Do Homeowners in Emerging Markets Care About Sea Level Rise and Government Adaptation?*

Yirong Liu† Yining Shi‡ Dragon Yongjun Tang§ Fumin Zhu¶

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Abstract

We examine how sea level rise (SLR) risk affects residential property prices in emerging markets. Using a comprehensive dataset of housing transactions in China from 2011 to 2023, we find a significant discount for properties with high SLR risk. This discount reflects buyer aversion, resulting in longer marketing time and larger seller price concessions. Importantly, we show that government-announced adaptation plans do not mitigate this discount; only observable, implemented adaptation measures attenuate the price effect. Original survey evidence from local residents further shows that the market response depends on public awareness of adaptation efforts and perceived effectiveness of these measures. These results establish that the credibility of climate adaptation, not merely its announcement, is a critical determinant of asset value resilience.

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Keywords: Climate change, Sea level rise, Housing, Adaptation policy, Emerging markets.

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†The University of Hong Kong, Hong Kong. Email: yrliu25@hku.hk

‡Corresponding author, University of International Business and Economics, Beijing, China. Email: yining.shi@uibe.edu.cn

§The University of Hong Kong, Hong Kong. Email: yjtang@hku.hk

¶Shenzhen University, Shenzhen, China. Email: zhufumin@szu.edu.cn

1 Introduction

Accelerating global sea level rise (SLR) poses severe threats to populations and economic activity in coastal areas, with important implications for housing markets.[1] For most households, properties constitute the largest assets they have. Unlike financial securities, they are particularly vulnerable to long-horizon physical risks due to their durability and geographic immobility.[2] Meanwhile, governments worldwide have been exploring long-term climate adaptation plans, which may shape homebuyers' risk perceptions and influence their housing decisions. While the impact of sea level rise risk on housing markets has been studied in developed economies (e.g., Baldauf, Garlappi, and Yannelis, 2020; Giglio, Kelly, and Stroebel, 2021), evidence from emerging countries remains limited. This gap is important because emerging economies host over 60% of the world's coastal population yet face tighter fiscal constraints and weaker institutional capacity for climate adaptation. This paper, therefore, examines how SLR risk affects housing transactions in emerging markets and evaluates whether government adaptation mitigates the associated valuation losses.

Compared with advanced economies, emerging economies often have tighter fiscal constraints and competing short-term policy objectives, such as economic growth and poverty alleviation.[3] These constraints can limit the priority and resources devoted to climate adaptation. In addition, structural frictions could further impede the management and pricing of climate risk: property valuation frameworks may fail to incorporate climate risk metrics and insurance markets remain too underdeveloped to provide effective risk transfer.[4] These features would amplify the impact of sea level rise on housing prices and increase household

[1] According to new research by Seeger and Minderhoud (2026), sea levels along the world's coastlines are much higher than previously assumed, some places, such as Southeast Asia and parts of the Pacific, reaching up to 3 feet higher.

[2] Piazzesi (2025) highlights housing is one of the three major asset classes in her presidential address.

[3] The World Bank highlights these trade-offs in its 2010 report. Report source: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/201001468159913657.

[4] Real estate sectors in the U.K. and the U.S. have increasingly integrated climate risk disclosures into property listings. Platforms such as Zillow (via First Street Foundation) and Redfin now provide granular flood and sea level rise exposure scores to prospective buyers.

welfare losses. Therefore, studying how climate risk such as sea level rise affects emerging markets is critical to equipping policymakers and residents to prepare for and adapt to climate shocks.

As the largest emerging economy, the Chinese housing market provides a unique laboratory to examine these questions. First, it is the largest real estate market in the world, with a market value of approximately $74 trillion, and accounts for 26% of global residential value by 2024.[5] Furthermore, housing accounts for more than 70% of wealth of Chinese residential families (Badarinza, Balasubramaniam, and Ramadorai, 2019). Second, speculative activity has been an important driver of the post-2010 housing boom in China (Fang, Gu, Xiong, and Zhou, 2016), raising the question of whether forward-looking coastal risks are reflected in transaction prices even when many buyers have relatively short holding horizons.[6] Third, the Chinese government has long recognized the growing risk exposure to flooding and sea level rise along the nation's extensive coastline. As a result, the central and local governments have taken various policies in order to adapt to climate changes and to manage climate risks. For example, in 2017, it launched the National Seawall Construction Plan, a ten-year initiative aimed at strengthening coastal defenses.[7] In 2018, the President emphasized the importance of building ecological seawalls to strengthen resilience against typhoons and storm surges.[8] These proactive actions allow us to conduct policy analyses regarding its effect on residents' perception of SLR risk and corresponding home-buying decisions.

We collect detailed granular data on housing transactions across 30 coastal cities from one of China's largest real estate agency platforms, covering the period from January 2011 to November 2023 and encompassing over 900,000 transactions. This extensive set of data includes not only final transaction prices for individual resale housing units, but also provides

[5] Please see https://impacts.savills.com/market-trends/where-are-the-worlds-most-valuable-residential-markets.html for details.

[6] According to the Survey on Assets and Liabilities of Urban Households in China conducted by the People's Bank of China, approximately 31% of urban households own a second property by 2019.

[7] Please see https://www.gov.cn/xinwen/2017-08/21/content_5219341.htm for details (in Chinese).

[8] Please see https://www.gov.cn/xinwen/2018-10/10/content_5329292.htm for details (in Chinese).

comprehensive information on buyers' online attention metrics, in-person property viewings, and sellers' listing behaviors and price adjustments. With such detailed information, we are able to investigate the underlying channels through which price effects may operate. In particular, to study the impact of sea level rise on housing prices, we link each transaction with a manually constructed, continuous measure of SLR exposure. This SLR exposure measure identifies the sea level threshold at which a property is projected to become inundated, allowing us to distinguish near-term from longer-horizon SLR risk.

Our baseline specification compares properties sold in the same year and city, within the same distance-to-coast group and elevation band, but with different SLR exposure, thereby narrowing comparisons to properties in similar local and geographic settings. We find that SLR risk has statistically and economically significant negative effect on house values. Specifically, a one-standard-deviation increase in SLR exposure reduces transaction prices by 1.54%, corresponding to an average loss of 42,258 RMB (approximately 6,051 USD) per property. This result is robust to alternative SLR exposure measures, finer fixed effects, different housing pricing variables, and changing market conditions.

We next turn to uncovering the underlying mechanisms driving our results. We first examine how SLR exposure affects buyers' interest and sellers' listing behavior. The intuition is that higher perceived inundation risk reduces buyer engagement with exposed listings, while sellers respond by adjusting listing prices during the marketing period. Consistent with this view, we observe significantly lower online engagement and fewer in-person viewings for properties with higher SLR exposure. On the supply side, sellers in high-exposure areas revise prices more frequently, and these properties take longer to sell. These findings suggest that perceptions of future inundation risks lead to changes in both buyer and seller behavior, reducing demand and increasing supply-side adjustments in the housing market. Together, these patterns suggest that SLR risk is reflected in transaction prices through reduced demand, sellers' repricing, and decreased market liquidity.

We then explore the role of sophisticated buyers, measured by the prevalence of speculative trading in the local housing market. This mechanism is particularly relevant in China, where speculative participation is prevalent. Financially oriented buyers may be more attentive to risks that threaten asset values (Chinco and Mayer, 2016). Despite their short holding horizons (Gao, Sockin, and Xiong, 2020), speculators remain sensitive to long-horizon risks such as sea level rise because these risks affect expected resale values and market liquidity. Consistent with this view, we show that the SLR-related price discount is larger in areas with higher speculative activity, suggesting that SLR risk is priced more strongly when marginal transactions are more likely to be set by sophisticated buyers. This finding is consistent with evidence from the U.S. housing market, where SLR price discounts are concentrated in non-owner-occupied properties (Bernstein, Gustafson, and Lewis, 2019).

Furthermore, in cities where residential land supply is more constrained, households face fewer within-city substitution options, which can limit their ability to adjust away from long-horizon coastal risks. Using a city-level land-supply-based measure, we find that the SLR-related price discount is concentrated in cities with more abundant residential land, where relocation is relatively more feasible. Finally, we examine whether SLR risk is priced more strongly when climate risk is salient. The SLR price discount is larger in cities with frequent typhoon events and in regions with greater public attention to climate risk, measured by internet search intensity for *sea level rise* and *climate change*, respectively. This pattern is consistent with Baldauf, Garlappi, and Yannelis (2020), who find that SLR-related discounts only exist in neighborhoods with stronger climate-change beliefs.

Given the profound effects of SLR exposure, we next explore the impact of local adaptation policies in alleviating its adverse effects on property prices. We hand-collect a comprehensive set of adaptation actions from local government announcements and official news releases, recording announcement and implementation dates, project content, and related government actions. In addition, we conduct an original survey of 1,423 residents across the

30 coastal cities in our sample from February to April 2026, capturing their awareness of local adaptation measures, knowledge of long-term coastal protection plans, and beliefs about the effectiveness of these measures. Empirically, we employ a staggered difference-in-differences design to estimate policy impacts and link city-level survey responses to the transaction data to examine how public perceptions shape the market response.

We find that the SLR-related price discount is smaller in cities where residents are more aware of adaptation efforts. Distinguishing implemented projects from announced plans, we show that only projects under implementation attenuate the price discount, whereas announcements alone have no significant impact. Moreover, this attenuation is concentrated in cities where residents believe the measures are effective and where local governments have stronger fiscal capacity. These results suggest that market responses hinge on the credibility of adaptation, shaped jointly by physical implementation, public confidence, and fiscal backing.

Our study contributes to several strands of literature. First, it extends research on the impact of sea level rise risk on residential housing markets.[9] Evidence from developed markets is mixed. For example, Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020), Giglio, Maggiori, Rao, Stroebel, and Weber (2021), Bakkensen and Barrage (2022), and Keys and Mulder (2026) document negative effects of SLR risk. Murfin and Spiegel (2020) find no significant results, and Baldauf, Garlappi, and Yannelis (2020) show that SLR-related price discounts depend on local climate beliefs. We provide large-sample evidence from an emerging country that SLR exposure, especially near term, is negatively priced in the housing markets. Second, our paper adds to the economic understanding of whether governments' adaptation efforts reduce climate-related property value losses. Agarwal, Qin, Sing, and Zhan (2025) emphasize the signaling value of national adaptation plans,

[9] Our study is also related to a growing literature on how flooding-related climate risk affects financial markets. Goldsmith-Pinkham, Gustafson, Lewis, and Schwert (2023) and Painter (2020) find higher long-term municipal bond yields in areas with greater SLR exposure. Dey (2025) demonstrates that sovereign CDS spreads increase for countries vulnerable to coastal flooding. Collier, Powell, Ragin, and You (2025) show that Hurricane Harvey led to substantial distress in small-business credit markets.

whereas Benetton, Emiliozzi, Guglielminetti, Loberto, and Mistretta (2025) and Liu, Constantz, Hale, and Beck (2025) document the valuation effect of tangible protection measures. We show that only implemented projects alleviate price discounts associated with SLR risk in China, whereas policy announcements have no discernible impact. Moreover, using original survey data, we provide direct evidence that public awareness and perceived effectiveness of adaptation are important channels shaping these market responses. Finally, our study is related to the broader literature on China's housing market by showing that climate risk and local government adaptation efforts materially affect property prices.[10]

The remainder of the article is organized as follows. Section 2 summarizes our data and measures. Section 3 documents our baseline empirical results. Section 4 examines the channels and mechanisms for the main findings. Section 5 discusses the role of local governments' adaptation plans. We conclude the paper in Section 6.

2 Data, Measures, and Descriptive Statistics

2.1 Real Estate Listing and Transaction Records

We obtain a unique dataset on resale housing from one of China's largest real estate agency platforms, Lianjia, covering 30 major coastal cities from January 2011 to November 2023. Lianjia maintains one of the largest proprietary housing databases in the country, covering more than one million residential transaction records across major urban areas.[11] The reliability of Lianjia transaction prices and housing characteristics has been benchmarked in prior work. For instance, Ge, Huang, and Shi (2025) show that prices and property sizes recorded by Lianjia are broadly consistent with official statistics. The dataset has been

[10] This body of work includes: Fang, Gu, Xiong, and Zhou (2016), Chen and Wen (2017), Glaeser, Huang, Ma, and Shleifer (2017), Liu and Xiong (2020), Ge, Huang, and Shi (2025), Qian, Tu, Wu, and Xu (2025), Tian and Wang (2026), Chang, Wang, and Xiong (2026), and Niu, Xiang, Yang, and Zhou (2026).

[11] The platform operates via city-level subdomains. For instance, the Shanghai site (`https://sh.lianjia.com/`) illustrates the typical data structure and property information available (in Chinese).

widely used in empirical studies of China's housing market. Agarwal, Li, Qin, Wu, and Yan (2020) utilize the dataset to study capital gains taxes and tax evasion in resale transactions; Zhao, Yang, and Zhang (2025) examine housing-market responses to flood events based on it; and Addoum, Cong, and Zhou (2025) analyze how extreme heat affects bargaining outcomes between buyers and sellers.

We focus on residential properties. Our initial dataset comprises more than one million transactions during the sample period. Each transaction record contains detailed information on property and transaction characteristics, such as transaction prices and dates, buyer demographics, initial and final listing prices, seller holding period, unit area, number of bedrooms, floor level, building age, interior decoration status, window orientation, and geographic coordinates. The transaction date corresponds to the date on which the buyer and seller agree on the final price and sign the sales contract on-site. In addition, the dataset provides other metrics that capture both demand- and supply-side behaviors around the transaction. On the demand side, it includes in-person housing viewings and online engagement metrics that reflect buyer interest. On the supply side, it records sellers' initial pricing decisions and subsequent price adjustments.[12] This rich set of supply and demand indicators enables a dynamic and granular analysis of market participants' behaviors, allowing us to explore mechanisms such as those driven by climate-related attention and other behavioral responses.

We exclude outlier transactions with unit prices above 200,000 RMB per square meter, which account for roughly 0.6% of the sample.[13] We further remove observations with extreme values in property attributes such as size and number of bedrooms.[14] We also exclude transactions with missing building age, as these primarily involve older residential

[12] Internet Appendix Figure IA1 provides an example of a transacted property's information in the platform.

[13] This threshold captures the commonly accepted cutoff for ultra-luxury properties, which operate in a niche market and hardly reflect typical residential demand.

[14] We identify potential outliers by conducting descriptive analyses of housing characteristics in each city (e.g., minimum and maximum values) and cross-checking them on the Lianjia platform to verify that the transaction exists and involves a residential unit before deciding on removal.

communities under renovation or redevelopment, where prices are more likely influenced by redevelopment expectations rather than climate risk exposure. We end up with a sample of 957,091 transaction records.

2.2 Sea Level Rise Exposure

To construct property-level exposure to sea level rise, we first use the dynamic maps provided by Climate Central to assess inundation risk for each property in our sample under different SLR scenarios.[15] Following Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020), we focus on three benchmarks, namely 1 foot, 3 feet, and 6 feet of sea level rise. For each scenario, we locate the community on the interactive map and record whether the community is inundated, which defines the inundation threshold.[16] We then map each SLR threshold to a projected inundation year using forecasts from the Intergovernmental Panel on Climate Change (IPCC). According to the IPCC, global mean sea level is expected to rise approximately 1 foot (0.30 meters) by 2050, between 1.41 feet (0.43 meters) and 3.61 feet (1.10 meters) by 2100, and between 2.30 feet (0.70 meters) and 6.56 feet (2.00 meters) by 2150, depending on future carbon emissions (IPCC, 2022). Based on these forecasts and local inundation thresholds, we classify each property into one of three exposure categories: (i) to be inundated under a 1-foot rise (by 2050), (ii) to be inundated under a 3-foot rise (by 2100), or (iii) to be inundated under a 6-foot rise (by 2150).[17] We then construct a property-specific SLR exposure measure as follows:

$$SLR\ Exposure_{i,t} = \begin{cases} \exp\left(-r_{u_i} \cdot (T_{u_i} - t_i)\right), & \text{if } u_i \in \{1\text{ft}, 3\text{ft}, 6\text{ft}\}, \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

[15] Please see https://coastal.climatecentral.org/ for details.

[16] Internet Appendix Figure IA2 shows the procedure for identifying the SLR inundation threshold for a specific community in the website.

[17] We adopt the upper bound (i.e., high-end scenario) from each projection range when mapping to specific years to avoid underestimating SLR risks.

where u_i denotes the inundation threshold (in feet) for property i, T_{u_i} is the projected year when the corresponding sea level rise is expected to occur (i.e., 2050, 2100, 2150), t_i is the transaction year of property i, and r_{u_i} is the discount rate that captures the time preference for future inundation risk. In the baseline specification, we allow the discount rate to vary by the SLR horizon. Consistent with evidence on discounting in China's housing market,[18] we use a short-horizon rate of 5% for the 1-foot (2050) scenario and a long-horizon rate of 2.9% for the 3-foot (2100) and 6-foot (2150) scenarios (i.e., $r_{1\text{ft}} = 5\%$ and $r_{3\text{ft}} = r_{6\text{ft}} = 2.9\%$). This choice is also consistent with a downward-slopping term structure of discount rates estimated from real estate markets in Giglio, Maggiori, Rao, Stroebel, and Weber (2021). Thus, $SLR\ Exposure_i$ reflects the present-value discount factor applied to a unit loss that materializes at the projected inundation year of a property.

Thus, our proposed measure reflects the discount factor for a unit inundation loss occurring in the projected inundation year of a property. It captures both severity and timing of SLR risk. A higher value of $SLR\ Exposure$ indicates a shorter time-to-inundation, and hence a larger present-value weight on future inundation loss. Holding the loss magnitude fixed, near-horizon inundation risk is discounted less and should exert a stronger effect on current property values, whereas more distant risks are discounted more heavily and should have a weaker contemporaneous impact. Furthermore, for properties sharing the same inundation threshold, the exposure value increases as the transaction date approaches the projected inundation year, reflecting the escalating climate risk as the horizon shortens.

