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

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Abstract

We examine how sea level rise (SLR) risk affects residential property prices in emerging markets. Analyzing a comprehensive dataset of coastal housing transactions in China from 2011 to 2023, we show that properties with higher SLR exposure have lower transaction prices. Property buyers are less interested in houses with greater SLR risks, while owners of higher SLR risks properties need to make more price adjustments to conclude a deal. While many local governments have announced adaptation strategies to protect properties from sea level rise, only implemented adaptation actions can attenuate the home value discount associated with SLR risk. Overall, our findings shed light on how long-term climate risks are capitalized into property values and highlight the role of credible local adaptation in enhancing climate resilience.

JEL classification: G10, R30, Q54.

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

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1 Introduction

Climate change has led to global sea level rise at an accelerating pace (IPCC, 2021), posing significant threats to residents and economic activities in coastal regions. Housing, as one of the three major asset classes (Piazzesi, 2025), is particularly vulnerable to climate change due to its durability and geographic immobility. Properties in coastal areas therefore face heightened exposure to climate-related risks. Understanding how households and housing markets react to these risks is crucial for effective design and implementation of climate policies. While the impact of sea level rise (SLR) risks on housing markets has been studied in developed economies (for example, Baldauf, Garlappi, and Yannelis, 2020; Giglio, Kelly, and Stroebel, 2021; Agarwal, Qin, Sing, and Zhan, 2025), evidence from emerging countries remains limited. In this paper, we examine how SLR risks affect housing transactions in an emerging market and evaluate whether local government adaptation strategies effectively mitigate these effects.

Different from the developed countries, which have largely peaked in carbon emissions and possess fiscal capacity to undertake various adaptation measures, emerging economies often face various short-term priorities such as economic growth and poverty reduction (World Bank, 2010). As a result, climate change adaptation may receive less immediate attention. For the same reason, emerging economies are particularly vulnerable to climate risks due to weaker infrastructure and lower resilience to environmental shocks (Dey, 2025). These structural constraints could cause more severe environmental damages. Therefore, studying how climate risk such as sea level rise affect emerging markets is critical for enabling policymakers and investors to better prepare for, mitigate, and adapt to climate change.

As the largest emerging economy, the Chinese housing market provides a unique laboratory to examine these questions. Firstly, 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.[1] Furthermore, housing accounts for more than 70% of wealth of Chinese residential families (Badarinza, Balasubramaniam, and Ramadorai, 2019). It is worthy to investigate

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

how environmental risks affect residential housing investment decisions. Secondly, various studies have shown that housing investment and speculation activities contribute substantially to China's property price boom during 2010 to 2021 (Fang, Gu, Xiong, and Zhou, 2016; Tian and Wang, 2025).[2] The dominance of short-term housing speculation raises an important question: are long-term climate risks, such as sea level rise, reflected in the housing market? Thirdly, 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.[3] The following year, the President emphasized the importance of building ecological seawalls to strengthen resilience against typhoons and storm surges.[4] These proactive actions allow us to conduct policy analysis on its effect on residents' home-buying decisions.

We collect detailed granular data on housing transactions across 30 coastal cities in China, covering the period from January 2011 to November 2023 and encompassing over 900,000 transactions. This extensive dataset includes not only final transaction prices for individual resale housing units, but also provides 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 study and isolate 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 variable allows us to pinpoint the sea level thresholds at which properties are projected to be underwater and differentiate distant and more near-term SLR risk.

Our first empirical setting, therefore, compares housing transactions prices between sea level rise exposed and unexposed properties with similar characteristics, sold in the same year and city, within the same coastal distance group and elevation band, but differing in

[2] 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 home by 2019.

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

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

SLR exposures. We find that SLR risks have statistically and economically significant negative effect on house values. Specifically, a one-standard-deviation increase in SLR exposure reduces property prices by 1.54%, corresponding to an average loss of 42,258 RMB (approximately 6,051 USD) per property. The results are robust to alternative exposure measures, finer fixed effects, different pricing variables, changing market conditions, and the exclusion of periods affected by pandemic lockdowns.

Furthermore, our results suggest that sea level rise exposure significantly depresses housing buyers' home purchase intentions by reducing their property online search activities and offline property viewings. Nevertheless, on the supply side, we find that sellers often revise their expectations in response to climate risk and exhibit more frequent price adjustment in areas exposed to higher SLR. These SLR-exposed proprieties also illustrate lower transaction efficiency by taking notably longer periods to sell. These results indicate that perceptions of future inundation risks shift both buyer and seller behaviors in the housing market.

Our findings enrich the existing literature exploring how sea level rise risks influence residential housing markets.[5] This body of work primarily focuses on advanced countries, particularly the U.S. and Singapore, and concludes with mixed evidence.[6] For example, studies such as Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020), Giglio et al. (2021), Bakkensen and Barrage (2022), Gourevitch et al. (2023), and Agarwal, Qin, Sing, and Zhan (2025) document negative effects of sea level rise on property values, Keys and Mulder (2026) further identify a SLR-associated reduction in housing market liquidity. However, Murfin and Spiegel (2020) find null results and Baldauf, Garlappi, and Yannelis (2020) suggest that price discount effects depend upon local climate beliefs.

We contribute to this line of literature by documenting distinct pricing effect in an emerging market, where price discounts are exclusively concentrated at the near-term, one-foot

[5] Several studies examine the impact of sea level rise risks on broader financial markets. For example, Goldsmith-Pinkham, Gustafson, Lewis, and Schwert (2023) and Painter (2020) document a positive relationship between SLR exposure and long-term municipal bond yields. Dey (2025) show that sovereign credit default swap spreads increase for countries vulnerable to coastal flooding. Bakkensen, Phan, and Wong (2025) analyze the effects of climate risk on the collateralized debt market.

[6] Evidence from other developed markets includes the U.K., where Bäcker-Peral, Hazell, and Mian (2026) find that areas with flood and subsidence risks are associated with higher housing yields.

inundation threshold rather than the six-foot benchmark established in developed market research. Methodologically, we introduce a continuous, time-sensitive measure that incorporates the temporal gap between transaction and projected inundation years. This allows us to capture the increasing present value of potential losses as the hazard horizon shortens. Our study is also related to recent work on China (Zhao, Yang, and Zhang, 2025; Huang, Cheng, and Zhang, 2025), we differ by focusing on ex ante expected inundation risk rather than realized flood events.

Next, we conduct three different investigations to explore how housing investment intentions, land availability, and the salience of climate risk shape the capitalization of sea level rise risk in housing markets. Firstly, housing speculators are generally sophisticated market participants who are more sensitive to risks that threaten asset values (Chinco and Mayer, 2016). This could lead to reduced housing demand from speculators for SLR-exposed properties. However, the myopic nature of housing speculators (Gao, Sockin, and Xiong, 2020) could cause them to be insensitive to long-term SLR risks compared to homeowners. Empirically, we find that SLR-related price discounts are significantly larger in areas with higher speculative activity, suggesting that speculators are more sensitive to risk. This finding is consistent with evidence from the U.S. housing market, where SLR-related discounts are concentrated in non-owner-occupied properties (Bernstein, Gustafson, and Lewis, 2019).

Secondly, in cities with limited developbale land, the inelastic housing supply may reduce the impact of climate risk on property values. Following Shi (2022) and Saiz (2010), we construct a city-level land availability ratio and compare SLR exposure effects across cities and that SLR price discounts arise only in cities with abundant residential land. Thirdly, prior natural disaster experience, such as repeated exposure to climate shocks, may heighten salience of climate risk and intensify the effect of SLR exposure on house prices (Zhao, Yang, and Zhang, 2025; Choi, Gao, and Jiang, 2020). The empirical evidence reveals stronger SLR-related price effects in cities with more frequent typhoon events. Finally, using internet search volume and media coverage of the term *sea level rise* as proxies for local public attention, we show that SLR risk is priced only in cities with high levels of climate change awareness, consistent with Baldauf, Garlappi, and Yannelis (2020), who find that SLR price discount is

concentrated in neighborhoods with strong belief in climate change.

Our study also contributes to literature on the determinants of housing prices in China (Chu, Duan, Yang, and Wang, 2021; Chang, Wang, and Xiong, 2025; Xiong, 2025), such as speculative activity (Chen and Wen, 2017; Glaeser, Huang, Ma, and Shleifer, 2017), land availability (Shi, 2022), and environmental issues such as water quality (Ge, Huang, and Shi, 2025).[7] More recently, Addoum, Cong, and Zhou (2025) document a positive relationship between heat exposure and housing prices in China. Yet, beyond this study, the role of climate risk in China's property market remains under-explored. We extend this strand of literature by showing that climate risk and local government adaptation efforts materially affect property prices.

Given the profound effect of sea level rise exposure on property transaction prices, we then attempt to explore the impact of local adaptation policies in alleviating the SLR price discounts. In particular, we compile a comprehensive policy dataset including the implementation dates, policy content and policy actions from government procurement documents and newspaper articles. Empirically, we employ a staggered difference-in-differences (DID) strategy to evaluate the policy impacts. We find that the effect of government climate adaptation measures depends on their perceived credibility, which is shaped by local governments' fiscal capacity. We further distinguish between implementation and announcement phases of these adaptation policies and find that only projects under implementation can attenuate the negative effects of SLR, while announcements have no observable significant impact. These findings emphasize the importance of credible and concrete government action in improving climate resilience in housing markets.

Recent evidence suggests that such efforts may play a critical role. For example, Agarwal, Qin, Sing, and Zhan (2025) show that the announcement of national adaptation plan in Singapore alleviates the price depreciation due to SLR. Benetton et al. (2025) find that

[7] Several studies examine China's housing market boom and policy interventions. Fang, Gu, Xiong, and Zhou (2016) highlight key features distinguishing China's housing boom from bubbles in Japan and the US. Liu and Xiong (2020) link widespread speculation to increasing price dynamics. Tian and Wang (2025) find that prolonged booms discourage entrepreneurship by encouraging speculative investment. In response to speculation, the government introduced house purchase restriction (HPR) policies, which Qian, Tu, Wu, and Xu (2025) find influence household capital allocation, and Liu and Zhang (2025) show lower birth rates.

property prices in Venice rise significantly after the activation of the city's sea wall. Liu, Constantz, Hale, and Beck (2025) highlight the resilience benefits of mangroves in Florida. Hsiao (2025) raises the concern of potential moral hazard arising from government-led adaptation in Jakarta. Contributing to this growing literature, we provide evidence from an emerging market that local implemented adaptation projects can substantially mitigate SLR price discounts, while policy announcements have no effect.

The rest of this paper is organized as follows: We describe the data and provide summary statistics in Section 2. Baseline results with robustness checks are presented in Section 3. We analyze several channels and mechanisms in Section 4. We discuss the effectiveness of adaptation measures by local governments in Section 5. Section 6 concludes.

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 across China and spanning the period between January 2011 and 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. The credibility of these data is verified by Ge, Huang, and Shi (2025), who show that the transaction prices and property sizes recorded by Lianjia are consistent with official government statistics. The dataset has also been used in prior research. For example, Agarwal et al. (2020) employ it to identify the impact of capital gains tax on resale transactions and tax evasion behavior. Zhao, Yang, and Zhang (2025) study the impact of flood events on the housing markets based on this database. Addoum, Cong, and Zhou (2025) use it to document that abnormal exposure to contemporaneous extreme heat plausibly affects the distribution of surplus between home buyers and sellers.

We focus on residential properties, and our initial dataset comprises more than one million transactions during the sample period. Each transaction record contains detailed

information on both property and transaction characteristics, such as transaction prices and dates, buyer demographics, initial and final listing prices, year of ownership of seller, unit size, number of bedrooms, floor level, building age, interior decoration status, window orientation, and geographic coordinates. The transaction date marks the point at which buyers and sellers, assisted by agents, agree on the final price and execute the sales contract on-site. In addition, the dataset provides other metrics that capture both demand- and supply-side transactional behaviours. 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.[8] 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.

