Do Homeowners in Emerging Markets Care About Sea-Level Rise?*

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Abstract

We investigate the impact of sea-level rise (SLR) on residential house prices in emerging markets using a novel exposure measure that incorporates inundation thresholds and discount rates. Analyzing a comprehensive dataset of coastal home transactions in China from 2011 to 2023, we find that a one-standard-deviation increase in SLR exposure is associated with a 1.3% drop in prices for exposed properties. The effect works through both the demand and supply channels of the housing market. The price discount is more pronounced in areas with higher public attention, greater typhoon activity, weaker flood resilience, and lower land constraints. Local adaptation strategies partially mitigate the price depreciation.

JEL classification: G10, R30, Q54.

Keywords: Climate change, Sea-level rise, Property prices, Adaptation strategies, Emerging markets.

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1 Introduction

Global sea level is rising at an accelerating pace due to climate change (IPCC, 2021), posing notable threats to coastal areas. While the impact of future SLR risks on coastal housing market has been extensively studied in the literature for developed economies (Agarwal, Qin, Sing, and Zhan, 2025; Giglio, Kelly, and Stroebel, 2021; Baldauf, Garlappi, and Yannelis, 2020, among others), its effects on coastal houses in developing countries remain largely unexplored. Governments worldwide are developing long-term action plans to mitigate climate change damage, such as emission controls and carbon taxes. While many developed countries have peaked in carbon dioxide emissions, developing economies face a major challenge in balancing economic growth with climate adaptation, as growth is linked to high carbon emissions (Bank, 2010). In this paper, we empirically examine how SLR risks affects residential properties prices and how the local reals estate markets respond to the government adaptation strategies in an emerging market.

The Chinese market provides an interesting case to address this question. First, coastal cities in China, home to a large portion of the population and economic activity, are particularly vulnerable to SLR (He et al., 2014). Second, as shown in Figure 1,[1] housing prices in China experienced a dramatic increase from 2010 to 2021, with speculative activity being the primary driver (Fang, Gu, Xiong, and Zhou, 2016; Glaeser, Huang, Ma, and Shleifer, 2017).[2] Since such behavior is typically motivated by short-term profits, while sea-level rise represents a long-term environmental threat, it is unclear whether homeowners in China incorporate SLR risk into property pricing decisions. Third, the real estate sector in China has frequently been subject to government intervention, such as the implementation of house purchase restrictions (HPR) (Qian, Tu, Wu, and Xu, 2022; Liu and Zhang, 2025). Such tight government control over the real estate market may distort property

[1] The data is obtained from Bank for International Settlements.

[2] Deng, Girardin, and Joyeux (2018) report that over 60% of households purchase secondary homes primarily for investment or speculative purposes.

prices, preventing them from accurately reflecting real market supply and demand. In this context, climate change risk, such as sea-level rise, may not be the first consideration when purchasing properties.

Meanwhile, the Chinese government has prioritized adaptation to climate risks, given that China has one of the longest coastlines in the world and has experienced several flooding events in recent years. Specifically, in 2017, it introduced the National Seawall Construction Plan to enhance coastal defenses over a ten-year period.[3] In 2018, President Xi Jinping emphasized the importance of ecological seawalls to strengthen resilience against typhoons and storm surges.[4]Therefore, whether residents react to SLR risks and long-term climate strategies in this market remains an important question.

Theoretically, in a world of rational expectations, housing prices in vulnerable areas should reflect the present value of anticipated flood risks associated with SLR (Bakkensen and Barrage, 2022). However, empirical findings on this issue remain inconclusive. On the one hand, several studies show that market prices do account for long-term and disaster risks (Bansal and Yaron, 2004; Hansen, Heaton, and Li, 2008).[5] Murfin and Spiegel (2020) find limited impact of SLR on house prices, suggesting that housing markets have fully priced this risk. On the other hand, some research highlights that financial markets do not always accurately price long-term risk (Hong, Li, and Xu, 2019; Kumar, Xin, and Zhang, 2019; Schlenker and Taylor, 2021). For instance, Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020) demonstrate that flood and climate risks are often underestimated in real estate prices, with properties projected to be underwater due to SLR facing significant price discounts. Our study, which examines the effect of

[3] Please see https://www.gov.cn/xinwen/2017-08/21/content_5219341.htm for details.
[4] Please see https://www.gov.cn/xinwen/2018-10/10/content_5329292.htm for details.
[5] The literature examines the impact of natural disaster events, such as extreme weather, wildfires, and flooding, on the pricing of financial assets, including studies by Kruttli, Tran, and Watugala (2025), Issler, Stanton, Vergara-Alert, and Wallace (2023), Bin and Landry (2013), Ortega and Taşpınar (2018), among others.

SLR on property prices in an emerging market, is expected to contribute to this ongoing debate.

Our sample spans from January 2011 to November 2023 and integrates data from four sources. First, we manually collect property-level inundation thresholds under different SLR scenarios based on maps from the Climate Central platform.[6] Second, we obtain proprietary data from HomeLink Real Estate Brokerage Co., Ltd. (hereafter HomeLink), including second-hand residential transaction prices and property characteristics, which we match to the SLR exposure forecasts. Third, following the method of Choi, Gao, and Jiang (2020), we construct an attention index using Baidu's search volume data for the term sea-level rise. Finally, we collect geographic and macroeconomic variables from the publicly available Wind database and the China Statistical Yearbook.

To quantify the SLR exposure of residential properties, we construct a property-level index that captures both the severity and timing of expected inundation. Each property is first assigned to the lowest sea-level rise scenario—1, 3, or 6 feet—under which it is projected to be underwater.We then convert these scenario-based thresholds into a continuous measure by incorporating the projected year of inundation and discounting future risk to account for its present value. A higher value of the index indicates both a more severe flooding scenario and a shorter expected time until inundation.

Our empirical analyses provide a host of interesting findings. Overall, we show that SLR risks exhibit a statistically significant negative impact on the prices of exposed residential properties in China. On average, a one-standard-deviation increase in SLR exposure is associated with a 1.3% decrease in the prices of properties located in SLR-prone areas. This effect remains robust when using alternative SLR exposure measures, excluding periods of strict government intervention, and across both cold and hot market trends. When examining the impact across different inundation thresholds, we find that the price discount is concentrated in properties exposed to 1- and 3-foot

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

SLR scenarios. However, no such pattern is observed for properties exposed solely to the 6-foot SLR scenario. This suggests that the housing market primarily responds to risks expected to materialize in the near future. This finding differs from findings for the U.S. market, where six-foot SLR exposure leads to a large price discount for exposed houses (Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020). This difference may be explained by more severe inundation risks faced by coastal cities in China.

Given that residential house prices are equilibrium outcomes shaped by the interaction of supply and demand (Sommer, Sullivan, and Verbrugge, 2013), we further explore how SLR risks affect housing market behavior from both the demand and supply sides. On the demand side, we show that properties located in SLR-exposed areas spend significantly more time on the market compared to properties in non-exposed areas. These properties also receive fewer visits and bookmarks on the Home-Link platform, indicating lower buyer interest and reduced attention. On the supply side, we demonstrate that properties in the flood zone are initially listed at lower prices than comparable homes in non-exposed areas and are subject to more frequent price adjustments. These patterns suggest that both buyers and sellers respond to SLR-related risks, contributing to the overall discount in transaction prices.

We document substantial variation in the SLR-related price discount across cities with different levels of public attention to SLR issue, typhoon experience, urban flood resilience, and land availability. In particular, the price depreciation effect is only significant in areas with above-median public attention, suggesting that greater investor awareness amplifies the pricing of SLR risk. Consistent with the notion that past exposure sharpens risk perception (Choi, Gao, and Jiang, 2020), we find larger discounts in typhoon-prone regions. However, the effect is weaker in cities with stronger flood protection and more limited land supply, indicating that both adaptive capacity and

development constraints can mitigate the impact of SLR exposure on property values.

Finally, we examine whether local adaptation efforts can mitigate the negative pricing effects of SLR risk. By leveraging cross-city variation in the timing of adaptation strategy announcements or implementation in China, we estimate a time-varying difference-in-differences (DID) specification. Our results show that local adaptation measures, such as the construction of seawalls, significantly mitigate the decline in both transaction and listing prices for properties exposed to SLR risk. This finding suggests that the housing market responds to adaptation efforts by partially capitalized their protective value in prices.

This study contributes to three strands of literature. First, we extend the literature on the impact of climate risk on housing market by investigating this issue in an emerging market.[7] Prior studies focusing on the developed countries typically use binary indicators that identify whether a property lies within a projected six-foot SLR flood zone (Baldauf, Garlappi, and Yannelis, 2020; Bakkensen and Barrage, 2022; Bernstein, Gustafson, and Lewis, 2019; Gourevitch et al., 2023, among others), we develop a continuous and nonlinear SLR measure, which incorporates the inundation threshold, the expected timing of to be underwater, and an appropriate discount rate. This approach allows us to capture not only whether a property is at risk, but also how soon and how severely that risk may materialize, thereby reflecting the time value of climate risk in a more nuanced and economically meaningful way. Based on this measure, we document a negative impact of SLR exposure on residential property prices in a developing country, where the housing market is characterized by high speculation and frequent government intervention.

Furthermore, while several studies have documented price discount associated with SLR ex-

[7]Several studies also explore the impact of sea-level rise on other financial markets. For example, Goldsmith-Pinkham, Gustafson, Lewis, and Schwert (2023) and Painter (2020) establish a positive relationship between SLR exposure and long-term municipal bond yields, while Dey (2024) find that sovereign credit default swap spreads increase for countries vulnerable to coastal flooding.

posure, relatively little attention has been paid to the extent to which adaptation strategies can mitigate these effects. Recent evidence suggests that such efforts may play an important role. For example, Agarwal, Qin, Sing, and Zhan (2025) find that the announcement of national adaptation measures in Singapore reduces SLR-related discount in public housing prices, using a fixed-time DID approach. Similarly, Benetton et al. (2022) show that property prices in Venice increased substantially following the activation of the city's sea wall. We contribute to the growing literature by providing evidence from China that local adaptation strategies mitigate the pricing impact of SLR risk. Using a time-varying DID framework, we find that both transaction and listing prices in exposed areas show smaller depreciation following the implementation of adaptation measures.

Finally, we complement the literature on the determinants of house prices in China. An extensive body of literature highlights the role of speculative activities (Chen and Wen, 2017; Glaeser, Huang, Ma, and Shleifer, 2017), counter-cyclical intervention policies (Fang, Gu, Xiong, and Zhou, 2016), urbanization and population aging (Xiong, 2023), and financial liberation (Shi, 2022) in driving house prices in China. More recently, Huang, Cheng, and Zhang (2025) link SLR risk to property prices but focus on a single province. Different from theirs, we construct a property-level SLR exposure measure based on inundation thresholds and discount rates, using a dataset that covers the majority of China's coastal cities.[8] We provide consistent evidence that SLR risks negatively affect coastal property prices, especially in areas with higher public attention, frequent typhoons, weaker flood resilience, and limited land supply. These findings offer valuable insights for other developing countries.

The rest of this paper is organized as follows: Section 2 describes the data and summary statistics, while Section 3 shows the main model specifications and baseline findings. Heterogeneity analysis is presented in Section 4. Section 5 discusses the impact of adaptation strategies. Finally,

[8]Due to the availability of house transaction data, our sample incorporates 31 out of 53 coastal cities in China.

Section 6 concludes.

