)	0.222 (0.230)	−0.179*** (0.032)	−0.239*** (0.030)
Post 2nd quarter	0.054*** (0.019)	0.116*** (0.026)	0.101 (0.095)	1.213*** (0.214)	0.132*** (0.033)	0.107*** (0.039)
Post 3rd quarter	0.004 (0.022)	0.035 (0.032)	0.095 (0.098)	1.293*** (0.2126)	0.068* (0.038)	0.038 (0.042)
ln (Building age)	−0.056* (0.041)	−0.063* (0.039)	−0.314** (0.023)	−0.087** (0.039)	−0.020*** (0.007)	−0.020*** (0.007)
ln (Square feet)	0.720*** (0.026)	0.733*** (0.029)	0.519*** (0.007)	0.735*** (0.042)	0.554*** (0.005)	0.554*** (0.005)
Transportation accessibility	0.042*** (0.012)	0.036*** (0.012)	0.046*** (0.003)	0.054*** (0.020)	0.295*** (0.029)	0.292*** (0.029)
ln (Green space)	0.018* (0.072)	0.001 (0.001)	0.180*** (0.019)	0.070 (0.062)	0.032*** (0.010)	0.032*** (0.010)
Flooding History	−0.313*** (0.020)	−0.316*** (0.020)	−1.388*** (0.065)	−1.455*** (0.059)	−0.005*** (0.002)	−0.002*** (0.001)
R^2/Pseudo R^2	0.775	0.778	0.900	0.916	0.787	0.788
Observations	33,141	33,141	18,807	18,807	14,334	14,334
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by buffer	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Non-business service centers						
Dependent Variable	Transacted Price	Transacted Price	Transacted Price	Transacted Price	Transacted Price	Transacted Price
Flood Type	All Floods	All Floods	Seasonal	Seasonal	CCI	CCI
Near × Post 1st quarter		−0.431*** (0.047)		−0.160*** (0.056)		−0.474*** (0.051)
Near × Post 2nd quarter		−0.468*** (0.040)		−0.387*** (0.054)		−0.558*** (0.043)
Near × Post 3rd quarter		−0.547*** (0.086)		−0.016* (0.058)		−0.570*** (0.087)
Near	0.151*** (0.030)	0.480*** (0.044)	0.095*** (0.021)	−0.014 (0.027)	0.122*** (0.034)	0.491*** (0.046)
Post 1st quarter	−0.114*** (0.014)	0.295*** (0.045)	−0.209*** (0.030)	−0.254*** (0.038)	−0.113*** (0.014)	0.340*** (0.049)
Post 2nd quarter	−0.103*** (0.010)	0.339*** (0.038)	0.310*** (0.030)	0.443*** (0.040)	−0.095*** (0.010)	0.436*** (0.041)
Post 3rd quarter	−0.103*** (0.014)	0.419*** (0.085)	0.259*** (0.030)	0.282*** (0.038)	−0.097*** (0.014)	0.454*** (0.086)
ln (Building age)	−0.011* (0.013)	−0.013* (0.013)	−0.418*** (0.076)	−0.522*** (0.103)	−0.109*** (0.019)	−0.107*** (0.022)
ln (Square feet)	0.534*** (0.008)	0.534*** (0.007)	1.052*** (0.027)	1.011*** (0.038)	0.602*** (0.021)	0.605*** (0.021)
Transportation accessibility	0.371*** (0.105)	0.369*** (0.104)	0.072*** (0.014)	−0.047** (0.020)	1.176*** (0.139)	1.175*** (0.145)
ln (Green space)	0.073*** (0.026)	0.072*** (0.026)	0.037** (0.010)	0.034*** (0.011)	0.396*** (0.071)	0.414*** (0.070)
Flooding History	−0.107*** (0.025)	−0.116*** (0.027)	0.325*** (0.045)	0.324*** (0.044)	−0.257*** (0.030)	−0.283*** (0.032)
R^2/Pseudo R^2	0.542	0.544	0.294	0.305	0.544	0.547
Observations	27,490	27,490	17,442	17,442	10,048	10,048
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by buffer	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression estimates analyzing the impact of seasonal and CCI flood events on commercial property prices in business service centers (Panel A) and non-business service centers (Panel B). For each panel, Columns 1 and 2 include all flood types, Columns 3 and 4 focus on seasonal floods, and Columns 5 and 6 focus on CCI floods. All specifications control for building age, square feet, transportation accessibility, green space, and flooding history, and include buffer fixed effects, quarter fixed effects, and cluster-robust standard errors by buffer. Business service centers are defined as Chinese cities with agglomerated advanced business services (including real estate and appraisal services) according to the GaWC 2020 ranking. Statistical significance levels are indicated as: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 7
The impacts of seasonal and CCI flooding events on commercial property transaction volumes in business and non-business service centers.