Following Zhao, Yang, and Zhang (2025), we exclude outlier transactions with unit prices above 200,000 RMB per square meter, which account for roughly 0.6% of the sample.[9] We further remove observations with extreme values in property attributes such as size and number of bedrooms.[10] We also exclude transactions with missing building age, as these primarily involve older residential 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.[11] Following Bernstein, Gustafson, and Lewis (2019) and Baldauf,

[8] Internet Appendix Figure IA.1 provides an example of details for transacted property in the platform.

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

[10] 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.

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

Garlappi, and Yannelis (2020), we focus on three benchmarks: 1 foot, 3 feet, and 6 feet of sea level rise. For each scenario, we configure the map, identify the residential community, and capture a screenshot once the location is fixed. We then analyze these images to determine whether the community is projected to be underwater under given SLR scenario, which serves as the inundation threshold.

We next map SLR scenarios to inundation timelines using projections 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).[12] We then construct a property-specific SLR exposure measure as follows:

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

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 year of the property transaction, and r_{u_i} is the discount rate that captures the time preference for future risk. Studies on China's real estate market suggest that residential properties are discounted at a rate of 5% for horizons under 30 years, and at 2.9% for time horizons exceed 60 years.[13] Consistent with Giglio et al. (2021), partial post-disaster mean reversion renders short-horizon cash flows riskier than post-recovery long-horizon flows, which implies higher short-horizon discount rates and a downward-sloping term structure.

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

[13] Please see http://www.aer.ruc.edu.cn/CN/Y2023/V03/I04/114 for details (in Chinese). We use such case-specific discount rates in order to isolate the impact of perceived inundation timing from discount rate manipulation. We also consider a wide range of discount rates for robustness check.

Therefore, our proposed measure incorporates both the timing and the severity of threat. A higher value of *SLR Exposure* indicates more severe and imminent inundation risk. For each unit of potential loss from future inundation risk, more immediate inundation risk carries a higher present value, resulting in larger reductions in property value. On the other hand, more distanced risks are discounted more heavily and therefore have a weaker impact on current prices. 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 hazard horizon shortens.

While sea level rise is a global threat, its pricing in the Chinese residential market depends on the local information environment. Several institutional facts 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, providing localized, authoritative data on sea level trends to the public.[14] Second, the National Strategy on Climate Change Adaptation 2035 explicitly identifies sea level rise as a critical threat to coastal urban infrastructure, which have significantly elevated the national salience of climate adaptation.[15] 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.[16] These facts collectively demonstrate that residents in our sample areas possess a high degree of climate risk perception, providing a solid foundation for our risk-based measure.

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

[15] 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).

[16] 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).

2.3 Geographic and Demographic Variables

Distance to the coastline is crucial for isolating the impact of sea level rise risk on property prices, as some buyers purchase coastal properties for their amenity value, while some buyers may avoid coastal properties for potential SLR risk. Using geographic information provided by Lianjia, we compute the distance from each residential community to the nearest coastline and calculate elevation based on its latitude and longitude. Then we use the distance to coastline and elevation as additional fixed effects in the regressions to control for potential omitted factors that affect residential housing choices. In addition, we further use these geographic identifiers to match each property to its corresponding county, city, and province, enabling us to integrate house-level data with regional demographic and economic variables from the Wind database, including GDP, population, and local policy indicators, which serve as controls in the subsequent analysis. The Appendix provides detailed descriptions of variables used in this study.

2.4 Descriptive Statistics

Table 1 presents summary statistics for our data. Panel A reports transaction characteristics, including prices, time on market, offline visits, online search activity, and listing price adjustments. Panel B describes property characteristics, and Panel C summarizes sea level rise exposure.

Our final dataset comprises 957,216 transaction records from 47,540 residential communities. The average transaction price is 2.74 million RMB (392,368 USD). Properties remain on the market for an average of 229.5 days, with 2.2 listing price adjustments on average. Each property is viewed in person 15.6 times on average, saved online 14.1 times, and virtually visited 1412.3 times. The average house is 83 square meters (893.6 square feet) in size, has approximately 2.25 bedrooms, and is located on the median floor level of a 15-year-old building. About 61% of homes have basic interior decoration, and over half are located in buildings with elevators. Roughly 64% of properties have windows oriented southward. The mean geodesic distance to the coast is 23.3 km, and the average elevation is 19.2 meters.

With respect to sea level rise exposure, the mean SLR Exposure in our coastal sample is 0.09, with a maximum of 0.26. SLR Exposure ranges from 0 to 1, where a value of 1 indicates immediate inundation and 0 reflects no projected flooding within any economically relevant horizon at the time of transaction. A mean of 0.09 suggests that the average property bears a discounted cost equal to 9 percent of the maximum possible impact. Based on property-specific inundation thresholds, we estimate that 34% of homes would be underwater under a one-foot sea level rise scenario. This proportion rises significantly to 64% under a six-foot scenario. By comparison, only 30% of homes in the United States are projected to be inundated under a similar six-foot scenario, as reported in Bernstein, Gustafson, and Lewis (2019).

Figure 1 plots the average sea level rise exposure and unit transaction prices of residential properties across coastal cities in our sample. The shading areas represent city-level average SLR exposure, with darker colors reflecting higher levels of inundation risk. Circles represent the mean unit property price, with larger circles indicating higher average prices. For example, cities in Zhejiang province, such as Ningbo and Wenzhou, exhibit particularly high SLR exposure, followed by cities in the neighboring 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.[17] These patterns underscore the widespread susceptibility of China's coastal housing markets to climate risk and motivate our empirical investigation of whether such risks are priced into residential property values.

Figure 2 plots the time series of average unit transaction prices (per square meter) across areas with different levels of sea level rise exposure. The red solid line represents properties in areas where SLR exposure is above the sample average, while the blue dashed line represents 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

[17] Please refer to the Internet Appendix Figure IA.3 for details.

magnitude of this discount has varied over time — increasing steadily 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 consistently negative relationship between SLR exposure and housing prices over time.

3 Sea Level Rise Risk Exposure and Property Prices

In this section, we conduct empirical investigations to better quantify the impact of sea level rise risk on residential house prices. We start with introducing our baseline specification model, followed with a discussion of main empirical findings. Afterwards, we propose various robustness investigations, including alternative measures of exposure and analyses of different market conditions.

3.1 Baseline Results

If homebuyers incorporate SLR risk into property purchase decision consideration, houses with more imminent inundation risk should receive lower prices than otherwise the same properties. To identify the effect of SLR exposure on house prices, we use the following regression specification as equation (2):

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

where LnP_{it} is the natural logarithm of the transaction price of property i in time t. The key explanatory variable, $SLR\ Exposure_i$, 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, we follow Chu, Duan, Yang, and Wang (2021), Zhao, Yang, and Zhang (2025), and Baldauf, Garlappi, and Yannelis (2020) and include following sets of control

variables in order to consider 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 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, 2025); 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}.[18] δ_t denotes the year-fixed effect to account for temporal variations throughout the sample period. 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

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

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 to 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 reports the coefficient estimates for the 1-, 3- and 6-foot inundation thresholds defined SLR exposures, respectively. $Underwater\ 1ft$ illustrates 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.[19] Nevertheless, coefficients for the 3-foot and 6-foot thresholds are economically negligible and statistically indistinguishable from zero.

This finding of near-term salience of 1-foot inundated SLR exposure is of emerging market specification, in notable contrast to the findings in developed markets. For example, Bernstein, Gustafson, and Lewis (2019) documents a significant 4.4% price discount at the 6-foot level in the U.S. market. Studies based on the developed markets such as (Baldauf, Garlappi, and Yannelis, 2020; Giglio, Kelly, and Stroebel, 2021; Agarwal, Qin, Sing, and Zhan, 2025) focus on the 6-foot threshold as a primary driver of risk. Our results suggest a different market dynamic in China, where price discounts are exclusively concentrated in properties facing imminent inundation risk rather than more distant risks. These differences suggest

[19] 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 $SLR\ Exposure$.

that risk horizons established in developed economies may not be directly applicable to the emerging market such as China, due to differences in market efficiency and the perceived credibility of long-term climate projections. As a result, we adjust the empirical setting in our content by focusing on the 1-foot inundation threshold. That is, the *SLR Exposure* defined in equation (1) is constructed hereafter exclusively using the 1-foot scenario.

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.[20] Across all four settings, the coefficients of *SLR Exposure* 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% ($= 0.14 \times 0.11$).[21] 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 equals to 2.16, implying that unobservables would need to be nearly three times as influential as observables to eliminate the effect. Therefore, the estimated relationship is unlikely to be driven by omitted variable bias.[22]

[20] Baseline results with the gradual inclusion of control variables are reported in Table IA.2 of the Internet Appendix.

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

[22] 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.

The baseline results show a significant price discount for properties with higher exposure to sea level rise, consistent with previous findings as Bernstein, Gustafson, and Lewis (2019); Bakkensen and Barrage (2022); Agarwal, Qin, Sing, and Zhan (2025). Different from binary indicators of whether a property would be inundated under six-foot sea level rise in the literature, our SLR exposure measure incorporates both the severity and timing of inundation risk. Higher SLR exposure reflects more imminent risk. Therefore, our results indicate that homebuyers in the emerging market discount near-term inundation risk more heavily than relatively distanced risk. Furthermore, our *SLR Exposure* is forward looking and focuses on homebuyers' expectation on future inundation risks, and hence is different from the study by Zhao, Yang, and Zhang (2025) that uses actual flood events as risk shocks.

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 larger discount effect in housing prices for properties that facing higher SLR inundation risk.

In columns (3) and (5) of Table 4, we following Bernstein, Gustafson, and Lewis (2019); 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. Our results remain robust across these rigorous specifications, with βs of SLR exposure remain negative and significant of similar magnitudes as the base-

line.

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.[23]

Thirdly, we examine whether the SLR price discount varies across different market conditions. Since China's real estate price exhibits cyclic movement with it reaches the peak in 2021 and starts to decline afterwards,[24], 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

[23] We also evaluate these findings using alternative measures in Table IA.3 and our results remain qualitatively the same.

[24] Please refer to Figure IA.4 in Internet Appendix for the times series of China's average house price.

rates: 3%, 5%, 7%, 10%, and 15%. As shown in Figure IA.5 of the Internet Appendix, the estimated coefficients for *SLR Exposure* remain negative and statistically significant. These results confirm that our baseline findings are not sensitive to the choice of discount rate.

4 Channels and Mechanisms

In this section, we proceed with series of analyses to explore channels and mechanisms through which sea level rise risks affect the housing market. We start by investigating the impact of expected SLR risk on buyer and seller behaviors in the housing market. It is followed by analysis of the heterogeneous responses from housing speculative activities, land constraint on the SLR price discount effects. We also provide relevant evidence on how households' prior disaster experience and public media attention to SLR affect the market's response to SLR risk.

4.1 Evidence based on transactions

House price is the ultimate outcome of housing market searching and matching equilibrium, whereas it provides limited information regarding the supply and demand dynamics in reaching such equilibrium outcomes (Sommer, Sullivan, and Verbrugge, 2013; Favilukis, Ludvigson, and Van Nieuwerburgh, 2017). To shed light on the underlying dynamics, we investigate the impact of SLR exposure on the searching and matching activities in the housing market and the corresponding market liquidity conditions. These property transactional level dynamics aids to provide complementary evidence on the housing markets responses to climate risk.