2 Data

2.1 Construction of SLR exposure

According to the Intergovernmental Panel on Climate Change (IPCC), global mean sea level is projected to rise by approximately 1 foot (0.30m) by 2050, and by between 1.41 feet (0.43m) and 3.61 feet (1.1m) by 2100 (Oppenheimer et al., 2019). Motivated by these forecasts and acknowledging the durable nature of houses, we construct a nonlinear measure of sea-level rise (SLR) exposure at the property level. This measure accounts for both the expected inundation year and the timing of the transaction, discounted appropriately to reflect the present value of future risk.

Due to the absence of publicly available, house-level inundation risk data for China, we manually assess whether each residential property in our sample is projected to be submerged under different SLR scenarios. We use Climate Central's Coastal Risk Screening Tool, an interactive global map that visualizes projected inundation areas under varying SLR forecasts. Following the literature (Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020), we consider three benchmark scenarios, 1 foot, 3 feet, and 6 feet of sea-level rise. For each of them, we configure the map, locate each residential community, and capture screenshots once the site is pinpointed. These images are then analyzed to determine whether the property is projected to be inundated under the given SLR scenario. Each property is categorized into one of three exposure levels based on the SLR forecast required to make it underwater: (1) inundated under 1-foot SLR rise (1 ft, by 2050), (2) inundated under 3-foot SLR rise (3 ft, by 2100), or (3) inundated under 6-foot SLR rise (6 ft,

by 2150). Then, we calculate the SLR exposure for each property as follows:

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

where u_i indicates the inundation threshold (in feet) for property i, T_{u_i} is the projected year in which the corresponding level of sea-level rise is expected to occur, y_i is the year of the property transaction, and r_{u_i} is the appropriate discount rate reflecting the time preference for future risk.[9] A higher value of *Exposure* reflects more severe and imminent inundation risk for a given property.

This measure captures that properties with imminent inundation risks are more exposed to SLR, as near-term risks have a greater impact on current values. In contrast, future risks are discounted more heavily, exerting less influence on present prices. Thus, the SLR measure reflects both the timing and severity of threats in a forward-looking manner.

2.2 Real estate prices

We collect data on house-level transaction price and house-level attributes from the HomeLink Real Estate Brokerage Co., Ltd, a major real estate platform in China. To the best of our knowledge, HomeLink is among the top ten largest national real estate databases, with information on over one million detailed public records spanning various districts across China. The platform provides data on the geographic location of each home, as well as key property-specific characteristics, such as size and number of bathrooms, which we use as control variables. Following the literature (Agarwal, Qin, Sing, and Zhan, 2025; Giglio, Kelly, and Stroebel, 2021; Murfin and Spiegel, 2020,

[9] Studies on China's real estate market suggest that residential properties are discounted at a rate of 5% for short-term horizons under 30 years, and 2.9% for long-term horizons of 60 years or more. Please see http://www.aer.ruc.edu.cn/CN/Y2023/V03/I04/114 for details.

among others), we restrict our sample to residential properties. We calculate the distance from each home to the nearest coastline and determine its elevation based on its latitude and longitude.[10] The geographic location is also used to assign each property to a specific county, city, or province, allowing us to merge house-level characteristics with other regional variables, which are obtained from Wind database. Table A1 of the Appendix outlines the main variables employed in this study. Our sample period is from January 2011 to November 2023.

2.3 Attention on sea-level rise

Several studies show that sea-level rise risk impacts asset prices primarily when individuals are aware of it (Baldauf, Garlappi, and Yannelis, 2020). These studies typically rely on survey data, especially responses to the question "Do you believe in global warming or climate change?" from Yale Climate Opinion Maps. However, this measure of belief fails to account for the time-varying nature of attention and lacks a specific focus on the issue of sea-level rise.

Building upon this strand of literature, and in light of the absence of property descriptions on Chinese housing transaction platforms, we adapt the methodology of Choi, Gao, and Jiang (2020), which takes advantage of the Google Search Volume Index to capture internet search activity related to climate change in the U.S. Build upon this study, we measure public attention to sea-level rise in China by utilizing the monthly Search Volume Index ($SVI_{c,t}$) for the search term "sea-level rise" of city c over January 2011 to November 2023 from Baidu, the most popular search engine in China. Unlike survey data on beliefs, our proxy captures high-frequency attention patterns across different cities, allowing us to study the learning process and analyze how updated beliefs about sea-level rise influence decisions regarding exposed properties.

[10] The calculations are conducted using the R programming language.

2.4 Past typhoon experience

To investigate whether cities with a history of more frequent typhoons are more sensitive to sea-level rise risk, we collect typhoon data for Chinese cities over the past 70 years from the China Meteorological Administration. Specifically, cities in the provinces of Fujian, Guangdong, and Hainan, which are known for frequent typhoon occurrences, are included in our study. These three provinces include 12 of the 31 coastal cities in our full sample. In particular, these cities include Fuzhou, Xiamen, and Zhangzhou in Fujian Province; Dongguan, Guangzhou, Huizhou, Jiangmen, Shenzhen, Zhanjiang, Zhongshan, and Zhuhai in Guangdong Province; and Haikou in Hainan Province. [11] We then categorize cities into two groups: those with more frequent typhoons and those with fewer. Finally, we analyze the difference in price discounts between the two groups.

2.5 Land constraint

To explore how housing prices in cities with varying land constraints are influenced by SLR exposure, we adopt the method of Shi (2022) to construct a measure that captures the geographic limitations of land at the city level. Specifically, we manually collect annual data from the Statistical Yearbook of China on the available residential land and total construction land in each city. We then calculate the ratio of residential land to total construction land and subtract this percentage from one.[12] This ratio captures the proportion of land in each city that is exogenously constrained for residential use. We refer to this variable as *Land constraint*.

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

[12] 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.

2.6 Summary statistics

Table 1 summarizes the key variables used in our regression analysis. We observe that the average transaction price of residential properties across coastal cities is 2.35 million Chinese Yuan (CNY), with a high standard deviation of 1.98, indicating considerable variability in both property prices and price volatility in the Chinese real estate market. The average SLR exposure is 0.10 and the maximum value is 0.26, suggesting that on average, exposed properties face a substantial and non-negligible level of inundation risk.

By focusing on the dummy indicators that captures the inundation threshold for each property, we find that approximately 37% of homes are projected to be underwater under a one-foot sea level rise scenario. This share increases significantly to 67% under a six-foot rise. These figures are substantially higher than those reported for the United States, where only 30% of houses are expected to be inundated under a comparable six-foot scenario, as documented in Bernstein, Gustafson, and Lewis (2019). One possible explanation for this difference is the high population density and concentrated housing development in China's coastal cities, such as Shanghai, which amplifies the exposure of residential properties to sea level rise.

To illustrate inundation risks across different regions of China, we calculate the average *Exposure* for each province and plot the results in Figure 2, with darker colors indicating higher risk. Notably, Zhejiang has the highest inundation risk, with a mean *Exposure* of 0.16, followed by Jiangsu, Tianjin, and Fujian, with mean values of 0.14, 0.12, and 0.12, respectively. This suggests that a significant portion of properties in these provinces are at risk of being underwater.

We also calculate sea-level rise exposure at the city level and present the findings in Figure 4. Of the 31 cities included in the sample, the inundation risk of 15 cities is higher than the sample average. These results further underscore the widespread vulnerability of homes in China's coastal

regions to flooding from sea-level rise. Therefore, it is crucial to investigate whether the residential housing market prices this exposure.

3 SLR risk and property prices

3.1 Model specification

We first aim to examine whether SLR risks affect house prices in this study. If real estate market participants anticipate potential losses due to sea-level rise, properties at risk of flooding should exhibit lower prices compared to equivalent properties not located in SLR areas.

To address the above question, following Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020), we adopt a hedonic pricing model. Our model compares properties that transact within the same year and city and are observationally equivalent (i.e., they have the same number of bedrooms, distance to the coastline, and elevation above sea level), but differ in the SLR exposure. The model is specified as follows:

$$LnP_{i,t} = \alpha_{cde} + \alpha_y + \beta Exposure_i + \lambda X_i + \eta X_{g,t} + \varepsilon_{i,t}, \tag{2}$$

where $LnP_{i,t}$ is the dependent variable, representing the natural logarithm of the transaction price of property i in month t. The key explanatory variable, $Exposure_i$, is a continuous measure of sea-level rise risk, calculated based on the SLR forecasts required to inundate properties, the transaction year, and the forecasted inundation year, as described in Eq.(1). The coefficient β is central to our identification strategy, reflecting the sensitivity of house prices to SLR risk. Additionally, We analyze multiple SLR scenarios by isolating the effects on properties uniquely exposed to each inundation level—those inundated only at one foot, three feet, or six feet. This approach enables

us to evaluate how the housing market prices risks across different level of inundation.

The variable X_i controls for property size and other house-level attributes, while $X_{g,t}$ represents geographic variables such as GDP, population density, and other geographic factors that influence house prices. Furthermore, Xiong (2023) highlights the role of urbanization and population aging in driving the Chinese real estate market, and economic uncertainty also significantly affects house prices in China (Glaeser, Huang, Ma, and Shleifer, 2017; Liu and Xiong, 2018; Yin et al., 2021). These factors are included in our model as geographic controls. For detailed variable descriptions, please see Table A1 of the Appendix.

To address the concern that homes closer to the coast may have higher values due to proximity to the beach or waterfront views, and that homes located in similar areas may have varying elevation levels, which could lead to different pricing effects of SLR exposure, following existing literature (Giglio et al., 2021; Baldauf, Garlappi, and Yannelis, 2020; Bernstein, Gustafson, and Lewis, 2019; Stroebel, 2016), we include city × distance × elevation fixed effects, denoted by α_{cde}, which varies by a city, distance of a home from the coast, and elevation. Year fixed effects are captured by α_y.[13] After incorporating this full set of interaction fixed effects, we argue that β provides a reliable estimate of the effect of sea-level rise exposure on house prices.

3.2 Baseline results

3.2.1 Overall effect of SLR

We begin our analysis by estimating the effect of SLR exposure on house transaction prices, as specified in Eq.(2). Prior to the regression, we plot the time series of average unit prices and

[13] We also incorporate district × distance × elevation or street × distance × elevation fixed effects in the main regression, and the results remain quantitatively the same.

monthly sales volumes, aggregated by county and month, for homes with high and low SLR risks, classified based on the sample mean. The top and bottom panels of Figure 3 displays the trends in prices (top panel) and sales volumes (bottom panel). Given that higher SLR exposure implies greater inundation risk, we expect such properties to have lower prices and fewer transactions. Consistent with this, homes with greater SLR exposure tend to exhibit lower prices and reduced sales volumes across most of the sample period. These properties also experience sharper price declines during economic downturns, such as the COVID-19 pandemic. The observed patterns suggest a negative relationship between SLR exposure and housing market performance.

The baseline regression results are reported in Table 2. The first two columns show the coefficients of *Exposure* without the inclusion of control variables or fixed effects. The results are mixed in the absence of fixed effects. The relationship between SLR risk and house prices is significant at the 1% level when year and city × distance × elevation fixed effects are included, as shown in Column (3). Specifically, a one-standard-deviation increase in *Exposure* is associated with a 1.3% decrease in property prices of affected areas. Following the approach in the literature (Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020), we incorporate more stringent fixed effects than those in Column (3) by introducing county × distance × elevation and street × distance × elevation fixed effects in Columns (4) and (5), respectively.[14] We continue to find negative coefficients of *Exposure*, albeit with smaller magnitudes. This suggests that our results remain robust to changes in the fixed effect structure.

Furthermore, we conduct tests using two alternative measures of SLR exposure. The first measure assigns values of three, two, and one to properties projected to be inundated under 1-foot, 3-foot, and 6-foot SLR scenarios, respectively. The second measure identifies the inundation

[14] We also perform the test proposed by Oster (2019) to evaluate the potential bias from omitted variable(s). The estimated value of δ, which represents the degree of selection on unobservables relative to observables required to explain away the result, is 2.88, indicating that the estimated relationship is unlikely to be driven entirely by omitted variable bias.

threshold for each property based on the SLR forecasts and calculates the inverse of the difference between the transaction year and the projected inundation year. The results, presented in Table A2 of the Appendix, are quantitatively consistent across both measures.

