# Does Climate Change Affect Real Estate Prices? Evidence from Government Announcement

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Abstract

This paper investigates the relationship between climate change information and property prices. We employ datasets of home transactions and a novel climate change information shock in Singapore, the sea level rise (SLR) projections announced by the government. Based on Difference-in-Differences estimations, we find that public properties in SLR areas experienced a 2.5% decline in price after the announcement, while private properties prices did not respond, relative to their respective control groups. We also show leasehold properties were more affected by the shock, and we estimate lower long-term discount rates further incorporated with climate risks.

Keywords: climate change, property prices, government announcement, Singapore

## Introduction

Climate change and sea level rise threaten residential safety and property value in low-lying island countries and coastal areas. IPCC predicts that the global mean sea level could rise between 0.43 m and 0.84 m by 2100, relative to 1986-2005[1]. Numerous studies focus on human adaptation to climate change[2-5]. To combat climate change, governments make commitments and take actions, and consequently, residents respond to climate policies and behave accordingly[5,6]. Understanding human responses, such as assets disposition, to climate policies is crucial in guiding climate policy design and implementation. It also helps to optimize evaluations of projects that aim to mitigate climate risks. This study employs a novel information shock of climate change directly announced by the Singapore government and investigates its impact on the residential real estate markets. Houses are the essential asset for most households, accounting for the most significant proportion (approximately 42% in Singapore). More importantly, compared with other financial assets, long-lasting properties are vulnerable to long-term climate-related risks.

Singapore is a city-state island country lying around one degree north of the equator. According to Singapore National Climate Change Secretariat, most of the land in Singapore has an elevation of no more than 15 meters, and approximately 30% of the total land is within 5 meters. The location and topography of Singapore makes this island country facing severe risks of climate change and sea level rise. On Aug 18, 2019, Singapore Prime Minister (PM) Lee Hsien Loong delivered a speech on the 2019 National Day Rally. He announced that climate change would threaten Singapore, and then he showed a Singapore topography map (Supplementary Fig. 1) where areas with higher risks of sea level rise (SLR areas) were marked. PM Lee also mentioned that "not only will property values be affected, but safety and liveability also." We treat this speech as vital information on climate, resulting in nationwide information transmission and a powerful shock on local real estate markets.

We digitize the original topography map into a vector map and identify SLR areas. We also obtain detailed transaction records of private and public housing (a.k.a. Housing and Development Board, HDB) in Singapore. We then locate each private property or HDB transaction on the map and identify if they are in government-disclosed SLR areas. For those buildings that are forecasted to be submerged, we define them as the treatment group. For those blocks outside SLR areas but within 500 m radius of treated blocks, we identify them as the control group. Fig. 1 shows maps and distributions of private properties and HDB.

[Fig. 1 about here]

We use the Difference-in-Differences (DID) model to examine the impact of climate change information on property prices. Empirical analyses are conducted in steps. First, our regression results show that relative to the control group, HDB prices of the treatment group significantly dropped after the Prime Minister's speech. Specifically, compared with the control group, the announcement led to a depreciated prices of treated HDB properties by approximately 3.2 log points to 3.4 log points (can be converted to 3.1% to 3.3% of decline). However, the price change of private properties is not distinguishable from zero. We then find older and larger HDB flats depreciated more after the announcement relative to their peer flats. While on the private housing market, leasehold (defined as 99 years of initial ownership) property prices dropped more than freehold (defined as 999 or perpetual years of initial ownership) property after the speech. Finally, we utilize the heterogeneous responses between leasehold and freehold properties and find that the announcement could lead to a lower estimation of long-term discount rates.

This study directly contributes to studies on the relationship between climate change and property prices. Most previous studies identify climate risks and find different negative impacts of climate change on local real estate prices[7-10], although one study fails to see this impact[11]. There are three sources of inundation measures in literature, i.e., projections made by research or professional institutes, government-issued maps, and topographic features and locations. Commonly used flood risk sources include forecasts made by National Oceanic and Atmospheric Administration (NOAA)[7,8], floodplain maps of Federal Emergency Management Agency (FEMA)[9], available elevation and tidal information[11], etc. Concerns on these data sources are whether individuals, e.g., homeowners and homebuyers, fully receive and believe the inundation information and whether they hold the beliefs when making home transaction decisions? Unlike the literature, our identification comes from a direct announcement by the government, which is a powerful nationwide warning on climate change. This characteristic ensures its efficiency of information transmission and strong influence on housing markets. By comparing Google trends of two related keywords, i.e., "climate change" and "sea level rise", it shows that this announcement did lead to significant public awareness of the climate risks (Supplementary Fig. 2). Hence, we could measure the effects of information shock on property prices free of concerns about the information transmission efficiency.

Our work also contributes to a stream of literature on information and disposition decisions, especially on the housing market. Studies investigate the price effects of various information shocks (signals, announcements), for instance, statements of toxic waste sites[12], gas explosions[13], airport expansion[14], cessation of railway operations[15], urban planning projects[16,17], among others. In our study, the inundation map displayed by the PM precisely shows the submerged and unsubmerged areas in the projection. After vectorizing the map using GIS tools, we could identify treated properties and households influenced by the information shock, which helps us compare vulnerable dwellers and adjacent invulnerable peers more precisely.