In particular, Zhao, Yang, and Zhang (2025); Genesove and Han (2012); Piazzesi, Schneider, and Stroebel (2020) use buyers online searches and in-person home-viewings as measures to capture buyers' searching interest and market matching activities from the demand side. On the other hand, Chu, Duan, Yang, and Wang (2021) shows that listing price adjustments prior to the transaction indicate sellers' expectations and bargaining power from the

supply side. Furthermore, Jiang, Kotova, and Zhang (2025) uses properties' listing time on market to capture its market liquidity conditions. Following the literature, we use vairous behavioral measures to captures the housing market supply and demand dynamics. Namely, houses' listing page views and saves (initial interest), offline viewings (purchase intent), the number of price adjustments (seller expectations), and listing time on the market (matching activities). We also aggregate these variables at the community-month level to mitigate transaction-level noise and better capture market-level responses.

SLR-exposed properties are perceived with higher inundation risk, hence attract fewer housing investment demands. Meanwhile, property owners would adjust the prices downward more frequently to attract investors. As a results, these properties would often illustrate longer transaction period with lower market liquidity. In this sense, we would expect properties with higher SLR-exposed risk illustrate fewer listing pages views, saves and offline viewings, more times of price adjustments from property sellers, and longer period listed on the market.

Columns (1) to (3) of Table 7 presents the estimated effects of sea level rise on potential home-buyers' activity. All three specifications show negative and statistically significant coefficients. These negative coefficients suggest that properties with higher SLR-exposed risk are less preferred by housing buyers in the housing seaching-marching market. In particular, a one-standard-deviation increases in SLR exposure leads to a 0.8% decline in listing page views, a 1.4% drop in listing page saves, and a 1.0% decrease in offline property viewings. These results suggest a clear shift in housing demand away from high-SLR-exposed areas.

Regarding the supply-side response and property market liquidity conditions, we employ the Poisson pseudo-likelihood regression, given the dependent variable (i.e., the number of price adjustments and the average district-level days of time on the market) is a countable variable. Column (4) of Table 7 reports the estimates that sellers of SLR-exposed properties adjust listing prices more frequently, with an average increase of 0.56% relative to unaffected properties($= 0.07 \times 0.08$, where 0.08 is the sample mean of $SLR\ Exposure\ (1ft)$). It suggests that homeowners adjust their pricing behavior in response to anticipated declines in buyer demand. Column (5) of Table 7 show the impact of SLR exposures on property's time on the

market. Consistent with our expectations, properties located in areas exposed to SLR risks stay as listed on the market for notable longer periods. A coefficient of 0.05 implies that properties in areas with average SLR exposure remain on the market approximately 0.92 days longer than those in non-exposed areas.[25] This increase reflects the combined effects of behavioral frictions and structural market responses to SLR risks. Our finding aligns with Keys and Mulder (2026), who argue that heightened SLR risk salience reduces market liquidity.

4.2 Housing Speculation

Fang, Gu, Xiong, and Zhou (2016) show that housing speculative activities contribute substantially to the China's housing market boom. On one hand, speculators are typically sophisticated investors (Chinco and Mayer, 2016). Therefore, anticipate future inundation risks could depress their demand for SLR exposed properties. On the other hand, speculative buyers often have shorter investment holding horizons and hence are less likely to consider long-term risks. Therefore, how housing speculative investors perceive SLR risk exposures is worthy detailed investigations and could provide valuable evidence of the price-risk tradeoff in housing market.

In order 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.[26] 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

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

[26] *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.

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, termed it as *Non-five-year ownership*. A higher ratio is associated with a higher level of housing speculation.

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 based on sample median. Columns (1) and (2), (3) and (4), (5) and (6) of Table 8 report sub-sample regression estimates based on low and high house speculation areas sub-samples defined by *Non-five-year ownership*, *Price-to-rent ratio*, and *Price-to-income ratio*, respectively. In all settings, SLR exposure illustrates negative coefficients, whereas statistically significant and larger price discount effects of SLR exposure are consistently observed in areas with high level of housing speculation. Furthermore, the differences between high- versus low-speculation areas are statistically significant. For example, in areas with a high *price-to-income ratio*, the impact of SLR exposure on house transaction prices is -0.22%. That is, for a property with mean SLR exposure, it suffers from an average loss of 48,294 RMB (approximately 6,916 USD). However, the coefficient for low speculation areas (i.e., column 5) is -0.05 and yet significant. Results based on the *non-five-year ownership* and *price-to-rent ratio* measures illustrate similar patterns.

The overall results suggest that sea level rise risks have more substantial impact on the housing markets with higher levels of speculative activity. In this sense, speculative buyers,

as typically more sophisticated market participants, are more sensitive towards property-related risks. The finding aligns with Bernstein, Gustafson, and Lewis (2019) that in the U.S. housing market, SLR price discounts are mainly driven by sophisticated investors.

4.3 Land Supply Constraint

Besides housing speculation, land supply elasticities shaped by both regulatory and geographic constraints also affect housing price sensitivities towards various pricing factors (Saiz, 2010; Shi, 2022; Mian and Sufi, 2022), such as sea level rise risks. Cities situated on plains generally have more developable land than those surrounded by mountains or intersected by rivers. Given limited housing choices in inelastic land supply areas, home buyers would consider more immediate living purpose of housing instead of long-term climate risk. In this sense, we would expect diminishing or insignificant SLR price discount effect in land constrained areas.

In order to capture land supply elasticities, we follow Shi (2022) and construct a city-level measure of geographic land constraints. We first collect annual data on residential and total construction land from the China Statistical Yearbook. Afterwards, we compute the share of non-residential land as one minus the ratio of residential to total construction land.[27] This measure reflects the extent to which land available for residential development is exogenously constrained. We then performance the sub-sample regression based on sample median, as well as the top- and button- 30th quintile value of the cross-sectional distribution of non-residential land ratios.

Table 9 reports the estimated coefficients. Columns (1) and (2) present estimates for sub-samples of loose and tight land constraints, respectively. In Column (1), the coefficient on SLR exposure is -0.17 (t-statistic = -3.26), indicating that a 10% increase in SLR exposure is associated with a 1.7% decrease in property transaction prices in regions with relatively

[27] Different from Shi (2022), who measures land constraints for Chinese cities by calculating the proportion of unavailable construction areas relative to the total administrative areas, our measure focuses on the percentage of residential land in the total construction land. This distinction arises from our focus on residential property prices, whereas Shi (2022) examines prices of both residential and non-residential commercial properties.

abundant residential land. However, the coefficient in Column (2) is only -0.09 (t-statistic = -1.31), suggesting insignificant relationship in more land-constrained areas. We further divide the sample based on the top- and button-30th percentile of cross-sectional land constraint distribution. Column (3) reports estimates for the bottom 30% of the land constraint (i.e., the 1st- to the 30th-percentiles), while Column (4) reports results for the top 30% (i.e., the 70th- to the 100th-percentiles). Again, we observe significant SLR price discount effect in areas with greater land development flexibility. The differences between the coefficients of two groups are statistically significant, suggesting that residents in cities with scarce residential land price less of the long-term climate risk, as limited housing supply reduces their relocation options.

4.4 Salience of Climate Risk

Recent work by Choi, Gao, and Jiang (2020) shows that short-term climate events can significant impact investors' perceptions regarding climate change. Direct experience of extreme weather events, such as typhoons and hurricanes, as well as intensified media coverage would enhance households' awareness of coastal flood risks. This heightened awareness can increase residents' sensitivity towards flooding risks associated with SLR. As a result, property prices in areas with more frequent extreme climate events would illustrate a stronger SLR price discount effect.

Specifically, we use typhoon occurrences to capture the salience of extreme climate events. The typhoon incidence data are obtained from the China Meteorological Administration, covering the past 70 years. With this dataset, we identify 12 cities with frequent typhoon exposure across three coastal provinces. That is, Fuzhou, Xiamen, and Zhangzhou in Fujian; Dongguan, Guangzhou, Huizhou, Jiangmen, Shenzhen, Zhanjiang, Zhongshan, and Zhuhai in Guangdong; and Haikou in Hainan.[28] Properties located in these cities are categorized as being in the frequent-typhoon zone, whilst others are classified as infrequent-typhoon zone. We then conduct the regression equation (2) based on the frequent- and infrequent-

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

typhoon sub-sample groups. In addition, Guangdong Province has historically experienced the highest number of typhoon incidences in China. We conduct a complementary analysis by separating the sample into Guangdong Province and all other coastal provinces.

Table 10 reports the corresponding estimations. In all sub-sample regressions, the coefficient estimates of SLR Exposure are significantly negative, reinforcing a robust SLR price discount effect. Nevertheless, the magnitude of *SLR Exposure* is substantially larger in cities with frequent typhoon experience (i.e., column (2)), so as for cities in the Guangdong province (i.e., column (4)). For example, for every 10% increase in SLR exposure, property prices in typhoon-prone areas declining by 3.9%, whiles the price drop is 1.2% in infrequent typhoon areas. It suggests that the price discount associated with SLR risk is more pronounced in areas with salient climate risk through repeated extreme weather events, indicating that repeated climate shocks could strengthen the impact of long-term risk on the housing market (Bin and Landry, 2013; Clayton, Devaney, Sayce, and Van de Wetering, 2021; Giglio et al., 2021).

4.5 Attention to Sea level Rise

While recurrent physical climate shocks prompt immediate reassessment of sea level rise risks, media coverage plays a critical role in shaping public perceptions and behavioral responses to climate risks. Stroebel and Wurgler (2021) find that individuals perceive physical climate risks as the most salient long-term climate threat, leading properties located in projected flood zones to trade at a discount. In this sense, public attention to SLR could intensify the extent of price discounts effect of SLR exposure in the housing market.

In the literature, Google search volume index is often used to measure climate change attention in the U.S.(Choi, Gao, and Jiang, 2020). For the Chinese market, we use the Baidu search volume for the term *sea level rise* to capture relevant public attention. We then scale the city-month Baidu search volume by the city population in order to construct a relative attention measure. As illustrated in the cross-sectional distribution in Figure IA.6 of the Internet Appendix, public attention to climate risk exhibits substantial variation across the

cities. The distribution is right-skewed, indicating that while climate concern is moderate for most cities, a notable subset exhibits particularly high awareness. Besides the search volume index, we also use the the Baidu Feed Index for the keyword *sea level rise* to capture the intensity and persistence of news coverage on the subject. Unlike search data, which reflects active user queries, the Feed Index tracks information consumption and social engagement by aggregating page views, comments, likes, and shares of content recommended by Baidu.

For empirical investigation, we divide cities into high- and low-attention groups based on the median value of each measure and conduct sub-sample analysis. Table 11 reports the estimated coefficients. As shown in columns (2) and (4), the negative impact of SLR exposure on property prices is only significant in regions with high attention to sea level rise. Taken column (2) for example, in high-attention regions, one standard deviation increase in sea level rise is associated with a 2.0% decline in transaction prices, 0.6% larger than the corresponding estimate in the full-sample analysis. It suggests that public attention substantially amplifies the price discount for properties exposed to SLR risk. Furthermore, the group differences remain statistically significant for both measures. Internet Appendix Figure IA.7 illustrates this relationship. We observe a downward sloping pattern between house prices and sea level rise exposure in areas with high attention to SLR. In contrast, cities with below-median public attention exhibit a more muted, slightly upward-sloping relationship. Our results are consistent with Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020) that price discounts are more concentrated in neighborhoods with stronger climate change beliefs.

5 Local Government Climate Adaptation Efforts

The previous sections reinforce the negative effect of sea level rise on the housing market with identified key channels and mechanisms. Meanwhile, these documented impacts also highlight the question of whether proactive responses from government can dampen or offset such price discount effect. Therefore, this section focuses on the effectiveness of local governmental adaptation measures and interventions in mitigating the negative impact of

SLR. In addition, we further explore how fiscal conditions affect the effectiveness of such interventions.

5.1 Government Adaptation Measures: Announcement versus Implementation

China has historically faced notable exposure to coastal flooding driven by tidal forces and storm surges, with substantial portions of its coastline remaining vulnerable (Wang et al., 2025). In response, the central government launched the National Seawall Construction Plan in 2017, followed by local governments' adaptation efforts focusing on seawall infrastructure. If these actions are effective and even shift local residents perceptions regarding sea level rise risks, housing prices in adapted regions would be expected to experience smaller depreciation.