While sea level rise is a global threat, its pricing in the Chinese residential market depends on the local information environment. Several pieces of evidence suggest that sea level rise risks are increasingly recognized by domestic market participants. First, the China Oceanic Information Network has released the annual China Sea Level Bulletin since 2000,

[18] See http://www.aer.ruc.edu.cn/CN/Y2023/V03/I04/114 for details (in Chinese). We adopt horizon-specific discount rates to isolate the role of perceived inundation timing from discount-rate choices, and we examine a wide range of alternative discount rates in robustness checks.

providing localized, authoritative data on sea level trends to the public.[19] Second, China's *National Strategy on Climate Change Adaptation 2035*, announced in 2023, explicitly identifies sea level rise as a critical threat to coastal urban infrastructure, thereby elevating the national salience of climate adaptation.[20] Importantly, recent survey evidence highlights a deep-seated climate awareness among the Chinese public. According to a joint study by the United Nations Development Programme (UNDP) and the Nanjing Institute of Environmental Sciences (NIES), 87% of Chinese respondents view climate change as a global emergency. Critically, this figure rises to 90% in eastern China, where our sample of coastal cities is concentrated. Furthermore, 92% of respondents emphasize the protection of sea as a key solution to climate change.[21] These facts collectively demonstrate that residents in our sample areas possess a high degree of climate risk awareness, providing a solid foundation for our risk-based measure.

2.3 Geographic and Demographic Variables

Distance to the coastline is crucial for isolating the pricing of sea level rise risk because coastal proximity also provides amenity value. Using the geographic information from Lianjia, we compute each community's distance to the nearest coastline and its elevation based on its latitude and longitude. Then we use the distance to the coastline and elevation as additional fixed effects in the regressions to control for potential omitted factors that affect residential housing choices. We further use these geographic identifiers to match each property to its county, city, and province, and we merge in regional demographic and economic variables from the Wind database (e.g., GDP, population, and local policy indicators) as

[19] Please see https://www.nmdis.org.cn/hygb/zghpmgb/2021nzghpmgb/ for details (in Chinese).

[20] This document provides details for the National Strategy on Climate Change Adaptation 2023. Data source: https://www.mee.gov.cn/xxgk2018/xxgk/xxgk03/202206/W020220613636562919192.pdf (in Chinese).

[21] This document offers a detailed description of the survey. Data source: https://www.undp.org/sites/g/files/zskgke326/files/2025-05/zhongguogongzhongqihoubianhuayishidiaoyanxiangmu.pdf (in Chinese).

controls. The Appendix provides detailed descriptions of variables used in this study.

2.4 Household Survey on Adaptation Awareness and Beliefs

To explore how public awareness and beliefs about climate adaptation shape housing market responses to sea level rise risk, we design and administer an original online survey targeting residents of the 30 coastal cities in our sample. The survey was conducted from February to April 2026, using a structured online questionnaire distributed through a professional survey platform.[22] A total of 1,500 questionnaires were distributed, and 1,423 valid responses were obtained after excluding incomplete or careless submissions, yielding an effective response rate of 94.9%.

The survey instrument consists of three modules. The first collects respondents' demographic information, including gender, age, and education level. The second assesses awareness of local government adaptation measures and long-term plans. Specifically, respondents are asked whether they know about existing local government measures addressing sea level rise or coastal flooding, such as seawalls, flood barriers, or related protective infrastructure, and whether they are aware of seawall construction plans or flood-control plans released by local governments in the past decade. Response options range from "know well" to "have not heard at all." The third module elicits beliefs about the effectiveness of these adaptation measures, asking whether respondents perceive local government measures as very effective, relatively effective, somewhat effective, or ineffective.

[22] The questionnaire was hosted on Wenjuanxing (www.wjx.cn), a widely used survey platform in China for academic research. Respondents were recruited via targeted sampling to ensure geographic coverage across all 30 cities.

2.5 Descriptive Statistics

Table 1 presents summary statistics. Our final dataset comprises 957,091 transaction records from 47,540 residential communities. As shown in Panel A, the average total transaction price is 2.74 million RMB (approximately 392,368 USD). In addition, the average building size is 83 square meters (893.6 square feet) with 2.25 bedrooms; the typical unit is located on the median floor, and the average building age is 15 years. About 61% of homes have basic decoration, and over half are in elevator buildings. Roughly 64% of properties have a south-facing orientation. The mean distance to the coastline is 23.3 km, and the average elevation is 19.2 meters.

The dataset provides a granular view of housing demand by capturing both on-site viewing counts and online attention metrics for each listed property. These measures serve as direct proxies for buyer interest and are essential for identifying the underlying economic channels. As reported in Panel B of Table 1, properties receive an average of 15.6 offline viewings before being sold. Online engagement is also high, specifically, property listings are saved 14.1 times and receive 1,412.3 visits on average. This search and matching process results in a mean time-on-market of 230 days. On the supply side, the data track initial listing prices and the frequency of subsequent price revisions. On average, each property undergoes 2.2 price adjustments prior to a completed sale. These metrics reflect sellers' dynamic pricing strategies, allowing us to examine how they adjust pricing behaviors in response to sea level rise risks.

With respect to sea level rise risk, based on community-level inundation thresholds, we estimate that 34% of properties in our sample would be underwater with a one-foot sea-level rise scenario. This proportion rises sharply to 64% under a six-foot scenario. In comparison to the risk intensity of the United States, where only 30% of coastal houses are projected to be inundated with a six-foot scenario according to Bernstein, Gustafson, and Lewis (2019), the SLR risk exposure is more than doubled in China. This indicates the acute vulnerability of

the coastal urban areas in our study. These physical vulnerabilities translate into substantial economic exposure. Specifically, *SLR Exposure* metric in our coastal sample has a mean of 0.09 and a maximum of 0.26. This measure ranges from 0 to 1, where 1 corresponds to immediate inundation (i.e., zero discounting horizon) and 0 indicates no projected inundation under the considered scenarios. A mean value of 0.09 implies that, on average, the discounted value at the transaction date is 9% of the property value loss in the projected inundation year. Regarding the highest-risk category of 1-foot inundation threshold, the sample average remains as high as 0.08.

Figure 1 plots average sea level rise exposure and unit transaction prices of residential properties across coastal cities in our sample. The shaded areas represent city-level average SLR exposure, with darker colors reflecting higher levels of inundation risk. Stars represent the mean unit property price, with different colors indicating different average prices. For example, cities in Zhejiang province, such as Ningbo and Wenzhou, exhibit particularly high SLR exposure, followed by cities in the nearby Jiangsu province. The high density of population and the concentrated economic activity in these cities also lead to high property prices, which could amplify their vulnerability to inundation risk. Furthermore, over half of the 30 cities in our sample exhibit above-average projected SLR exposure, as shown in Internet Appendix Figure IA3. These patterns underscore the widespread vulnerability of China's coastal housing markets to climate risk and motivate further empirical investigation.

Figure 2 plots the time series of average unit transaction prices (per square meter) for areas high versus low sea level rise exposure. The red solid line shows average prices in areas where SLR exposure is above the sample average, while the blue dashed line denotes those below it. We observe that properties that are more exposed to SLR consistently trade at lower prices than those in low-exposure areas, indicating that the price discount associated with SLR exposure is persistent rather than driven by a specific period. Moreover, the magnitude of this discount has varied over time, increasing gradually from 2011 to 2018,

followed by a small decline since 2019. This trend may reflect growing public concern about climate change during the earlier period, and a shift in attention away from environmental issues in the aftermath of the pandemic. These patterns suggest a preliminary negative relationship between SLR exposure and housing prices over time.

Regarding the survey sample, the gender composition is nearly balanced (49.83% female, 50.17% male). The age distribution is concentrated in working-age cohorts most active in housing markets, with respondents aged 26–45 accounting for nearly 60% of the sample. The majority of respondents hold at least a bachelor's degree, consistent with the educational profile of China's major coastal cities. Detailed demographic distributions are reported in Internet Appendix Figure IA4.

3 Sea Level Rise Exposure and Housing Prices

In this section, we conduct empirical analyses to better quantify the impact of sea level rise risk on residential house prices. We start by introducing the baseline specification and summarizing the main empirical results. We then present robustness checks, including alternative measures of SLR exposure and pricing variables, as well as analyses of different market conditions.

3.1 Baseline Results

If homebuyers incorporate SLR risk into their purchase decisions, properties with greater near-term inundation exposure should command lower prices than observationally similar properties. To identify the effect of SLR exposure on house prices, we use the following regression specification as in equation (2):

$$LnP_{it} = \alpha_1 + \beta SLR\ Exposure_{i,t} + \lambda X_i + \gamma X_{gt-1} + \eta_{ced} + \delta_t + \varepsilon_{it}, \tag{2}$$

where LnP_{it} is the natural logarithm of the transaction price of property i at time t. Here, t refers to the date of contract execution. The key explanatory variable, $SLR\ Exposure_{i,t}$, is a continuous measure of the exposure to sea level rise as described in equation (1). Coefficient β captures how property transaction prices change with variation in SLR exposure.

Furthermore, following Chu, Duan, Yang, and Wang (2021) and Baldauf, Garlappi, and Yannelis (2020), we include a rich set of control variables to account for other important determinants of housing prices in China. Specifically, X_i denotes property-level attributes, including number of bedrooms, property size, building age, whether the property has elevator, floor level, types of decoration, and house window orientation. In addition, X_{gt-1} represents one year (month) lagged demographic and economic control variables, including logarithm of annual GDP, logarithm of annual population density, annual natural gas coverage percent and annual green area coverage percent at the city-level; proportion of urbanization at the provincial-level (Xiong, 2023); and monthly economic policy uncertainty index at the national-level (Glaeser, Huang, Ma, and Shleifer, 2017; Liu and Xiong, 2020). Please refer to the Appendix for detailed variable construction.

Coastal properties tend to be more valuable due to amenities such as ocean views, but they are also more vulnerable to environmental risk such as flooding and SLR. Therefore, we include distance to the coastline to control for potential omitted variables such as amenities preferences. Similarly, properties at higher elevations face lower inundation risk, making elevation another critical factor to consider. Furthermore, the city where the property locates also differ in geographic conditions and coastal flood defense infrastructure, which may also cause different impact of SLR exposure on housing market. To address these concerns, we follow Baldauf, Garlappi, and Yannelis (2020) and Bernstein, Gustafson, and Lewis (2019) and include the city $\times$ distance (distance-to-coast group) $\times$ elevation (elevation group) fixed effect, denoted as η_{ced}.[23] δ_t is the year-fixed effect to account for temporal variations

[23] Distance to the coast and elevation are each divided into five groups when constructing the fixed effects.

throughout the sample period.[24] We cluster the standard errors at the district level.

In such a setting of equation (2), we are comparing properties transacted in the same city and year, and are observationally equivalent in terms of location amenities, yet with variations in the sea level rise exposure. That is, even within the same city, distance, and elevation, granular micro-topographic features, hydrological connectivity, as well as localized land subsidence can drive differences in SLR exposures among properties. For example, consider properties A and B in the same city, as well as the same distance and elevation group. However, property A faces an open waterway due to proximity to unblocked waterways or lack of flood defenses, while house B is protected by a sea wall. The Climate Central model consider such differences and contribute to the variations in SLR exposure in our model.

Prior to the main investigation, we conduct a sensitivity analysis of house prices towards various inundation thresholds (1,3, and 6 feet) to explore the relevant economic significance. Following Bernstein, Gustafson, and Lewis (2019), we define inundation thresholds with the minimum SLR required to put a property underwater. Because properties projected to be inundated at higher SLR levels (e.g., 3 or 6 feet) are often already affected at lower levels (e.g., 1 or 3 feet, respectively), we therefore focus on the incremental rather than cumulative effect of exposure by excluding properties inundated at 1 foot (and 3 feet) from the 3 feet (6 feet) threshold. That is, a dummy variable $Underwater\ 3ft$ equals 1 if the property is inundated with only 3 feet sea level rise and 0 otherwise. We then perform the regression equation (2) with different inundation thresholds dummies to capture the incremental SLR risk exposure on property prices.

Columns (1), (2) and (3) of Table 2 report the coefficient estimates for the 1-, 3- and 6-foot inundation thresholds defined SLR exposures, respectively. $Underwater\ 1ft$ illus-

[24] We acknowledge that these fixed effects may not fully capture micro-level variation in coastal amenities and local topography. As a robustness check, we further re-estimate our baseline specification using finer fixed effects that interact street (similar to ZIP code) with distance-to-coast and elevation groups; the estimated SLR price discount remains robust. We retain the baseline fixed effects in the main specification because finer geographic fixed effects substantially reduce within-cell variation in $SLR\ Exposure\ (1ft)$, which weakens identification of the SLR price effect.

trates a negative and statistically significant coefficient of -3.09, suggesting that properties in the 1-foot flood zone experience a 3.1% price discount relative to non-exposed assets.[25] Nevertheless, coefficients for the 3-foot and 6-foot thresholds are economically negligible and statistically indifferent from zero.

The greater salience of near-term inundation risk, as captured by the one-foot threshold, appears to be a distinctive feature of our emerging-market setting. By contrast, studies based on developed markets emphasize exposure under a six-foot SLR scenario as an important driver of price discounts. For example, Bernstein, Gustafson, and Lewis (2019) document a significant 4.4% price discount with exposure at a 6-foot SLR level in the U.S. market. Our estimates for China instead indicate that price discounts are concentrated among properties facing more imminent inundation risk, with limited evidence of pricing at more distant scenarios. This difference suggests that settings from developed economies could not directly carry over to emerging markets, potentially reflecting differences in market structure and perception of long-term climate risks. Accordingly, in the remainder of the paper we focus on the one-foot inundation threshold. Specifically, the $SLR\ Exposure$ in equation (1) is constructed hereafter using only the 1-foot scenario.[26]

With that adjustment of SLR exposure, Table 3 reports the baseline estimation results from equation (2). In addition to the year fixed effect, the fixed effects in columns (1), (2), (3) and (4) are city, city × distance, city × elevation, and city × distance × elevation fixed effects, respectively.[27] Across all four settings, the coefficients of $SLR\ Exposure\ (1ft)$ are consistently negative and statistically significant, suggesting that sea level rise risks reduce the prices of exposed properties. According to column (4), a one-standard-deviation increase in SLR exposure is associated with a decrease in property prices by 1.54% ($= 0.14 \times 0.11$).[28]

[25] For ease of interpretation, we scale the variables of interest by 1/100, such that the reported coefficients represent the impact of a 100-unit change in the indicator.

[26] The overall results remain robust if all the 1-, 3- and 6-foot inundation thresholds are considered.

[27] Baseline results with the gradual inclusion of control variables are reported in Table IA2 of the Internet Appendix.

[28] Since we focus on the 1-foot scenario, 0.11 is the standard deviation of $SLR\ Exposure\ (1ft)$ as shown in Table 1.

The magnitude is economically significant, corresponding to an average loss of 42,258 RMB (approximately 6,051 USD) per property.

We also conduct the Oster (2019) test to evaluate the potential omitted variable bias. This test jointly considers coefficient movements and changes in model fitness as controls are added. A large increase in R^2 coupled with a stable treatment coefficient estimate suggests that selection on unobservables is unlikely to change the estimate, while substantial coefficient shifts indicate greater sensitivity. The statistics δ captures the relative strength of selection on unobservables versus observables required to explain away the estimated effect. In our setting, δ is equal to 2.16, implying that unobservables would need to be nearly two times as influential as observables to eliminate the effect. Therefore, the estimated relationship is unlikely to be driven by omitted variable bias.[29]

Consistent with Bernstein, Gustafson, and Lewis (2019) and Bakkensen and Barrage (2022), we document a significant price discount for properties with greater sea level rise exposure. Unlike these studies, which rely on binary indicator based on six-foot inundation threshold, our SLR exposure is continuous and captures time-to-inundation given one-foot SLR. Higher SLR exposure implies more imminent inundation risk. Our estimates suggest that Chinese homebuyers discount near-term inundation risk more strongly than risk projected further into the future. Moreover, our *SLR Exposure* is forward looking and reflects homebuyers' expectations about future inundation, differing from Zhao, Yang, and Zhang (2025), which uses realized flood events as shocks.

[29] The test is estimated following this specification, $\beta^* = \tilde{\beta} - \delta(\dot{\beta} - \tilde{\beta})\frac{R_{\max} - \tilde{R}^2}{\tilde{R}^2 - \dot{R}^2}$, where β^* denotes the bias-adjusted treatment effect. $\dot{\beta}$ ($\dot{R}^2$) and $\tilde{\beta}$ ($\tilde{R}^2$) are the treatment coefficient (R^2) from the baseline- and full-control specifications, respectively. $R_{\max}$ is an assumed upper bound on the attainable R^2 (often set to 1). The parameter δ measures the degree of selection on unobservable relative to observables required to eliminate the estimated effect.

3.2 Robustness Tests

We perform a series of tests to verify the robustness of our results. First, we consider two alternative measures of sea level rise exposure and report the results in the left panel of Table 4. The timing measure in column (1) captures the immediacy of inundation risk, defined as the inverse of the time difference between the housing transaction year and the projected inundation year (i.e., $1/(T_{u_i} - t_i)$). The linear measure in column (2) assigns values of three, two, and one to properties projected to be inundated under 1-, 3-, and 6-foot SLR scenarios, respectively. Consistent with the baseline findings, both alternative measures of SLR risk illustrate significantly negative coefficients, suggesting a larger price discount for properties facing higher SLR exposure.

In columns (3) and (5) of Table 4, we follow Bernstein, Gustafson, and Lewis (2019) and Agarwal, Qin, Sing, and Zhan (2025) and incorporate more granular fixed effects, wherein the year fixed effects are replaced with year–quarter, year–month fixed effects, respectively. Furthermore, to address potential issue that price trends might be mechanically city-specific, in column (5), we include city×year×distance×elevation fixed effects to absorb granular local trends in housing markets. Across specifications, the estimated coefficients on *SLR Exposure* $(1ft)$ remain negative and statistically significant, with magnitudes comparable to the baseline.

Secondly, we use alternative dependent variables to examine the pricing of SLR risk, with results reported in Table 5. The left panel reports estimates using unit transaction prices, and the right panel uses listing prices. Across all specifications, the coefficients on SLR exposure are negative and statistically significant, consistent with the baseline results and indicating that SLR-exposed properties trade at a discount in both transaction and listing prices.[30]

[30] We also evaluate these findings using alternative SLR exposure measures in Table IA3 and our results remain qualitatively the same.