Moreover, this study is also related to estimating long-term discount rates, which are heavily relied on when evaluating long-lasting future projects, such as climate change mitigation and GHG control, and there have been disputes on what discount rate to use[18-22]. Previous studies propose long-run discount rates such as 1.4%[20], 2%[23], 2.6%[24], 4%[25], among others. Real estate transactions in UK, Singapore, and Hong Kong with the favorable freehold-leasehold tenure structure for estimations are also employed by empirical research, and estimated long-term discount rates range from 2% to 6%[24,26-28].Researchers also argue and test the decreasing trend of the discount rate over time as a result of uncertainty[27,29-31]. In practice, disagreements also exist in adopting discouting strategies, for instance, US Office of Management and Budget (OMB) recommends two estimates using discount rates 3% and 7%, while UK governments suggests a declining term structure of discount rate capped at 3%. In this study, we re-estimate long-term discount rates based on discounts between leasehold and freehold properties after the announcement of climate change, and calibarate lower discount rates indicating higher NPVs of climate change mitigation projects.

Finally, as distinguished from previous studies focusing on housing markets in the US, our study provides new evidence from an island country more threatened by climate change. Singapore government is known for its strength and robust implementation, ensuring transmission effectiveness of climate change information. More importantly, two separated and standardized housing markets allow us to test responses of households with different levels of income and living conditions, which may also indicate the difference of beliefs held among groups of people.

**Empirical Strategy**

**SLR areas.** We first download the topography map shown by the Prime Minister at the event (Supplementary Fig. 1). The original map in raster has a resolution of 1852×945. We first rectify the original map using GIS tools based on the coordinates SVY21/Singapore TM. Then we identify the flood areas based on pixel values and convert flood areas to the vector type. We run topology checks, fill holes in continuous SLR areas, and conduct manual checks. We finally obtain the digitized map of SLR areas, as Fig.1 shows.

**Data.** We collect non-landed private property transactions between 2018 and Aug 2021 from the Real Estate Information System (REALIS), an online portal that Urban Redevelopment Authority (URA) operates. For HDB, we obtain resale transaction records between 2018 and Aug 2021 from the HDB database. One favorable characteristic of Singapore properties is that each postcode can be uniquely matched with one building. Therefore, we first use the Geocoding service of Google Map to translate flat postcodes into spatial coordinates. Then we generate maps of private property transactions and HDB transitions based on the same coordinate system as the SLR map. Finally, we could identify blocks in SLR areas and define them as the treatment group. To make better comparisons, we set 500-meter buffers of treated blocks, and identify transactions within buffers but in non-SLR areas, and define them as the control group. Fig. 1 shows their distributions. To exclude the interference of extreme values, we winsorize unit prices and flat areas in the private property sample and the HDB sample at 1% and 99% thresholds.

Supplementary Table 1 Panel A displays summary statistics of the private property sample divided into the treatment and control groups. We collect property attributes: unit transaction price, building age, floor level, freehold or not, purchaser type, and sale types. Purchaser type indicates the purchaser's address is private property or HDB, and we also a dummy variable to measure it. There are three sale types: new sale, resale, and sub-sale (one type of private property transaction, which refers to a property purchased by a buyer and then sold to another buyer before the unit is completed.). We generate two resale and sub-sale dummies, leaving new sales as the benchmark.

Besides property attributes, we also gather geographical distributions of Mass Rapid Transit (MRT, Singapore's urban rail transit system) stations, bus stops, top 30 primary schools, and the Central Business District from the online database (data.gov.sg). Hence, using GIS tools, we could generate four variables of locational characteristics, i.e., distance to nearest MRT station, distance to the nearest bus stop, distance to nearest top 30 primary school, and distance to the CBD (defined as the location of the City Hall MRT station, where is the core location of Singapore).

Supplementary Table 1 Panel B shows summary statistics of the HDB sample. We include transactions' property attributes, i.e., unit price, building age, flat area, and floor level (the raw data only gives a storey range of each HDB transaction, so we derive the average level of storey range as the floor level). We also calculate their distances to the nearest MRT station, bus stop, top 30 primary schools, and the CBD. Since HDB new sale prices are determined and highly regulated by the government, so we only consider HDB resales. Moreover, all HDB flats are sold with 99-year tenures, and we could not know purchasers' types. Therefore, we do not have dummies indicating tenure and purchaser types in the private property sample.