To test this hypothesis, we compile a comprehensive dataset of policy events, including announcement and implementation dates, policy content, and associated government actions. These data are hand-collected from government procurement records and regional newspaper articles. Moreover, we distinguish between implemented adaptation projects from plan announcements (without implementation). Because these local government measures vary significantly in timing and scope due to differences in physical exposure, governance capacity, and local planning priorities,[29] we adopt a staggered difference-in-differences model to estimate the impact of adaptation efforts on housing prices as below:

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

where $Treat_i$ is a dummy variable equal to 1 if property i is located in an area exposed to sea level rise, and 0 otherwise. $Adapted_{ic,t}$ ian indicator variable that takes the value of one if city c, where property i is situated, has announced or started to implement adaptation strategies prior to time t. X_i and $X_{g,t-1}$ stands for aforementioned control variables as in equation (2). μ_{cde} stands for city $\times$ distance $\times$ elevation fixed effect, and τ_t denotes year

[29] Internet Appendix Table A.1 provides detailed information on the adaptation strategies implemented by each coastal city.

fixed effect.

The coefficient of interest, θ, captures the mitigating effect of adaptation strategies on the prices of SLR-exposed properties. In particular, we estimate the effects of adaption policy announcements and implemented strategies separately. On one hand, adaption projects implementations could directly reduce SLR uncertainty through visible sea wall infrastructure or investment. On the other hand, the effectiveness of adpation policy announcements depends on the perception of local market participants on the creditworthiness of local government.

Table 12 reports the coefficient estimates of equation (3) for adaption project implementation (columns 1 and 3) and announcement (without adaption) (columns 2 and 4). Columns (1) and (2) of the left panel report regression results based on the full sample, wherein we no significant impact of adaptation measures on housing prices. Columns (3) and (4) of the right panel report results based on SLR exposed cities. As expected, implemented adaption projects illustrate a positive and statistically significant coefficient of 0.11 (t-stat = 4.46). That is, cities that implemented adaptation action can significantly reduce the SLR price discount in the local housing market by approximately 11%, relative to cities that merely announced adaption plans. On the other hand, the coefficient in Column (4) is negative and insignificant, suggesting that mere announcements without execution do not help to alleviate market concerns. This finding may stem from the fact that most sea wall construction plans in our sample followed national plans in 2017 and were announced relatively late. Our findings suggest that climate adaptation actions can help to mitigate negative SLR price impact in the housing market, but concentrated in areas directly exposed to sea level rise risk and only for executed adaption projects.

Furthermore, to address potential bias with stagged DID setting, we conduct the robust multi-period DID estimator proposed by Callaway and Sant'Anna (2021). Specifically, we utilize both not-yet-treated unit as the control group and employ a doubly robust estimation strategy that combines outcome regression with inverse-probability weighting based on a propensity-score model. Internet Appendix Table IA.4 reports the corresponding estimates and reinforce the findings that only physical adaptation action can mitigate the SLR price

discount. For the sub-sample of properties in SLR-exposed areas, the estimated average treatment effect on the treated (ATT) for implemented projects is positive and statistically significant (0.14, p-value = 0.04).[30] Nevertheless, the coefficients for announcement are insignificant. In addition, we conduct an event study for SLR-exposed areas with implemented adaptation actions. Figure 3 plots the dynamics of θ of equation (3). It is clear that the coefficients on the interaction term become significantly positive after adaption actions executed.[31]

As an addition test, we examine whether a city's flood resilience influences the market capitalization of sea level rise risk by focusing on another nationwide initiative to address sea level rise risk. It is the Sponge City pilot program, which is launched in 2015 designed to enhance rainwater absorption and drainage.[32] Followed with a similar regression setting as equation (3), Internet Appendix Table IA.7 reports coefficient estimates. The consistent and robust positive and statistically significant coefficients suggest that the SLR price discount is significantly alleviated in pilot cities.

These findings suggest that enhanced flood management infrastructure reduces the perceived risk of SLR exposure, effectively attenuating its negative impact on property valuations. Various studies based on the developed economies have highlighted the effectiveness of government adaptation efforts in mitigating negative price effect of SLR price, such Agarwal, Qin, Sing, and Zhan (2025) for the Singapore housing market, Benetton et al. (2025) for the Venice housing market, and Liu, Constantz, Hale, and Beck (2025) for Florida. Although informative, these studies offer limited insight into the context of emerging markets. A recent study by Hsiao (2025) raises concerns about moral hazard stemming from government-led adaptation efforts in Jakarta but fail to address the policy impact on SLR exposure or hous-

[30] The decomposition results show that pre-treatment effects are indistinguishable from zero, while post-treatment effects are positive and significant.

[31] We also use listing prices and unit transaction prices as alternative dependent variables and conduct the event study. Estimation results and time dynamics of θs are reported in Internet Appendix Table IA.5 and Figure IA.8 for listing price, and in Internet Appendix Table IA.6 and Figure IA.9 for the unit transaction price.

[32] 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).

ing prices. Our study contributes to this strand of literature by providing empirical evidence from the largest developing country, showing that local adaptation actions can reduce the price discount associated with SLR exposure. In particular, we distinguish between announced and implemented projects, and find that only implementation leads to measurable market responses.

5.2 Local Fiscal Condition

Strong fiscal conditions enable timely and adequate adaptation measures, enhance urban resilience, and influence public and market perceptions of government effectiveness. Therefore, the effectiveness of local adaptation measures in mitigating sea level rise effect depends critically on the fiscal capacity of local government. These perceptions, in turn, shape households' expectations regarding future adaptation efforts and ultimately affect housing market outcomes. We therefore examine the mechanism of local fiscal condition on the effectiveness of adaption policies.

We consider two measures of local fiscal conditions. One is the local fiscal deficit, which is calculated as the difference between general public budget expenditure and revenue, normalized by GDP at the city-year level (Chen et al., 2025). Greater government fiscal deficit typically reflects weaker fiscal capacity and a lower creditworthiness of local government in completing planned adaptation projects. Another is based on corporate bonds issued by local government financing vehicles (LGFVs). In China, LGFVs are state-owned entities created to circumvent borrowing constraints and finance infrastructure projects on behalf of local governments (Chang, Wang, and Xiong, 2025). Due to their close ties to local authorities, the credit risk associated with LGFV bonds often used to serve as a proxy for local fiscal health (Hu, Li, Yang, and Zhang, 2025). For each city, we calculate the average monthly credit spread of seven-year LGFV bonds as the difference between their issuance yield and the yield on treasury bonds of the same maturity. Higher credit spreads indicate greater credit risk and weaker fiscal capacity.[33]

[33] Since only a small fraction of LGFV bonds is publicly traded, we use the issuance credit spreads rather than secondary-market spreads. Secondary-market data also suffer from limited coverage and infrequent

Empirically, we conduct regression of equation (3) based on sub-samples separated by the sample median of each fiscal measure. The sample is restricted to properties exposed to SLR risks and located in areas that have started to implement adaptation measures. Table 13 reports the corresponding estimates, with the left panel is the results based on the fiscal deficit and the right panel is that based on LGFV bond credit spreads. In Columns (1) and (3), where fiscal constraints are low, characterized by low fiscal deficits and low LGFV bond credit spreads, the coefficients on $Treat \times Adapted$ are 0.05 ($t = 3.89$) and 0.05 ($t = 3.11$), respectively. Both are statistically significant at the 1% and 5% levels, respectively. However, in columns (2) and (4), which represent cities with high fiscal deficits or high credit risk, the interaction coefficients are statistically insignificant. These findings suggest that market participants internalize the long-term execution risk of climate adaptation measures with consideration of the credibility of local government. High fiscal deficits or elevated borrowing costs may signal weak local fiscal condition to support adaptation projects, which could be delayed, underfunded, or abandoned. Such perception would reduce the market's expectation of government adaptation efficacy in reducing sea level rise threats.

6 Conclusion

Evidence on the extent to which long-term climate risks are capitalized into housing prices remains limited in emerging economies, where governments face the dual challenge of sustaining economic growth while adapting to climate change. This study examines the impact of sea level rise risk on housing market transactions in the world's largest developing country. We find that properties with greater exposure to sea level rise risk transact at significantly lower prices than less-exposed properties. 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 cities characterized by high speculative

trading issues. Moreover, LGFV bonds issued in coastal cities are primarily of 5-, 7-, and 10-year maturities. To maximize sample size after merging LGFV bond data with our main dataset, we focus on the 7-year maturity.

activity, abundant land supply, frequent typhoon exposure, and greater public awareness of sea level rise 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 mitigate the adverse price effects associated with sea level rise, whereas policy announcements alone have no discernible impact. In addition, the mitigating 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 within emerging economies and highlight the importance of credible, proactive adaptation investments 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
Real estate 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
Time on market	Number of days a property is listed before being sold.	District × Month	Lianjia
Offline views	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
Sea level rise exposure			
SLR Exposure	Main measure of sea level rise risk, defined in equation (1).	Property	Climate Central
Timing Exposure	Inverse of the time difference between the transaction year and the projected inundation year.	Property	Climate Central
Linear Exposure	Takes values of 3, 2, and 1 for properties projected to be inundated under 1-foot, 3-foot, and 6-foot SLR scenarios, respectively.	Property	Climate Central
Underwater $1ft$	Dummy equal 1 if the house is projected to be inundated under a 1-foot SLR, 0 otherwise.	Property	Climate Central
Underwater $3ft$	Dummy equal to 1 if the house is projected to be inundated under a 3-foot SLR, and 0 otherwise.	Property	Climate Central
Underwater $6ft$	Dummy equal to 1 if the house is projected to be inundated under a 6-foot SLR, and 0 otherwise.	Property	Climate Central
House 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 'Bare Shell', 3 for 'Simple Decoration', and 4 for 'Luxurious Decoration'.	Property	Lianjia
Elevator	Dummy equal to 1 if the house has an elevator, and 0 otherwise.	Property	Lianjia

Continued on next page

Appendix: Variable Definitions-Continued

Name	Description	Data cell	Source
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 from latitude and longitude offered by Lianjia
Elevation	Elevation in meters of the area where a property is located, grouped into five categories for fixed effects.	Property	Calculated from latitude and longitude offered by Lianjia
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 (scaled by 100).	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 in a province.	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 if property is in a city that has experienced frequent typhoons over the past 70 years, and 0 otherwise.	City	China Meteorological Administration
Relative attention	Baidu search volume index for the term "sea level rise" in a city during a month, scaled by population.	City × Month	Baidu
Media coverage index	Baidu news index for the term "sea level rise" in a city during a month.	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 five-year LGFV bonds and treasury bonds of the same maturity.	City × Month	Wind