Thirdly, we examine whether the SLR price discount varies across different market conditions. Since China's housing prices exhibit cyclical movements, peaking in 2021 and declining thereafter,[31] we divide the sample into two sub-periods: up periods with rapid house price growth (2011–2013, 2016–2021) and down periods with price declines (2014–2015, 2022–2023), and perform sub-sample regressions of equation (2). Columns (1) and (2) of Table 6 report the estimates, which show consistently negative and statistically significant coefficients on SLR exposure. In addition, because in-person property visits were severely restricted during China's three-year COVID lockdown, the impact of SLR exposure on housing prices might have been muted. We therefore conduct the regression analysis by excluding the lockdown period of 2019 to 2022. Columns (3) and (4) of Table 6 show the estimate with and without the lockdown period. Across all four sub-sample settings, our results remain robust, suggesting that SLR price discounts in the housing market are robust across different market conditions.

Finally, a substantial literature suggests that Chinese households function as short-horizon, return-driven investors rather than long-term owners. For instance, Fang, Gu, Xiong, and Zhou (2016) document that buyers frequently expect annual price appreciation of 8% to 15%, hold properties for less than ten years on average, and trade primarily on speculative motives. These behavioral patterns suggest that households may discount long-run outcomes at rates exceeding the 5% level employed in our primary specification. To evaluate the robustness of our results, we re-estimate the baseline model using a range of alternative rates: 3%, 5%, 7%, 10%, and 15%. As shown in Figure IA6 of the Internet Appendix, the estimated coefficients for $SLR\ Exposure$ $(1ft)$ remain negative and statistically significant. These results confirm that our baseline findings are not sensitive to the choice of discount rate.

[31] Please refer to Figure IA5 in Internet Appendix for the time series of China's average house price.

4 Channels and Mechanisms

Price discounts are the equilibrium outcome of housing market adjustments and therefore provide limited information about the channels through which sea level rise risk is priced. In this section, we investigate the mechanisms underlying the SLR-related price discount. We first examine buyers' interest and sellers' listing behavior to understand how SLR exposure affects search activity, seller repricing, and market liquidity. We then study the impact of the share of sophisticated buyers and relocation constraints. Finally, we evaluate the role of prior disaster experience and public attention to sea level rise.

4.1 Buyers' Interest and Sellers' Behavior

As emphasized by Gargano, Giacoletti, and Jarnecic (2023), housing markets are segmented, and transactions occur through a search-and-matching process. Building on this view, the SLR price discount may operate through the search and matching process between buyers and sellers in the housing market. The effective demand for properties with greater inundation risk would be lower with reduced searching activities from buyers. This in turn deteriorates market liquidity for such properties and makes them take longer to complete a transaction. Sellers respond to reduced demand by adjusting listing prices more frequently during the listing period in order to facilitate potential matches.

To test this channel, we draw on transaction-level measures that capture buyers' activity, sellers' responses, and liquidity outcome. Following Addoum, Cong, and Zhou (2025), we use online listing-page views and saves, as well as onsite home viewings, to proxy for buyers' search interest and purchase intent. On the supply side, Chu, Duan, Yang, and Wang (2021) show that listing price revisions prior to sale reflect sellers' expectations and bargaining positions. Accordingly, we use the number of listing price adjustments as a measure of seller response. Finally, following Jiang, Kotova, and Zhang (2025), we measure market

liquidity using the listing time on market. To mitigate transaction-level noise and capture market-wide responses, we aggregate these measures to the community-month level.

Columns (1) to (3) of Table 7 report the estimated effects of sea level rise exposure on buyers' activity. Across all three specifications, the coefficients of *SLR Exposure* $(1ft)$ are negative and statistically significant, indicating lower buyer engagement for more SLR exposed properties. Economically, a one-standard-deviation increase in SLR exposure is associated with a 0.8% decline in listing page views, a 1.4% decline in listing page saves, and a 1.0% decline in onsite property viewings. These results suggest a clear demand shift away from properties located in high-SLR-exposed areas.

Regarding the sellers' response and housing market liquidity, we employ the Poisson pseudo-maximum likelihood (PPML) regression, given these outcomes (i.e., the number of price adjustments and the number of days of property on the market) are counts. Column (4) of Table 7 shows that sellers of more SLR-exposed properties adjust listing prices more frequently. Evaluated at the sample mean of *SLR Exposure* $(1ft)$ (0.08), the estimates imply an increase of approximately 0.56% in price adjustments $(= 0.07 \times 0.08)$, consistent with sellers responding to weaker buyer demand. Column (5) of Table 7 shows that SLR exposure also reduces liquidity: properties in more exposed areas remain listed for longer. A coefficient of 0.05 implies that a property with average SLR exposure stays on the market about 0.92 days longer than a comparable non-exposed property.[32] These results suggest lower buyer interest, more active seller repricing, and weaker liquidity for SLR-exposed properties. Our finding aligns with Keys and Mulder (2026), who argue that heightened SLR risk salience reduces market liquidity.

[32]This is calculated as $229.52 \times \left(e^{0.05 \times 0.08} - 1\right) \approx 229.52 \times 0.0040 \approx 0.92$, where 229.52 and 0.08 are the sample means of time on market and *SLR Exposure* $(1ft)$, respectively.

4.2 Sophisticated Buyers

The capitalization of climate risk may depend on the sophistication of marginal buyers. A common proxy for sophisticated buyer in the literature is whether the buyer is an investor rather than an owner-occupier, since non-owner-occupiers are more likely to treat housing purchases as financial investments and to price risks through expected resale values and market liquidity. This mechanism is particularly relevant in China, where Fang, Gu, Xiong, and Zhou (2016) document pervasive housing speculative activities. Although these speculators may have shorter holding horizons, long-run risks such as sea level rise can still be reflected in current prices if they anticipate that exposed properties will command lower resale prices or become harder to sell in the future. We therefore use measures of speculative activities to proxy for the extent of sophisticated-buyer participation in the housing market and examine its impact on the pricing of sea level rise risk.

To capture housing speculation activities, we consider three different measures. Firstly, we follow Wu, Shi, and Tang (2025) and use the *Non-five-year ownership* ratio, which indicates how quickly a given property is traded and how many properties a family has (Mian and Sufi, 2022; Gao, Sockin, and Xiong, 2020). *Five-year ownership and only property* is a regulatory terminology that indicates the given property is the family's only property and its ownership exceeds at least five years.[33] That is, if a property does not satisfy the *Five-year ownership and only property* category, it suggests the house is bought and sold within 5 years and is one of multiple properties of the owner, which has a higher tendency to be a speculative transaction. Therefore, for each district, we calculate the monthly ratio of housing transactions that do not meet the *Five-year ownership and only property* criteria and term this variable as *Non-five-year ownership*. A higher ratio is associated with a higher level of housing speculation.

[33] *Five-year ownership and only property* is a crucial criteria in China's housing transaction system. If the sale property is the family's only property and the ownership exceeds five years, the transaction is subject to a waiver of taxation, including a 5% on the full sale price Value-Added Tax; 30% to 60% Land Appreciation Tax; and 20% personal income tax on the difference between the sale price and the purchase price.

Secondly, we also use the *Price-to-rent ratio* to capture the investment value of owning a property (Brunnermeier and Julliard, 2008; Himmelberg, Mayer, and Sinai, 2005). It is calculated as the average transaction price per square meter divided by the average rent price per square meter within a city-month. A persistently high price-to-rent ratio suggests that housing prices are deviating from underlying rental fundamentals, likely to be driven by speculative expectations. Thirdly, as a robust measure, we calculate the *Price-to-income ratio* to capture the extent of housing affordability (Himmelberg, Mayer, and Sinai, 2005). A higher ratio indicates that housing prices are elevated relative to residents' purchasing power, suggesting possible speculative overpricing. It is computed as the average transaction price per square meter divided by per capita income in a given city-year.

Empirically, we separate the sample into high- and low-speculation groups using the median of each proxy. Columns (1)-(2), (3) -(4), (5)-(6) of Table 8 report sub-sample estimates based on *Non-five-year ownership*, *Price-to-rent ratio*, and *Price-to-income ratio*, respectively. Across all three measures, the estimated SLR price discount effects are consistently larger and statistically significant in markets with high speculation (as in columns (2), (4), and (6)). The differences between the high- and low-speculation coefficients are statistically significant for each indicator. For example, in high *price-to-income* areas, the coefficient on SLR exposure is -0.22 (columns (6)). That is, for a property with mean SLR exposure, it suffers from an average loss of 48,294 RMB (approximately 6,916 USD) in high-speculation areas. However, the coefficient for low speculation areas is -0.05 and yet significant (column (5)).

These results suggest that sea level rise risk is more pronounced in markets with higher speculative activity, where marginal transactions are likely to be shaped by sophisticated buyers. These speculative buyers are considerably more sensitive towards property-related risks with beliefs that higher sea level rise exposure yields expected lower resale values, leading to larger price discount effect of SLR. This finding aligns with Bernstein, Gustafson,

and Lewis (2019) that in the U.S. housing market, where SLR price discounts are mainly driven by sophisticated investors.

4.3 Relocation Constraints

Besides housing speculation, limited relocation options can shape how households price long-horizon climate risks. When housing supply is inelastic due to regulatory and geographic constraints, moving away from high coastal-risk locations becomes more difficult.[34] Cities situated on plains generally have more developable land than those surrounded by mountains or intersected by rivers. Households in cities with inelastic land supply face fewer within-city substitution opportunities and are unlikely to consider climate risks when valuing properties.[35] Accordingly, we expect the SLR-related price discount to be weaker in cities with higher relocation constraints.

To capture *relocation constraints*, we construct a city-level measure of land supply constraints. We collect annual data on residential and total construction land from the China Statistical Yearbook. Motivated by Shi (2022), who measures land constraints using the share of land unavailable for construction within a city's administrative area, we modify the measure by computing the non-residential land share, defined as one minus the ratio of residential land to total construction land. A higher non-residential share implies a tighter constraint on land availability for residential development, and thus more limited within-city substitution opportunities for households. We then perform subsample regressions by splitting cities at the sample median of the land-constraint measure. For robustness, we also separate the samples by comparing cities in the bottom and top 30 percents of the

[34]This mechanism relates to work showing that geographic constraints shape housing supply elasticities (Saiz, 2010), that land and housing supply constraints affect housing price dynamics in China (Shi, 2022), and that limited housing supply and mobility frictions shape housing market outcomes and household choices (Mian and Sufi, 2022).

[35]Relocation across cities is possible, but it is subject to substantial frictions related to employment opportunities, children's schooling that are tied to China's household registration system (hukou), family networks, and housing transaction costs. These frictions can limit households' ability to mitigate long-horizon climate risks through migration.

cross-sectional distribution of the non-residential land share.

Table 9 reports the estimated coefficients. Columns (1) and (2) present estimates for subsamples of loose and tight relocation constraints, respectively. In column (1), the coefficient on *SLR Exposure* ($1ft$) is -0.17 (t-statistic = -3.26), implying that a 10-percentage-point increase in SLR exposure is associated with a 1.7% lower transaction price in cities with more abundant residential land. However, the coefficient in column (2) is only -0.09 (t-statistic = -1.31) and is not statistically significant, indicating a weaker link between SLR exposure and prices in more land-constrained cities. We obtain similar results when focusing on the tails of the distribution. Column (3) reports estimates for the bottom 30 percent (the 1st to 30th percentiles), while column (4) reports results for the top 30 percent (the 70th to 100th percentiles). The SLR-related price discount is again concentrated in cities with lower relocation constraints, and the difference in coefficients across groups is statistically significant. Overall, these findings suggest tighter land supply constraints limit within-city substitution and relocation options, leading to weaker pricing of long-term climate risk in the housing market.

4.4 Salience of Climate Risk

Sea level rise is a slow-moving risk and might not be persistently salient to households. Consequently, the extent to which SLR is capitalized into housing values likely depends on local information and experiences that make the risk more visible. This salience channel may be particularly important in China, where property-level climate-risk disclosure is limited and flood-insurance coverage remains low. Motivated by these considerations, we examine two mechanisms that plausibly increase climate-risk awareness, which are the exposure to physical climate shocks and the heightened public attention to climate risk.

Households' response to physical climate shocks. Evidence from credit markets in Correa, He, Herpfer, and Lel (2026) suggests that climate risk is most strongly reflected in

asset prices following direct experience with hurricanes and floods. Analogously, recurrent extreme-weather events could increase households' awareness of SLR risk and hence strengthen SLR-related price discounts in housing markets. In particular, we focus on the typhoon, the most frequent and economically salient shocks affecting China's coastal cities. We obtain typhoon incidence data from the China Meteorological Administration spanning the past 70 years and use these data to identify cities with frequent typhoon exposure in three coastal provinces, namely Fuzhou, Xiamen, and Zhangzhou in Fujian; Dongguan, Guangzhou, Huizhou, Jiangmen, Shenzhen, Zhanjiang, Zhongshan, and Zhuhai in Guangdong; and Haikou in Hainan.[36] Properties located in these cities are categorized as being in the frequent-typhoon zone, while others are classified as infrequent-typhoon zone. We then estimate equation (2) separately for these two subsamples. Furthermore, because Guangdong has historically experienced the highest number of typhoon events, we also conduct a complementary test that compares Guangdong to all other coastal provinces.[37]

Table 10 reports the subsample estimates. Across all specifications, the coefficient on *SLR Exposure* ($1ft$) is negative and statistically significant, confirming a robust SLR-related price discount. However, the magnitude of the effect is substantially larger in cities with frequent typhoon exposure (column (2)) and in Guangdong Province (column (4)). For example, a 10-percentage-point increase in SLR exposure is associated with a 3.9% decline in property prices in typhoon-prone areas, compared with a 1.2% decline in areas with infrequent typhoon exposure. These patterns indicate that the capitalization of SLR risk is stronger when climate risk is more salient, consistent with repeated shocks heightening awareness of long-horizon risks in the housing market.

Attention to climate risk. While physical shocks can trigger immediate reassessments of SLR risk through direct experience, households' beliefs and attention to climate change

[36] Please see https://www.cma.gov.cn/2011xzt/20160518/20190809/201908/t20190809_532518.html for detailed information.

[37] Huang, Cheng, and Zhang (2025) document the negative effect of sea level rise on housing prices in Guangdong Province.

also shape how long-horizon risks are perceived and priced. Baldauf, Garlappi, and Yannelis (2020) show that SLR-related price discounts are concentrated in areas with stronger climate-change beliefs, and Bakkensen, Phan, and Wong (2025) find that discounts are larger when homebuyers are more climate pessimistic. Building on these insights, we examine whether greater public attention to climate risk amplifies the price discount associated with SLR exposure.

To measure public attention to climate risk, prior studies commonly use online search intensity—for example, the Google Search Volume Index in the United States (e.g., Choi, Gao, and Jiang, 2020). We follow this approach in the Chinese setting and use the Baidu Search Index as a proxy for public attention. Specifically, we use two search indices for the terms *climate change* and *sea level rise*, respectively. We construct the attention measure at the city-month level by scaling each index with city-year population, which yields a comparable per-capita attention indicators across cities. As shown in Internet Appendix Figure IA6, attention to climate risk varies substantially across cities. The distribution is right-skewed, suggesting that concern is moderate in most locations but markedly higher in a subset of cities.

For the empirical analysis, we divide cities into high- and low-attention groups based on the median value of each measure and re-estimate our baseline specification within each sub-sample. Table 11 reports the results. In columns (2) and (4), which correspond to the above-median attention sub-samples, the coefficients on SLR exposure are negative and statistically significant. For example, column (2) implies that in high-attention cities, a one-standard-deviation increase in SLR exposure is associated with approximately 2% lower transaction price, about 0.6 percentage points larger in absolute value than the corresponding full-sample estimate. The difference in coefficients between the high- and low-attention groups is statistically significant for both attention indicators. Internet Appendix Figure IA7 provides a graphical illustration. Prices exhibit a clear downward relationship with SLR exposure in

high-attention regions, whereas the relationship is substantially weaker and slightly positive in low-attention cities. These results suggest that greater public attention is associated with stronger capitalization of SLR risk in housing prices, consistent with salience and beliefs amplifying climate-risk discounts in real estate markets.

5 Local Government Climate Adaptation Efforts

In response to sea level rise risks, governments often implement various adaptation strategies, including ex-ante prevention, in-event management, and ex-post recovery. However, the extent to which such measures offset the negative impact of SLR remains an open question. This question is particularly relevant in China, where coastal flood protections are provided primarily through public infrastructure rather than private insurance markets, and where the credibility, execution, and fiscal backing of these investments vary widely across cities. In this section, we examine whether local adaptation measures alleviate the SLR-related price discount from several complementary angles. We first use original survey data to assess whether public awareness of adaptation efforts moderates the pricing of SLR risk. We then distinguish between announced and implemented adaptation projects and test whether residents' perceived effectiveness of these measures conditions the market response. Finally, we explore how local fiscal capacity shapes the credibility and impact of adaptation interventions.

5.1 ublic Awareness of Adaptation Efforts

Before examining whether the form of adaptation matters for the housing market response, we first study whether public awareness of these measures shapes the pricing of SLR risk. If adaptation measures are to influence market perceptions, local residents must first be cognizant of these efforts. Greater awareness of adaptation may reduce households' per-

ceived exposure to SLR, thereby attenuating the associated price discount. Conversely, in cities where residents have limited awareness of local adaptation actions, SLR risk remains fully salient and should exert a stronger negative effect on property values.

To test this hypothesis, we draw on the city-level survey responses described in Section 2.4. We consider two dimensions of awareness. First, we use the share of respondents who reported that they know, know a little, or have heard about local government measures addressing sea level rise or coastal flooding, such as seawalls, flood barriers, or related protective infrastructure. Second, we use the share of respondents who reported that they know, know a little, or have heard about seawall construction plans or flood-control plans released by local governments over the past decade. For each dimension, we classify cities with awareness shares above the sample median as high-knowledge groups and the remaining cities as low-knowledge groups. We then re-estimate the baseline specification of equation (2) within each sub-sample and test for differences in coefficients across groups.