**Models.** We mainly examine the impact of the climate change information shock on housing prices. We use the regression model to estimate the results based on the transaction-level data, as equation (1) shows. The dependent variable is the unit transaction price in log-form of transaction $i$ in area $j$ at time $t$. Dummy variable $treat_j$ denotes 1 if the transacted flat locates in SLR areas, i.e., areas to be inundated on the Prime Minister's topography map. It denotes 0 if the flat locates in non-flood areas and within 500 m radiuses of treated flats. Dummy variable $after_t$ takes value 1 if the transaction was completed after the information shock, i.e., Aug 18 in 2019, otherwise, 0. The main coefficient of interest is $\beta$, which measures the impact of the information shock on housing prices. $X'_{ijt}$ is the vector of control variables, including property attributes and locational characteristics as discussed above, and $\Gamma$ is the vector of their coefficients. We convert flat area, distance to MRT station, distance to bus stop, distance to top 30 primary schools, and distance to CBD into log forms. We also include two sets of fixed effects to capture between-group variations. $\lambda_j$ represents year-month fixed effects. $\mu_t$ Indicates location fixed effects, and we control for planning area[1] fixed effects or postal code fixed effects. $\varepsilon_{ijt}$ is the error term. In all specifications in this study, robust standard errors are clustered at the postal code level.

$$ln(unitpirce)_{ijt} = \alpha + \beta treat_j \times after_t + X'_{ijt}\Gamma + \lambda_j + \mu_t + \varepsilon_{ijt} \quad (1)$$

We further investigate the dynamic trends of property prices before and after the shock. As equation (2) shows, we divide the sample period into 12 sub-periods based on year and quarter, and interact year-quarter dummies $yq_k$ with $treat_j$. We take the first two quarters (i.e., 2018q1 and 2018q2) as the benchmark and the estimates of coefficients $\delta_k$ can be seen as an event study. We expect housing prices to start to decline in the year-quarter when the prime minister announced, and there should be no significant price difference between the treatment group and the control group before the announcement.

$$ln(unitpirce)_{ijt} = \alpha + \sum_{k=3}^{12} \delta_k \, treat_j \times yq_k + X'_{ijt}\Gamma + \lambda_j + \mu_t + \varepsilon_{ijt} \quad (2)$$

Estimations of long-term discount rates are based on the Gordon Growth Model. We assume the annual rent flows during the remaining tenure years in the future are discounted as a constant rate $r$, i.e., the long-term discount rate of interest, and long-term rent grows at a rate $g$. Therefore, as derived by Giglio (2015)[24], a property with $T$ remaining years of tenure at year $t$ is valued as equation (3), where $D_t$ is the rent at year $t$.

[1] Planning areas are the urban planning and census divisions the most frequently used administrative areas in Singapore. There are 55 planning areas in total, our private property sample covers 37 planning areas, while the HDB sample covers 31 planning areas.

$$P_t^T = \frac{D_t}{r-g}(1 - e^{-(r-g)T}) \tag{3}$$

For properties with perpetual years of tenure, they are valued at $P_t = \frac{D_t}{r-g}$. Therefore, the price discount of a finite-tenure property compared with perpetual-year properties can be derived as equation (4). Setting $g$ as 0.2%, 0.4%, and 0.6%, respectively, we could calibrate the long-term discount rate $r$ based on transactions before and after the government announcement of climate change.

$$Disc_t^T = \frac{P_t^T}{P_t} - 1 = -e^{-(r-g)T} \tag{4}$$

**Impacts of climate change information on property prices**

We first test the impacts of climate change information on property prices. The climate information was directly announced by Singapore PM Lee Hsien Loong, the current leader of the Singapore government, and the People's Action Party, the largest party in Singapore that has been in power since the foundation of the Republic of Singapore in 1965. Moreover, the 2019 National Day Rally was broadcast on local TV channels and radio stations and live-streamed on public social media.

There are three sectors in the Singapore housing system, i.e., the private sector, the public sector (HDB), and the public-private hybrid sector. The hybrid sector and landed private sector (properties sold with land ownership) are small markets, and the new sale HDB market is under strict price control and application restrictions. Therefore, in this study, we investigate price responses of the non-landed private sector (new sale, resale, and sub-sale) and the resale public sector, which are mature markets without price control. Sample periods range from Jan 2018 to Aug 2021, and analyses are conducted based on transaction-level data.

Table 1 shows baseline results. Columns (1) and (2) show the results of the private property prices. Estimated coefficients of $treat_j \times after_t$ are negative but indistinguishable from zero, indicating no significant price difference after the announcement. Larger and significant effects are found in the HDB transactions. As columns (3) and (4) show, HDB resale prices in SLR areas declined by 3.2 log points (dropped by 3.1%) to 3.4 log points (dropped by 3.3%) after the announcement, relative to the control group. We also show the event study patterns, i.e., dynamic price evolutions, of the private property sample and the HDB sample, as shown in Fig. 2. We could not detect significant changes in private property prices during the sample period. While for the HDB sample, transaction prices in SLR areas decreased after the announcement, compared with the control group. The magnitude of price depreciation is approximately 2% to 6%, and this decreasing trend persisted for years after the shock.

Why did public housing respond to the climate change information while private housing did not? We could propose two possible reasons. First, private housing residents usually are more wealthier and educated than those living in HDB. Therefore, we suppose that private property holders might already be aware of climate risks in advance, while HDB dwellers just received this information from the announcement. In other words, pre-shock private property prices were incorporated with climate change risks, while the HDB market did not price in climate change until the speech. Second, because of the application regime of public housing, HDB residents are mostly Singapore citizens, while private property residents, mostly permanent residents (with foreign nationality) and foreigners. This disparity implies that HDB residents have a longer expected residence time in Singapore, which means they care more about future uncertainty.