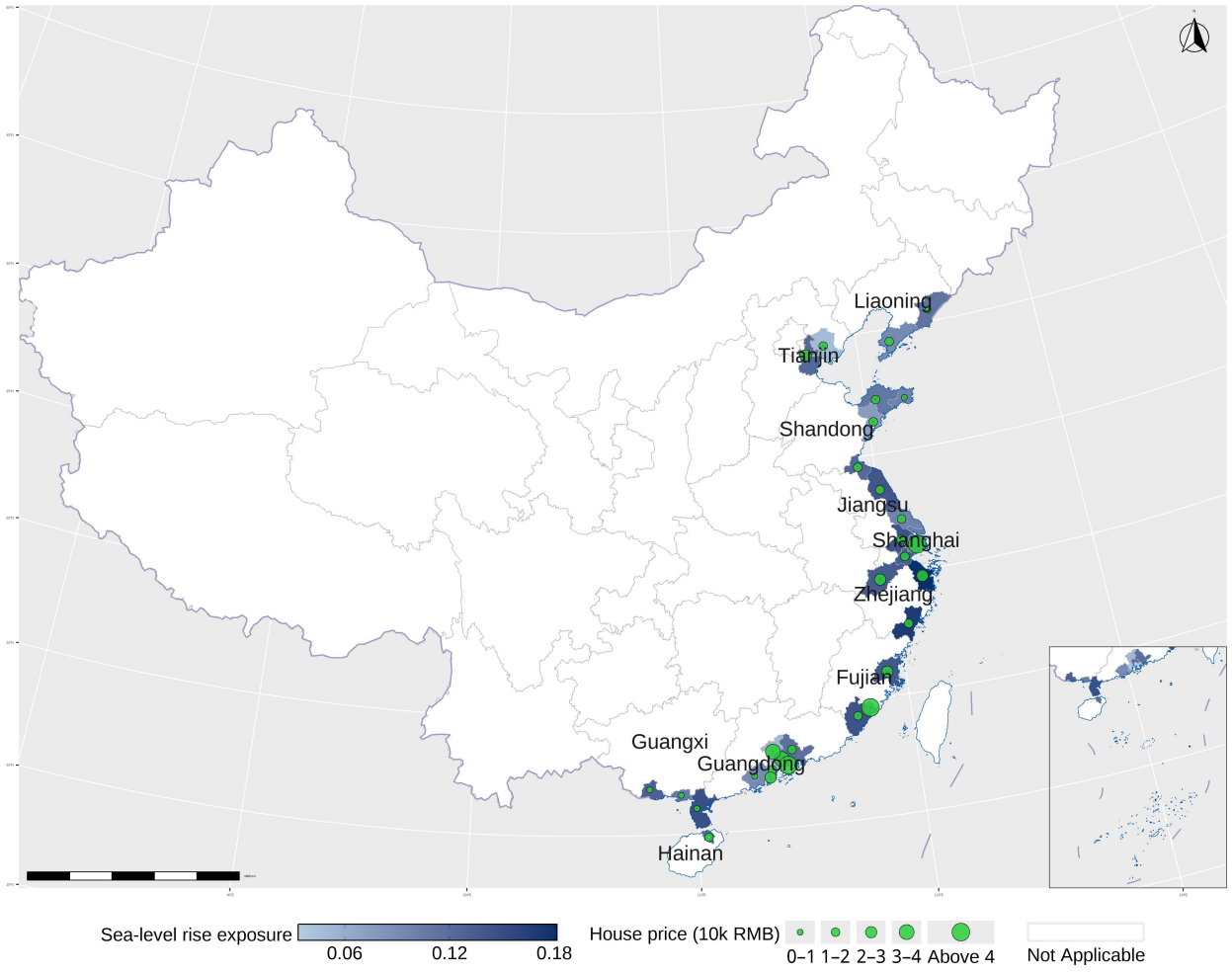


Figure 1 Sea Level Rise Exposure and Property Prices Across Cities

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. Circles denote average unit house prices of cities, with larger ones representing higher unit prices.

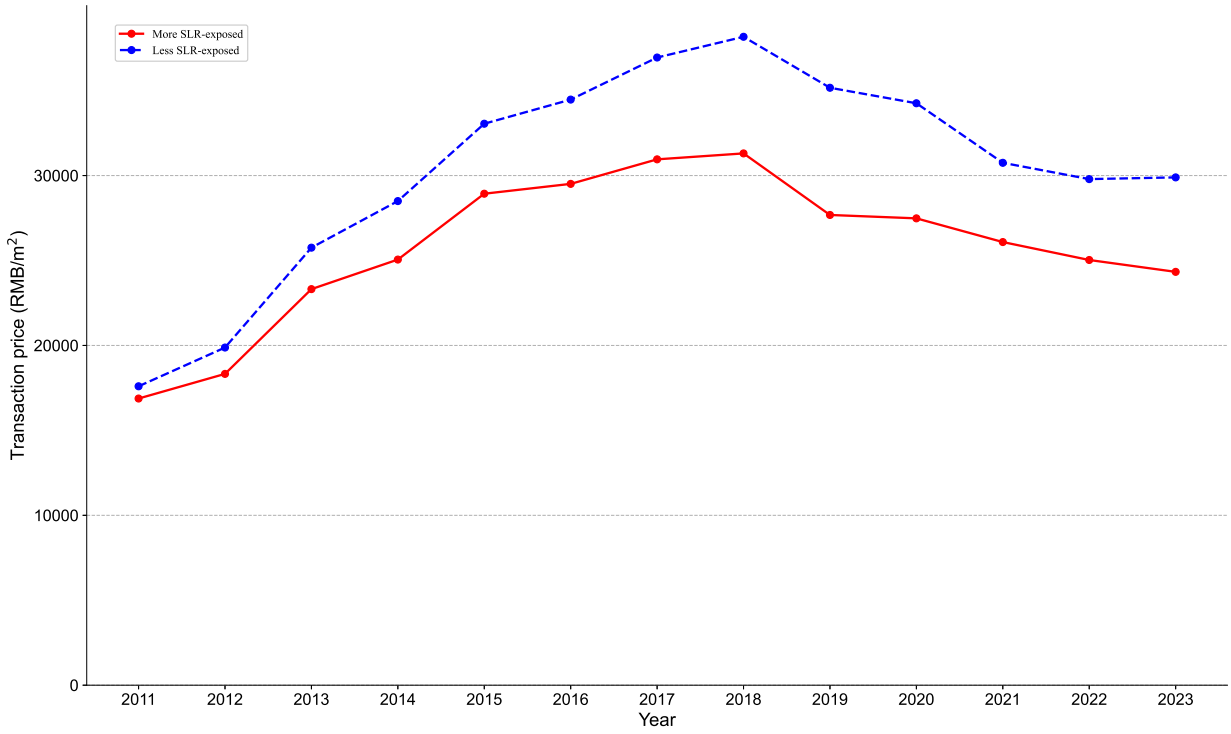


Figure 2 House Prices and Sea Level Rise Exposure

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.

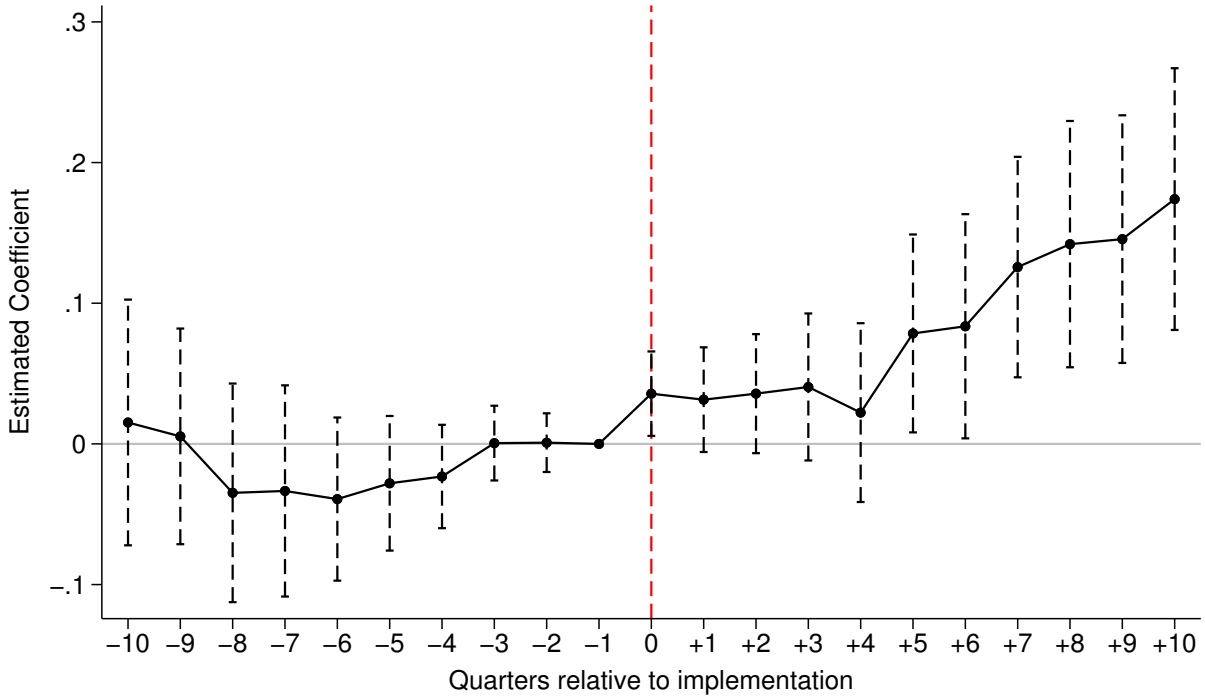


Figure 3 The Impact of Adaptation Polices on House Prices

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:

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

where i denotes property, t represents quarter, and $LnP_{i,t}$ is the log transaction price. The sample is restricted to properties located in areas exposed to SLR risk and have implemented adaptation measures. $Treat$ is an indicator equal to 1 for properties in cities that implemented an adaptation project. $Adapted_{ic,t+\iota}$ is an indicator equal to 1 in quarter $t+\iota$ if city c is ι quarters away from its implementation quarter, with $\iota \in \{-7, \ldots, 7\}$ (negative values denote pre-implementation periods and positive values denote post-implementation periods). Thus, $Treat \times Adapted_{ic,t+\iota}$ identifies properties in treated cities ι quarters before, in, or after the implementation quarter. The sample period is from 2011 to 2023.

Table 1 Summary Statistics

This table reports summary statistics of variables used in this paper, including number of observations, mean, median, standard deviation, minimum and maximum. Panel A, B and C are variables for real estate transactions, housing attributes 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: Real estate transactions						
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
Time on market (days)	943,001	229.52	130.13	327.25	1	2132
Offline views	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	957103	2.20	1.50	2.43	0	17
Panel B: Housing attributes						
Number of bedrooms	957,091	2.25	2	0.86	1	6
Size	914255	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	84.71
Elevation (m)	957,091	19.22	8.00	24.66	0	217
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
Timing Exposure	957,091	0.01	0.01	0.01	0	0.04
Linear Exposure	957,091	1.43	1	1.28	0	3
SLR Exposure $(1ft)$	957,091	0.08	0	0.11	0	0.26
Timing Exposure $(1ft)$	957,091	0.01	0	0.02	0	0.04
Linear Exposure $(1ft)$	957,091	1.01	0	1.41	0	3

Table 2 Housing Price Effects with Different Inundation Thresholds

This table reports the impacts of SLR risks on log transaction prices. The independent variables *Underwater* $1ft$, *Underwater* $3ft$, and *Underwater* $6ft$ are dummies that equal to 1 (scaled by 100 for readability) if a property is projected to be underwater under a 1-, 3-, or 6-foot SLR, respectively. Column (1) includes the full sample, column (2) excludes properties in the 1-foot SLR zone, and column (3) further excludes those in the 3-foot zone. Robust t-statistics are reported in parentheses. The sample period is 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)
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 and House Prices

This table reports the estimated coefficients of baseline regression that investigates the impact of sea level rise risk on house prices. The dependent variable is the logarithm of housing transaction price ($LnP_{i,t}$). *SLR Exposure* 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)	(4)
SLR Exposure	-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 exposures		More granular FE		
	Timing	Linear	Year -quarter	Year -month	City -Year
	(1)	(2)	(3)	(4)	(5)
SLR Exposure	-0.93***	-0.01***	-0.14***	-0.14***	-0.14***
	(-3.84)	(-3.85)	(-3.80)	(-3.80)	(-3.82)
House 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 Pricing

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 logarithm of unit price, while columns (3) and (4) report that of listing price. The main independent variable of interest is *SLR Exposure*. 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	-0.12***	-0.12***	-0.14***	-0.14***
	(-3.20)	(-3.23)	(-3.83)	(-3.82)
House 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 Market Trends and COVID-19 Lockdown

This table reports coefficient estimates of baseline regression under different market conditions. Columns (1) and (2) are the regression results based on sub-sample periods of rising and declining house prices, respectively. Columns (3) and (4) are the regression results based on sub-sample periods of COVID-19 pandemic lockdown and non-lockdown periods. Control variables and specified fixed effects are included accordingly. Robust t-statistics are reported in parentheses. The group difference and the corresponding p-value are obtained from the permutation test, implemented via 2,000 bootstrap resampling iterations. 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.