Taken together, the findings provide robust evidence for a price discount for houses exposed to SLR, consistent with previous literature (Agarwal, Qin, Sing, and Zhan, 2025; Bernstein, Gustafson, and Lewis, 2019; Bakkensen and Barrage, 2022). Different from prior studies that use a binary indicator for properties in flood zones with a six-foot rise, we introduce a continuous measure that accounts for both the severity and timing of inundation risk. Specifically, we distinguish between houses in flooded and non-flooded zones and further separate them in flooded zones based on transaction timing and inundation thresholds. The closer the transaction date is to the projected inundation time, the higher the price discount. Our findings suggest that investors in the residential housing market account for the timing of inundation, with greater discounts for properties expected to be inundated sooner. This aligns with economic intuition, as home buyers tend to prioritize more imminent and severe risks, thereby confirming the face validity of this metric.

3.2.2 Separated effects

To further examine the impact of specific inundation thresholds on property sale prices, we perform the test using three separate dummy variables. Given the concern that properties projected to be inundated by higher sea-level rises (e.g., 3 or 6 feet) may already be affected by lower levels, complicating the isolation of their effects, we address this issue by classifying properties based on their specific inundation thresholds. For the 1-foot SLR, we include the full sample. For the 3-foot SLR, we exclude properties already submerged at 1-foot SLR, and for the 6-foot SLR, we exclude properties affected by 1- or 3-foot SLR. This approach ensures that properties with lower

inundation thresholds, which have already priced in the risks of earlier rises, do not adjust prices in response to higher levels of SLR exposure.

The results are shown in Table 3. We find that the negative impact of sea-level rise exposure on house prices is statistically significant only for properties exposed to 1-foot and 3-foot SLR. Specifically, properties in the 1-foot SLR flood zone experience an 2.9% price depreciation compared to those outside this area. Additionally, houses inundated at the 3-foot SLR threshold experience a 2.4% discount compared to unexposed properties, although this discount is smaller than that observed for properties with 1-foot inundation threshold. No significant price discount is found for homes exposed only to 6-foot SLR, suggesting that the relationship between SLR exposure and property values is driven by more near-term and practical concerns.

Bernstein, Gustafson, and Lewis (2019) document a monotonic decrease in price discounts for U.S. coastal houses as SLR threshold increases from one foot to six feet. We observe a similar pattern in China between 1-foot and 3-foot SLR exposure, but the discount diminishes at the 6-foot threshold. This may be attributed to the long-term nature of the 6-foot scenario, which is expected to materialize over more than a century, causing investors to perceive it as a distant risk. Furthermore, the fact that approximately 50% of the coastal areas in Chinese cities will be underwater under a 3-foot SLR, as shown in Table 1, may also help explain this difference.

3.3 Robustness tests

3.3.1 Policy intervention

Since 2010, the Chinese housing market has been subject to several intervention policies aimed at curbing speculative activities, including the house purchase restriction (HPR), based on the

central government's principle that "houses are for living, not for speculation" (Qian, Tu, Wu, and Xu, 2022; Liu and Zhang, 2025). During these periods, property prices were more heavily influenced by government interventions than by market forces. As a result, these policy measures may distort our ability to accurately identify the impact of SLR exposure on house prices. In this section, we evaluate the robustness of our findings by excluding the periods affected by these policy interventions..

Given that China has implemented two rounds of HPR policies, Table 4 reports the results excluding these policy periods. Columns (1) to (3) show the findings for excluding the first policy period (2011–2014), the second policy period (2016–2021), and both policy periods combined, respectively.[15] [16] [17] Across all three settings, we consistently observe a negative impact of SLR exposure. In comparison to Table 2, the sub-sample coefficient for *Exposure* in Column (3) remains both economically and statistically significant, with a comparable magnitude of -0.12 (-0.13 in Column (3) of Table 2) when excluding two sample periods with high government intervention. This suggests that our results remain robust in the absence of these policy influences.

3.3.2 Different price trends

The average house prices in China experienced rapid growth from 2010 to 2021, peaking in 2021 before beginning to decline, as shown in Figure 1. Given this notable shift in housing market dynamics, we divide the sample into two sub-periods: the hot period (2011–2013, 2016–2021),

[15]The first round of HPR policies was in effect from 2011 to 2014, while the second round began in 2016. Several cities lifted the HPR policy starting in 2022. For the purpose of this analysis, we restrict the second round of HPR policy to the period from 2017 to 2019, as 2017 was the first full year of implementation (Liu and Zhang, 2025). We do not consider 2020 and 2021 as policy implementation years due to the COVID-19 lockdowns, during which the effectiveness of the HPR policy may have been reduced.

[16]Given that 21 out of the 31 cities in our sample have been subject to the HPR policies, and the remaining seven cities have limited observations, we refrain from separately analyzing the effects of the HPR policies for these cities.

[17]The details of these policies for different cities can bee seen in Liu and Zhang (2025) and Qian, Tu, Wu, and Xu (2022).

characterized by rising house prices, and the cold period (2014–2015, 2022–2023), when prices declined. We then examine how different phases of the housing market cycle influence the price discount effect of sea-level rise. The results, presented in Columns (4) and (5) of Table 4, reveal consistent negative coefficients in both sub-periods with statistical significance. This indicates our baseline results remain unchanged across different market trends.

3.4 Mechanism analysis

Real estate prices are equilibrium outcomes that reflect the interaction between supply and demand forces (Sommer, Sullivan, and Verbrugge, 2013). To explore the mechanism through which SLR risk impacts residential property prices, we investigate its effect on both the demand and supply sides of the housing market.

On the demand side, we measure housing demand using three proxies. First, days on market at the property level captures housing liquidity and reflects the intensity of buyer interest (Jiang, Kotova, and Zhang, 2024). Second, the number of online visits recorded on the HomeLink platform shows active search behavior by potential buyers. Third, the number of online followers or bookmarks captures latent buyer interest and beliefs about the property's value. If prospective buyers are attentive to SLR risk, we expect properties in high-risk areas to remain on the market longer, attract fewer visits, and receive less online attention.

On the supply side, we focus on the listing price and the frequency of price adjustments, as these variables reflect house sellers' price expectations and their responsiveness to market signals (Grimes and Aitken, 2010). If existing homeowners are aware of the risks posed by SLR, we expect them to initially list properties at lower prices or adjust listing prices downward more frequently to facilitate a sale.

The regression results and model specifications are shown in Table 5. Consistent with our expectations, properties located in areas exposed to SLR risks remain on the market for notable longer periods. Specifically, with a coefficient of 0.09, this translates to properties in areas with the mean SLR exposure spending approximately 2.45 more days on the market compared to those in non-exposed areas.[18] Furthermore, one-standard-deviation increase in the SLR exposure is associated with 0.7% fewer visits and fewer bookmarks on the Home-Link platform, indicating a decline in buyer interest and attention.

From the perspective of supply, we find that 10% increase in the *Exposure* causes 1.3% decrease in the list prices for exposed properties. Furthermore, they undergo more frequent price adjustments, with an average increase of 2.50% in the number of price adjustments for houses located in flood zones compared to non-SLR exposed areas if the *Exposure* is at its mean. These patterns suggest that sellers in high-risk areas adjust their expectations and pricing behavior in response to anticipated reductions in buyer demand.

4 Heterogeneity in the SLR impacts

In this section, we explore the heterogeneity in the relationship between SLR exposure and coastal property prices. Our first set of tests investigate how public attention to sea-level rise influences the SLR exposure discount documented above. Next, we examine whether a history of frequent typhoons is linked to changes in house prices due to SLR. Furthermore, we evaluate the impact of urban flood resilience on SLR-exposed properties. Finally, we investigate how land constraints affect the pricing of properties exposed to SLR. To address these questions, we regress

[18] This is calculated as follows: $271.21 \times \left(e^{0.09\times 0.1} - 1\right) = 271.21 \times \left(e^{0.009} - 1\right) \approx 271.21 \times 0.00904 \approx 2.45$.

the log of house prices on SLR exposure and its interaction with three empirical proxies as follows:

$$LnP_{i,t} = \alpha_{cde} + \alpha_y + \delta Exposure_i + \chi F + \xi Exposure_i \times F + \rho' X_i + \omega' X_{g,t} + \varsigma_{it}, \tag{3}$$

where F represents the empirical proxies for city-level public attention to sea-level rise risk ($SVI_{c,t}$), the indicator for cities that have experienced frequent typhoons over the past 70 years ($Typhoon$), proxy indicating the resilience of a city, and the measure of city-level land constraint, respectively. To address potential serial correlation, we cluster standard errors at the county level.

4.1 Attention to sea-level rise and house prices

The survey results show that people view physical risk, such as the sea-level rise risk, as the top climate risk over the long-run Stroebel and Wurgler (2021). Moreover, the existing literature suggests that properties projected to be in flood zone are sold at a discount in communities concerned about climate change or global warming (Baldauf, Garlappi, and Yannelis, 2020), with this effect being more pronounced when prices are determined through bilateral negotiation (Piazzesi and Schneider, 2009). To investigate the influence of public belief or attention about sea-level rise influences the price discount of SLR for real estate prices, we merge house-level data with the monthly Search Volume Index ($SVI_{c,t}$) of the search term "sea-level rise" on Baidu at the city level and regress property prices on the interaction term of attention and SLR exposure, as shown in Eq.(4). If house prices are driven by investor attention, we expect attention on SLR to amplify the price discounts due to sea-level rise.

Figure 5 illustrates the time-series trends of average monthly search volume index for the term "sea level rise" from 2011 to 2023. We observe a general upward trend in attention on SLR from 2011 to 2020, with notable peaks observed in late-2018, suggesting heightened concern during this

period, potentially due to the Conference of the Parties 24. Following 2020, the SVI exhibits a gradual decline, particularly during the COVID-19 pandemic years (2020–2022), potentially reflecting competing societal priorities. Hence, it is interesting to explore whether the time-varying attention on SLR is associated with the impact of SLR on house prices documented above.

We first plot the average search volume index for each city in Figure 6. We observe that 13 out of the 31 coastal cities have an attention level on sea-level rise higher than the mean, suggesting that most people in Chinese coastal cities exhibit relatively low attention to this issue. Then, we sort cities into two groups based on the median of the average search volume index. Finally, we conduct separate regression analyses for each group to assess the impact of attention on the price discount effects of SLR for house prices. The coefficients for $Exposure$ obtained from estimating Eq.(2) for each group are reported in Table 6.

Columns (1) to (2) reveal that the negative impact of SLR on the prices of exposed homes is only significant in regions with greater public attention to SLR. Specifically, only in areas with above-median levels of attention in Column (2), the estimated coefficient of $Exposure$ is negative and statistically significant. However, in areas where relatively fewer people focus on the risks of sea-level rise, as seen in the group of low attention, the relationship between home prices and flood risk is not significant. This suggests that the negative impact of SLR on property prices is only pronounced in regions where public attention to the issue is relatively high, consistent with the finding in previous studies, such as Baldauf, Garlappi, and Yannelis (2020) and Bunten and Kahn (2014).

In the last Column of Table 6, we regress property transaction prices on the interaction between $Exposure$ and public attention (SVI). The $Exposure \times SVI$ interaction is highly significant, with a point estimate of -0.14. The combined effect of $Exposure$ and the interaction term suggests that,

for properties exposed to SLR risks, a 10% increase in *Exposure*, coupled with 10% increase in the public attention to the SLR issue, results in 2.1% greater price discount for exposed properties.[19] Our analysis incorporates year, distance-to-coast, and elevation fixed effects, along with house and geographic controls, therefore the relationship originates from exposure and attention variation.