[Table 1 about here]

[Fig. 2 about here]

**Heterogeneity analysis**

We test heterogeneous effects by property attribute. Considering older flats and larger families are more vulnerable to flooding risks, we generate two dummy variables, $oldflat_i$ and $largeflat_i$, indicating older flats (building age > 20 years) and larger families (flat area > 80 m$^2$), respectively, and we interact them with $treat_j \times after_t$. Results are shown in Table 2. We find older and larger HDB flats in SLR areas experienced more price depreciation after the announcement, but still no significant difference on the private housing market. Furthermore, we also test heterogeneity by tenure type of private properties, i.e., freehold (999 or perpetual years of initial ownership) or not. Results show that leasehold properties depreciated more relative to freehold properties. Similar to the differentiation between public and private markets, a possible explanation is that wealthier freehold dwellers already priced climate risks, while leasehold residents did not fully aware of climate risks until the government announcement.

[Table 2 about here]

**Long-term discount rates with climate information**

Previous estimations of very-long term discount rates based on housing transaction prices rely on the price gap between freehold and leasehold properties. We find that leasehold private properties responded more to the information shock. To be specific, leasehold properties are less valuable relative to freehold properties. Therefore, we could re-estimate long-term discount rates under this circumstance. Based on the Giglio (2015)[24] and the Gordon Growth Model, we separate the private property sample into the pre-shock period (climate risks partially priced) and the post-shock period (climate risks fully priced) and estimate long-term discount rates based on these two sub-samples respectively. Taking perpetual-tenure properties as the benchmark, we obtain price discounts of finite properties (99 or 999 years of initial ownership) $Disc_t^T$ with $T$ remaining years at time $t$. We then calibrate the equation $Disc_t^T = -e^{-(r-g)T}$, where $g$ is the long-lasting rent growth rate. Finally, we derive that, after the announcement of climate change, estimated long-term discount rate drops from 3.65% to 2.66% when $g$ is set as 0.2%, from 3.85% to 2.86% (g=0.4%), or from 4.05% to 3.06% (g=0.6%). In other words, the climate information shock could result in lower estimations of long-term discount rates. A slight change in the long-term discount rate can lead to huge differences in discounted costs and benefits. Therefore, choosing a proper discount rate is crucial to evaluate public policies, especially those last for decades or centuries. Our finding offers new insights on the relationship between climate information and discount rate estimations.

**Natural disasters and property prices**

We demonstrate that the government announcement of climate change in Singapore negatively impacts public housing prices in SLR areas. Do natural disasters, e.g., urban floods and natural disasters influence property prices as effectively as the government announcement? To investigate this question, we gather real flood event addresses in Singapore between 2018 and 2021 and compare property prices near flood events and prices in farther areas. We also test the impact of the Super Typhoon Mangkhut, which was the strongest super typhoon near Singapore in 2018 and made landfill on Sep 15, 2018, on property prices near the island border of Singapore. Regression models are set as equation (1). As results in Table 3 show, we could not find significant price changes in the private and public housing market affected by flood events and Typhoon Mangkhut. Therefore, in our research setting, natural meteorological events are not as effective in awaking the market response as the government announcement. Threfore, the government's direct climate change announcement is particularly important compared with natural disasters, and we call for more attention and prudent decision-making of climate change policies.

[Table 3 about here]

**Robustness checks**

Our baseline analyses compare the treated transactions within flood areas and other transactions within 500 m radiuses. To check the robustness of baseline results, we adjust the control group to transactions within 2 km radiuses of treated transactions or using all other transactions without radius restriction. Results are shown in Supplementary Table 2, and HDB prices in SLR areas dropped significantly relative to prices in non-SLR areas, which are consistent with baseline results.

Another concern is that the 2019 National Day Rally audience might not precisely locate their properties on the topography map. In other words, visual deviations could make it difficult for viewers to judge whether their home will be inundated concisely. To alleviate this concern, we artificially divide the Singapore map into multiple square grids with lengths of 2 km. Then we construct a new index, flood ratio, which is defined as the proportion of flood areas in the 2 km×2 km grid. As shown in Supplementary Fig. 3, we define transactions located in grids with flood ratios larger than 30% as the treatment group, and all other transactions are in the control group. We run the same modes as equation (1) and list results in Supplementary Table 3. For private properties in higher flood ratio areas, we do not find significant changes in price after the announcement. There is significant price depreciation for HDB flats in higher flood ratio areas after the shock, and estimations are consistent with our baseline results. Finally, we conduct a falsification test by setting a false information shock on Aug 18, 2018. Results in Supplementary Table 4 indicate no significant difference in price before and after the false shock.

**Conclusion**

There are debates on whether property markets respond to climate change. Previous studies provide evidence by comparing areas projected to be submerged and non-flood areas, and residents' beliefs on climate change are also analyzed. This paper employs a novel shock of climate change, i.e., the climate change information directly announced by the governments marking clear boundaries of SLR areas. Our empirical results indicate that the public housing prices in SLR areas dropped in response to the announcement while no significant price changes in the private housing market were detected. Besides, we also find heterogeneity effects, i.e., prices of older and larger HDB flats in SLR areas decreased more after the announcement. More importantly, results show that leasehold private properties responded more to the information shock relative to freehold properties. Utilizing this finding, we could derive lower long-term discount rates, which means higher NPV when evaluating long-term public projects. Finally, in this Singapore setting, we find natural climate events, i.e., actual flood events and typhoon, are not strong enough to drive the housing prices as powerful as the government announcement.