	Market condition		Lockdown	
	Up	Down	Yes	No
	(1)	(2)	(3)	(4)
SLR Exposure	-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)	
House 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 Transactional-Level Evidence in Housing Markets

This table investigates the impact of sea level rise exposure on housing market conditions. Columns (1), (2) and (3) estimate the coefficients of effect SLR exposure on homebuyers, proxied by the property listing page views, property listing page saves, and offline views (logarithm), respectively. Column (4) uses Poisson pseudo-likelihood regression to examine impact of SLR exposure on house sellers' behaviours, measured by the monthly number of price adjustments of each community. Column (5) presents Poisson pseudo–likelihood regression estimates of market liquidity on SLR exposure. Market liquidity is measured by the time a property stays on the market, aggregated to the district–month level. Control variables and specified fixed effects are included accordingly. Robust t-statistics for Columns (1) to (3) and z-statistic for Columns (4) to (5) are reported in parentheses. The sample period is from 2011 to 2023. Standard errors are clustered at the district level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Listing page views (1)	Listing page saves (2)	Offline views (3)	#Price adjustments (4)	Time on market (5)
SLR Exposure	-0.08***	-0.13**	-0.10***	0.07***	0.05**
	(-3.27)	(-2.41)	(-2.65)	(3.45)	(2.44)
House 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
Observations	837,570	915,813	915,813	915,801	908,625
Adjusted / Pseudo R^2	0.697	0.454	0.535	0.165	0.843

Table 8 Speculation and the Price of Exposure

This table investigates the relationship between housing speculative activity and the SLR price discount based on sub-sample regressions. The dependent variable is log transaction house prices, while the independent variable is *SLRExposure*. Columns (1)-(2), (3)-(4) and (5)-(6) report coefficient estimates based three proxies of speculation: the district-month share ratio of transactions that do not satisfy the *five-year ownership and only property*, the city-month *price-to-rent ratio*, and 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 mediant. The group difference and the corresponding p-value are obtained from the permutation test, implemented via 2,000 bootstrap resampling iterations. 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	-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)	
House 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
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 Land Supply Constraint and Sea Level Rise Price Discount

This table reports estimates of baseline regression for different levels of land supply constraints. Land constraint is measured as the ratio of unavailable residential land to total construction area in a city at a given year. Columns (1) and (2) report results based on the sample median: Column (1) presents estimates for property transactions in areas where the land constraint is below the median, while Column (2) shows estimates for areas where it is above the median. 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%. The group difference and the corresponding p-value are obtained from the permutation test, implemented via 2,000 bootstrap resampling iterations. 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	Loose	Tight
	(1)	(2)	(3)	(4)
SLR Exposure	-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)	
House 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 Salience of Climate Risk

This table reports estimates for the impact of past typhoon experience on SLR-related discount. Columns (1) and (2) represent estimated coefficients based on sub-sample of areas categorized by historical typhoon frequency: "Frequent" denotes cities that have experienced more than 100 typhoons over the past 70 years, while "Infrequent" denotes those with fewer. Columns (3) and (4) provide a top-tier frequency analysis by isolating the most impacted region: "Guangdong" represents properties located within Guangdong Province, the region with the highest cumulative typhoon frequency in China, while "Others" refers to all other coastal areas in the sample. The dependent variable is log transaction price, while the independent variable is *SLR Exposure*. The group difference and the corresponding p-value are obtained from the permutation test, implemented via 2,000 bootstrap resampling iterations. 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		Top-tier Frequency	
	Infrequent	Frequent	Others	Guangdong
	(1)	(2)	(3)	(4)
SLR Exposure	-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)	
House 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 The Effect of Attention to Sea Level Rise

This table examines the impact of public attention on SLR price discount. The attention measure is constructed from two city-level Baidu indices. Attention is measured using two city-level Baidu indices: (i) population-scaled search volume for *sea level rise* (relative attention) and (ii) a news index capturing the intensity and persistence of *sea level rise* coverage over time. 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. The group difference and the corresponding p-value are obtained from the permutation test, implemented via 2,000 bootstrap resampling iterations. 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.

	Internet search index		Media coverage index	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
SLR Exposure	-0.06	-0.20***	-0.06	-0.18***
	(-1.52)	(-4.99)	(-1.54)	(-3.51)
Test for Group Diff	0.14***		0.12***	
p-value	(0.00)		(0.00)	
House 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	322,331	326,404
Adjusted R^2	0.760	0.728	0.731	0.772

Table 12 Effectiveness of Adaptation Efforts

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 SLR exposed area. *Adapted* equals one if the city has announced or begun implementing adaptation measures by 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)
House 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 13 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, 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 bootstrap resampling iterations. All regressions controls for residential house features and geographic characteristics, and includes fixed effects as specified. 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.

	Fiscal deficit		Bond credit spreads	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Treat × *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)	
House 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
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?"

Yirong Liu, Yining Shi, Dragon Yongjun Tang, and Fumin Zhu

Abstract

This Internet Appendix provides data descriptions and robustness tests. Section A provides descriptions of housing transaction data source and identification of sea level rise inundation thresholds. Section B provides detailed policy intervention that local governments took to mitigate the sea level rise impact. Section C provides additional figures and tables supporting the main text.

A. Housing Data Sources and Validation

Panel A: Platform Coverage



Panel B: Transaction and Listing Records



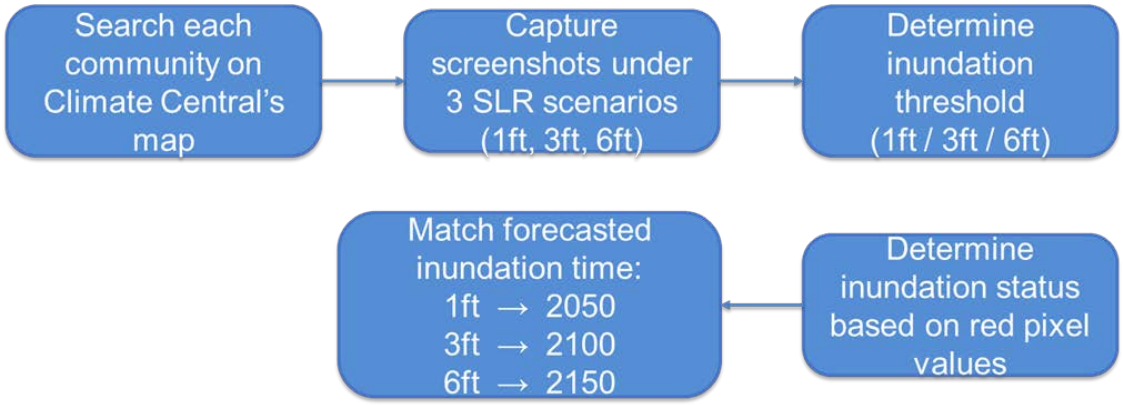
Panel C: Basic Information of A Property



Figure IA.1. 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

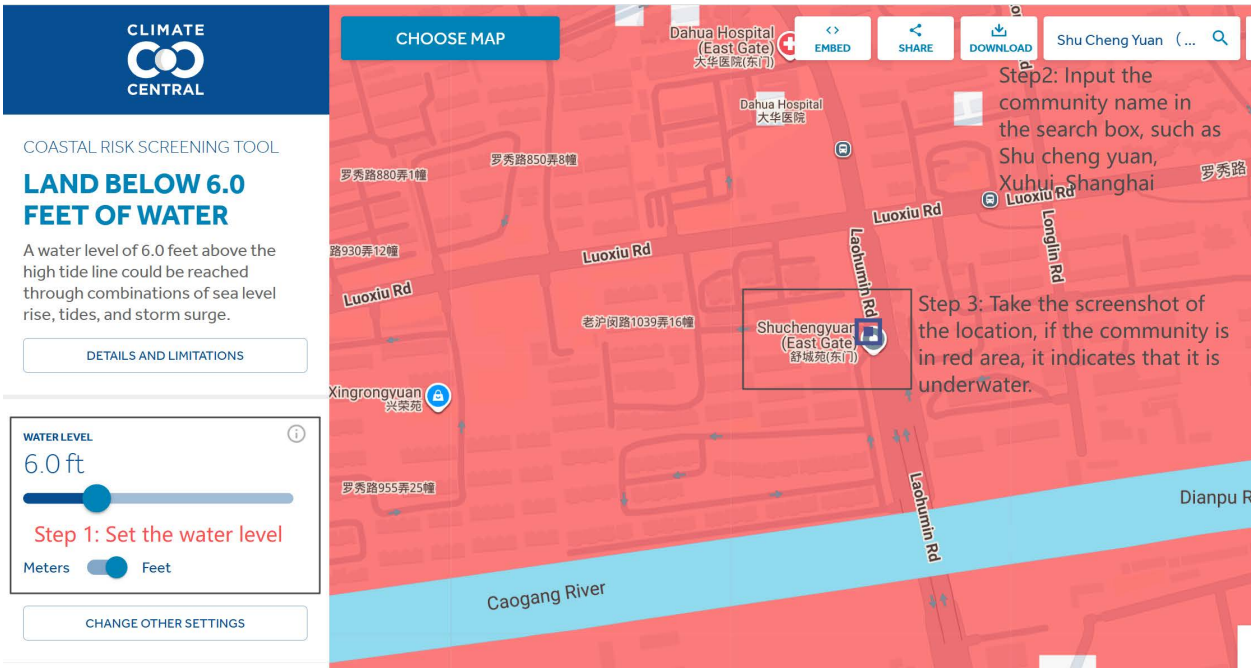


Figure IA.2. Identification of Sea Level Rise Inundation Thresholds

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.

B. Adaptation Efforts by Local Governments

Table IA.1. 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
Fangchenggang	January 2012	Started the construction of Xiwan Hongsha Ring ecological sea-wall project.
Guangzhou	December 2018	Completed the Lingshan Daojian North Shore super-ecological sea-wall project.
Haikou	September 2019	Started the Jiangdong New District sea-wall and coastal ecological restoration project.
Nantong	December 2018	Started the reinforcement of the Jiang-Hai sea-wall 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 sea-wall constructed.
Shenzhen	February 2019	Started the reconstruction of the eastern sea-wall.
Weihai	November 2016	Started the Coastal zone ecological restoration under the Blue Bay Program.
Yancheng	November 2022	Implemented sea-wall 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 sea-wall.
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 sea-wall 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 sea-walls.