Baldauf, Garlappi, and Yannelis (2020) find that houses in flood zones sell at a 2.88% discount compared to unexposed properties when incorporating agents' beliefs, Bernstein, Gustafson, and Lewis (2019) show that belief differences among investors impact the prices of sea-level rise-exposed properties only in the owner-occupied market segment. These studies, which rely on survey data to measure investors' beliefs and focus on the U.S. market. Our results yield similar findings, but with a focus on the Chinese housing market, utilizing a time-varying measure of investor attention, thereby extending this line of research. Overall, our findings indicate that in areas with greater awareness of sea-level rise, the price discount effect of *Exposure* is more pronounced, highlighting the crucial role of investor attention in shaping the relationship between SLR exposure and property prices.

4.2 The impact of prior typhoon experience

Our findings suggest a demand-side explanation for the decline in home transaction prices in areas more exposed to SLR risk. Recent research by Choi, Gao, and Jiang (2020) highlights that short-term climate events, such as extreme weather, can shape public perceptions of climate change and influence market behavior. Gibson, Mullins, and Hill (2017) demonstrate that heightened climate risk awareness after hurricanes lowers the relative value of more exposed properties in New York. Ortega and Taşpınar (2018) and Eichholtz, Steiner, and Yönder (2019) obtain similar results. Additionally, residents in regions that have experienced frequent flooding may develop

[19] Our results remain unchanged when the sample is divided based on the quintile of SVI.

greater awareness of the risks associated with sea-level rise. Coastal cities, particularly those prone to typhoons, are more vulnerable to seawater inundation and flooding, which can amplify concerns over future SLR impacts.

To further explore this dynamic, we examine whether the effects of SLR exposure on property prices differ between cities that experience frequent typhoons and those that do not. Using data from the China Meteorological Administration, we identify 12 cities across three provinces, Fujian, Guangdong, and Hainan, that have been hit by typhoons more than 100 times over the past 70 years. We define an indicator variable, *Typhoon*, which equals one for homes located in these high-frequency typhoon areas and zero otherwise, to evaluate how exposure to frequent typhoons influences the relationship between SLR risk and house prices.

Table 7 presents the regression results. Columns (1) and (2) display the findings for areas with infrequent and frequent typhoon occurrences, respectively. We observe a statistically significant negative association between *Exposure* and residential prices only in typhoon-prone areas in Column (2), while no such pattern is found in less typhoon-exposed areas in Column (1). The coefficient in Column (2) is -0.27,, which is notably larger than the coefficient for the full sample reported in Table 2 (-0.13). This suggests that residents in typhoon-exposed cities are more sensitive to flood risk, thereby amplifying the price discount associated with SLR exposure.

In Column (3) of Table 7, we regress house transaction price on the interaction between *Exposure* and *Typhoon*. The results show that houses in areas with frequent typhoons significantly amplifies the impact of SLR exposure on coastal property prices, as evidenced by the statistically significant negative coefficients of the interaction term. When there is 10% increase in SLR risk, the overall price discount effect increases by 2.7% in typhoon-prone areas compared to areas experiencing less typhoons, suggesting that prior experience with frequent flooding due to

typhoons makes households more sensitive to long-term sea-level rise risk. This finding is consistent with existing literature, which demonstrates that regions with a history of frequent flooding tend to experience larger declines in house prices (Bin and Landry, 2013; Clayton, Devaney, Sayce, and Van de Wetering, 2021; Giglio et al., 2021)

4.3 Urban flood resilience and SLR price discount

Since 2015, the Chinese government has actively promoted the development of Sponge Cities, which aims to enhance urban resilience to flooding and improve ecological sustainability.[20] To this end, we investigate whether the designation of a city as a sponge city serves as a channel through which the negative effects of SLR risk on residential property prices are attenuated. Cities selected as official sponge city pilots are expected to implement infrastructure and planning improvements that enhance stormwater retention and drainage capacity—such as permeable pavements, green roofs, and integrated water systems. These interventions may reduce the perceived inundation risk associated with rising sea levels and increase public confidence in local governments' ability to manage future water-related threats.

Based on the official list of pilot sponge cities, [21] we classify residential properties into two groups: those located within sponge cities (Sponge = 1) and those outside (Sponge = 0). Regression results reported in Table 8 indicate that the estimated SLR exposure discount is no longer statistically significant within sponge cities as in Column (1). Moreover, the interaction term between *Exposure* and *Sponge* is also statistically insignificant, suggesting that city-level resilience measures may offset the potential depreciation effect. This finding implies that in cities with

[20] 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.

[21] Data source: https://jjs.mof.gov.cn/tongzhigonggao/201504/t20150402_1211835.htm and https://jjs.mof.gov.cn/zxzyzf/csgwzxzj/201604/t20160425_1964216.htm.

stronger adaptive infrastructure and water management capacity, the real estate market perceives SLR risk as more manageable, thereby weakening its influence on housing prices.

4.4 Land availability

On the supply side, the cost of acquiring land usage rights is a primary expense for real estate developers and construction firms. The literature indicates that urban land supply is constrained by both regulatory policies and geographic factors, leading to lower housing supply elasticity and higher prices in cities with limited developable land (Shi, 2022; Saiz, 2010). Therefore, we expect that in highly constrained cities, housing scarcity may keep prices elevated even for properties exposed to SLR, resulting in smaller price discounts. If demand remains strong, this scarcity effect can further limit price declines in flood-prone areas.

Table 9 reports the results on the role of land constraints in shaping SLR-related price discounts, with Columns (1) and (2) presenting findings for "Low constraint" and "High constraint" subsamples, respectively, based on the median of *Land constraint*. Consistent with our expectations, only the coefficient in Column (1), with cities having higher land availability, is statistically significant, whereas no such effect is observed in Column (2), where land constraints are more severe than the sample median. This finding suggests that housing supply inelasticity, driven by geographic constraints, mitigates the negative impact of SLR exposure on house prices. Cities with less available residential land exhibit lower housing supply elasticity, offering fewer relocation options for residents and making the housing market less responsive to climate change compared to cities with fewer constraints. This finding is consistent with Mian and Sufi (2022) and Gao, Sockin, and Xiong (2020) that cities with lower supply elasticity exhibit more pronounced house price boom-and-burst patterns.

In Column (3), we regress house prices on the interaction term of *Exposure* and *Land constraint*. While the coefficient on *Exposure* remains negative and statistically significant, the interaction term is not of statistical and economical significance. This suggests that in more constrained cities, the price discount effect of SLR exposure is mitigated by the scarcity effect driven by housing supply inelasticity. The difference between the median-based estimates in Columns (1) and (2) and the interaction term in Column (3) lies in their interpretation: the former captures price discounts above and below the median, while the latter quantifies how price discounts evolve with increasing land constraints. Overall, our results demonstrate that the SLR-driven price depreciation effect is more evident in cities with lower land constraints.

5 Do house prices reflect climate change adaptation?

So far, we have shown that properties exposed to SLR risk in the coastal cities face price depreciation. However, the extent to which adaptation strategies can alleviate this negative impact remains an important policy and empirical question. Recent studies provide supportive evidence. Recently, Agarwal, Qin, Sing, and Zhan (2025) find that in Singapore, the announcement of national adaptation measures mitigate the price discount in public housing prices in SLR-exposed areas. Similarly, Benetton et al. (2022) show that housing prices in Venice increased substantially following the activation of the sea wall.

The adaptation efforts vary widely across Chinese coastal cities due to differences in physical exposure, governance capacity, and local planning.[22] Some cities began implementing mitigation projects even before the national policies were announced. This raises a central question: how did local housing markets respond to these adaptation efforts?

[22] Detailed information on the adaptation strategies implemented by each coastal city is provided in Table A3 of the Appendix.

To address this question, we exploit cross-city variation in the timing of adaptation policy announcements or implementation and estimate a time-varying difference-in-differences specification as follows:

$$\ln P_{i,t} = \alpha_{cde} + \alpha_y + \theta \cdot \text{Treat}_i \times \text{Adapted}_{ic,t} + \kappa' X_i + \gamma' X_{g,t} + \zeta_{i,t}, \tag{4}$$

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. $Adapted_{ic,t}$ is a dummy variable equal to 1 if property i is located in city c that has announced or implemented adaptation strategies to mitigate the SLR risks by year t, and the transaction after the year. Other control variables and fixed effects are similar defined as in Eq.(1). The coefficient of interest, θ, captures the effect of adaptation strategies on the prices of properties exposed to sea-level rise risk.

Table 10 shows the main regression results for both transaction and listing prices. In Columns (1) and (3), we examine whether the announcement of an adaptation strategy mitigates the negative pricing effect of SLR exposure. In Columns (2) and (4), we restrict the sample to properties located in SLR-exposed areas and compare the pricing effects between cities that did and did not announce or implement any adaptation strategies.

The interaction term $Treat \times Adapted$ is positive and statistically significant in Columns (1) and (3), with a magnitude of 3%, suggesting that the announcement or implementation of adaptation strategies attenuates the negative impact of SLR risk on housing prices. Put it differently, while properties exposed to SLR risk are discounted relative to those in non-exposed areas, this discount becomes less pronounced following the mitigation measures.

Furthermore, when focusing exclusively on SLR-exposed properties in Columns (2) and (4), we find that those located in cities with adaptation plans experience a relative increase in prices of 4% and 6% for transaction and listing prices, respectively, compared to those in cities without

such plans. This provides further evidence that adaptation strategies are priced by the market and partially offset the expected cost of future inundation.

6 Conclusion

In this study, we address the issue of how sea-level rise influences residential property prices in China, focusing on properties with various inundation thresholds for the sample period from 2011 to 2023.

We develop a novel SLR exposure measure that accounts for the inundation thresholds, the expected time of inundation, and appropriate discount rates. This approach allows us to capture not only whether a property is at risk, but also how soon and how severely that risk may materialize, thereby reflecting the time value of climate risk in a more nuanced and economically meaningful way. Based on this measure, our analysis reveals that sea-level rise exposure exhibits negative and statistically significant impact on residential home prices in China, which is driven by both demand and supply sides. By isolating the effects of SLR on houses at different inundation thresholds, we show that the price discount is significant only for properties that would be submerged by 1- or 3-foot of SLR, with it decreasing for more distant risk. Furthermore, we find stronger effects in areas with higher public attention, more frequent typhoons, lower urban flood resilience, and fewer geographical land constraints.

Finally, by utilizing cross-city variation in the timing of adaptation strategy announcements or implementation in China, we demonstrate that local adaptation measures, including the construction of seawalls, significantly mitigate the decline in both transaction and listing prices for properties exposed to SLR risk. These findings deepen our understanding of how sea-level rise influences property prices in an emerging market and provide valuable insights for policymakers

and investors navigating climate change risk.