This paper has limitations. First, we could not test changes in homebuyers' and homeowners' beliefs on climate change. In other words, whether the announcement evoked their belief in climate change. Second, our results are based on Singapore and may not be fully applicable to other countries. Understanding the relationship between climate change and property markets can provide a critical perspective to assess the cost of climate change-related disasters and a basis for policy implements. We wait for future research to further investigate individual and household disposition behavior responding to climate change and related public policies.

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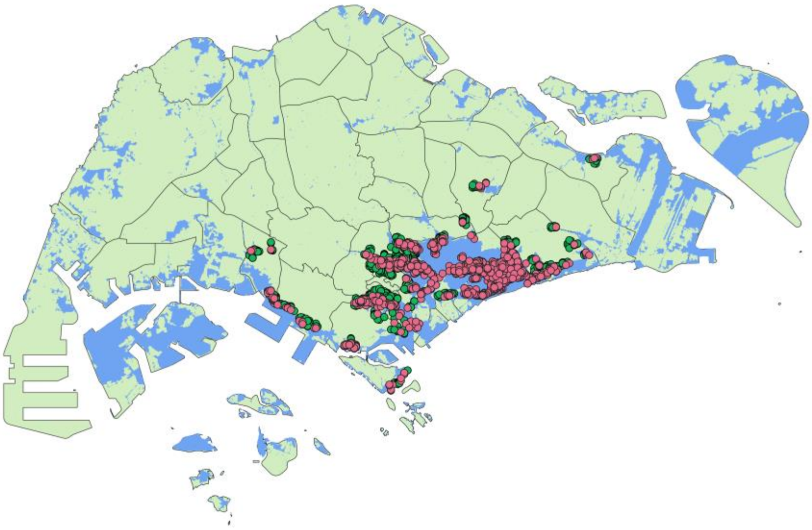
**a**



**b**

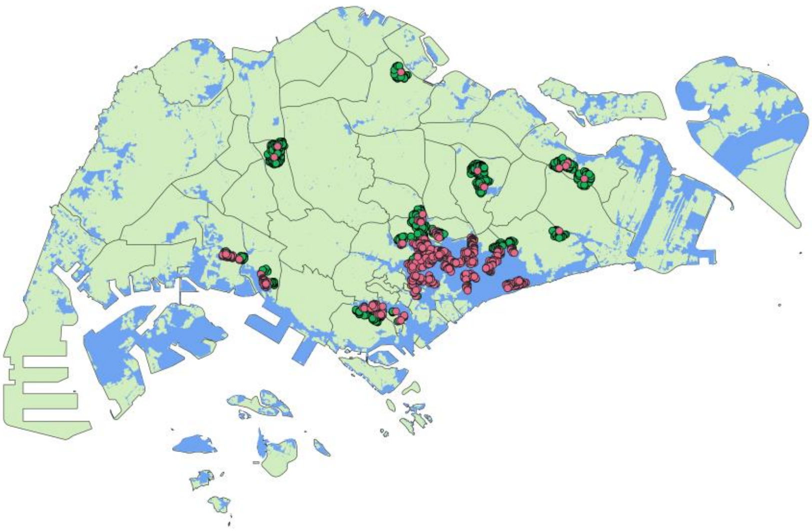
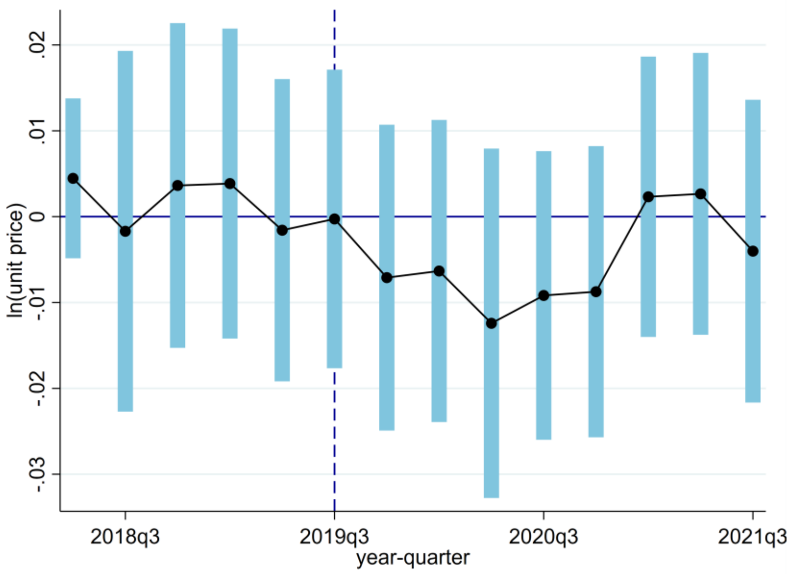


**Fig. 1 Digitized map and property transactions. a,** Distribution of private properties. **b,** Distribution of HDB. This figure shows the digitized map of SLR areas (in blue) and property transactions. Each dot represents one single block that may include multiple transactions. We identify transactions in SLR areas as the treatment group (red dots), while transactions outside SLR areas but within 500 m radius as the control group (green dots).