C. Additional Figures and Tables

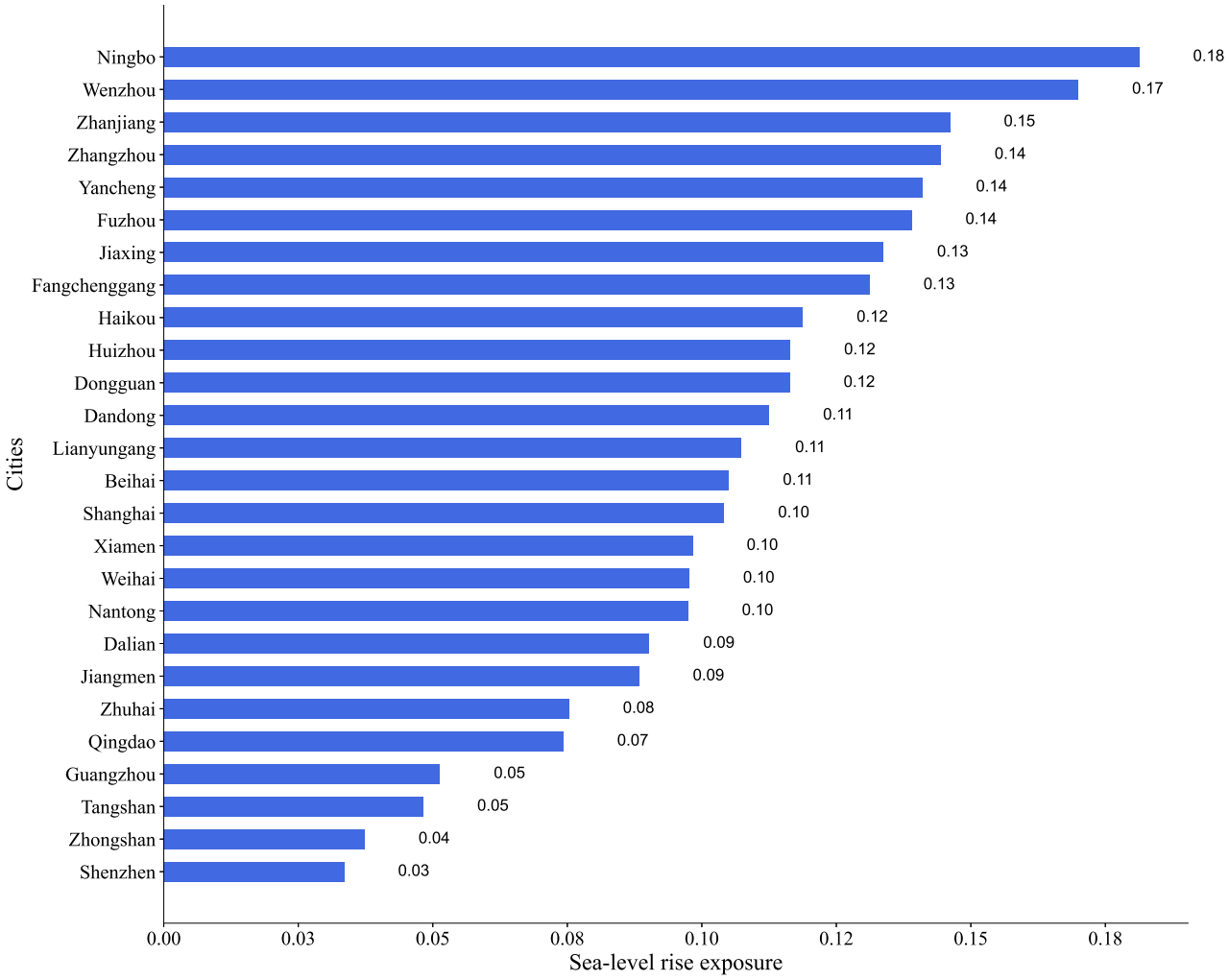


Figure IA.3. Sea Level Rise Exposure Across Cities

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.

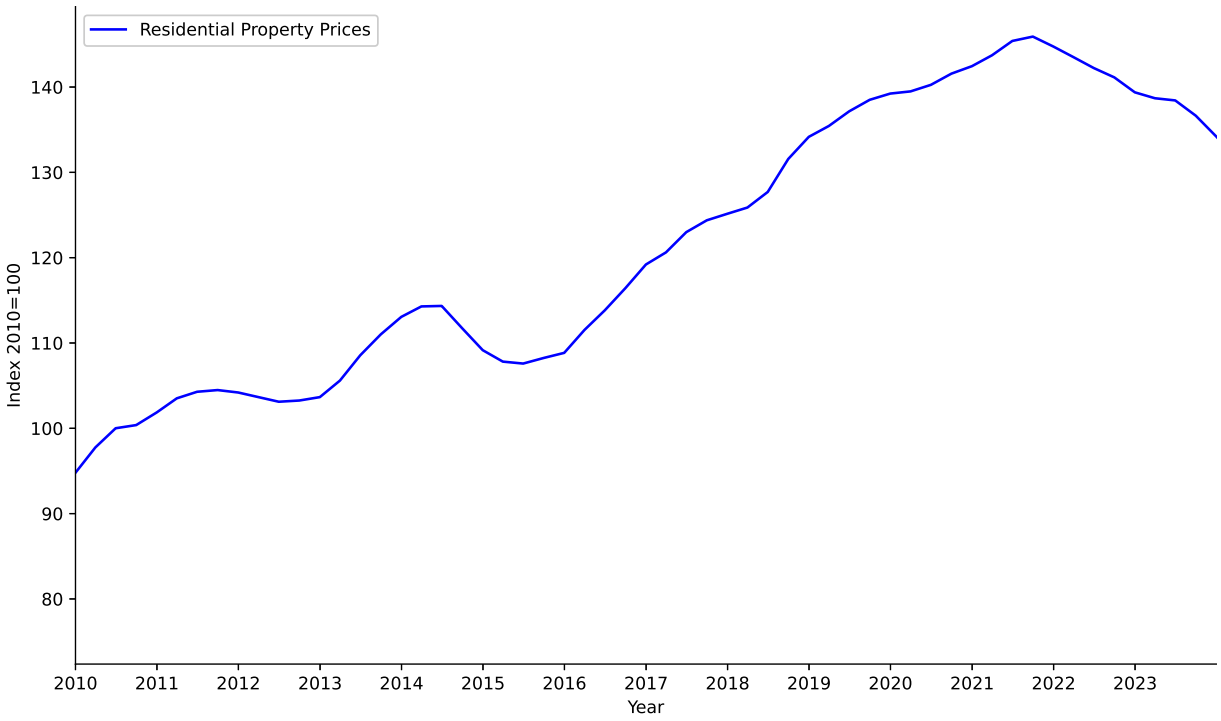


Figure IA.4. Residential Property Price of China

This figure depicts the time series of China's nominal residential housing price index from 2010 to 2024, using 2010 as the base period. The data is provided at a quarterly frequency and obtained from Bank for International Settlements.

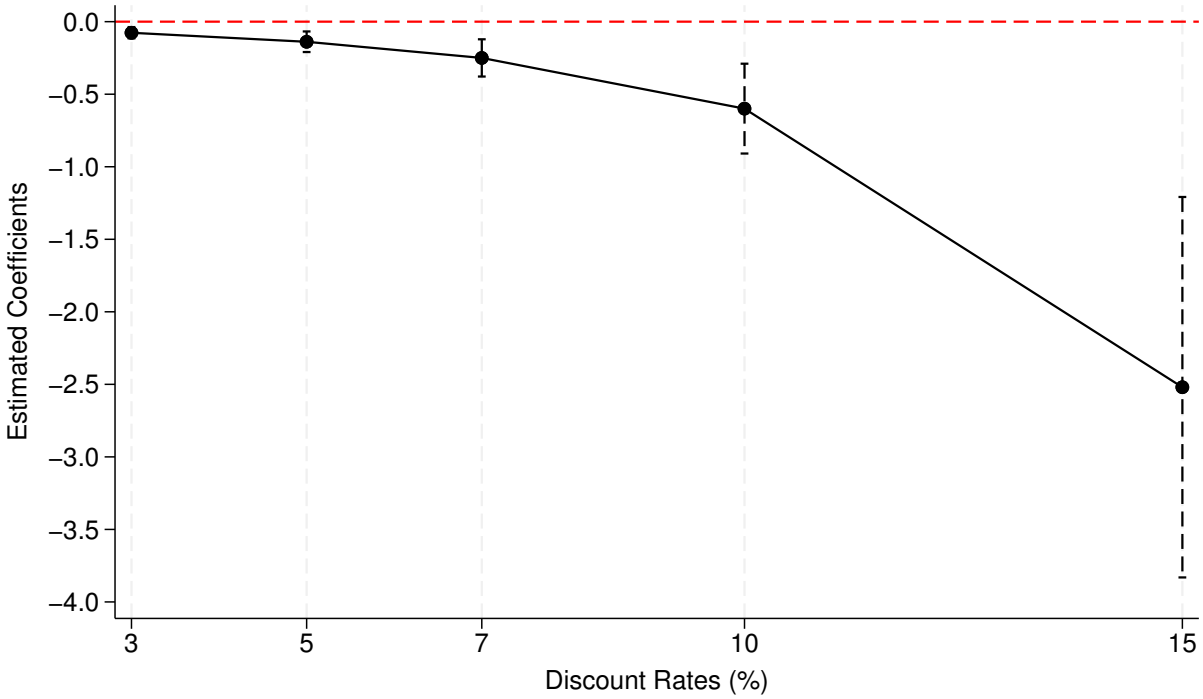


Figure IA.5. Sensitivity of sea level rise price discounts to discount rates

This figure plots the estimated coefficients of *SLR Exposure* 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.

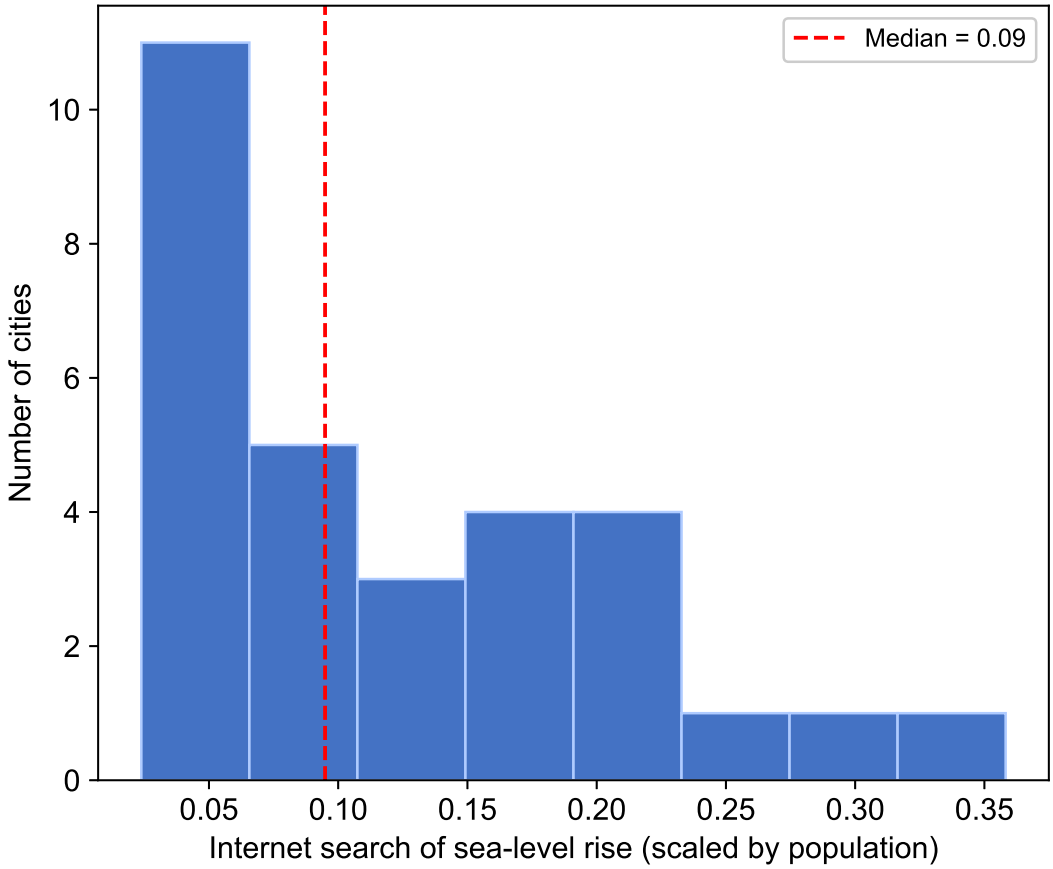


Figure IA.6. Distribution of City-level Attention to Sea Level Rise

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.