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Table A1: Variable definitions

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

Name	Description	Frequency	Source
$P_{i,t}$	Dollar transaction price of home i at time t in Chinese Yuan.	Daily	HomeLink
$LP_{i,t}$	Dollar listing price of home i at time t in Chinese Yuan.	Daily	HomeLink
Exposure	A continuous measure of SLR exposure that accounts SLR forecasts, projected year of inundation and discount rates as defined Eq.(1).	Cross-sectional	Climate Central
Underwater 1ft	An indicator which equals 1 if a house is projected to be underwater at 1-foot sea-level rise and zero otherwise.	Cross-sectional	Climate Central
Underwater 3ft	An indicator which equals 1 if a house is projected to be underwater at 3-foot sea-level rise and zero otherwise.	Cross-sectional	Climate Central
Underwater 6ft	An indicator which equals 1 if a house is projected to be underwater at 6-foot sea-level rise and zero otherwise.	Cross-sectional	Climate Central
$SVI_{c,t}$	Baidu Search Volume Index of the search topic of "sea-level rise" of city c on month m.	Monthly	Baidu search engine
Typhoon	An indicator which equals 1 if a house is located in a city that experienced typhoon frequently over the past 70 years and zero otherwise.	Cross-sectional	China Meteorological Administration
Sponge	for whether a property is located in a sponge city or not, based on the official pilot list released by the Chinese central government.	Cross-sectional	HomeLink
Land constraint	The proportion of residential land to total construction land within a city, subtracted from one.	Yearly	Statistical yearbook of China
Days on market	The number of days a property remains listed before it is sold	Cross-sectional	HomeLink
Number of visits	The number of online visits recorded on the HomeLink platform	Cross-sectional	HomeLink
Number of bookmarks	The number of online followers or bookmarks	Cross-sectional	HomeLink
Number of price adjustments	The frequency of price adjustments	Cross-sectional	HomeLink
House-level attributes			
Number of bedrooms	Count of the number of bedrooms of a property	Cross-sectional	HomeLink
Size	The size of the house	Cross-sectional	HomeLink
Number of bathrooms	Count of the number of bathrooms of a property	Cross-sectional	HomeLink
Orientation	A variable denotes the orientation of the house, which equals 1 for southeast orientation, 2 for south orientation, 3 for East orientation, 4 represents southwest orientation, 5 for west orientation, 6 for North orientation, 7 for northeast, southeast, and southwest corner orientations, and 8 for northwest orientation.	Cross-sectional	HomeLink
Layout	A variable that takes the value of 1 if the house is a loft, 2 if it is a split-level, 3 if it is a duplex apartment, 4 if it is a flat, and 5 if it is a multi-story unit.	Cross-sectional	HomeLink
Decoration	A variable that equals 1 for 'Other', 2 for 'Bare Shell', 3 for 'Simple Decoration', and 4 for 'Luxurious Decoration'	Cross-sectional	HomeLink
Elevator	A dummy variable which equals to 1 if the house has elevator and zero otherwise.	Cross-sectional	HomeLink
Latitude/longitude	Geographical coordinates of a property	Cross-sectional	HomeLink
Distance to coast	Distance of a property to the closest coast line	Cross-sectional	Calculated based on latitude and longitude
Elevation	Elevation (in meters) of the area that a property is located	Cross-sectional	Calculated based on latitude and longitude
Geographic characteristics			
GDP	Logarithm of gross domestic product of countt d at year y	Yearly	Statistical yearbook of China
Population density	Logarithm of population density of city c at year y	Yearly	Statistical yearbook of China
EPU	Economic policy uncertainty index at month m (scaled by 100)	Monthly	CSMAR
% Gas coverage	Gas coverage rate of city c at year y	Yearly	WIND
% Green coverage	Green area coverage rate of city c at year y	Yearly	WIND
% Urbanization population	Proportion of the urban population of province p at year y	Yearly	WIND
% Elderly	Percentage of people aged 65 and older at year y	Yearly	WIND

Figure 1: Residential property prices for China

This figure illustrates the nominal residential housing price index for China from 2010 to 2024, using 2010 as the base period. The data is provided at a quarterly frequency.

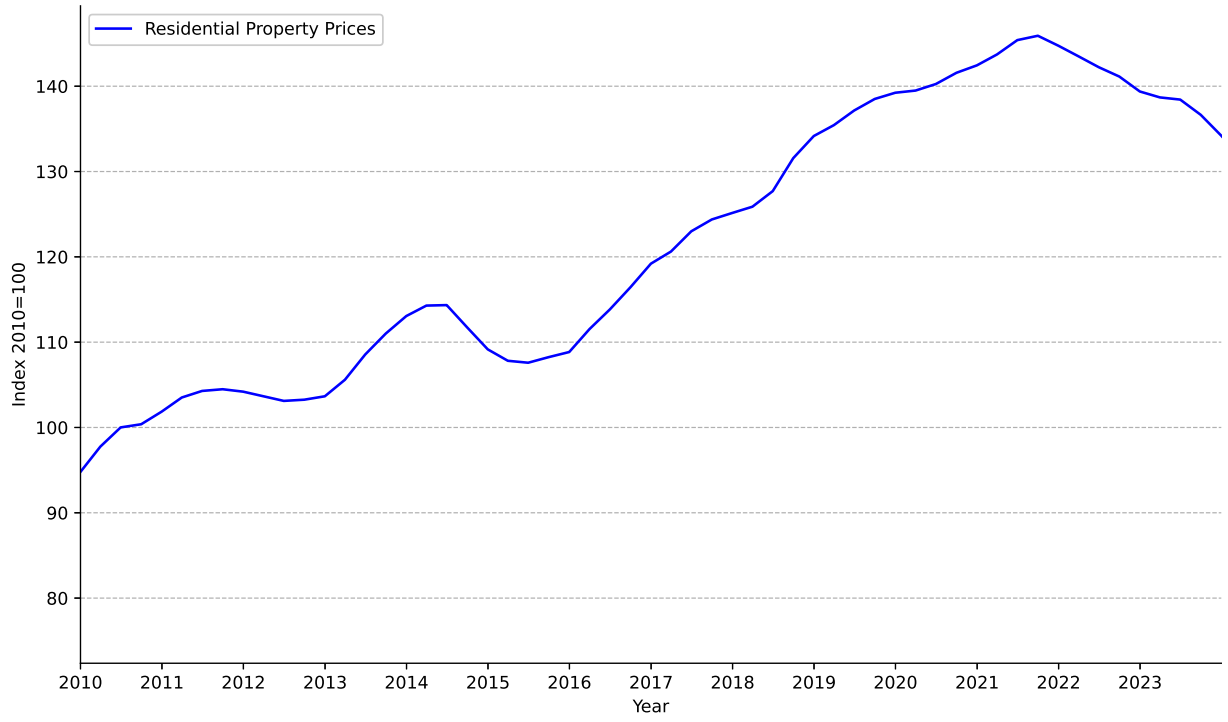


Figure 2: Sea level rise exposure of Chinese coastal provinces

This figure depicts the average sea-level rise exposure of residential houses in coastal cities within our sample. The SLR exposure is measured by the indicator *Exposure*, which is a continuous measure of projected sea-level rise risk and calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). The house-level SLR exposures are averaged by provinces and categorized into five groups, each represented by a different color. Darker colors indicate higher sea-level rise risk.

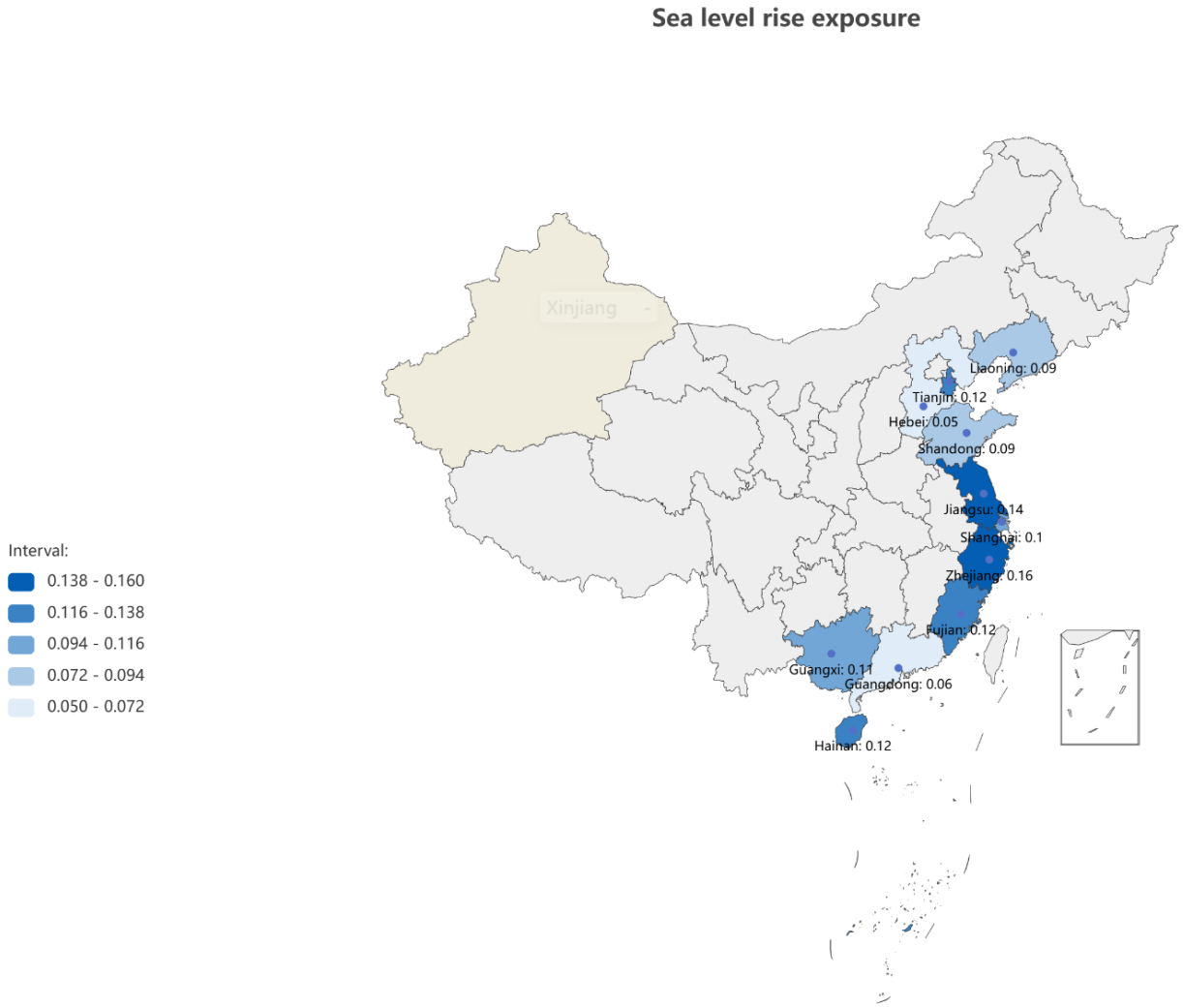


Figure 3: Sea level rise exposure of Chinese coastal cities

This figure depicts the average sea-level rise exposure for residential houses across all coastal cities in our sample. SLR exposure is measured by the indicator *Exposure*, which is a continuous measure of projected sea-level rise risk and calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). House-level SLR exposures are averaged by cities and denoted by the blue bar. Cities are ranked by the value of $UnderWater$, with higher values indicating higher sea-level rise risk.