Table 12 reports the results. In the left panel, which uses awareness of existing adaptation measures as the grouping variable, the coefficient on $SLR\ Exposure$ $(1ft)$ is -0.09 (t-statistic $= -1.34$) and statistically insignificant in the high-awarness group (column (2)), compared with -0.15 (t-statistic $= -2.80$) and significant in the low-knowledge group (column (1)). The difference between the two coefficients is statistically significant (p-value $= 0.02$), suggesting that the SLR-related price discount is meaningfully attenuated in cities where residents are more aware of local adaptation actions. In the right panel, the grouping variable is awareness of long-term adaptation plans. The coefficient is -0.12 (t-statistic $= -2.06$) for the high-awareness group (column (4)) and -0.14 (t-statistic $= -3.01$) for the low-knowledge group (column (3)), with the difference again statistically significant (p-value $= 0.04$)

These results suggest that public awareness of local government adaptation partially mitigates the capitalization of SLR risk into property prices, with the attenuation substan-

tially larger for awareness of concrete, implemented measures than for long-term plans alone. This asymmetry is consistent with observable adaptation investments being more credible to market participants than plans whose execution remains uncertain. The persistence of a significant negative coefficient even in the high-awareness group under the plans dimension motivates our subsequent analysis of announced versus implemented adaptation projects.

5.2 Announced vs. Implemented Adaptation Projects

China has long faced coastal flooding caused by storm surges, typhoons, and tidal dynamics. At the same time, rapid coastal urbanization has increased the value of assets exposed to these hazards. In response, the central government has elevated coastal defense on the national policy agenda, such as launch of the 2017 National Seawall Construction Plan. Under this policy framework, local governments are incentivized to upgrade seawalls and invest in complementary flood-management infrastructure. If these adaptation measures are effective, they should mitigate perceived SLR risk and, consequently, attenuate the price discount observed for exposed properties in jurisdictions that undertake such actions.

To test this hypothesis, we construct a comprehensive dataset of local adaptation policy events that captures announcement dates, implementation start dates, project scope, and associated government actions. We hand-collect these records from local government announcement bulletins and official news releases. We further supplement them with reports from local newspapers. We differentiate between (i) policy announcements that describe intended adaptation plans and (ii) adaptation projects that are subsequently implemented (e.g., seawall construction or upgrades). Because cities adopt these measures at different times and with varying intensity,[38] we estimate the policy effect using a staggered difference-

[38] Internet Appendix Table IA1 provides detailed information on the adaptation strategies implemented by each coastal city.

in-differences specification:

$$LnP_{it} = \alpha_2 + \theta \cdot Treat_i \times Adapted_{ic,t} + \kappa X_i + \rho X_{g,t-1} + \mu_{cde} + \tau_t + \zeta_{i,t}, \tag{3}$$

where $Treat_i$ equals one if property i is located in an area exposed to SLR and zero otherwise. $Adapted_{ic,t}$ is an indicator that equal to one if, prior to time t, city c (where property i is located) has either announced an adaptation plan or initiated an adaptation project. X_i and $X_{g,t-1}$ denote the control variables as in equation (2). μ_{cde} denotes city $\times$ distance-to-coast group $\times$ elevation group fixed effects, and τ_t denotes year fixed effects.

The coefficient of interest, θ, measures the extent to which local adaptation efforts attenuate the price discount for SLR-exposed properties. We estimate the effects of policy announcements and project implementation separately. In China, large-scale coastal defense investments typically involve lengthy planning, approval, and construction phases. As a result, an announcement often primarily signals a local government's alignment with national policy priorities rather than the near-term delivery of risk-reducing infrastructure. Market participants generally cannot infer implementation progress, construction quality, or completion timelines from announcements alone, leaving substantial uncertainty about the ultimate effectiveness of the announced measures. In contrast, implemented projects are observable and more likely to be viewed as credible risk-mitigation actions. Accordingly, completed as well as actively executed adaptation investments should reduce expected SLR-related losses by strengthening beliefs about local coastal protection and thereby moderating the SLR-related price discount.

Table 13 reports the estimated coefficients from equation (3) separately for adaptation projects that are implemented (columns (1) and (3)) and for announcements without subsequent implementation (columns (2) and (4)). Columns (1) and (2) in the left panel report results for the full sample and show no significant average effect, consistent with adaptation being most relevant in locations with meaningful SLR exposure. Columns (3) and (4) in

the right panel restrict the sample to SLR-exposed cities. Within these areas, implemented adaptation projects are associated with a positive and statistically significant interaction coefficient of 0.11 (t-stat = 4.46, column (3)), suggesting that implementation materially attenuates the SLR-related price discount relative to cities that only announce plans. By contrast, announcements without subsequent execution yield an insignificant coefficient in column (4).

The insignificance of announcement does not imply that SLR risks are inherently immitigable. Rather, announcements may convey limited information about whether, when, and how effectively adaptation will be delivered. In contrast, the significant results for implemented projects suggest that the market responds to credible, observable risk-reduction actions. Hence, it is really about whether adaptation will be carried out by local government, not that the sea level rise effect is not manageable. Overall, the evidence suggests that adaptation measures attenuate SLR-related valuation losses in exposed areas, and that this effect is driven by implementation rather than by announcements alone.

To address concerns about bias in staggered-treatment settings, we also employ the multi-period DID estimator of Callaway and Sant'Anna (2021). We define not-yet-treated units as comparison controls and implement a doubly robust procedure that combines outcome regression with inverse-probability weighting based on a propensity-score model. Internet Appendix Table IA4 reports the corresponding estimates and corroborates our main finding: only implemented projects attenuate the SLR-related price discount. Among properties in SLR-exposed areas, the estimated ATT for implemented projects is positive and statistically significant (0.14, p-value = 0.04), whereas the estimated effects of announcements remain insignificant. We further examine the timing of the implementation effect using an event-study design for SLR-exposed areas that undertake adaptation projects. Figure 3 plots the dynamics estimates of θ of equation (3). The interaction coefficients become significantly positive only after adaptation actions are executed, consistent with markets responding to

observable risk-mitigation investments rather than policy intent alone.[39]

As an additional test, we examine a second nationwide initiative aimed at enhancing flood resilience: the Sponge City pilot program launched in 2015, which promotes urban drainage upgrades and rainwater retention through improved infiltration and storage.[40] Using a specification analogous to equation (3), Internet Appendix Table IA7 reports positive and statistically significant interaction coefficients, indicating that the SLR-related price discount is attenuated in pilot cities. The evidence suggests that investments in flood-management infrastructure reduce perceived exposure and mitigate the negative capitalization of SLR risk into property values.

Evidence from developed economies indicates that public adaptation investments can mitigate SLR-related price discounts in housing markets. Agarwal, Qin, Sing, and Zhan (2025) document such effects in Singapore, Benetton, Emiliozzi, Guglielminetti, Loberto, and Mistretta (2025) provide evidence from Venice, and Liu, Constantz, Hale, and Beck (2025) report related patterns for Florida. Emerging markets, however, may differ along key dimensions—including institutional capacity, policy credibility, and fiscal constraints—that shape both the provision and perceived effectiveness of adaptation. Relatedly, Hsiao (2025) highlight the potential for moral hazard associated with government-led adaptation in Jakarta, although they do not directly study housing-price responses to SLR exposure. Against this backdrop, our findings from China emphasize the importance of implementation: housing markets respond to observable, realized adaptation projects, whereas announcements that are not followed by execution have little effect.

[39] We also use listing prices and unit transaction prices as alternative dependent variables and conduct event studies. Estimation results and time-varying dynamics are reported in Internet Appendix Table IA5 and Figure IA8 for listing price, and in Internet Appendix Table IA6 and Figure IA9 for unit transaction price.

[40] Please see https://www.gov.cn/zhengce/content/2015-10/16/content_10228.htm for the guiding opinions on promoting the construction of Sponge Cities, issued by the General Office of the State Council (in Chinese). Data source of pilot cities: https://jjs.mof.gov.cn/tongzhigonggao/201504/t20150402_1211835.htm and https://jjs.mof.gov.cn/zxzyzf/csgwzxzj/201604/t20160425_1964216.htm (in Chinese).

5.3 Perceived Effectiveness of Adaptation

The previous subsection establishes that only implemented adaptation projects, not announcements, significantly attenuate the SLR-related price discount. A natural follow-up question is whether the effectiveness of implementation depends on how credible or effective residents perceive these measures to be. If market participants believe that adaptation projects are well designed and genuinely reduce coastal flood risk, the price-attenuating effect of implementation should be stronger. Conversely, in cities where residents are skeptical of adaptation effectiveness, even implemented projects may fail to restore confidence in property values.

To test this mechanism, we exploit city-level variation in residents' beliefs about the effectiveness of local government adaptation measures. Using the survey data described in Section 2.4, we identify the share of respondents in each city who rate local government measures as "very effective" or "relatively effective" in addressing sea level rise or coastal flooding. Cities with effectiveness shares above the sample median are classified as the high-belief group, while the remaining cities form the low-belief group. We then re-estimate the staggered DID specification of equation (3), restricting the adaptation measure to implemented projects, and compare the interaction coefficient $Treat \times Adapted$ across the two groups.

Table 14 reports the results. The left panel presents estimates for the full sample, and the right panel restricts the sample to SLR-exposed areas. In the full sample, the interaction coefficient is 0.01 (t-statistic = 1.20) and statistically insignificant in the low-belief group (column (1)), whereas it is 0.09 (t-statistic = 2.52) and significant in the high-belief group (column (2)). The difference between the two coefficients is 0.08 (p-value = 0.03). Within SLR-exposed areas, a similar pattern emerges. The coefficient is -0.01 (t-statistic = 1.50) and insignificant in the low-belief group (column (3)), while it is 0.08 (t-statistic = 2.18) and significant in the high-belief group (column (4)). The group difference is 0.09 (p-value

$= 0.04$).

These findings demonstrate that the market response to adaptation implementation is mediated by perceived credibility. Implemented projects significantly attenuate the SLR price discount only in cities where residents believe the measures are effective; in skeptical cities, the effect is negligible even when infrastructure has been built. This reinforces a central theme of our analysis: credible adaptation, shaped by both physical implementation and public confidence, is the critical channel through which government action affects climate-related housing pricing.

5.4 Local Fiscal Condition

Local governments bear primary responsibility for financing and delivering coastal protection infrastructure. Their ability to undertake large-scale adaptation, however, depends critically on fiscal capacity and local financing conditions. Greater fiscal capacity should facilitate timely project execution and ongoing maintenance, thereby strengthening the credibility of adaptation commitments. In contrast, fiscal stress can increase the likelihood of delays, underfunding, or partial completion. Accordingly, cross-sectional differences in local fiscal capacity should shape how investors perceive the effectiveness of adaptation and, in turn, the extent to which adaptation attenuates the SLR-related price discount.

We use two measures of local fiscal conditions. The first is the local fiscal deficit, defined as the difference between general public budget expenditures and revenues, scaled by city-year GDP (Chen, Chen, Cong, Gao, and Ponticelli, 2025). Larger deficits imply tighter fiscal space and may weaken confidence in a local government's ability to finance and maintain adaptation investments. The second measure is based on bond issuance by local government financing vehicles (LGFVs). LGFVs are state-owned entities that finance infrastructure investment on behalf of local governments and often rely on implicit government support (Chang, Wang, and Xiong, 2026). Because LGFVs are closely linked to local fiscal conditions,

their credit spreads are widely used as proxies for local fiscal health and borrowing costs (Hu, Li, Yang, and Zhang, 2025). For each city, we compute the average monthly issuance spread of seven-year LGFV bonds relative to same-maturity local government yields. Higher spreads indicate greater perceived credit risk and weaker fiscal capacity.[41]

Empirically, we restrict the sample to SLR-exposed properties located in cities that have initiated the implementation of adaptation projects and estimate equation (3) separately across subsamples defined by the median of each fiscal measure. Table 15 illustrates the estimation results, where the left panel reports results based on fiscal deficit, while the right panel is that of the LGFV spread. In columns (1) and (3), which correspond to cities with stronger fiscal capacity (below-median deficits and below-median LGFV spreads), the interaction term $Treat \times Adapted$ is positive and statistically significant, with coefficients of 0.05 ($t = 3.89$) and 0.05 ($t = 3.11$), respectively. This evidence suggests that, where fiscal capacity is strong, implemented adaptation projects meaningfully attenuate the SLR-related price discount. In contrast, in columns (2) and (4), which correspond to fiscally weaker cities (above-median deficits or higher borrowing costs), the interaction coefficients are statistically insignificant. Overall, the results indicate that housing markets capitalize adaptation efforts primarily when local governments have sufficient fiscal capacity to make implementation—and continued maintenance—credible.

6 Conclusion

Evidence on how climate risks are capitalized into housing prices remains limited in emerging economies, where governments face competing policy priorities over adaption to climate changes. This study examines the impact of sea level rise risk on housing transactions in the world's largest developing country. We find that properties with greater exposure to sea

[41] Because only a small fraction of LGFV bonds is actively traded, we use issuance spreads rather than secondary-market spreads. LGFV issuance in coastal cities is concentrated at 5-, 7-, and 10-year maturities; we focus on the 7-year maturity to maximize coverage in the merged sample.

level rise risk transact at significantly lower prices than less-exposed properties. Importantly, this price discount concentrates at the near-term inundation thresholds, such as the one-foot SLR scenario. This price discount is primarily driven by weaker buyer demand and more frequent price revisions by sellers in high-risk areas. Moreover, the magnitude of the effect varies systematically with both market and environmental conditions, and is more pronounced in markets characterized by high speculative activity, abundant land supply, frequent typhoon exposure, and greater public awareness of sea level risks.

We further investigate the role of local government adaptation in shaping housing market responses to climate risk. Our results indicate that only implemented adaptation projects alleviate the adverse price effects associated with sea level rise, whereas policy announcements alone have no discernible impact. In addition, the effects of adaptation are stronger in cities with greater fiscal capacity. Taken together, our findings provide new evidence on the capitalization of long-term climate risks in housing markets in an emerging economy and highlight the importance of credible, proactive adaptation actions in enhancing local climate resilience.

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Appendix: Variable Definitions

This table reports the name, description, frequency, and source of variables used in this study.

Name	Description	Data cell	Source
Housing Transactions			
Transaction price	Transaction price of house i at deal date t (RMB).	Property	Lianjia
Listing price	Listing price of house i at deal date t (RMB).	Property	Lianjia
Unit price	Transaction price per square meter of house i at deal date t (RMB).	Property	Lianjia
Property Attributes			
Number of bedrooms	Number of bedrooms of a property.	Property	Lianjia
Size	Size of a property.	Property	Lianjia
Age	Difference between the transaction year and the year the property was built.	Property	Lianjia
Floor level	Categorical variable equal to 1 for low floors, 2 for middle floors, and 3 for high floors.	Property	Lianjia
Decoration	Categorical variable equal 1 for 'Other', 2 for 'No decoration', 3 for 'Basic decoration', and 4 for 'Intensive decoration'.	Property	Lianjia
Elevator	Dummy equal to 1 if the house has an elevator, and 0 otherwise.	Property	Lianjia
Window orientation	Dummy variable equal to 1 if the window faces south, and 0 otherwise.	Property	Lianjia
Distance	Distance in meters from a property to the nearest coastline, grouped into five groups for fixed effects.	Property	Calculated based on latitude and longitude
Elevation	Elevation in meters of the area where a property is located, grouped into five categories for fixed effects.	Property	Calculated based on latitude and longitude
Buyers' and Sellers' Behavior			
Onsite viewings	Number of in-person visits to a property.	Community × Month	Lianjia
Listing page saves	Number of times a property's online listing is bookmarked saved by users.	Community × Month	Lianjia
Listing page views	Number of times a property's online listing page is viewed by users.	Community × Month	Lianjia
#Price adjustments	Number of listing price changes for a property.	Community × Month	Lianjia
Time on market	Number of days a property is listed before being sold.	District × Month	Lianjia

Continued on next page

Appendix: Variable Definitions-Continued

Name	Description	Data cell	Source
Sea Level Rise Exposure			
Underwater $1ft$	A dummy variable equal to one for houses with a 1-foot SLR inundation threshold.	Property	Climate Central
Underwater $3ft$	A dummy variable equal to one for houses with a 3-foot SLR inundation threshold.	Property	Climate Central
Underwater $6ft$	A dummy variable equal to one for houses with a 6-foot SLR inundation threshold.	Property	Climate Central
SLR Exposure	Main SLR risk measure from equation (1), with *SLR Exposure* ($1ft$) using only the 1-foot SLR scenario.	Property	Climate Central
Timing Exposure	Inverse of the time difference between the transaction year and the projected inundation year.	Property	Climate Central
Linear Exposure	Equals 3, 2, and 1 if projected to be inundated under 1-, 3-, and 6-foot SLR scenarios.	Property	Climate Central
Geographic and Demographic Characteristics			
GDP	Log annual gross domestic product.	City × Year	WIND
Population density	Log annual population density.	City × Year	WIND
EPU	Economic policy uncertainty index.	Month	CSMAR
% *Gas coverage*	Annual gas coverage rate of a city.	City × Year	WIND
% *Green coverage*	Annual green area coverage rate of a city.	City × Year	WIND
% *Urbanization population*	Annual share of the urban population.	Province × Year	WIND
Mechanism Variables			
Price-to-rent ratio	Average transaction price per square meter relative to average rent price per square meter.	City × Month	Wind
Price-to-income ratio	Average transaction price per square meter divided by personal income per capita.	City × Year	Wind
Non-five-year ownership	Share of properties that do not meet the *Five-year ownership and only property* criteria.	District × Month	Lianjia
Land constraint	Proportion of unavailable residential land in a city's total construction area.	City × Year	Statistical Yearbook of China
Frequent typhoon	Dummy equal to 1 for cities with frequent typhoons over past 70 years.	City	China Meteorological Administration
Relative attention	Population-scaled Baidu Search Volume Index for terms of *sea level rise* and *climate change*.	City × Month	Baidu
Media coverage index	Population-scaled Baidu News Index for "sea level rise".	City × Month	Baidu
Fiscal deficit	Difference between general public budget expenditure and revenue, normalized by GDP.	City × Year	Wind
Bond credit spreads	Average yield spread between seven-year LGFV bonds and treasury bonds of the same maturity.	City × Month	Wind