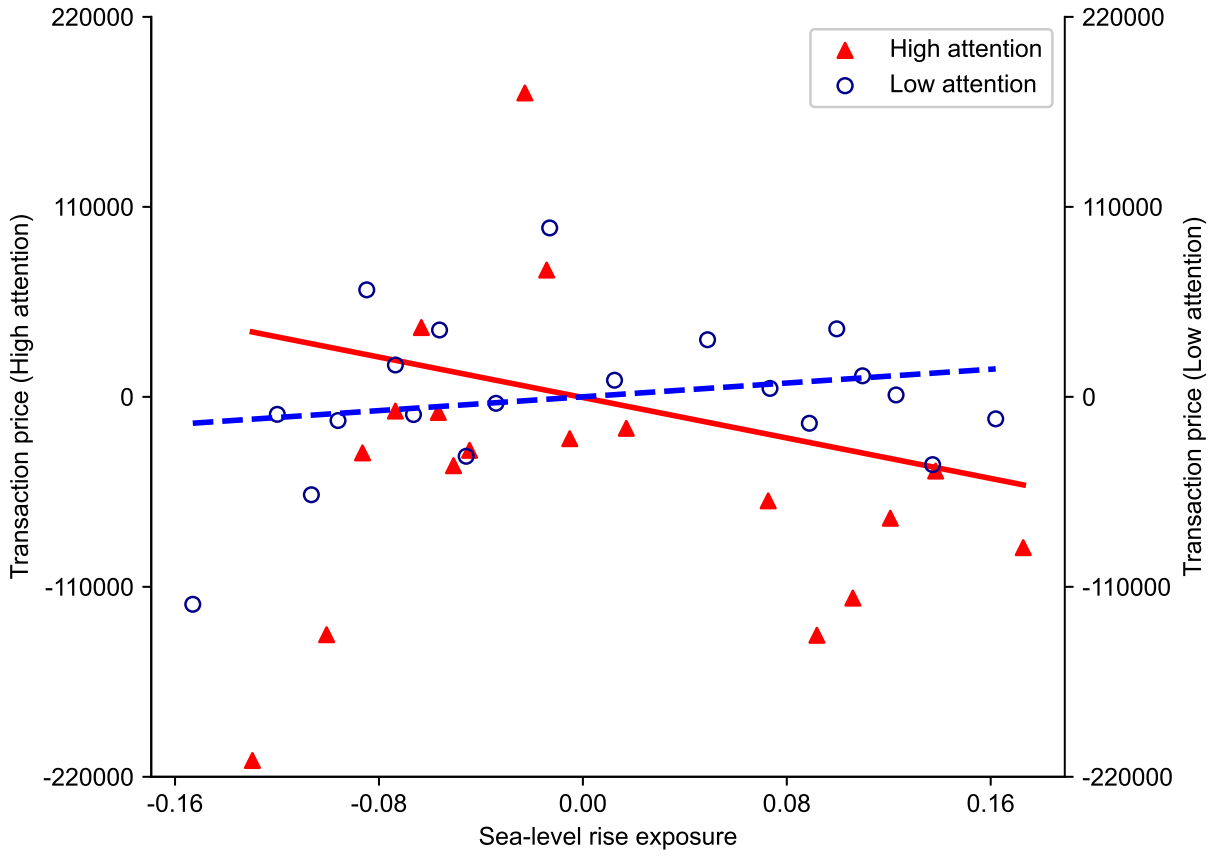


Figure IA.7. Property Prices and Attention to Sea Level Rise

This figure plots demeaned house transaction prices in ventiles of demeaned SLR exposure from 2011 to 2023. All variables are demeaned at the city, distance-to-coast, elevation, and year levels by subtracting the respective averages. Each red solid triangle (units in left axis) represents the demeaned average property transaction prices in the corresponding ventile for cities with high relative attention to sea level rise issue, while each blue open circles (units in right axis) represents that information for cities with low relative attention. The red solid and blue dashed lines are the projected estimation for the high and low attention groups, respectively.

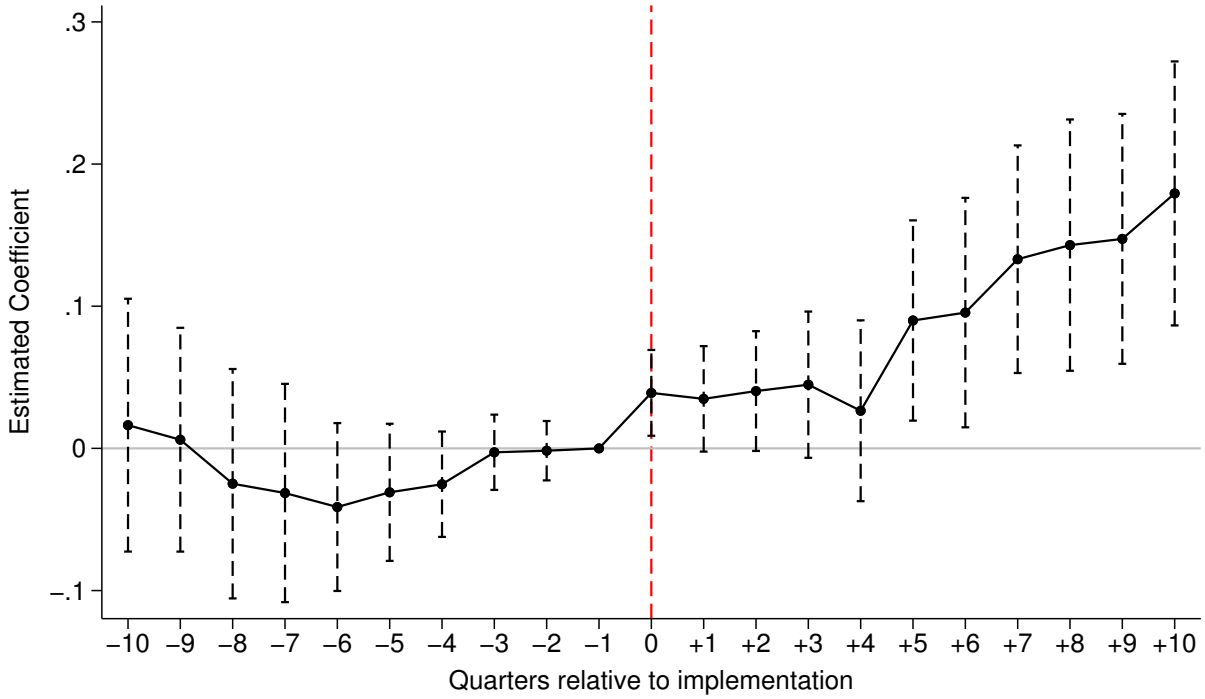


Figure IA.8. The Impact of Adaptation Policies on Listing Housing Prices

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:

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

where i denotes property, t represents quarter, and $LnlP_{i,t}$ is the log listing price. The sample is restricted to properties located in areas exposed to SLR risk and have implemented adaptation measures. $Treat$ is an indicator equal to 1 for properties in cities that implemented an adaptation project. $Adapted_{ic,t+\iota}$ is an indicator equal to 1 in quarter $t+\iota$ if city c is ι quarters away from its implementation quarter, with $\iota \in \{-10, \ldots, 10\}$ (negative values denote pre-implementation periods and positive values denote post-implementation periods). Thus, $Treat \times Adapted_{ic,t+\iota}$ identifies properties in treated cities ι quarters before, in, or after the implementation quarter. The sample period is from 2011 to 2023.

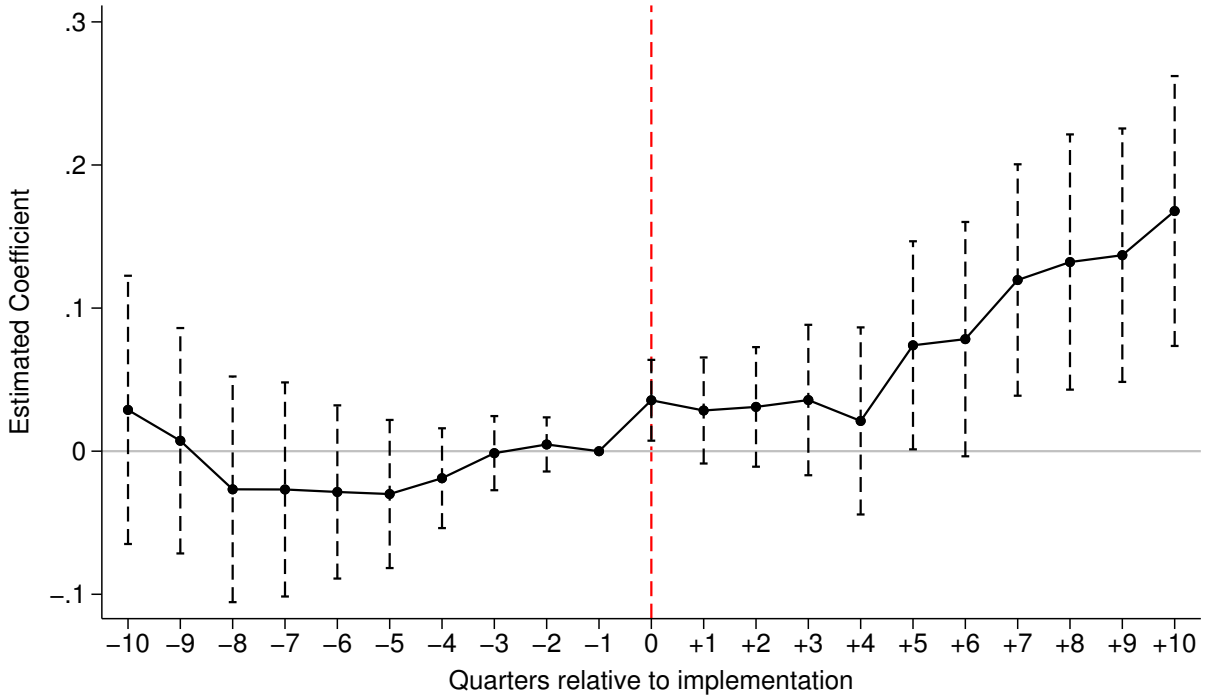


Figure IA.9. The Impact of Adaptation Policies on Unit Housing Prices

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:

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

where i denotes property, t represents quarter, and $LnuP_{i,t}$ is the log unit price. The sample is restricted to properties located in areas exposed to SLR risk and have implemented adaptation measures. $Treat$ is an indicator equal to 1 for properties in cities that implemented an adaptation project. $Adapted_{ic,t+\iota}$ is an indicator equal to 1 in quarter $t+\iota$ if city c is ι quarters away from its implementation quarter, with $\iota \in \{-10, \ldots, 10\}$ (negative values denote pre-implementation periods and positive values denote post-implementation periods). Thus, $Treat \times Adapted_{ic,t+\iota}$ identifies properties in treated cities ι quarters before, in, or after the implementation quarter. The sample period is from 2011 to 2023.

Table IA.2. 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 the main independent variable *SLR Exposure* 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	-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 IA.3. Alternative 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	-0.78***	-0.01***	-0.94***	-0.01***
	(-3.21)	(-3.22)	(-3.84)	(-3.85)
House 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 IA.4. 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 *times* distance to coast *times* elevation, year-level 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 IA.5. Role of Adaptation Efforts 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 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)
House 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 IA.6. Role of Adaptation Efforts 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 listing 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)
House 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 IA.7. 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. 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 the interaction term $Treat \times Sponge\ City$. In this specification, $Treat$ is a dummy variable equal to one if a property is located in an SLR-exposed area. *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. The sample is restricted to SLR-exposed 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 city level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Transaction prices	Listing prices	Unit prices
	(1)	(2)	(3)
$Treat \times Sponge\ City$	0.20**	0.18**	0.21**
	(2.66)	(2.73)	(2.72)
House 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