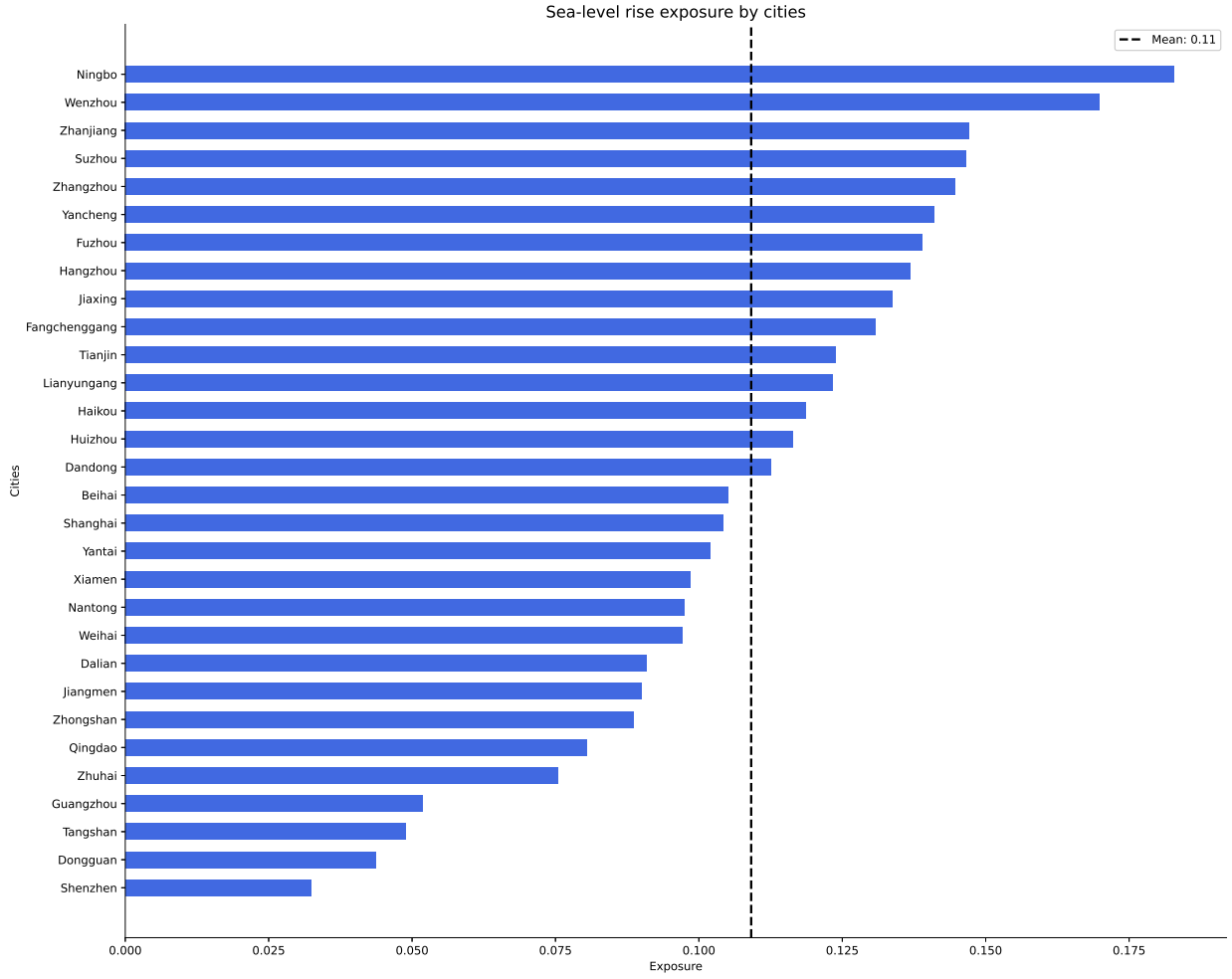


Figure 4: House prices, sales volume, and SLR exposure

The top panel in this figure shows trends of unit home price, while the bottom panel displays trends of house liquidity for coastal cities in China, categorized by high (dark blue) versus low (light blue) SLR exposure. Liquidity is measured as the logarithm of county-level home sales volume, normalized by year, month, and city. Properties are classified as "More SLR exposed" or "Less SLR exposed" based on whether their SLR exposure is above or below the median. SLR exposure, measured by the indicator *Exposure*, is a continuous measure of projected sea-level rise risk and calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). All variables are averaged monthly. The sample period is from January 2011 to November 2023.

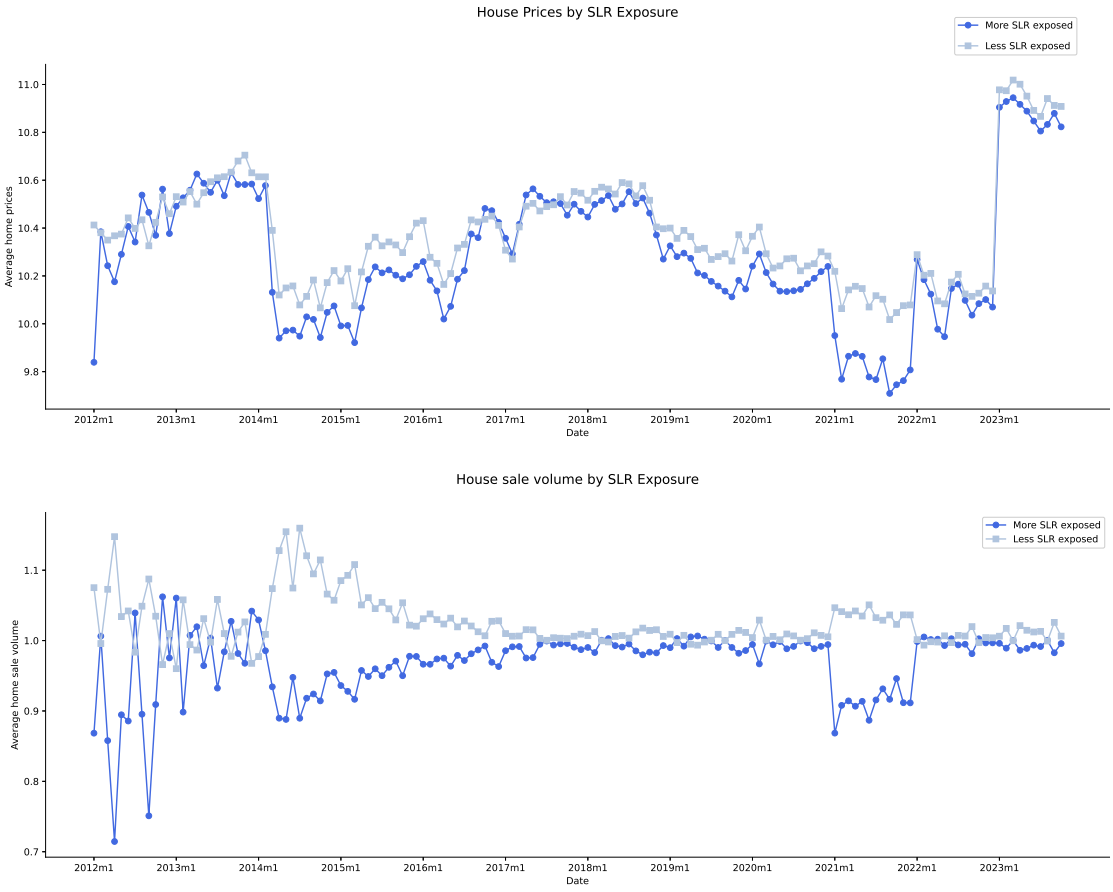


Figure 5: Attention on sea-level rise

This figure shows the time-series trends of average search volume index SVI for the term "sea-level rise" from Baidu, the most popular search engine in China. The sample period is from January 2011 to November 2023.

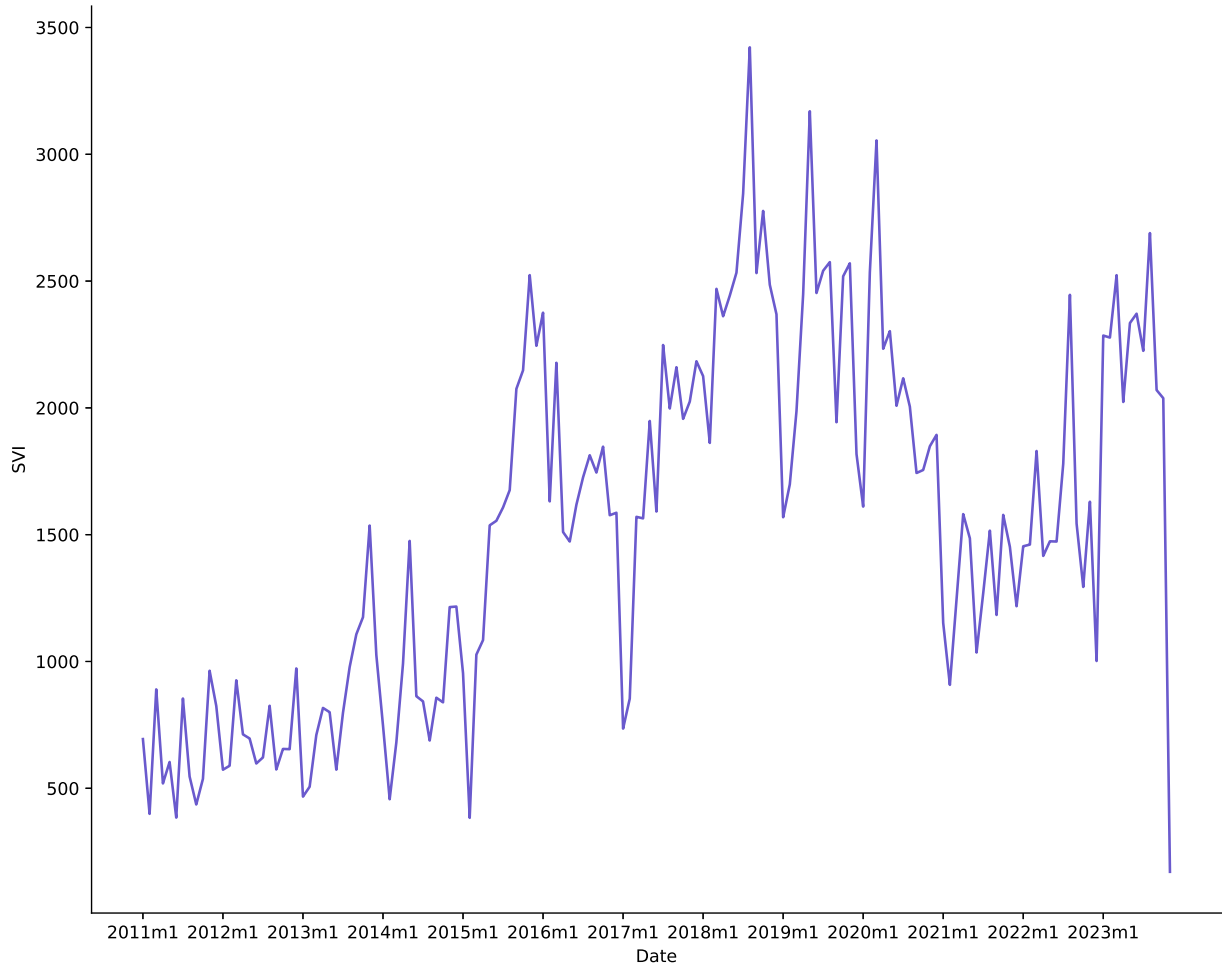


Figure 6: Attention on sea-level rise across cities

This figure illustrates the average search volume for the topic of 'sea level rise' on Baidu, denoted as SVI, across coastal cities in our sample. Cities are ranked by the value of logarithm of SVI, represented by the blue bar, with higher values indicating more attention on this issue.