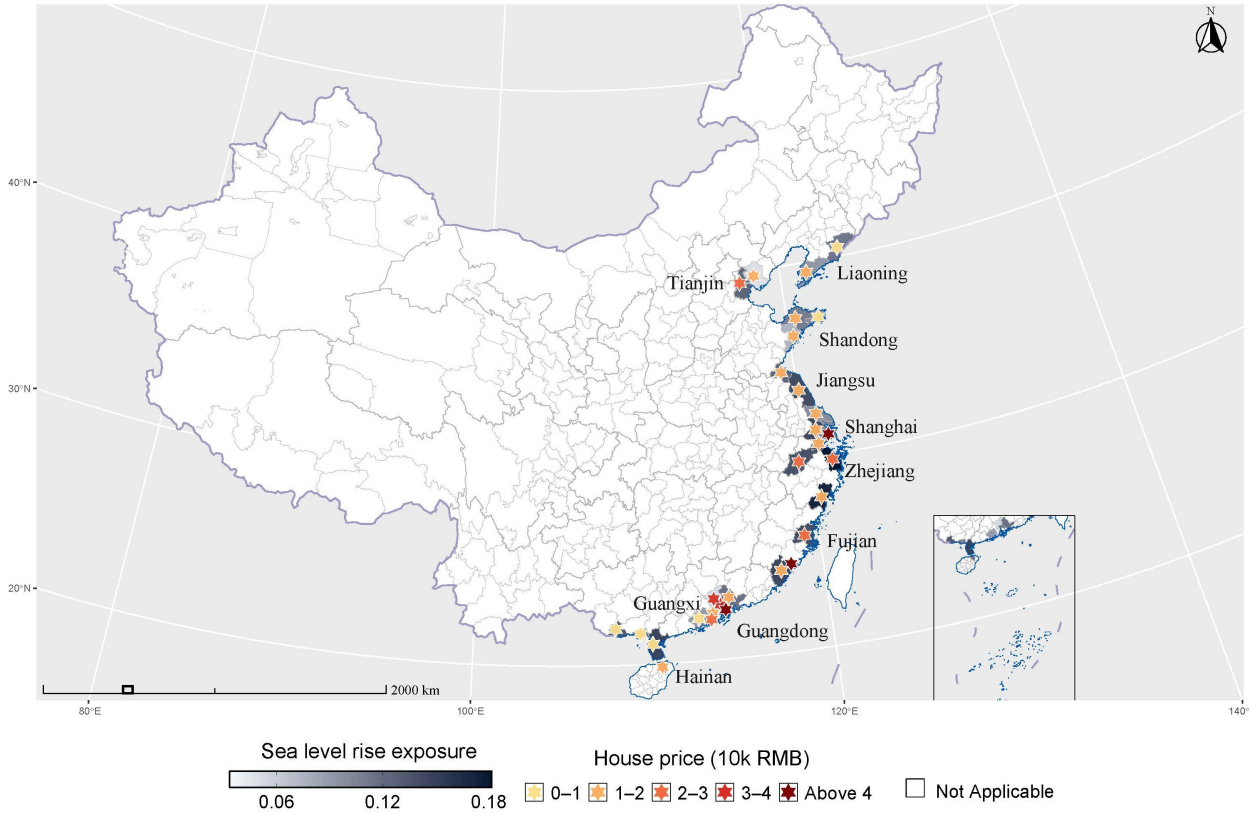


Figure 1 Sea Level Rise Exposure and Property Prices Across Cities

This figure plots the average sea level rise exposure and residential unit house prices for coastal cities in our sample. The shading of each city on the map reflects its SLR exposure, with darker colors indicating higher SLR exposure. Stars denote average unit house prices of cities, with different colors representing different levels of average unit prices.

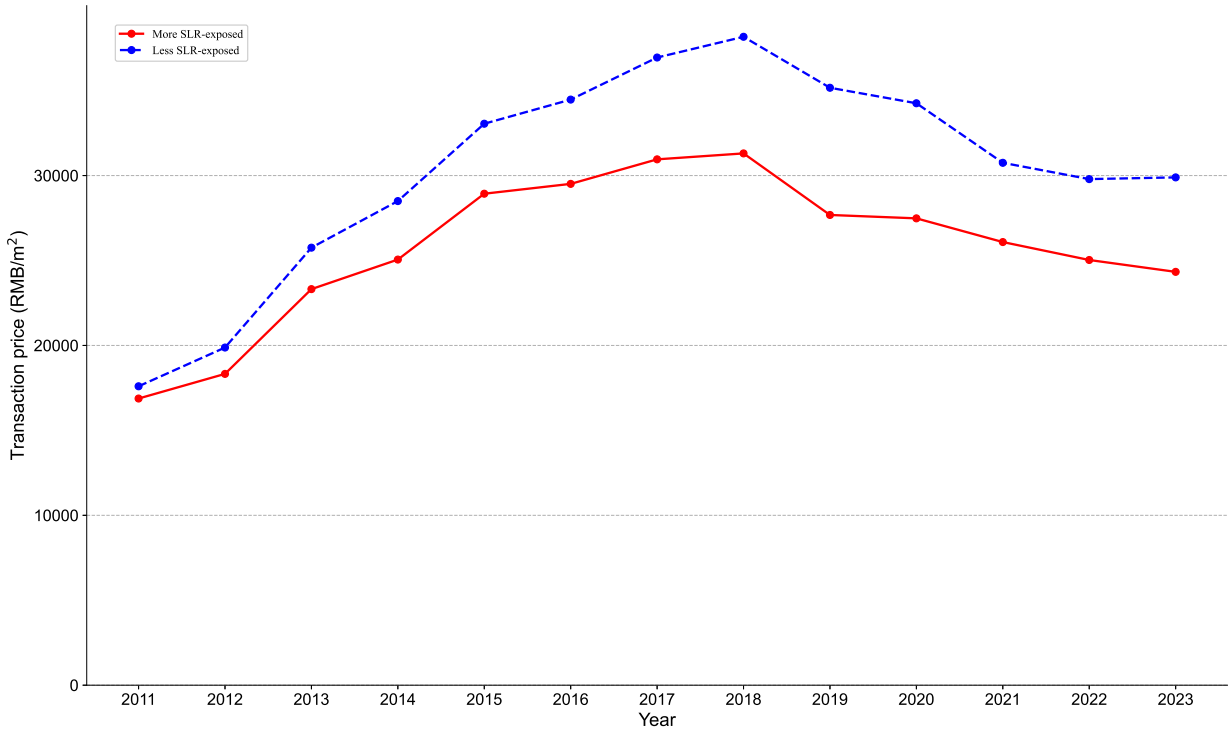


Figure 2 House Prices and Sea Level Rise Exposure

This figure plots the time series of annual average unit prices for residential properties in coastal cities of China from 2011 to 2023. The red solid line shows the average unit prices in more SLR-exposed, defined as those with sea level rise exposure above the sample average, while the blue dashed line shows the average unit prices in less SLR-exposed groups, whose sea level rise exposure is below the sample mean.

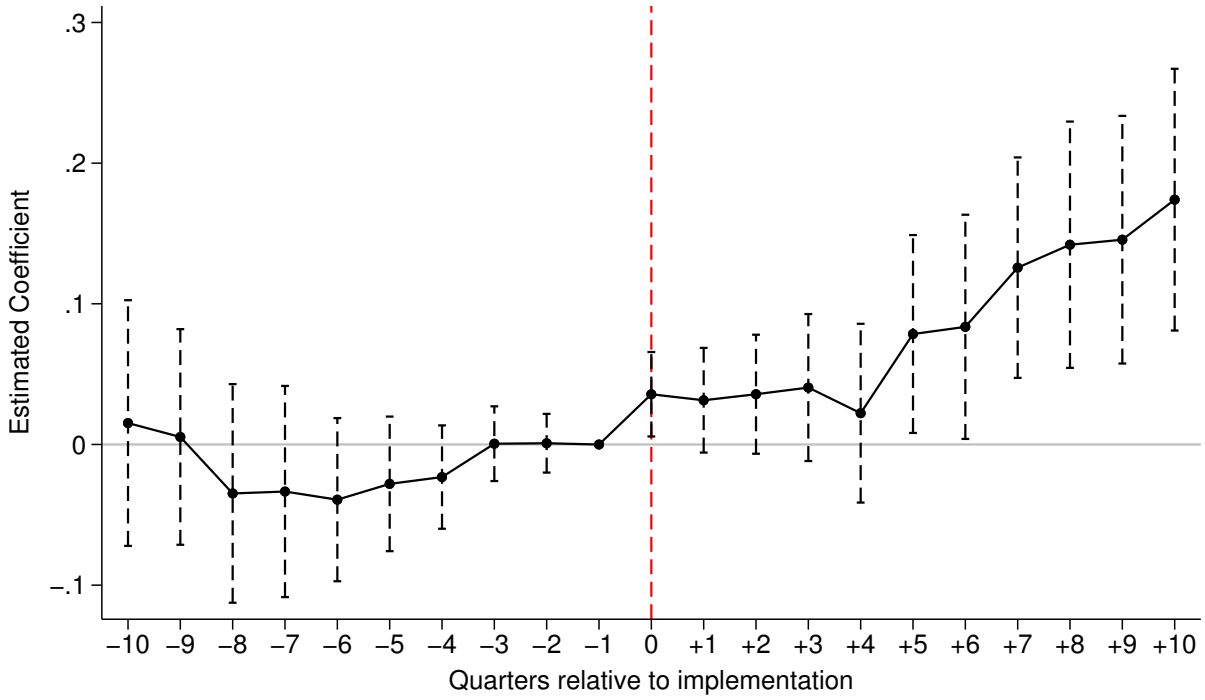


Figure 3 The Impact of Implemented Adaptation Projects on Housing Prices

This figure illustrates the local housing markets' response around the implementation of adaptation policies. Specifically, it plots the estimated coefficients θs (dots) and the corresponding 95% confidence intervals (dashed lines) estimated from the following regression:

$$\ln P_{i,t} = \alpha_2 + \sum_{\iota=-10}^{10} \theta_\iota \, Adapted_{ic,t+\iota} + \kappa X_i + \rho X_{g,t-1} + \mu_{cde} + \tau_t + \zeta_{i,t},$$

where i denotes property, t represents quarter, and $LnP_{i,t}$ is the log transaction price. The sample is restricted to properties located in SLR-exposed areas and in cities that either announce an adaptation plan or implement an adaptation project during the sample period. $Adapted_{ic,t+\iota}$ equals 1 if quarter $t+\iota$ is ι quarters away from city c's implementation quarter. We consider $\iota \in \{-10, \ldots, 10\}$, with negative (positive) values indicating pre-implementation (post-implementation) quarters. Thus, $Adapted_{ic,t+\iota}$ identifies properties in treated cities ι quarters before, during, or after the implementation quarter. The sample period is from 2011 to 2023.

Table 1 Summary Statistics

This table reports summary statistics for the primary variables used in this paper, including the number of observations, mean, median, standard deviation, minimum and maximum values. Panels A, B and C report variables related to real estate transactions and property characteristics, buyers' and sellers' behavior, and sea level rise exposure, respectively. The sample period ranges from 2011 to 2023. Detailed descriptions of variables are provided in Appendix.

	N	Mean	Median	*SD*	Minimum	Maximum
Panel A: Housing Transactions and Property Attributes						
Transaction price (10,000 RMB)	957,091	274.40	206.00	249.99	14	2320
Listing price (10,000 RMB)	924,441	287.50	215.60	265.58	5	2500
Unit price (10,000 RMB/m^2)	957,091	3.38	2.77	2.37	0.26	14.21
Number of bedrooms	957,091	2.25	2	0.86	1	6
Size	914,255	83.02	79.58	35.41	13.92	320
Age	957,091	15.01	13	9.28	0	63
Floor level	956,611	2.08	2	0.78	1	3
Decoration	957,091	2.70	3	1.26	1	4
Elevator	957,091	0.54	1	0.50	0	1
Window orientation	916,482	0.64	1	0.48	0	1
Distance (km)	957,091	23.25	22.13	18.42	0.02	84.94
Elevation (m)	957,091	19.22	8.00	24.66	0	217
Panel B: Buyers' and Sellers' Behavior						
Onsite viewings	956,905	15.59	9.67	18.83	0	128
Listing page saves	956,905	14.09	6.25	20.67	0	138
Listing page views	861,667	1412.28	420	2045.21	25	12967
# Price adjustments	957,103	2.20	1.50	2.43	0	17
Time on market (days)	943,001	229.52	130.13	327.25	1	2132
Panel C: Sea Level Rise Exposure						
Underwater $1ft$	957,091	0.34	0	0.47	0	1
Underwater $3ft$	957,091	0.45	0	0.50	0	1
Underwater $6ft$	957,091	0.64	1	0.48	0	1
SLR Exposure	957,091	0.09	0.04	0.10	0	0.26
SLR Exposure $(1ft)$	957,091	0.08	0	0.11	0	0.26
Timing Exposure	957,091	0.01	0.01	0.01	0	0.04
Linear Exposure	957,091	1.43	1	1.28	0	3

Table 2 Sea Level Rise Inundation Thresholds and House Prices

This table reports the effects of SLR risk on log house transaction prices. The independent variables *Underwater* $1ft$, *Underwater* $3ft$, and *Underwater* $6ft$ are indicator variables that equal 1 (multiplied by 1/100 for readability) if a property is projected to be underwater under a 1-, 3-, or 6-foot SLR scenario, respectively. Column (1) uses the full sample; column (2) excludes properties in the 1-foot SLR zone; and column (3) further excludes those in the 3-foot zone. t-statistics are reported in parentheses, with standard errors clustered at the district level. The sample period spans 2011–2023. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Underwater $1ft$	-3.09***		
	(-3.85)		
Underwater $3ft$		-0.42	
		(-0.34)	
Underwater $6ft$			3.95
			(1.55)
Number of bedrooms	0.15***	0.14***	0.14***
	(16.94)	(15.37)	(15.09)
Size	0.23***	0.23***	0.23***
	(29.28)	(27.55)	(23.96)
Age	-0.01	-0.01	-0.01
	(-1.44)	(-1.46)	(-0.95)
Orientation	-0.01	-0.01	-0.01
	(-0.51)	(-0.94)	(-1.49)
Elevator	0.18***	0.19***	0.19***
	(10.34)	(9.29)	(8.34)
Middle floor	0.01***	0.01**	0.00
	(2.87)	(2.21)	(1.09)
High floor	-0.03***	-0.03***	-0.03***
	(-9.14)	(-8.94)	(-9.96)
GDP	0.06	0.06	0.10
	(0.40)	(0.37)	(0.57)
Population density	-0.05*	-0.04	-0.05
	(-1.77)	(-1.15)	(-1.30)
EPU	0.03***	0.03***	0.02***
	(8.53)	(7.43)	(5.91)
% *Gas coverage*	0.16	0.20	0.30
	(0.29)	(0.37)	(0.58)
% *Green coverage*	0.45	0.28	0.05
	(0.94)	(0.66)	(0.13)
% *Urbanization population*	-2.32***	-2.10***	-1.83***
	(-3.42)	(-3.08)	(-2.94)
Decoration indicator	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes
Number of observations	915,926	602,531	497,094
Adjusted R^2	0.789	0.791	0.789

Table 3 Sea Level Rise Exposure and House Prices

This table reports the estimated coefficients from the baseline regression examining the impact of sea level rise risk on house prices. The dependent variable is the log of housing transaction prices ($LnP_{i,t}$). *SLR Exposure* ($1ft$) is the key independent variable. The decoration indicator is a categorical variable for decoration levels, included as dummies in the regression. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period spans 2011–2023. Standard errors are clustered by district. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
SLR Exposure ($1ft$)	-0.20***	-0.15***	-0.18***	-0.14***
	(-4.22)	(-3.40)	(-4.64)	(-3.82)
Number of bedrooms	0.13***	0.14***	0.14***	0.15***
	(11.67)	(13.57)	(14.90)	(16.96)
Size	0.24***	0.23***	0.23***	0.23***
	(26.43)	(26.74)	(26.89)	(29.30)
Age	0.01***	0.01	-0.01	-0.01
	(2.93)	(0.70)	(-0.40)	(-1.45)
Orientation	-0.01	-0.01	-0.01	-0.01
	(-0.81)	(-0.80)	(-0.59)	(-0.51)
Elevator	0.25***	0.22***	0.19***	0.18***
	(10.96)	(12.12)	(9.84)	(10.34)
Middle floor	0.01**	0.01**	0.01**	0.01***
	(2.00)	(2.56)	(2.22)	(2.87)
High floor	-0.03***	-0.03***	-0.03***	-0.03***
	(-8.05)	(-8.48)	(-8.92)	(-9.14)
GDP	-0.02	0.02	0.04	0.06
	(-0.13)	(0.11)	(0.26)	(0.40)
Population density	-0.05	-0.05	-0.05	-0.05*
	(-1.44)	(-1.52)	(-1.45)	(-1.77)
EPU	0.02***	0.03***	0.02***	0.03***
	(6.84)	(8.30)	(7.80)	(8.53)
% *Gas coverage*	0.16	0.14	0.19	0.17
	(0.28)	(0.24)	(0.33)	(0.31)
% *Green coverage*	0.31	0.32	0.39	0.44
	(0.68)	(0.70)	(0.85)	(0.94)
% *Urbanization population*	-1.52*	-2.30***	-2.10**	-2.32***
	(-1.72)	(-3.20)	(-2.56)	(-3.43)
Decoration indicator	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	No	No	No
City×distance FE	No	Yes	No	No
City×elevation FE	No	No	Yes	No
City×distance×elevation FE	No	No	No	Yes
Number of observations	915,934	915,933	915,933	915,926
Adjusted R^2	0.741	0.767	0.767	0.789

Table 4 Alternative Sea Level Rise Measures and More Granular Fixed Effects

This table reports coefficients estimates from various further investigations. Column (1) adopts a timing-based measure of sea level rise exposure, which is defined as the inverse of the difference between the transaction year and the projected inundation year. Column (2) employs a numerical intensity SLR exposure measure, assigning values of 3, 2, and 1 to properties projected to be inundated under 1-foot, 3-foot, and 6-foot SLR scenarios, respectively. Columns (3) to (4) estimate coefficients of baseline regression with more granular year-quarter and year-month time fixed effects, respectively. Column (5) includes city-year fixed effects to absorb time-varying local shocks to the housing market. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Alternative SLR Exposures		More Granular FE		
	Timing	Linear	Year -quarter	Year -month	City -Year
	(1)	(2)	(3)	(4)	(5)
SLR Exposure ($1ft$)	-0.93***	-0.01***	-0.14***	-0.14***	-0.14***
	(-3.84)	(-3.85)	(-3.80)	(-3.80)	(-3.82)
Property attributes	Yes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	No	No	No
Year-quarter FE	No	No	Yes	No	No
Year-month FE	No	No	No	Yes	No
City×distance×elevation FE	Yes	Yes	Yes	Yes	No
City×year×distance×elevation FE	No	No	No	No	Yes
Number of observations	915,926	915,926	915,926	915,926	915,845
Adjusted R^2	0.789	0.789	0.791	0.791	0.796