Panel A: Business service centers						
Dependent Variable	Transaction Volume	Transaction Volume	Transaction Volume	Transaction Volume	Transaction Volume	Transaction Volume
Flood Type	All Floods	All Floods	Seasonal	Seasonal	CCI	CCI
Near × Post 1st quarter		0.282** (0.118)		0.583*** (0.126)		−0.063 (0.043)
Near × Post 2nd quarter		0.203** (0.143)		0.298* (0.169)		−0.187*** (0.035)
Near × Post 3rd quarter		0.215** (0.135)		0.662*** (0.181)		−0.048 (0.062)
Near	0.036 (0.055)	−0.105 (0.124)	0.086 (0.072)	−0.145 (0.152)	−0.161** (0.069)	−0.096 (0.076)
Post 1st quarter	0.071 (0.050)	−0.108 (0.115)	−0.071 (0.060)	−0.464*** (0.123)	0.361*** (0.023)	0.401*** (0.030)
Post 2nd quarter	0.268*** (0.063)	0.146 (0.142)	0.234*** (0.078)	0.055 (0.166)	0.159*** (0.016)	0.284*** (0.028)
Post 3rd quarter	−0.049 (0.046)	−0.183 (0.120)	−0.087 (0.063)	−0.539*** (0.154)	0.179*** (0.031)	0.210*** (0.049)
Flooding History	−0.199*** (0.055)	−0.196*** (0.055)	−0.426*** (0.054)	−0.433*** (0.054)	−0.266* (0.065)	−0.268* (0.068)
R^2/Pseudo R^2	0.072	0.075	0.100	0.110	0.078	0.054
Observations	30,409	30,409	18,166	18,166	12,243	12,243
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by buffer	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Non-business service centers						
Dependent Variable	Transaction Volume	Transaction Volume	Transaction Volume	Transaction Volume	Transaction Volume	Transaction Volume
Flood Type	All Floods	All Floods	Seasonal	Seasonal	CCI	CCI
Near × Post 1st quarter		−0.433*** (0.089)		0.241 (0.187)		−0.432*** (0.089)
Near × Post 2nd quarter		0.014 (0.080)		−0.703*** (0.183)		0.012 (0.080)
Near × Post 3rd quarter		−0.357*** (0.080)		−0.331* (0.189)		−0.357*** (0.080)
Near	0.881*** (0.122)	1.014*** (0.148)	−0.305** (0.141)	−0.259 (0.174)	0.876*** (0.123)	−0.014*** (0.148)
Post 1st quarter	−0.021*** (0.008)	0.407*** (0.089)	−0.008 (0.047)	−0.069** (0.030)	−0.024*** (0.008)	−0.405*** (0.089)
Post 2nd quarter	−0.024*** (0.006)	−0.038 (0.080)	−0.613*** (0.061)	−0.499*** (0.045)	−0.020*** (0.006)	−0.036 (0.080)
Post 3rd quarter	−0.118*** (0.014)	0.235*** (0.079)	−0.524*** (0.140)	−0.644*** (0.125)	−0.113*** (0.014)	0.236*** (0.079)
Flooding History	2.616*** (0.039)	2.611*** (0.040)	−0.373*** (0.141)	−0.337** (0.132)	2.611*** (0.039)	2.606*** (0.040)
R^2/Pseudo R^2	0.296	0.297	0.631	0.637	0.293	0.294
Observations	26,625	26,625	13,773	13,773	12,852	12,852
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by buffer	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression estimates analyzing the impact of seasonal and CCI flood events on commercial property transaction volumes in business service centers (upper panel) and non-business service centers (lower panel). For each service center type, Columns 1 and 2 include all flood types, Columns 3 and 4 focus on seasonal floods, and Columns 5 and 6 focus on CCI floods. All specifications control for flooding history and include buffer fixed effects, quarter fixed effects, and cluster-robust standard errors by buffer. Statistical significance levels are indicated as: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

post-flood, particularly in seasonal floodplains, as investors act swiftly where risks are calculable but adopt a wait-and-see approach in CCI floodplains, aligning with real options theory; third, local investors secure higher discounts and disproportionately target seasonal floodplains, while non-local investors focus on CCI floodplains, underscoring the contingent nature of informational asymmetries.