**a**




**b**

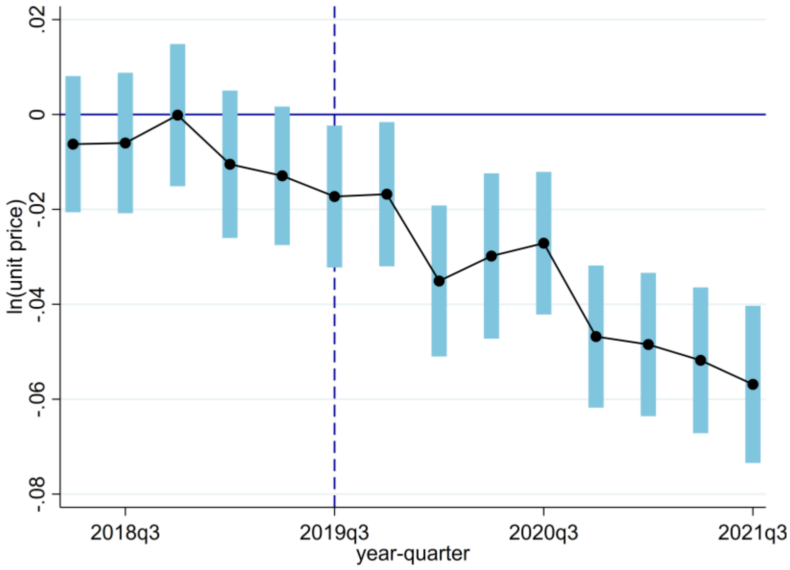



**Fig. 2 Event study.** Dynamic price changes of the private property sample (**a**) and the HDB sample (**b**). The dependent variable is the log of the unit transaction price. Each column represents one regression at the transaction level. Both two samples include property transactions between 2018 to August 2021. We divide the sample period into 12 year-quarters and take 2018q1 as the benchmark. Black dots are estimated coefficients of interactions between year-quarter dummies and $treat_j$, i.e., the dummy variable indicating SLR areas. Shadow areas indicate 95% confidence intervals. Property attributes, location attributes, year-month fixed effects, location fixed effects (6-digit FE) are controlled. We also control project-aftercool (indicating transactions after 2018 Singapore cooling measures) fixed effects for the private property sample.

**Table 1 The impact of climate change information on property prices**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Private property | | HDB | |
| | ln(unit price) | ln(unit price) | ln(unit price) | ln(unit price) |
| $treat_j \times after_t$ | -0.005 | -0.006 | -0.034*** | -0.032*** |
| | (0.004) | (0.004) | (0.004) | (0.003) |
| Property attributes | √ | √ | √ | √ |
| Location attributes | √ | √ | √ | √ |
| Year-month FE | √ | √ | √ | √ |
| Project-aftercool FE | √ | √ | | |
| 4-digit location FE | √ | | √ | |
| 6-digit location FE. | | √ | | √ |
| Observations | 37,603 | 37,461 | 12,133 | 12,070 |
| R-squared | 0.961 | 0.966 | 0.857 | 0.941 |

The dependent variable is the log of unit transaction price. Each column represents one regression at the transaction level. Columns (1) to (2) report results of the private property sample, and columns (3) and (4), the HDB sample. Both the two samples include property transactions between 2018 to August 2021. Dummy variable $treat_j$ takes value 1 if the transacted property locates in SLR areas, and takes 0 if within 500 m buffer of SLR areas. Dummy variable $after_t$ takes value 1 if the transaction was completed after the announcement, i.e., Aug 18 in 2019. Property attributes, location attributes, year-month fixed effects, location fixed effects (4-digit FE or 6-digit FE) are controlled. We also control project-aftercool (indicating transactions after 2018 Singapore cooling measures) fixed effects for the private property sample. Robust standard errors shown in parentheses are clustered at the postal code level. *** p<0.01, ** p<0.05, * p<0.1.

**Table 2 Heterogeneity by property attributes**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Private property | | | HDB | |
| | ln(unit price) | ln(unit price) | ln(unit price) | ln(unit price) | ln(unit price) |
| $treat_j \times after_t$ | -0.007* | -0.013* | -0.019*** | -0.015** | -0.015** |
| | (0.004) | (0.008) | (0.005) | (0.006) | (0.006) |
| $treat_j \times after_t \times oldflat_i$ | 0.005 | | | -0.020*** | |
| | (0.008) | | | (0.007) | |
| $treat_j \times after_t \times largeflat_i$ | | 0.010 | | | -0.019*** |
| | | (0.009) | | | (0.007) |
| $treat_j \times after_t \times freehold_i$ | | | 0.028*** | | |
| | | | (0.008) | | |
| Property attributes | √ | √ | | √ | √ |
| Location attributes | √ | √ | | √ | √ |
| Year-month FE | √ | √ | | √ | √ |
| Project-aftercool FE | √ | √ | | | |
| 6-digit location FE. | √ | √ | √ | √ | √ |
| Observations | 37,461 | 37,461 | 37,461 | 12,070 | 12,070 |
| R-squared | 0.966 | 0.966 | 0.966 | 0.941 | 0.942 |