Table 5 Alternative Housing Price Measures

This table reports coefficient estimates of baseline regression with alternative dependent variables. Columns (1) and (2) report the estimated results with dependent variable of the log unit price, while columns (3) and (4) report that of listing price. The main independent variable of interest is *SLR Exposure* ($1ft$). Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Unit Price (RMB/m^2)		Listing Price	
	(1)	(2)	(3)	(4)
SLR Exposure ($1ft$)	-0.12***	-0.12***	-0.14***	-0.14***
	(-3.20)	(-3.23)	(-3.83)	(-3.82)
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	No	Yes	No
City×distance×elevation FE	No	Yes	No	Yes
City×year×distance×elevation FE	No	Yes	No	Yes
Number of observations	915,926	915,845	905,305	905,229
Adjusted R^2	0.786	0.794	0.781	0.788

Table 6 Different Market Conditions

This table reports sub-sample estimates from the baseline regression under varying market conditions. Columns (1) and (2) split the sample into periods of rising and declining house prices, respectively. Columns (3) and (4) split the sample into COVID-19 lockdown and non-lockdown periods. All control variables and fixed effects from the baseline specification are included. t-statistics are reported in parentheses, with standard errors clustered at the district level. We report the difference in coefficients across sub-samples and its p-value from the permutation test with 2,000 permutations. The sample period spans 2011–2023. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Market Trends		COVID-19 Lockdown	
	Up	Down	Yes	No
	(1)	(2)	(3)	(4)
SLR Exposure ($1ft$)	-0.16***	-0.12***	-0.11*	-0.17***
	(-3.61)	(-3.67)	(-2.01)	(-4.34)
Test for Group Diff	0.04		0.07***	
p-value	(0.25)		(0.00)	
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes	Yes
Number of observations	438,310	477,602	441,658	474,256
Adjusted R^2	0.805	0.780	0.773	0.806

Table 7 Buyers' Interest, Sellers' Response, and Housing Market Liquidity

This table examines how sea level rise exposure affects housing market activity. Columns (1), (2) and (3) report estimates of the effect of SLR exposure on buyer interest, proxied by the property listing page views, property listing page saves, and onsite viewings (logarithm), respectively. Column (4) uses Poisson pseudo-maximum likelihood to examine seller responses, measured by the number of listing price adjustments aggregated to the community-month level. Column (5) uses PPML to examine market liquidity, measured by days on market aggregated to the district-month level. All control variables and fixed effects from the baseline specification are included. t-statistics (columns (1)-(3)) and z-statistics (columns (4)-(5)) are reported in parentheses, with standard errors clustered at the district level. The sample period spans 2011-2023. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Listing Page Views (1)	Listing Page Saves (2)	Onsite Viewings (3)	#Price Adjustments (4)	Time on Market (5)
SLR Exposure ($1ft$)	-0.08***	-0.13**	-0.10***	0.07***	0.05**
	(-3.27)	(-2.41)	(-2.65)	(3.45)	(2.25)
Property attributes	Yes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes	Yes	Yes
Number of observations	837,570	915,813	915,813	915,801	908,588
Adjusted / Pseudo R^2	0.697	0.454	0.535	0.165	0.843

Table 8 Buyers' Sophistication

This table examines whether the SLR-related price discount varies with the share of sophisticated buyers, proxied by local speculative activity. The dependent variable is log transaction house prices, while the independent variable is *SLR Exposure* ($1ft$). Columns (1)-(2), (3)-(4) and (5)-(6) report coefficient estimates based three proxies of speculation: (i) the district-month share ratio of transactions that do not satisfy the *five-year ownership and only property*, (ii) the city-month *price-to-rent ratio*, and (iii) the city-year *price-to-income ratio*, respectively. Columns (1), (3) and (5) are sub-samples of high speculation periods that each proxy lies above the sample median, while columns (2), (4) and (6) are sub-samples of low speculation periods that each proxy fall below the sample median. We report the difference in coefficients across sub-samples and its p-value from the permutation test with 2,000 permutations. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Non-Five-Year Ownership		Price-to-Rent Ratio		Price-to-Income Ratio	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposure ($1ft$)	-0.12***	-0.14***	-0.10**	-0.16***	-0.05	-0.22***
	(-2.74)	(-3.70)	(-2.20)	(-3.22)	(-0.85)	(-4.58)
Test for Group Diff	0.03***		0.06***		0.17***	
p-value	(0.00)		(0.00)		(0.00)	
Property attributes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	424,992	490,924	267,295	407,508	340,122	376,195
Adjusted R^2	0.749	0.831	0.711	0.701	0.685	0.617

Table 9 Relocation Constraints

This table reports baseline estimates for loose- and tight-relocation constraint sub-samples. Relocation constraint is measured by land supply constraint, calculated as the ratio of unavailable residential land to total construction area in a city at a given year. Columns (1) and (2) split the sample at the median of the land-constraint measure: column (1) reports estimates for city-years below the median (loose constraints), and column (2) for those above the median (tight constraints). Columns (3) and (4) present results based on the top and bottom 30th percentile of the land constraint distribution: Column (3) corresponds to the bottom 30%, and Column (4) to the top 30%. We report the difference in coefficients across sub-samples and its p-value from the permutation test with 2,000 permutations. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Median		30th Percentile	
	Loose	Tight	Bottom	Top
	(1)	(2)	(3)	(4)
SLR Exposure ($1ft$)	-0.17***	-0.09	-0.17**	-0.05
	(-3.26)	(-1.31)	(-2.67)	(-0.58)
Test for Group Diff	0.08***		0.12***	
p-value	(0.00)		(0.00)	
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes	Yes
Number of observations	476,607	325,092	309,098	309,098
Adjusted R^2	0.792	0.787	0.768	0.768

Table 10 Physical Climate Shocks

This table reports estimates of the impact of past typhoon experience on SLR-related discount. Columns (1)–(2) split the sample by historical typhoon frequency. "Frequent" ("Infrequent") denotes cities that experienced more than 100 (100 or fewer) typhoons over the past 70 years. Columns (3)–(4) split the sample by typhoon hotspot status, comparing properties in Guangdong province (the typhoon hotspot) with those in all other coastal areas. The dependent variable is log transaction price, while the independent variable is *SLR Exposure* ($1ft$). We report the difference in coefficients across sub-samples and its p-value from the permutation test with 2,000 permutations. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Typhoon Frequency		Typhoon Hotspot	
	Infrequent	Frequent	Other Regions	Guangdong Province
	(1)	(2)	(3)	(4)
SLR Exposure ($1ft$)	-0.12***	-0.39***	-0.13***	-0.48***
	(-2.74)	(-4.38)	(-3.32)	(-4.11)
Test for Group Diff	0.27***		0.35***	
p-value	(0.00)		(0.00)	
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province×distance×elevation FE	Yes	Yes	Yes	Yes
Number of observations	614,358	301,572	506,940	245,282
Adjusted R^2	0.811	0.667	0.788	0.669

Table 11 Attention to Climate Risk

This table examines the impact of public attention on SLR price discount. Attention is measured using two city-level Baidu indices: (i) population-scaled search volume for *sea level rise* (relative attention) and (ii) population-scaled search volume for *climate change* (relative attention). Columns (1) and (3) are estimated coefficients based on sub-samples of each measure below the sample median level, while columns (2) and (4) are that of groups with high public attention. We report the difference in coefficients across sub-samples and its p-value from the permutation test with 2,000 permutations. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Sea Level Rise		Climate Change	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
SLR Exposure ($1ft$)	-0.06	-0.20***	-0.05	-0.17***
	(-1.52)	(-4.99)	(-1.15)	(-3.53)
Test for Group Diff	0.14***		0.12***	
p-value	(0.00)		(0.00)	
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes	Yes
Number of observations	360,011	555,900	273,901	374,829
Adjusted R^2	0.760	0.728	0.725	0.711

Table 12 Awareness of Adaptation Measures and Long-Term Plans

This table examines whether public awareness of local government adaptation efforts moderates the SLR-related price discount. Using city-level responses from an original survey administered to 1,423 residents across 30 coastal cities from February to April 2026, we classify cities into high- and low-knowledge groups. In the left panel, the grouping is based on the share of respondents who reported that they know, know a little, or have heard about local government measures addressing sea-level rise or coastal flooding, such as seawalls, flood barriers, or related protective infrastructure. In the right panel, the grouping is based on the share of respondents who reported that they know, know a little, or have heard about seawall construction plans or flood-control plans released by local governments in the past decade. Cities with shares above the median among the surveyed cities are classified as high-knowledge groups, and the remaining cities are classified as low-knowledge groups. The dependent variable is the log transaction price. The key independent variable is *SLR Exposure* $(1ft)$. The group difference and the corresponding p-value are obtained from the permutation test, implemented via 2,000 permutations. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Adaptation Measures		Long Term Plans	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
SLR Exposure $(1ft)$	-0.15**	-0.09	-0.14***	-0.12**
	(-2.80)	(-1.34)	(-3.01)	(-2.06)
Test for Group Diff	0.06**		0.02**	
p-value	(0.02)		(0.04)	
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes	Yes
Number of observations	771,888	144,038	547,163	368,763
Adjusted R^2	0.765	0.750	0.830	0.709

Table 13 Announced vs. Implemented Adaptation Projects

This table reports regression results on the effect of local government SLR adaptation strategies on housing transaction prices. The left panel presents estimates for the full sample, while the right panel restricts focus to SLR-exposed areas. *Treat* equals one if a property is in an SLR exposed area given one-foot SLR scenario. *Adapted* equals one if the city has announced or begun implementing adaptation measures before the transaction date. The independent variable is the interaction of *Treat* and *Adapted*. The dependent variable is the log transaction price. Models (1) and (3) compare the effects of implementation versus announcement, whereas Models (2) and (4) compare announced strategies with non-adapted areas. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample		SLR Exposed Areas	
	Implemented Announced	Announced No-adaptation	Implemented Announced	Announced No-adaptation
	(1)	(2)	(3)	(4)
Treat × *Adapted*	-0.01	-0.02	0.11***	-0.02
	(-0.63)	(-1.10)	(4.46)	(-0.74)
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes	Yes
Number of observations	730,468	319,415	237,909	122,047
Adjusted R^2	0.740	0.745	0.746	0.742

Table 14 Belief in the Effectiveness of Adaptation Measures

This table examines whether residents' belief in the effectiveness of local government adaptation measures moderates the price-attenuating effect of adaptation implementation. Using city-level responses from an original survey administered to 1,423 residents across 30 coastal cities from February to April 2026, we classify cities into high- and low-belief groups based on whether the city-level share of respondents who rated local government measures as "very effective" or "relatively effective" in addressing sea-level rise or coastal flooding is above the median among the surveyed cities. The left panel presents estimates for the full sample, while the right panel restricts the sample to SLR-exposed areas. The dependent variable is the log transaction price. The main independent variable is the interaction of *Treat* and *Adapted*. *Treat* equals one if a property is in an SLR-exposed area under the one-foot SLR scenario, and *Adapted* equals one if the property is located in a city that had begun implementing adaptation projects by the transaction date. The group difference and the corresponding p-value are obtained from the permutation test, implemented via 2,000 permutations. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample		SLR Exposed Areas	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Treat × *Adapted*	0.01	0.09**	-0.01	0.08**
	(1.20)	(2.52)	(1.50)	(2.18)
Test for Group Diff	0.08**		0.09**	
p-value	(0.03)		(0.04)	
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes	Yes
Number of observations	194,274	119,115	109,388	111,020
Adjusted R^2	0.822	0.702	0.724	0.715

Table 15 Fiscal Condition of Local Government

This table reports regression results on how local fiscal conditions influence the effectiveness of government adaptation efforts against SLR threats. The sample is restricted to properties in SLR-exposed areas for cities that started to take adaptation actions. Fiscal conditions are proxied by the difference between annual fiscal expenditures and revenues, normalized by the GDP (city-level, left panel) and 7-year LGFV bond credit spreads (city–month level, right panel), respectively. The dependent variable is the log transaction price. The independent variable is the interaction of $Treat$ and *Adapted*. The variable $Treat$ equals one for exposed properties with one-foot SLR scenario, and *Adapted* equals one for property located in cities that begun implementing adaptation projects by the transaction date. The group difference and the corresponding p-value are obtained from the permutation test, implemented via 2,000 permutations. All regressions control for residential house features and geographic characteristics, and include fixed effects as specified. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Fiscal Deficit		Bond Credit Spreads	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
$Treat \times Adapted$	0.05***	-0.05	0.05**	-0.02
	(3.89)	(-0.68)	(3.11)	(-0.64)
Test for Group Diff	0.10***		0.07***	
p-value	(0.00)		(0.00)	
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes	Yes
Number of observations	145,854	77,046	66,188	56,198
Adjusted R^2	0.784	0.659	0.723	0.650

Internet Appendix for

"Do Homeowners in Emerging Markets Care About Sea Level Rise and Government Adaptation?"

Appendix IA. Additional Figures and Tables

Panel A: Platform Coverage



Panel B: Transaction and Listing Records



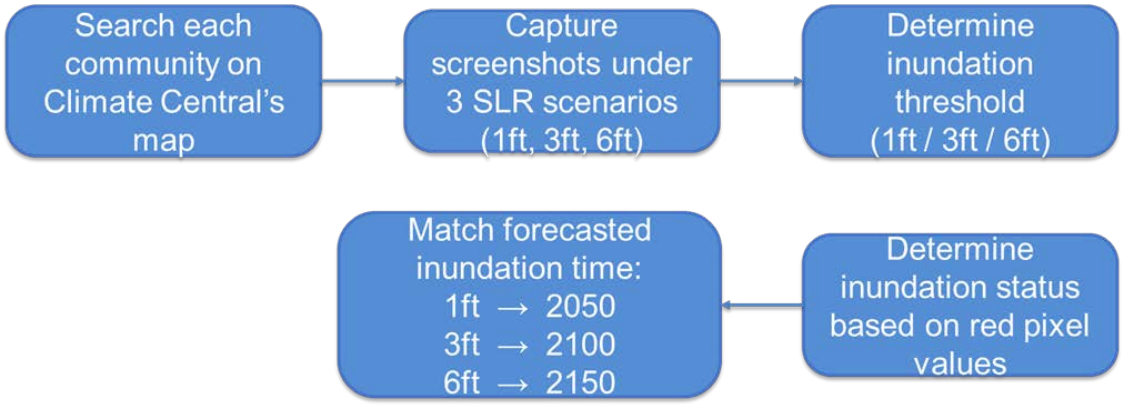
Panel C: Basic Information of a Property



Figure IA1. Example of Platform Coverage and a Transacted Property

The figure shows an example webpage from Lianjia, a well-established housing transaction platform in China. Panel A displays the coverage of a regional housing market. Panel B illustrates transaction and listing records, while Panel C presents the basic property information available on the platform.

Panel A: Procedure for Identifying Sea Level Rise Inundation Thresholds



Panel B: Illustrative Example Using Climate Central Map

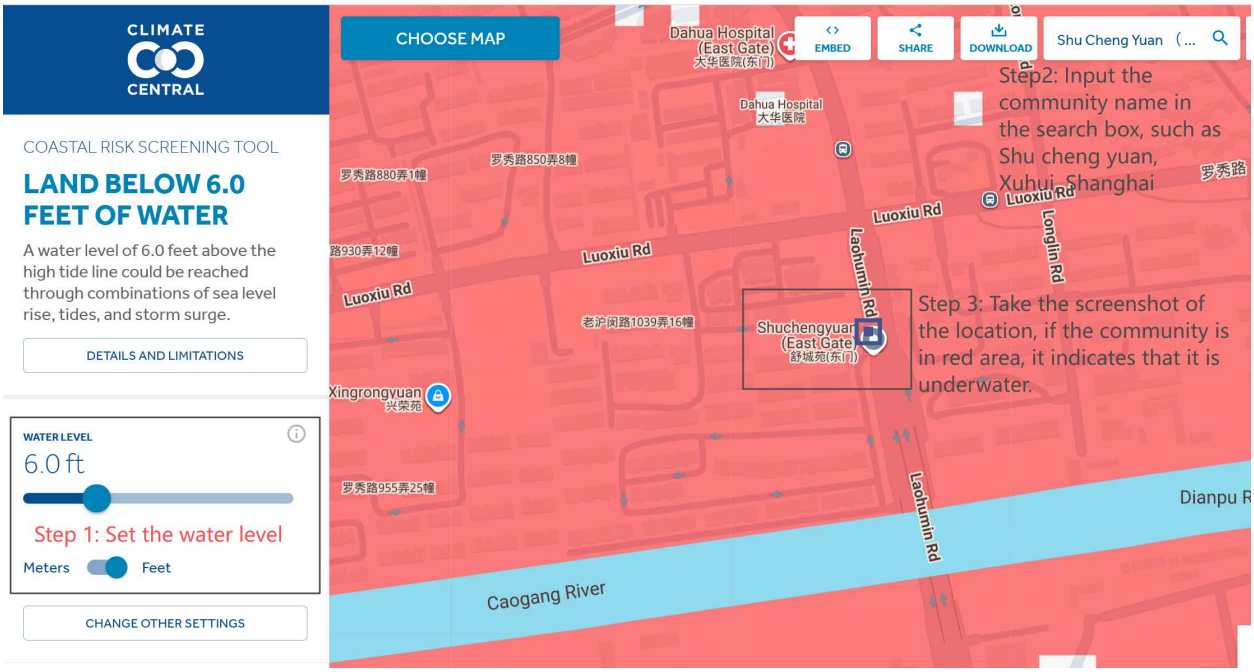


Figure IA2. Identification of Sea Level Rise Inundation Thresholds

Panel A illustrates the procedure used to identify sea level rise inundation thresholds. Panel B presents an illustrative example based on maps from Climate Central, showing how inundation thresholds are determined under different sea level rise scenarios.