These findings reveal critical insights for risk premium heterogeneity, information asymmetries, and climate resilience, offering theoretical advancements in understanding how environmental risks shape market dynamics. First, the divergence in risk premiums between seasonal and CCI floods exposes the limits of traditional discounted cash flow models in climate-volatile markets. Seasonal floods, with calculable risks, allow investors to exploit risk premiums, increasing discounts and liquidity. In contrast, CCI floods, characterised by non-stationary uncertainties, hinder rational pricing, necessitating frameworks incorporating stochastic climate scenarios. Second, local investors' advantage in seasonal floodplains underscores spatial finance paradigms, where place-based informational rents and tacit knowledge prevail. However, this advantage fades in CCI floodplains, as climate uncertainty neutralises spatial embeddedness, shifting the focus to diversification and long-term strategies. This challenges "local knowledge" theories, showing how climate risks recalibrate informational hierarchies, aligning with information asymmetry theory. Third, systemic gaps in climate risk internalization, even among sophisticated investors, reveal market mechanisms' inadequacy in addressing long-term vulnerabilities. This highlights the need to integrate climate resilience into financial decision-making, as traditional models often underweight distant risks. Together, these insights deepen understanding of how environmental risks and localised knowledge shape

Table 8
The impacts of seasonal and CCI flooding events on local/non-local investors' purchasing prices and transaction volumes in business and non-business service centers.

Panel A: Business service centers						
Post 1st Quarter						
Dependent Variable	Transacted Price	Transacted Price	Transacted Price	Transaction Volume	Transaction Volume	Transaction Volume
Flood Type	All Floods	Seasonal	CCI	All Floods	Seasonal	CCI
Local vs non-local	−1.266*** (0.092)	−1.129*** (0.109)	−0.469*** (0.172)	0.235*** (0.062)	0.240*** (0.070)	−0.319* (0.191)
ln (Building age)	−0.081* (0.142)	−0.124*** (0.042)	−0.048*** (0.010)			
ln (Square feet)	0.111* (0.231)	0.274*** (0.030)	0.538*** (0.010)			
Transportation accessibility	0.104** (0.051)	0.077*** (0.003)	−0.001 (0.054)			
ln (Green space)	0.177* (1.142)	0.257*** (0.032)	0.053*** (0.017)			
Flooding History	−3.233*** (0.941)	0.322 (0.021)	0.002 (0.001)	−0.257*** (0.351)	−0.091 (0.043)	0.017 (0.120)
R^2/Pseudo R^2	0.678	0.426	0.997	0.161	0.028	0.248
Observations	2,673	1,403	1,270	2,690	1,230	1,460
Post 2nd Quarter						
Local vs non-local	−1.581*** (0.152)	−1.887*** (0.151)	−0.090* (0.266)	0.096*** (0.026)	0.251** (0.099)	−0.183* (0.312)
ln (Building age)	−0.044** (0.300)	−0.062* (0.058)	−0.019** (0.009)			
ln (Square feet)	0.374*** (0.064)	0.290*** (0.030)	0.567*** (0.009)			
Transportation accessibility	0.193* (0.127)	0.052*** (0.008)	0.166** (0.071)			
ln (Green space)	0.604* (3.181)	−0.068 (0.059)	−0.003 (0.016)			
Flooding History	−0.099*** (0.187)	0.077 (0.022)	−0.028 (0.234)	−0.006 (0.052)	−0.031 (0.159)	0.279 (0.278)
R^2/Pseudo R^2	0.709	0.684	0.461	0.217	0.364	0.930
Observations	2,453	1,263	1,190	2,550	1,070	1,480
Post 3rd Quarter						
Local vs non-local	−0.076*** (0.023)	−0.170*** (0.044)	−0.391*** (0.068)	0.073* (0.107)	0.164** (0.021)	−0.085* (0.026)
ln (Building age)	−0.952*** (0.182)	−0.114* (0.067)	−0.007* (0.010)			
ln (Square feet)	1.112*** (0.158)	0.271*** (0.034)	0.608*** (0.012)			
Transportation accessibility	0.912*** (0.262)	0.073*** (0.003)	0.395*** (0.093)			
ln (Green space)	0.087*** (0.137)	0.255** (0.060)	0.042** (0.019)			
Flooding History	−0.094*** (0.022)	−0.414 (0.016)	0.212 (0.109)	−0.145 (0.066)	−0.031 (0.158)	0.260 (0.014)
R^2/Pseudo R^2	0.999	0.999	0.901	0.184	0.157	0.134
Observations	2,220	1,140	1,080	2,880	1,590	1,290
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	No	No	No	No	No	No
Cluster by buffer	Yes	Yes	Yes	No	No	No
Panel B: Non-business service centers						
Post 1st Quarter						
Dependent Variable	Transacted Price	Transacted Price	Transacted Price	Transaction Volume	Transaction Volume	Transaction Volume
Flood Type	All Floods	Seasonal	CCI	All Floods	Seasonal	CCI
Local vs non-local	−0.197*** (0.025)	−0.297*** (0.044)	−0.012*** (0.144)	0.109*** (0.005)	0.142*** (0.033)	−0.490** (0.217)
ln (Building age)	−0.054*** (0.016)	−0.326*** (0.018)	−0.008* (0.036)			
ln (Square feet)	0.524*** (0.017)	0.385*** (0.008)	0.454*** (0.005)			
Transportation accessibility	1.351*** (0.215)	0.013*** (0.002)	0.569*** (0.014)			
ln (Green space)	0.012 (0.034)	0.022* (0.013)	0.693*** (0.023)			
Flooding History	−1.974*** (0.362)	0.217** (0.096)	−0.479 (0.615)	0.583*** (0.062)	−0.520*** (0.171)	0.114 (0.146)