The dependent variable is the log of the unit transaction price. Each column represents one regression at the transaction level. Columns (1) to (3) report results of the private property sample, and columns (4) and (5), the HDB sample. Both two samples include property transactions between 2018 to August 2021. Dummy variable $treat_j$ takes value 1 if the transacted property locates in SLR areas, and takes 0 if within 500 m buffer of SLR areas. Dummy variable $after_t$ takes value 1 if the transaction was completed after the announcement, i.e., Aug 18 in 2019. We test heterogeneities by three property attributes: (a) $oldflat_i$ (=1 if building age > 20 years), (b) $largeflat_i$ (=1 if flat area > 80 $m^2$), (c) $freehold_i$ (=1 if 999 or perpetual years of initial ownership, only for the private property sample). Property attributes, location attributes, year-month fixed effects, location fixed effects (6-digit FE) are controlled. We also control project-aftercool (indicating transactions after 2018 Singapore cooling measures) fixed effects for the private property sample. Robust standard errors shown in parentheses are clustered at the postal code level. *** p<0.01, ** p<0.05, * p<0.1.

**Table 3 The impact of natural disasters on property prices**

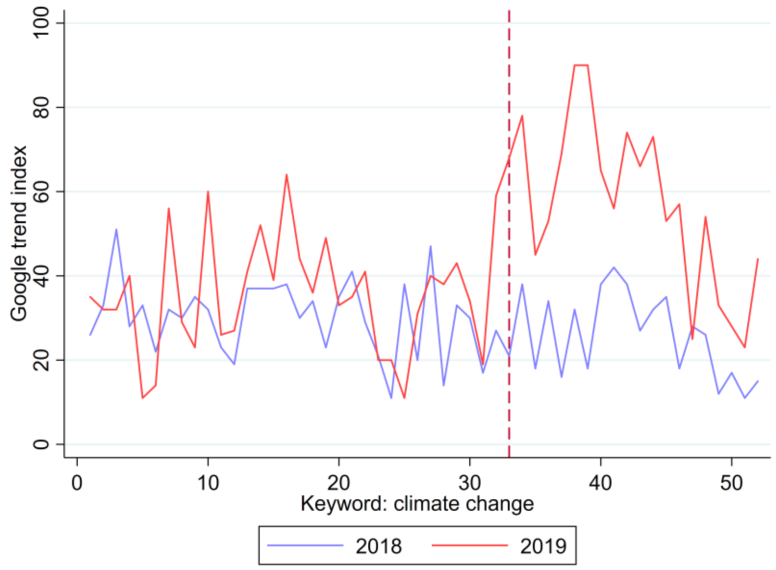
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Private property | | HDB | |
| | ln(unit price) | ln(unit price) | ln(unit price) | ln(unit price) |
| $floodarea_j \times afterflood_t$ | -0.011 | | -0.004 | |
| | (0.014) | | (0.011) | |
| $dist\_border_j \times aftertyphoon_t$ | | 0.002 | | -0.001 |
| | | (0.002) | | (0.001) |
| Property attributes | √ | √ | √ | √ |
| Location attributes | √ | √ | √ | √ |
| Year-month FE | √ | √ | √ | √ |
| Project-aftercool FE | √ | √ | | |
| 6-digit location FE. | √ | √ | √ | √ |
| Observations | 785 | 11,307 | 1,180 | 18,221 |
| R-squared | 0.969 | 0.973 | 0.962 | 0.955 |

The dependent variable is the log of unit transaction price. Each column represents one regression at the transaction level. Columns (1) to (2) report results of the private property sample, and columns (3) and (4), the HDB sample. In columns (1) and (3), we keep transactions within 1 km buffers of flood areas and transactions 3 months before and 3 months after flood dates. We define dummy $floodarea_j$ (=1 if within 500 m, =0 if 500 m - 1 km) and dummy $afterflood_t$ (=1 if after flood date). In columns (2) and (4), we include transactions in 2018, define continuous variable $dist\_border_j$ (distance to island border) and $aftertyphoon_t$ (=1 if after landfall of Typhoon Mangkhut, i.e., Sep 15, 2018). Property attributes, location attributes, year-month fixed effects, location fixed effects (6-digit FE) are controlled. We also control project-aftercool (indicating transactions after 2018 Singapore cooling measures) fixed effects for the private property sample. Robust standard errors shown in parentheses are clustered at the postal code level. *** p<0.01, ** p<0.05, * p<0.1.