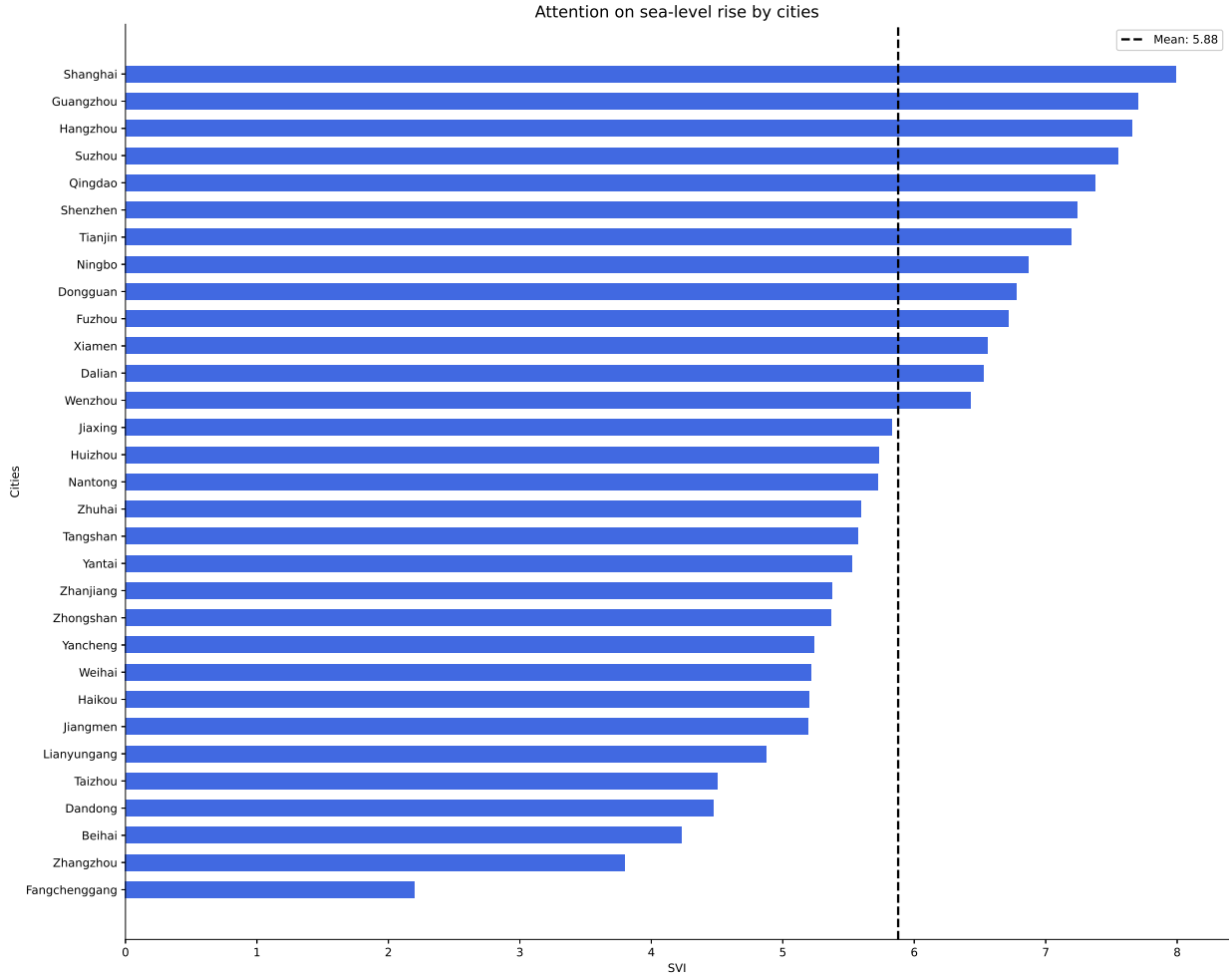


Table 1: Summary statistics

This table reports the number of observations (Obs), mean (Mean), standard deviation (Std. Dev.), minimum (Min), and maximum (Max) for all variables employed in the full sample. See Table A1 of the Appendix for detailed variables descriptions. The sample period is from January 2011 to November 2023.

	Obs	Mean	Median	Std. Dev.	Min	Max
Transaction price (million, Chinese yuan)	1,400,935	2.35	1.74	1.98	0.31	11.38
List price (million, Chinese yuan)	1,345,620	2.46	1.80	2.11	0.30	12.45
Exposure	1,400,935	0.10	0.04	0.10	0	0.26
Underwater 1ft	1,400,935	0.37	0	0.48	0	1
Underwater 3ft	1,400,935	0.50	0	0.50	0	1
Underwater 6ft	1,400,935	0.67	1	0.47	0	1
SVI (thousand)	1,400,935	7.01	7.24	1.00	4.04	8.37
House-level attributes						
Number of bedrooms	1,400,935	1.18	2	0.94	0	37
Size (m^2)	1,357,475	82.34	80	33.42	26.55	203
Number of bathrooms	1,400,935	1.18	1	0.53	0	21
Age	973,705	15.04	13	8.92	1	40
Floor level	1,399,809	2.08	2	0.78	1	3
Orientation	1,400,935	5.56	3	3.12	1	11
Layout	980,151	3.02	3	0.34	1	6
Decoration	1,400,935	2.67	3	1.26	1	4
Elevator	1,400,935	0.57	1	0.50	0	1
Elevation (m)	1,400,935	16.36	7	20.78	0	104
Distance to coast (km)	1,400,935	27.84	26.88	21.68	0.22	85.00
Geographic characteristics						
GDP (logarithm, yuan)	1,400,935	28.07	28.11	0.71	24.97	29.18
Population density (logarithm, people/km^2)	1,400,935	8.23	8.25	0.38	6.25	9.49
EPU (logarithm)	1,400,935	5.59	5.69	0.49	4.08	6.50
% Gas coverage	1,400,935	0.99	1	0.02	0.78	1.02
% Green coverage	1,400,935	0.41	0.42	0.04	0.15	0.56
% Urbanization population	1,400,935	0.77	0.74	0.09	0.51	0.90
% Elderly	1,400,935	0.14	0.14	0.04	0.07	0.21
Other variables						
Dyas on market	1,382,880	217.21	84	373.58	1	2,132
Number of visits	1,294,704	1,445.30	374	2,306.89	25	1,2967
Number of bookmarks	1,400,738	13.78	5	23.55	0	138
Number of price adjustments	1,400,738	2.52	1	3.2	0	16
Typhoon	1,400,935	0.26	0.00	0.44	0	1
Sponge	1,400,935	0.72	1	0.45	0	1
Land constraint	1,195,690	0.71	0.72	0.039	0.61	0.77

Table 2: Sea-level rise and house prices

This table reports regression results on the relationship between sea-level rise and the house prices. The dependent variable in each specification is the logarithm of the transaction price ($LnP_{i,t}$). The main independent variable *Exposure*, is a continuous measure of projected sea-level rise risk. It is calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). Distance to the coast (distance) and elevation are computed at the home level based on latitude and longitude. Control variables and fixed effects are specified in each regression. Geographic characteristics, such as GDP and population density, take the values from the previous year as their lagged values. See Table A1 of the Appendix for detailed variables descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	$LnP_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Exposure	-0.32*	-0.02	-0.13***	-0.07*	-0.04**
	(-1.70)	(-0.18)	(-2.89)	(-1.87)	(-2.28)
Number of bedrooms		0.16***	0.19***	0.20***	0.20***
		(11.67)	(21.47)	(30.27)	(30.16)
Size		0.27***	0.29***	0.30***	0.28***
		(15.96)	(29.33)	(26.26)	(29.32)
Number of bathrooms		-0.22***	-0.08**	-0.12***	-0.14***
		(-2.78)	(-2.30)	(-4.21)	(-5.58)
Age		0.08***	0.02	-0.08***	-0.11***
		(3.02)	(0.90)	(-6.29)	(-22.05)
Orientation		0.09**	0.06***	0.03***	0.03***
		(2.24)	(3.98)	(3.46)	(5.84)
Layout		0.03***	0.02***	0.02***	0.02***
		(2.81)	(3.05)	(3.96)	(3.37)
Decoration		0.03***	0.02***	0.02***	0.01***
		(4.21)	(7.92)	(7.69)	(8.32)
Elevator		0.25***	0.19***	0.14***	0.10***
		(9.87)	(10.96)	(11.20)	(9.84)
Floor level		-0.02***	-0.01***	-0.01***	-0.01***
		(-6.47)	(-7.60)	(-6.38)	(-6.56)
GDP		0.45***	0.18	0.01	-0.04
		(6.40)	(1.10)	(0.07)	(-0.64)
Population density		0.43***	-0.09***	-0.09***	-0.09***
		(2.98)	(-2.79)	(-3.46)	(-3.62)
EPU		-0.01	0.03***	0.02***	0.02***
		(-0.41)	(7.24)	(7.99)	(8.29)
% Gas coverage		0.90*	1.91***	2.05***	1.98***
		(1.88)	(3.37)	(4.21)	(4.40)
% Green coverage		-3.98***	-0.73**	-0.68*	-0.48
		(-4.68)	(-2.11)	(-1.93)	(-1.56)
% Urbanization population		0.09	-4.69***	-3.68***	-3.64***
		(0.17)	(-7.83)	(-6.76)	(-7.15)
% Elderly		-0.07	-2.57**	-2.79***	-2.39***
		(-0.05)	(-2.50)	(-3.10)	(-2.66)
Constant	14.42***	-1.60	11.44***	15.63***	17.01***
	(20.31)	(-1.06)	(2.65)	(7.20)	(8.33)
Year FE	No	No	Yes	Yes	Yes
City × distance × elevation FE	No	No	Yes	No	No
District × distance × elevation FE	No	No	No	Yes	No
Street × distance × elevation FE	No	No	No	No	Yes
Observations	1,400,935	619,621	619,617	619,579	619,465
Adjusted R^2	0.002	0.62	0.77	0.85	0.90

Table 3: House price effects under different SLR forecasts

This table presents regression results examining the association between sea-level rise and prices of houses under different forecasts. The sample partitioned by the amount of SLR required to make the property underwater is defined as follows: for a one-foot sea-level rise, the full sample is used; for a three-foot rise, only properties requiring three feet of SLR to be inundated are considered, excluding those primarily affected by a one-foot of SLR; for six-foot of SLR, only houses requiring six feet of SLR projected to be underwater are included, excluding those affected by lower SLRs. The dependent variable in each specification is the logarithm of the transaction price ($LnP_{i,t}$). The independent variables *Underwater* 1ft, *Underwater* 3ft, and *Underwater* 6ft are dummy indicators equal to 1 if a property is projected to be underwater under a 1-foot, 3-foot, or 6-foot sea-level rise, respectively, and 0 otherwise. To improve the readability of the coefficient magnitude, we scale the three independent variables by dividing them by 10. Distance to the coast (distance) and elevation are measured at the home level based on latitude and longitude. Control variables and fixed effects are specified in each regression. Geographic characteristics take the values from the previous year as their lagged values. See Table A1 of the Appendix for detailed variable descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	$LnP_{i,t}$		
	(1)	(2)	(3)
Underwater 1ft	-0.29***		
	(-3.15)		
Underwater 3ft		-0.24***	
		(-2.69)	
Underwater 6ft			-0.06
			(-0.50)
House level attributes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes
Observations	619,617	406,360	343,088
Adjusted R^2	0.77	0.77	0.77

Table 4: Policy interventions and different price trends

This table presents regression results for robustness tests across different subsample periods. Columns (1) to (3) show subsamples based on the timing of house purchase restrictions. Specifically, Column (1) excludes properties transacted between 2011 and 2014, Column (2) excludes properties transacted between 2017 and 2019, and Column (3) excludes properties transacted during the policy interventions in both periods. Columns (4) and (5) separate the sample by transaction periods: the hot period (2011–2013, 2016–2021), when house prices rose, and the cold period (2014–2015, 2022–2023), when prices fell. The dependent variable in all specifications is the logarithm of the transaction price ($LnP_{i,t}$). The main independent variable *Exposure*, is a continuous measure of projected sea-level rise risk, calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). To improve the readability of the coefficient magnitude, we scale the *Exposure* by dividing it by 10. Distance to the coast (distance) and elevation are measured at the home level based on latitude and longitude. Geographic characteristics take the values from the previous year as their lagged values. Control variables and fixed effects are specified in each regression. See Table A1 of the Appendix for detailed variable descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	$LnP_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
	Exclude HPR1	Exclude HPR2	Exclude two periods	Hot	Cold
Exposure	-0.13***	-0.12***	-0.12***	-0.13**	-0.12***
	(-2.83)	(-2.83)	(-2.76)	(-2.36)	(-3.10)
House-level attributes	Yes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes	Yes	Yes
Observations	607,573	477,103	465,059	285,128	334,487
Adj. R^2	0.77	0.75	0.76	0.78	0.75