(continued on next page)

Table 8 (*continued*)

Panel B: Non-business service centers						
Post 1st Quarter						
Dependent Variable	Transacted Price	Transacted Price	Transacted Price	Transaction Volume	Transaction Volume	Transaction Volume
Flood Type	All Floods	Seasonal	CCI	All Floods	Seasonal	CCI
R^2/Pseudo R^2	0.529	0.311	0.595	0.268	0.051	0.117
Observations	3,621	2,478	1,143	3,484	1,844	1,640
Post 2nd Quarter						
Local vs non-local	−0.126*** (0.027)	−0.182*** (0.030)	−0.403*** (0.064)	0.064*** (0.005)	0.058*** (0.022)	−0.008 (0.064)
ln (Building age)	−0.032* (0.017)	−0.157*** (0.019)	−0.052* (0.043)			
ln (Square feet)	0.448*** (0.016)	0.376*** (0.008)	0.480*** (0.016)			
Transportation accessibility	1.083*** (0.209)	0.011*** (0.002)	0.450*** (0.056)			
ln (Green space)	0.160*** (0.051)	0.038*** (0.014)	0.455*** (0.092)			
Flooding History	−1.404*** (0.172)	0.340*** (0.050)	−2.402*** (0.110)	1.288*** (0.080)	−0.197*** (0.048)	0.031** (0.076)
R^2/Pseudo R^2	0.665	0.236	0.572	0.272	0.112	0.102
Observations	5,731	4,022	1,709	3,247	1,327	1,920
Post 3rd Quarter						
Local vs non-local	−0.523*** (0.062)	−0.443*** (0.055)	−0.774*** (0.099)	0.047*** (0.013)	0.402*** (0.115)	−0.170* (0.799)
ln (Building age)	0.022 (0.020)	−0.314*** (0.019)	−0.032* (0.043)			
ln (Square feet)	0.443*** (0.024)	0.361*** (0.008)	0.474*** (0.016)			
Transportation accessibility	1.386*** (0.206)	−0.003 (0.003)	0.480*** (0.056)			
ln (Green space)	0.084* (0.043)	−0.019 (0.015)	0.487*** (0.096)			
Flooding History	0.699*** (0.014)	0.145** (0.061)	0.453 (0.041)	−1.503*** (0.262)	−0.474*** (0.127)	0.391 (0.086)
R^2/Pseudo R^2	0.741	0.161	0.664	0.496	0.029	0.103
Observations	2,766	1,470	1,296	2,790	1,580	1,210
Buffer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	No	No	No	No	No	No
Cluster by buffer	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression estimates analyzing how seasonal and CCI flood events differentially affect transaction prices and volumes for local versus non-local investors in business service centers (Panel A) and non-business service centers (Panel B). The analysis is segmented by post-flood quarter (1st, 2nd, and 3rd), with each segment showing results for transaction prices (Columns 1–3) and transaction volumes (Columns 4–6) across all flood types, seasonal floods, and CCI floods. Price regressions (Columns 1–3) control for building age, square footage, transportation accessibility, green space, and flooding history. Volume regressions (Columns 4–6) control for flooding history. All models include buffer fixed effects and are clustered by buffer; quarter fixed effects are excluded. Statistical significance levels are indicated as: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