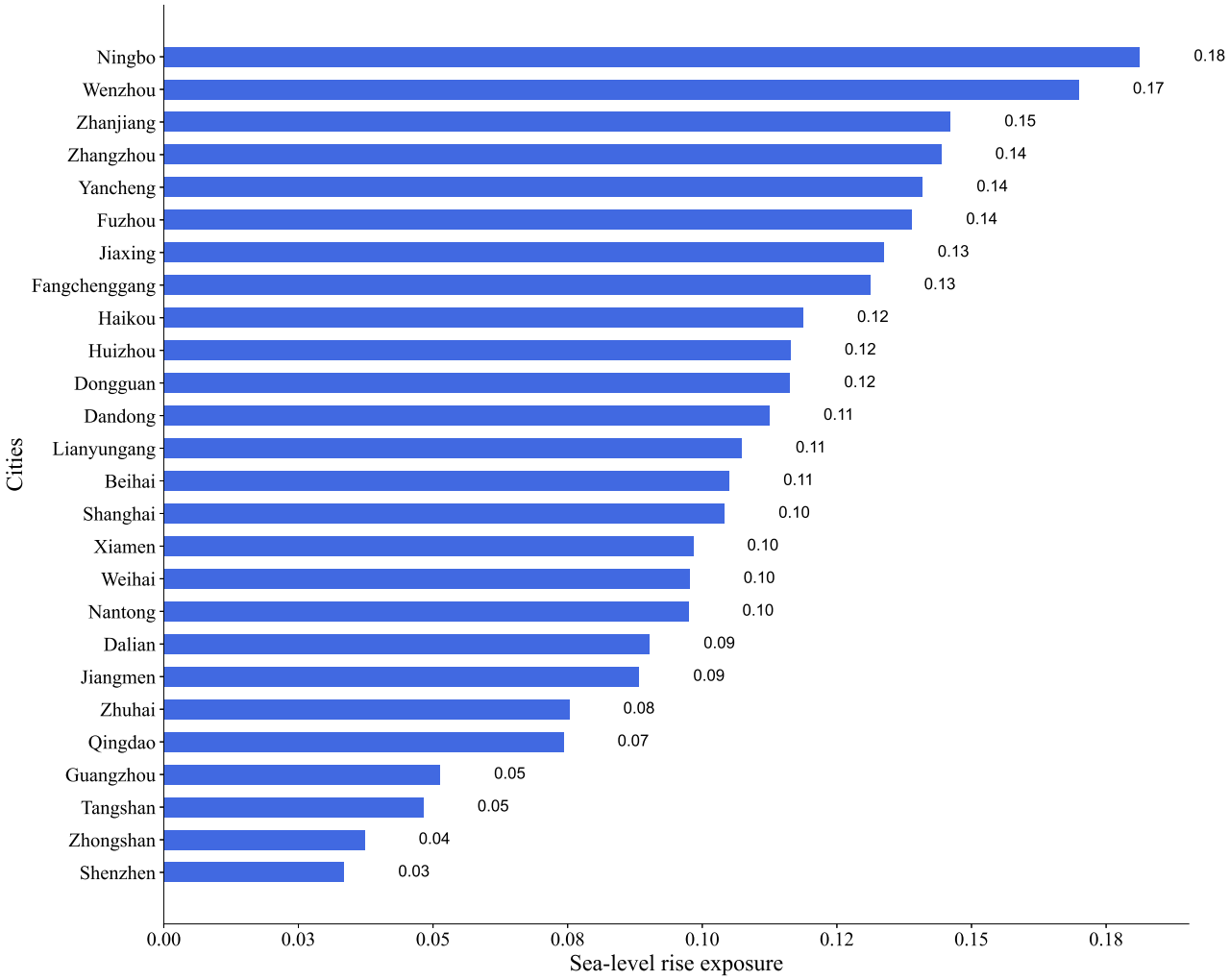
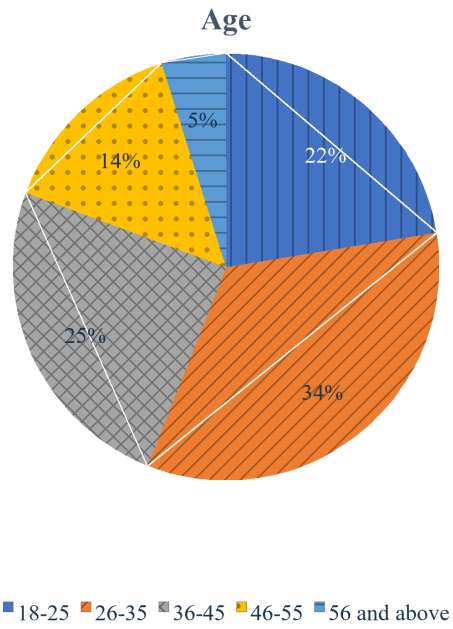


Figure IA3. Sea Level Rise Exposure Across Cities

This figure plots the average sea level rise exposure for residential houses across all coastal cities in our sample. House-level sea level rise exposures are averaged by cities and denoted by the blue bar. Cities are ranked by the value of sea level rise exposure, with higher values indicating higher inundation risk.

Panel A: Age



Panel B: Education

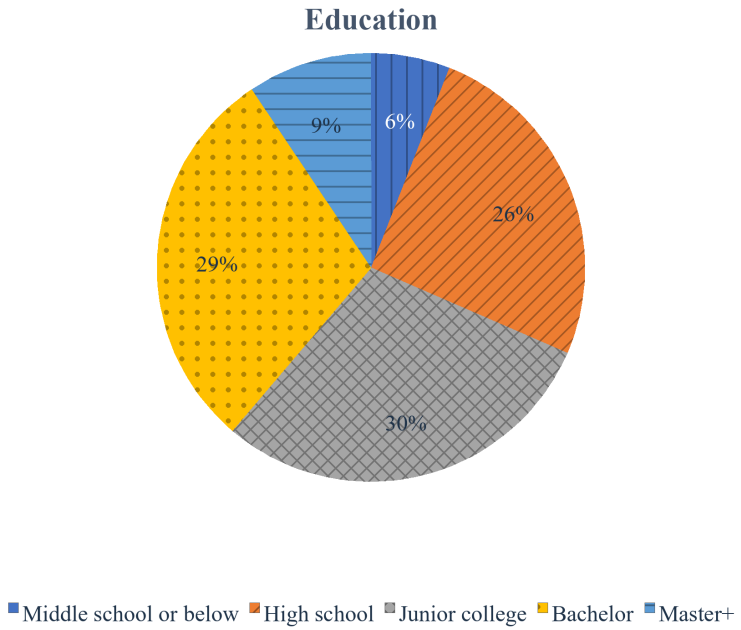


Figure IA4. Demographic Composition of Survey Respondents

This figure summarizes the demographic composition of the survey sample. An original online survey was administered to residents across the 30 coastal cities in our sample from February to April 2026, yielding 1,423 valid responses. Panel A displays the distribution of respondents by age group. Panel B reports the distribution by highest education level attained.

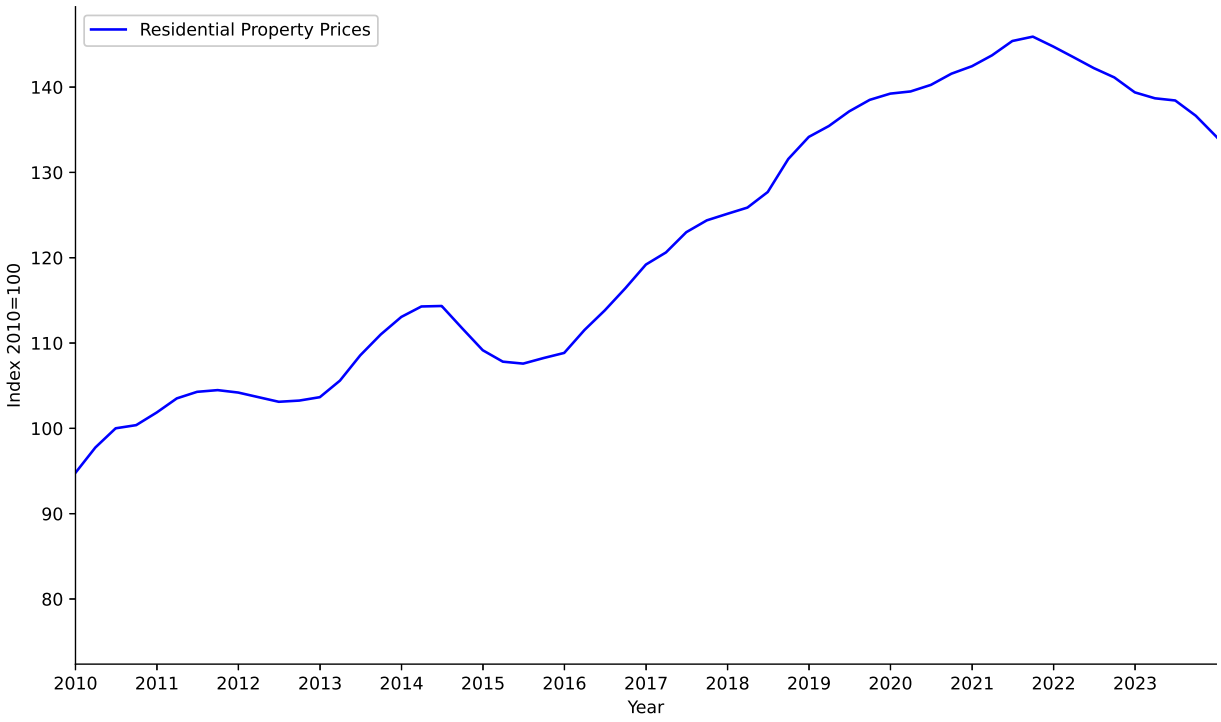


Figure IA5. Residential Property Price of China

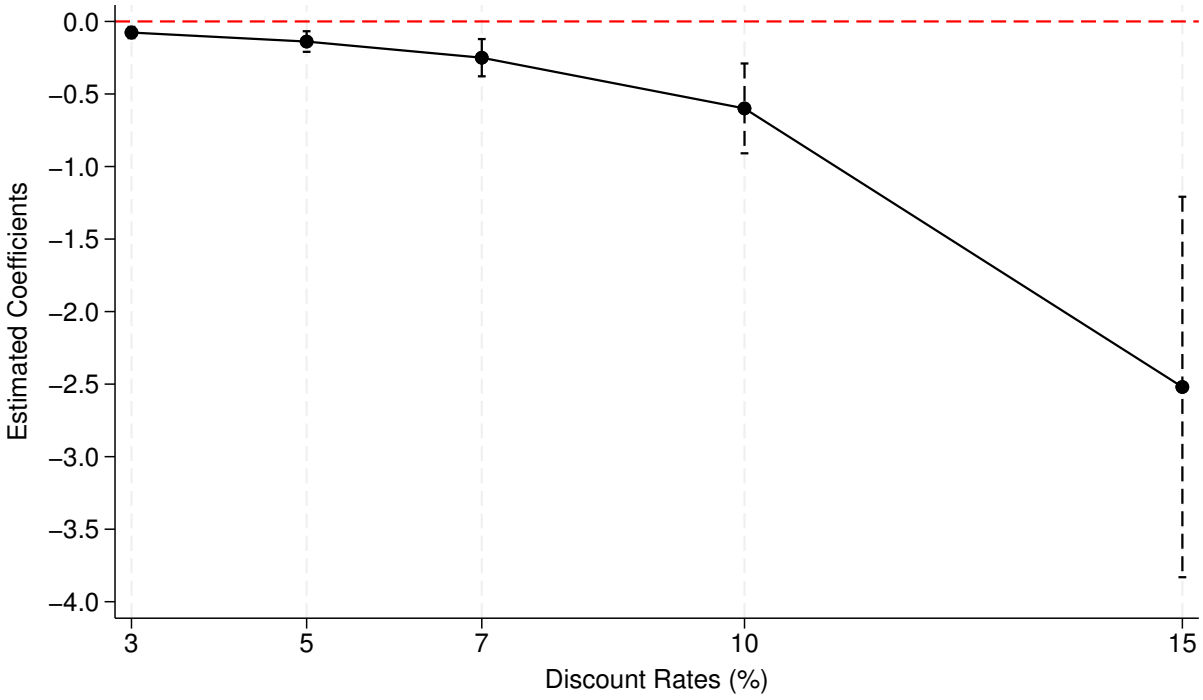


Figure IA6. Sensitivity to Interest Rates

This figure plots the estimated coefficients of $SLR\ Exposure\ (1ft)$ using alternative discount rates, including 3%, 7%, 10%, and 5%. The 5% discount rate corresponds to our primary specification. The solid dots represent point estimates, and the dashed vertical lines indicate the 95% confidence intervals. Control variables and fixed effects are included as the baseline model.

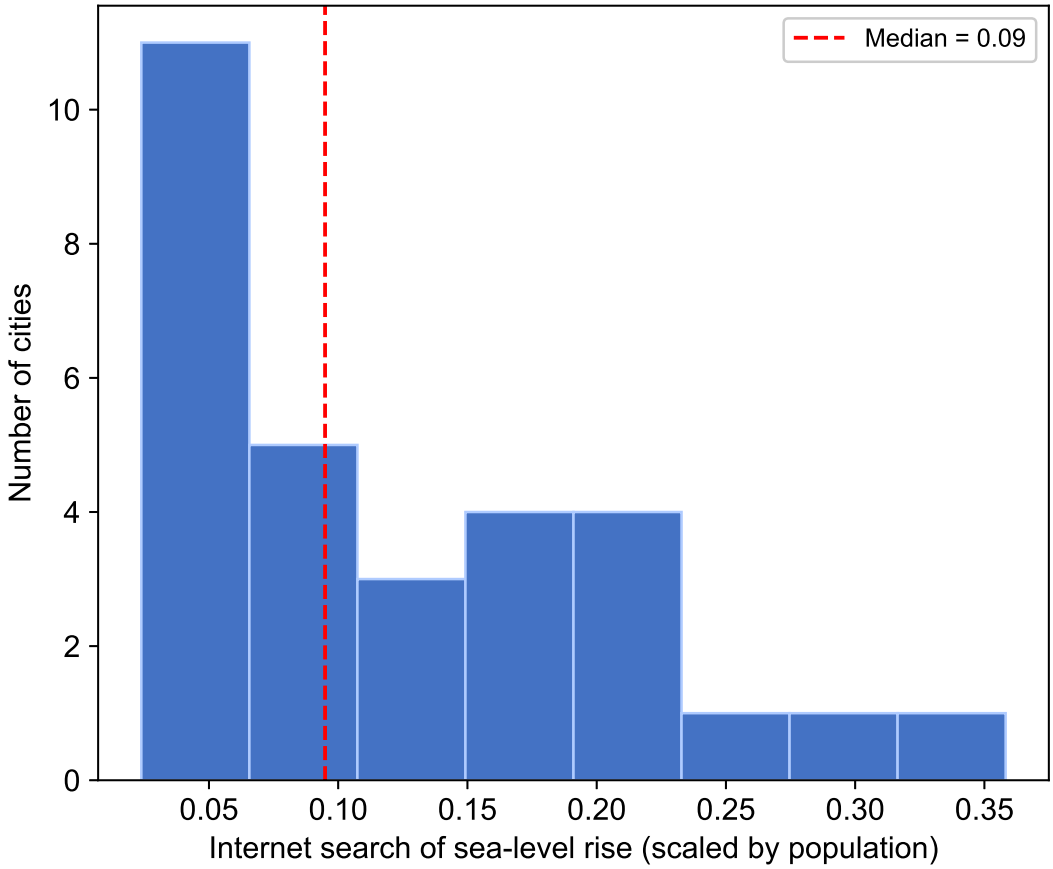


Figure IA6. Distribution of City-Level Attention to Sea Level Rise

This figure displays the distribution of city-level attention to sea level rise. For each coastal city, the monthly Baidu search volume for the topic *sea level rise* is normalized by the city's annual population and multiplied by 1,000 for ease of interpretation. The resulting per-capita search index is then averaged across months to obtain a city-level measure of relative attention. Higher values indicate greater public attention to SLR risks. The vertical dashed line marks the sample median. The sample period is from 2011 to 2023.

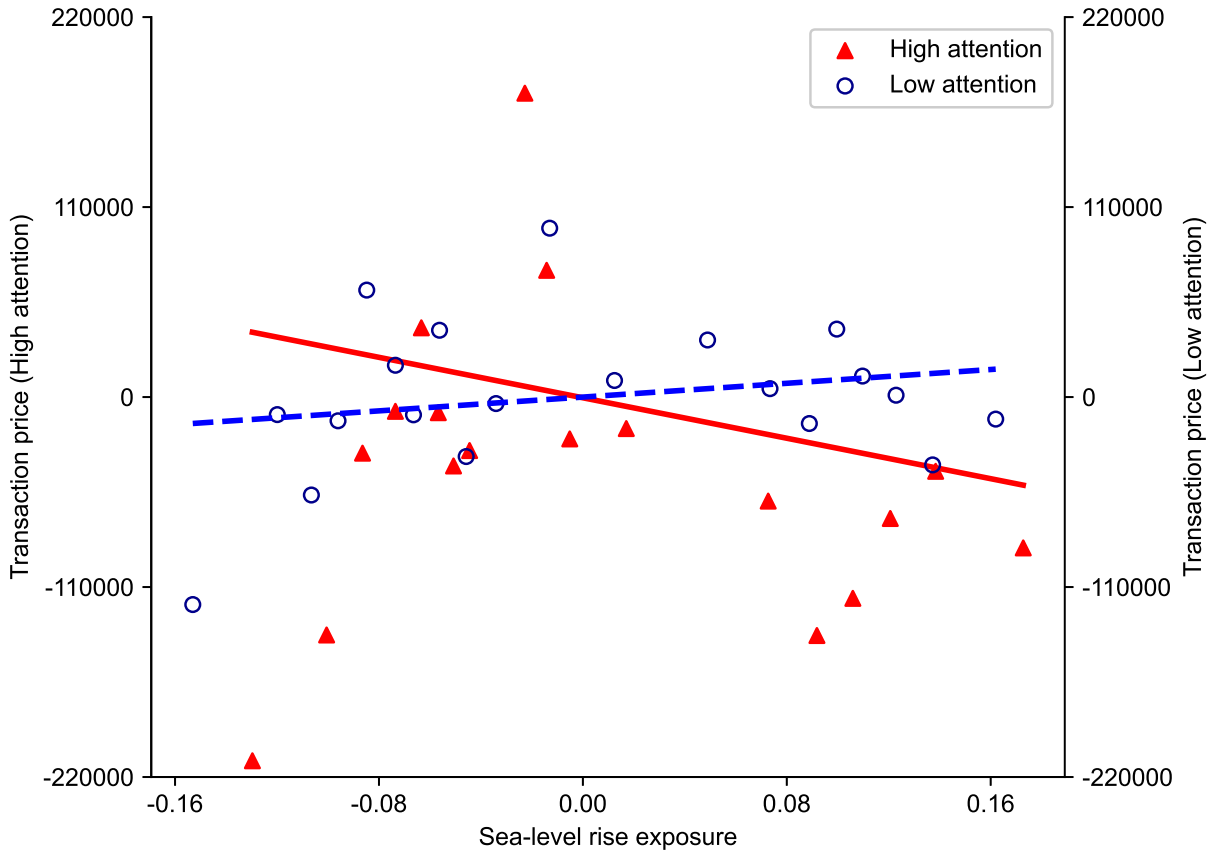


Figure IA7. Property Prices and Attention to Sea Level Rise

This figure plots demeaned house transaction prices against ventiles of demeaned SLR exposure (one-foot) from 2011 to 2023. Prices and exposure are residualized by subtracting means at the city, distance-to-coast, elevation, and year levels. Red solid triangles (left axis) report the mean residualized transaction price within each exposure ventile for cities with high relative attention to sea-level rise, and blue open circles (right axis) report the same for cities with low relative attention. The red solid and blue dashed lines show fitted values for the high- and low-attention groups, respectively.