Table 5: SLR risks, housing market supply and demand

This table reports house-level regressions of demand- and supply-side outcomes on sea-level rise risks (*Exposure*). Demand is measured by three indicators: Days on market (logarithm), online view count for a property on the Homelink platform (No. visits, logarithm), and the number of bookmarks (No. bookmarks, logarithm), reported in Columns (1), (2), and (3) respectively. Supply is measured using two variables: List price (logarithm) and number of price adjustments (No. price adjustments), shown in Columns (4) to (5). All dependent variables are log-transformed to reduce skewness. The main independent variable *Exposure*, is a continuous measure of projected sea-level rise risk, calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). To improve the readability of the coefficient magnitude, we scale the *Exposure* by dividing it by 10. Distance to the coast (distance) and elevation are measured at the home level based on latitude and longitude. Geographic characteristics take the values from the previous year as their lagged values. Control variables and fixed effects are specified in each regression. See Table A1 of the Appendix for detailed variable descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	Demand			*Supply*	
	(1)	(2)	(3)	(4)	(5)
	Days on market	No. visits	No. bookmarks	List price	No. price adjustments
Exposure	0.09**	-0.07**	-0.07*	-0.13***	0.25***
	(2.05)	(-2.34)	(-1.76)	(-2.85)	(3.11)
House level attributes	Yes	Yes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes	Yes	Yes
Observations	612,128	549,121	619,494	598,927	619,494
Adjusted R^2	0.18	0.48	0.25	0.77	0.20

Table 6: Attention on sea-level rise and house prices

This table reports regression results of analyses on the impact of attention on the effect of sea level rise on residential houses prices. The attention of city c on month t is measured by the search volume of the topic of "sea level rise" on Baidu, denoted as $SVI_{c,t}$. We divide the sample into two groups based on the median level of attention: high attention (above the median) and low attention (below the median). The dependent variable in each specification is the log of the transaction price ($LnP_{i,t}$). The main independent variable $Exposure$, is a continuous measure of projected sea-level rise risk, calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). Control variables and fixed effects are specified in each regression. Geographic characteristics take the values from the previous year as their lagged values. See Table A1 of the Appendix for detailed variable descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	$LnP_{i,t}$		
	(1)	(2)	(3)
	Low attention	High attention	Full sample
$Exposure$	-0.06	-0.19***	-0.14***
	(-1.69)	(-2.91)	(-3.16)
$Exposure \times SVI$			-0.07***
			(-2.72)
House level attributes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes
Observations	281,394	338,217	619,617
Adjusted R^2	0.73	0.67	0.77

Table 7: Sea-level rise and house prices: Cities experiencing more typhoons

This table reports regression results examining the association between sea-level rise and the house prices considering typhoon frequency. "More typhoon" refers to properties located in cities experiencing more than 100 typhoons over past 70 years, while "Less typhoon" refers to those with fewer. Column (3) estimates the effect of the interaction term of sea level rise exposure and typhoon frequency. The dependent variable in each specification is the logarithm of the transaction price $LnP_{i,t}$. The main independent variable $Exposure$, is a continuous measure of projected sea-level rise risk, calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). Distance to the coast (distance) and elevation are measured at the home level based on latitude and longitude. Control variables and fixed effects are specified in each regression. Geographic characteristics take the values from the previous year as their lagged values. See Table A1 of the Appendix for detailed variable descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	$LnP_{i,t}$		
	(1)	(2)	(3)
	Less typhoon	More typhoon	Full sample
$Exposure$	-0.07	-0.27***	-0.06
	(-1.29)	(-3.30)	(-1.05)
$Exposure \times Typhoon$			-0.27**
			(-2.44)
House level attributes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province × distance × elevation FE	Yes	Yes	Yes
Observations	410,371	209,247	619,618
Adjusted R^2	0.79	0.69	0.75

Table 8: Flood resilience and SLR price discount

This table presents regression results examining whether urban flood resilience, measured by a city's designation as a national sponge city pilot, mitigates the negative effect of SLR exposure on housing prices. The dependent variable in all specifications is the logarithm of the transaction price ($LnP_{i,t}$). The key variable of interest is a binary indicator for whether a property is located in a sponge city ($Sponge = 1$) or not ($Sponge = 0$), based on the official pilot list released by the Chinese central government. The independent variable $Exposure$, is a continuous measure of projected sea-level rise risk, calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). Distance to the coast (distance) and elevation are measured at the home level based on latitude and longitude. Geographic characteristics take the values from the previous year as their lagged values. Control variables and fixed effects are specified in each regression. See Table A1 of the Appendix for detailed variable descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	$LnP_{i,t}$		
	(1)	(2)	(3)
	Sponge city	Non-sponge city	Full sample
$Exposure$	-0.09	-0.21***	-0.22***
	(-1.30)	(-2.97)	(-2.36)
$Exposure \times Sponge$			0.13
			(1.18)
House level attributes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes
Observations	452,207	167,410	619,617
Adjusted R^2	0.78	0.68	0.77

Table 9: Land constraint and the exposure discount effect

This table presents regression results examining the impact of housing liquidity on the discount effect associated with sea-level rise (SLR) exposure on house prices. The dependent variable in all specifications is the logarithm of the transaction price ($LnP_{i,t}$). *Landconstraint* is the proportion of unavailable residential land over the total construction area of a city, normalized by year and province. Properties are classified as "Low constraint" or "High constraint" based on whether *Landconstraint* is below or above the median of the full sample. The main independent variable *Exposure*, is a continuous measure of projected sea-level rise risk, calculated using scientific SLR forecasts (Oppenheimer et al., 2019), the property's transaction year, and level-specific discount rates, as defined in Eq.(1). Distance to the coast (distance) and elevation are measured at the home level based on latitude and longitude. Geographic characteristics take the values from the previous year as their lagged values. Control variables and fixed effects are specified in each regression. See Table A1 of the Appendix for detailed variable descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	$LnP_{i,t}$		
	(1)	(2)	(3)
	Low constraint	High constraint	Full sample
Exposure	-0.17**	-0.07	-0.17**
	(-2.55)	(-1.27)	(-2.35)
Exposure×*Land constraint*			0.09
			(1.13)
House level attributes	Yes	Yes	Yes
Geographic characteristics	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes
Observations	262,650	264,433	526,951
Adjusted R^2	0.77	0.75	0.77

Table 10: SLR adaptation and property prices

This table reports the estimates of the impact of SLR adaptation strategies on both transaction and listing prices of residential properties. The variable *treat* is a dummy equal to one if the property is located in an SLR-exposed area, and zero otherwise. The variable *adapted* is an interaction term equal to 1 if the property is located in a city that has announced or implemented adaptation strategies to mitigate the SLR risks, and the transaction occurred after the announcement year. It takes the value 0 otherwise. Columns (1) and (3) use the full sample to examine whether adaptation strategies mitigate the negative pricing effect of SLR exposure. Columns (2) and (4) restrict the sample to properties exposed to SLR risk, comparing price differences between cities with and without announced adaptation plans. Distance to the coast (distance) and elevation are measured at the home level based on latitude and longitude. Geographic characteristics take the values from the previous year as their lagged values. Control variables and fixed effects are specified in each regression. See Table A1 of the Appendix for detailed variable descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	Transaction price		Listing price	
	(1)	(2)	(3)	(4)
	Full sample	Adapted vs. non-adapted SLR	Full sample	Adapted vs. non-adapted SLR
Treat×*Adapted*	0.03**	0.04**	0.03**	0.06**
	(1.97)	(3.39)	(2.32)	(5.03)
House level 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	619,617	379,579	598,927	373,014
Adjusted R^2	0.78	0.77	0.78	0.77

Table A2: Sea-level rise and house prices using alternative measure

This table reports estimates of the impact of SLR risks on both transaction and listing prices using two alternative exposure measures. The first measure, termed as *Linear exposure*, assigns values of three, two, and one to properties projected to be inundated under 1-foot, 3-foot, and 6-foot SLR scenarios, respectively. The second measure, termed as *Timing exposure*, identifies the inundation threshold for each property based on the SLR forecasts and calculates the inverse of the difference between the transaction year and the projected inundation year. To improve readability, we scale the measures by dividing them by 10. Distance to the coast (distance) and elevation are computed at the home level based on latitude and longitude. Control variables and fixed effects are specified in each regression. Geographic characteristics take the values from the previous year as their lagged values. See Table A1 of the Appendix for detailed variables descriptions. Robust t-statistics are reported in parentheses. Standard errors are clustered at the county level. The sample period is from January 2011 to November 2023. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *.

	Linear exposure		*Timing exposure*	
	(1)	(2)	(3)	(4)
	Transaction price	Listing price	Transaction price	Listing price
Exposure	-0.09**	-0.09**	-0.85***	-0.86***
	(-2.36)	(-2.34)	(-2.77)	(-2.74)
Year FE	Yes	Yes	Yes	Yes
City × distance × elevation FE	Yes	Yes	Yes	Yes
Observations	649,617	598,927	619,617	598,927
Adjusted R^2	0.77	0.76	0.77	0.77

Table A3: Adaptation strategies for coastal cities

This table summarizes the timing and content of SLR adaptation strategies that were announced or implemented by individual cities included in our sample. The strategies reflect local governments' efforts to mitigate SLR-related risks through planning, infrastructure, or policy interventions. Given that our sample period spans from January 2011 to November 2023, we include only adaptation measures that were introduced in or before 2023.

City	Year	Adaptation strategies
Fangchenggang	2012	Implemented the Xiwan Hongsha Ring Ecological Seawall Improvement Project.
Zhuhai	2018	The municipal government approved and implemented the Zhuhai Sea Dike Flood Control Standard and Capacity Improvement Construction Plan.
Shenzhen	2019	Reconstruction of the eastern sea wall.
Shanghai	2019	Launched a pilot project to soften the ecological sea wall.
Tianjin	2022	The Tianjin Development and Reform Commission proposed a blue bay ecological sea wall project.
Weihai	2016	Started coastal zone ecological restoration under the Blue Bay.
Yantai	2021	Released the 14th Five-Year Plan for Marine Ecological Protection at the end of 2021.
Qingdao	2016	Issued a storm surge prevention plan for the West Coast New Area of Qingdao (2016–2035).
Dongguan	2022	Issued Dongguan City Flood (Tide) Drainage Plan (2022–2035).
Zhongshan	2022	Issued ecological sea wall construction.
Guangzhou	2018	Completed the Ling shan Daojian north shore super ecological sea wall Project.
Huizhou	2021	Reinforcement of Daya Bay sea wall.
Zhanjiang	2021	Marine ecological protection and restoration project approved in 2021.
Nantong	2018	Initiated reinforcement and standardization of the Jiang-Hai sea wall. Simultaneous upgrade of sluice gates in Nantong.
Yancheng	2022	Marine ecological protection and reinforcement project of sea wall.
Ningbo	2021	Phase I of Zhenhai coastal belt ecological restoration and sea wall safety project.
Haikou	2019	Jiangdong New District sea wall and coastal ecological restoration project.
Xiamen	2023	Xiamen Marine ecological restoration project supported by the Central government.
Wenzhou	2023	Lingni sea wall breach and tidal connection project.