market outcomes in China's commercial property market context.

Local governments are suggested to adopt a multifaceted approach informed by the findings and theoretical insights. First, to reduce information asymmetries for non-local investors, local governments are suggested to establish open-data platforms that provide high-resolution flood risk data, including historical patterns, climate projections, and real-time monitoring. This would level the playing field by enabling non-local investors to make more informed decisions. Second, enhancing market rationality and pricing mechanisms requires integrating stochastic climate scenarios into asset pricing models to account for non-stationary uncertainties in CCI floodplains. Governments could incentivise long-term investments in flood-resilient infrastructure and properties, particularly in CCI floodplains, through tax incentives or subsidies. Third, strengthening urban resilience to floods involves implementing zoning laws and building codes that mandate flood-resistant construction practices, particularly in high-risk areas. Finally, addressing systemic gaps in climate risk internalization requires policy interventions that mandate institutional investors to disclose climate risk exposures and integrate resilience into their investment strategies. This would address the systemic underweighting of long-term climate vulnerabilities. By implementing these measures, local governments can reduce information asymmetries, enhance market rationality, and strengthen urban resilience to floods, aligning private investment decisions with broader climate resilience goals.

While this study provides valuable insights into how institutional investors perceive and respond to flood risks in commercial property markets, it is important to acknowledge its potential limitations. First, due to data availability, the observation data period (from 2010 to 2018) may limit the generalizability of the findings, as a longer time frame could capture a broader range of flood events and market responses. In addition, parcel-level information on structural integrity, flood-resistant design, or building-code compliance are not available for our quasi-natural experiment due to the data limitations. Moreover, regardless of a comprehensive satellite-based dataset encompassing the universe of floods, MSCI commercial property dataset may omit transactions occurred at cities without historical flood events. Second, the focus on institutional investors, while advantageous for isolating rational decision-making, may introduce selection bias, as smaller investors could exhibit different behaviours that are not captured in this analysis. Third, notwithstanding the two-way buffer and time fixed effects, omitted variables, such as macroeconomic conditions, regulatory changes, or other environmental risks, could influence market dynamics and asset pricing via unobserved pathways. Another potential caveat is the variation in urban topography and drainage capacity across cities, which may affect the strength of flooding impacts on affected properties and lead to inconsistent validity of the buffer zones used in the analysis. However, this impact is likely to be trivial, as the study's focus on institutional investors and their reliance on standardised risk assessments mitigates the influence of these omitted confounders. Despite these limitations, the study offers critical theoretical and empirical contributions, providing a foundation for further exploration of the intersection between climate risks, market dynamics, and urban resilience.

CRediT author statement

Shi Shuai: Conceptualization, Resources, Writing - Original Draft, Writing - Review & Editing, Supervision, Funding acquisition. Lin Ziwei: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization. Zhang Yue: Software, Data Curation, Writing - Review & Editing, Visualization. Kathy Pain: Conceptualization, Writing - Review & Editing.

Conflict of interest

The authors declare that they have no known conflict of interest or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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