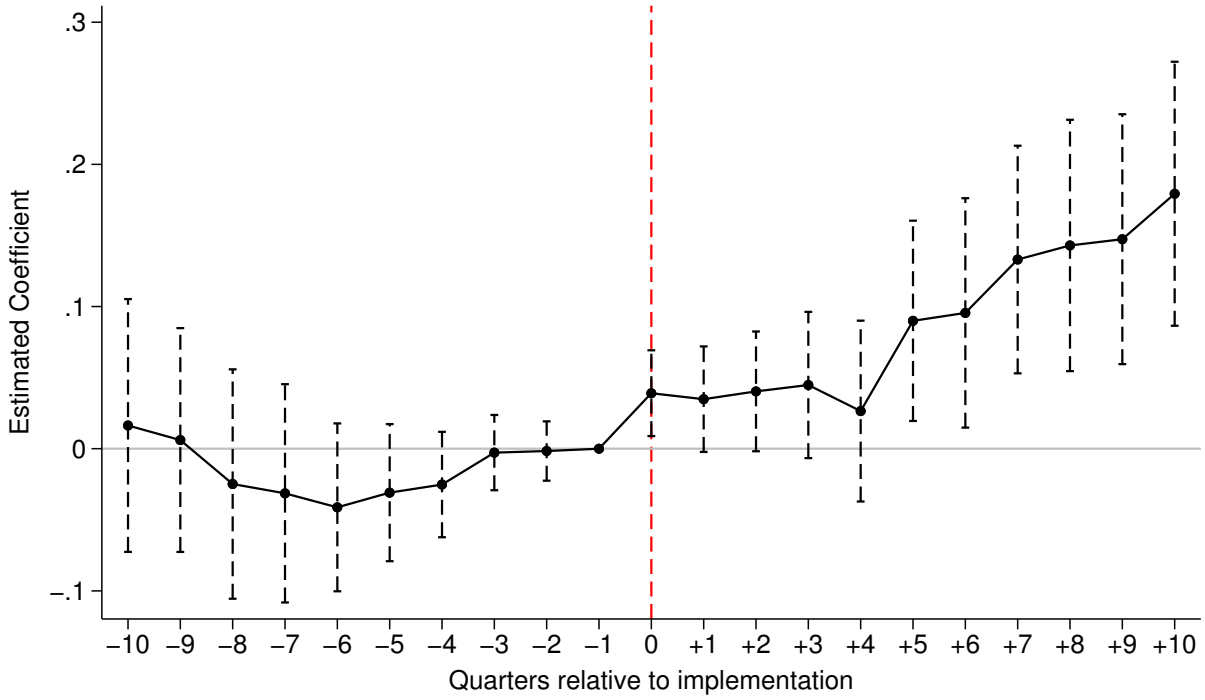


Figure IA8. The Impact of Implemented Adaptation Projects on Listing Housing Prices

This figure illustrates the local housing market's response around the implementation of adaptation policies. Specifically, it plots the estimated coefficients ϑs (dots) and the corresponding 95% confidence intervals (dashed lines) estimated from the following regression:

$$LnlP_{i,t} = \alpha_3 + \sum_{\iota=-10}^{10} \vartheta_\iota \, Adapted_{ic,t+\iota} + \omega X_i + \varphi X_{g,t-1} + \nu_{cde} + \upsilon_t + \varsigma_{i,t},$$

where i denotes property, t represents quarter, and $LnlP_{i,t}$ is the log listing price. The sample is restricted to properties located in SLR-exposed areas and in cities that either announce an adaptation plan or implement an adaptation project during the sample period. $Adapted_{ic,t+\iota}$ equals 1 if quarter $t+\iota$ is ι quarters away from city c's implementation quarter. We consider $\iota \in \{-10, \ldots, 10\}$, with negative (positive) values indicating pre-implementation (post-implementation) quarters. Thus, $Adapted_{ic,t+\iota}$ identifies properties in treated cities ι quarters before, during, or after the implementation quarter. The sample period is from 2011 to 2023.

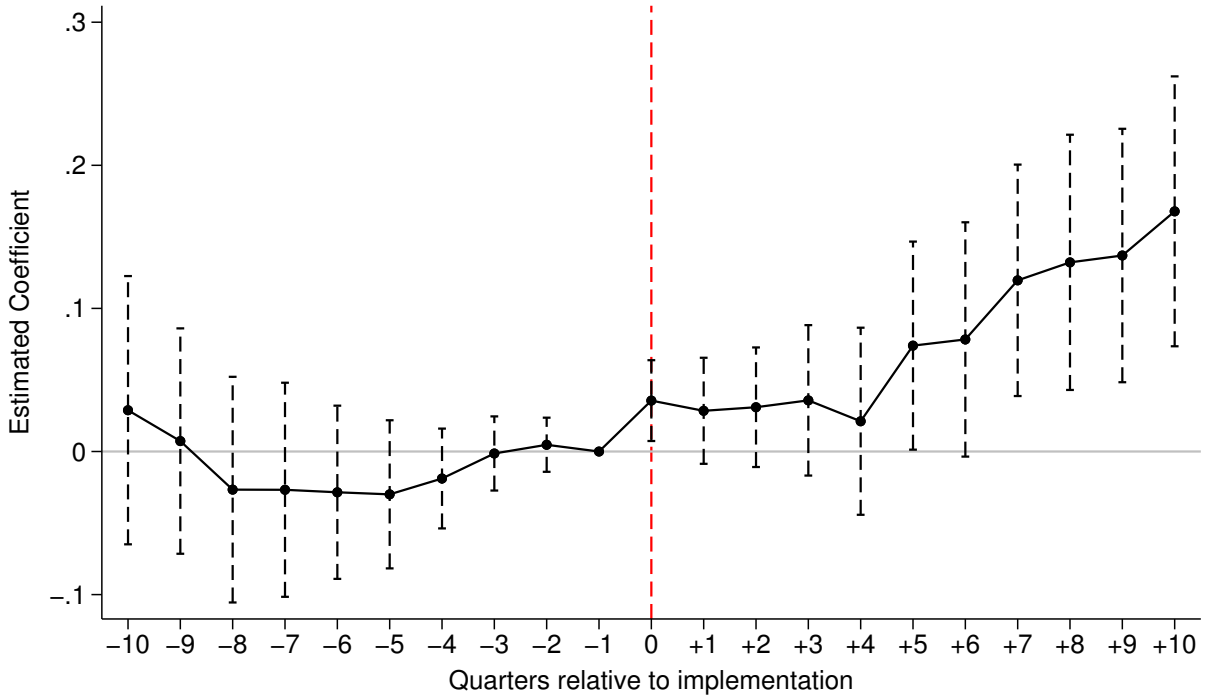


Figure IA9. The Impact of Implemented Adaptation Projects on Unit Housing Prices

This figure demonstrates the response of local housing market around the implementation of adaptation policies by local government. Specifically, it plots the estimated coefficients χs (dots) and the corresponding 95% confidence intervals (dashed lines) estimated from the following regression:

$$LnuP_{i,t} = \alpha_4 + \sum_{\iota=-10}^{10} \chi_\iota \, Adapted_{ic,t+\iota} + \varpi X_i + \phi X_{g,t-1} + \psi_{cde} + \sigma_t + \xi_{i,t},$$

where i denotes property, t represents quarter, and $LnlP_{i,t}$ is the log listing price. The sample is restricted to properties located in SLR-exposed areas and in cities that either announce an adaptation plan or implement an adaptation project during the sample period. $Adapted_{ic,t+\iota}$ equals 1 if quarter $t+\iota$ is ι quarters away from city c's implementation quarter. We consider $\iota \in \{-10, \ldots, 10\}$, with negative (positive) values indicating pre-implementation (post-implementation) quarters. Thus, $Adapted_{ic,t+\iota}$ identifies properties in treated cities ι quarters before, during, or after the implementation quarter. The sample period is from 2011 to 2023.

Table IA1. Adaptation Measures of Coastal Cities

This table summarizes the time and specific measures of sea level rise adaptation strategies that were announced or implemented by local governments of coastal cities in our sample. Since our sample period is from January 2011 to November 2023, we exclude adaptation strategies introduced in 2023.

City	Start month	Adaptation strategies
		Panel A: Implementations
Guangzhou	December 2018	Completed the Lingshan Daojian North Shore super-ecological seawall project.
Haikou	September 2019	Started the Jiangdong New District seawall and coastal ecological restoration project.
Nantong	December 2018	Started the reinforcement of the Jiang-Hai seawall and upgrade of sluice gates in Nantong.
Ningbo	March 2021	Completed the Phase I of the Zhenhai coastal belt ecological restoration and sea-wall improvement project.
Shanghai	May 2019	A pilot ecological sea-wall project was launched, with 520 km seawall constructed.
Shenzhen	February 2019	Started the reconstruction of the eastern seawall.
Weihai	November 2016	Started the Coastal zone ecological restoration under the Blue Bay Program.
Yancheng	November 2022	Implemented seawall and sea conservation projects at Sheyang County and Binhai County.
		Panel B: Announcements
Dongguan	November 2022	Issued the Flood (Tide) Drainage Plan (2022–2035).
Huizhou	April 2022	A plan was formulated to reinforce the Daya Bay seawall.
Qingdao	April 2016	Issued a storm surge prevention plan for the West Coast New Area of Qingdao (2016–2035).
Tianjin	September 2022	The Tianjin Development and Reform Commission proposed a blue bay ecological seawall project.
Zhuhai	January 2018	The Zhuhai Sea Dike Flood Control Standard and Capacity Enhancement Plan was approved.
Yantai	December 2021	Issued the 14th Five-Year Plan for Marine Ecological Protection.
Zhanjiang	October 2021	The marine ecological protection and restoration project was approved.
Zhongshan	November 2021	Issued the marine ecological restoration project plan was released, with a target of reinforcing over 41 km of seawalls.

Table IA2. Sea Level Rise and House Prices

This table reports the estimated coefficients of the regression that examines the impact of sea level rise risk on house prices without fixed effects. The dependent variable is the logarithm of housing transaction price, while $SLR\ Exposure\ (1ft)$ is the main independent variable. Decoration indicator refers to the categorical variable for decoration levels, included in the regression as a series of dummies. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
$SLR\ Exposure\ (1ft)$	-0.70***	-0.53***	-0.20**
	(-3.95)	(-3.72)	(-2.08)
$Number\ of\ bedrooms$		0.07	0.13***
		(1.61)	(7.23)
$Size$		0.27***	0.23***
		(8.18)	(15.29)
Age		0.03***	0.01**
		(8.80)	(2.56)
$Orientation$		0.28***	0.03
		(5.71)	(1.43)
$Elevator$		0.37***	0.28***
		(6.25)	(10.32)
$Middlefloor$		-0.04***	0.00
		(-6.22)	(0.80)
$Middlefloor$		-0.04***	-0.04***
		(-7.81)	(-7.17)
GDP			0.38***
			(5.31)
$Population\ density$			0.39***
			(3.59)
EPU			0.01
			(0.51)
$\%\ Gas\ coverage$			-0.36
			(-0.34)
$\%\ Green\ coverage$			-2.85***
			(-2.97)
$\%\ Urbanization\ \ population$			1.25**
			(2.33)
Number of observations	957,091	916,033	915,934
Adjusted R^2	0.009	0.282	0.646

Table IA3. Alternative Sea Level Rise Measures for Listing and Unit Prices

This table reports regression results on the responses of house prices to sea level rise risks using alternative measures. Columns (1) and (3) adopt a timing-based measure defined as the inverse of the difference between the transaction year and the projected inundation year. Columns (2) and (4) employ a numerical intensity measure, assigning values of 3, 2, and 1 to properties projected to be inundated under 1-foot, 3-foot, and 6-foot SLR scenarios, respectively. Control variables and fixed effects are specified in each regression. See the Appendix for detailed variables descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the district level. The sample period is from 2011 to 2023. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Listing price		Unit price (RMB/m^2)	
	Timing Exposure	Linear Exposure	Timing Exposure	Linear Exposure
	(1)	(2)	(3)	(4)
SLR Exposure ($1ft$)	-0.78***	-0.01***	-0.94***	-0.01***
	(-3.21)	(-3.22)	(-3.84)	(-3.85)
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes	Yes
Number of observations	915,926	915,926	905,305	905,305
Adjusted R^2	0.786	0.786	0.781	0.781

Table IA4. Alternative Difference-in-Differences Estimators

This table provides estimations of the effect of government adaptation efforts on housing prices using multi-period DID estimator. The sample is restricted to sea level rise exposed areas. The dependent variable is the log transaction price. All regressions include city × distance to coast × elevation, and year fixed effects, and control variables. Robust p-values are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the city level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Implemented Announced (1)	Announced No-adaptation (2)
Overall ATT	0.14**	-0.14
	(0.04)	(0.78)
Pre-treatment average	-0.06	0.16
	(0.13)	(0.50)
Post-treatment average	0.35***	-0.35
	(0.00)	(0.60)

Table IA5. Announced vs. Implemented Adaptation Projects for Listing Prices

This table reports regression results on the effect of local government SLR adaptation strategies on house listing prices. The left panel presents estimates for the full sample, while the right panel restricts focus to SLR-exposed areas. The dependent variable is the log listing price. The independent variable is the interaction of *Treat* and *Adapted*. *Treat* equals one if a property is in an SLR exposed area. *Adapted* equals one if the city had implemented or announced adaptation measures by the transaction date. Models (1) and (3) compare the effects of implementation versus announcement, whereas Models (2) and (4) compare announced strategies with non-adapted areas. All regressions control for baseline variables and include fixed effects as specified. Variable definitions are provided in the Appendix. Robust t-statistics are reported in parentheses. Standard errors are clustered at the district level. The sample period is from 2011 to 2023. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full sample		SLR exposed areas	
	Implemented Announced	Announced No-adaptation	Implemented Announced	Announced No-adaptation
	(1)	(2)	(3)	(4)
Treat × *Adapted*	-0.01	-0.02	0.11***	-0.02
	(-0.68)	(-1.03)	(4.66)	(-0.64)
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes	Yes
Number of observations	719,877	319,229	233,617	121,979
Adjusted R^2	0.727	0.747	0.737	0.743

Table IA6. Announced vs. Implemented Adaptation Projects for Unit Prices

This table reports regression results on the effect of local government SLR adaptation strategies on house unit prices. The left panel presents estimates for the full sample, while the right panel restricts focus to SLR-exposed areas. The dependent variable is the log unit price. The independent variable is the interaction of *Treat* and *Adapted*. *Treat* equals one if a property is in SLR exposed area. *Adapted* equals one if the city had implemented or announced adaptation measures by the transaction date. Models (1) and (3) compare the effects of implementation versus announcement, whereas Models (2) and (4) compare announced strategies with non-adapted areas. All regressions control for baseline variables and include fixed effects as specified. Variable definitions are provided in the Appendix. Robust t-statistics are reported in parentheses. Standard errors are clustered at the district level. The sample period is from 2011 to 2023. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full sample		SLR exposed areas	
	Implemented Announced	Announced No-adaptation	Implemented Announced	Announced No-adaptation
	(1)	(2)	(3)	(4)
Treat × *Adapted*	-0.01	-0.02	0.10***	-0.03*
	(-0.48)	(-1.31)	(4.12)	(-1.65)
Property attributes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes	Yes
Number of observations	730,468	319,415	237,909	122,047
Adjusted R^2	0.747	0.631	0.753	0.624

Table IA7. The Role of Flood Resilience

This table reports regression results examining whether urban flood resilience mitigates the impact of sea level rise risk on housing valuations. The sample is restricted to SLR-exposed areas. We measure resilience based on a city's designation as a national pilot in the Sponge City program, which was announced in two waves on April 2, 2015, and April 25, 2016. The dependent variables are the log of the transaction price, the log of the listing price, and the log of the unit price. Our primary independent variable of interest is *Sponge City*. In this specification, *Sponge City* is an indicator variable equal to one if the city was selected as a pilot for the Sponge City program during the 2015 or 2016 announcement waves. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The sample period ranges from 2011 to 2023. Standard errors are clustered at the city level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Transaction prices	Listing prices	Unit prices
	(1)	(2)	(3)
Sponge City	0.20**	0.18**	0.21**
	(2.66)	(2.73)	(2.72)
Property attributes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City×distance×elevation FE	Yes	Yes	Yes
Number of observations	313,389	309,083	313,389
Adjusted R^2	0.786	0.781	0.776