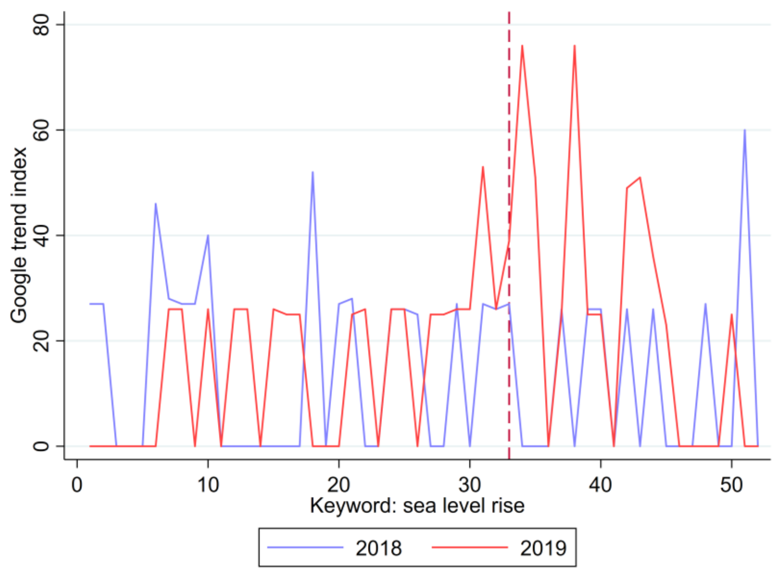
# Supplementary Figures


**Supplementary Fig. 1 Original map displayed by Singapore Prime Minister.** This figure is the map showed by Singapore Prime Minister Lee Hsien Loong at 2019 Singapore National Day Rally to indicate the projection of floods. Areas in red are projected to be submerged, i.e., sea level rise areas. This figure was downloaded from Lee Hsien Loong's Facebook.

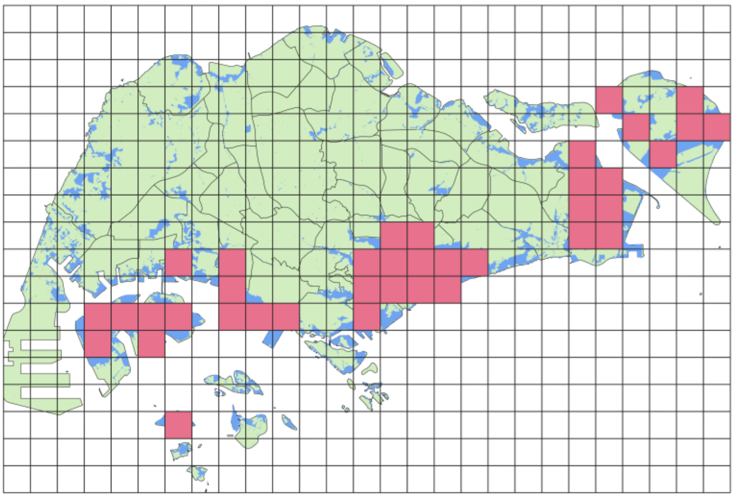
**a**




**b**




**Supplementary Fig. 2 Google Trends of climate change and sea level rise. a,** Google trend of the keyword “clime change”. **b,** Google trend of the keyword “sea level rise”. We show trends in Singapore in 2018 and 2019. Data is collected from Google Trends (https://trends.google.com/) and aggregated at the week level. The vertical red line marks the 2019 National Day Rally in the 33rd week in 2019.



**Supplementary Fig. 3** This figure shows the digitized map of SLR areas. Areas in blue are identified locations projected to be submerged, i.e., SLR areas. We divide the map into multiple 2 km×2 km grids, and derive an index flood ratio, i.e., the proportion of SLR areas in the grid. Grids in red have larger flood ratios of 30%, and we define transactions in these grids as the treatment group, while other transactions are in the control group, to test the robustness of baseline results.

**Supplementary Table 1 Summary statistics**

| | Treatment (SLR areas) | | | Control (non-SLR areas) | | |
|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD |
| Panel A: private property | | | | | | |
| Unit price (S$/m$^2$) | 11064 | 16810.580 | 4891.297 | 27009 | 16242.720 | 4970.707 |
| Building age | 11064 | 10.253 | 9.424 | 27009 | 5.496 | 7.946 |
| Floor level | 11064 | 10.019 | 8.396 | 27009 | 9.650 | 7.701 |
| Area (m$^2$) | 11064 | 100.883 | 45.110 | 27009 | 89.886 | 39.545 |
| Freehold | 11064 | 0.553 | 0.497 | 27009 | 0.217 | 0.412 |
| Private purchaser | 11064 | 0.687 | 0.464 | 27009 | 0.531 | 0.499 |
| New sale | 11064 | 0.168 | 0.374 | 27009 | 0.512 | 0.500 |
| Resale | 11064 | 0.821 | 0.383 | 27009 | 0.475 | 0.499 |
| Sub-sale | 11064 | 0.011 | 0.102 | 27009 | 0.014 | 0.116 |
| Distance to MRT station (km) | 11064 | 0.767 | 0.573 | 27009 | 0.296 | 0.364 |
| Distance to bus stop (km) | 11064 | 0.155 | 0.210 | 27009 | 0.103 | 0.125 |
| Distance to top 30 primary school (km) | 11064 | 1.636 | 0.752 | 27009 | 2.285 | 0.566 |
| Distance to CBD (km) | 11064 | 4.585 | 2.192 | 27009 | 1.372 | 2.656 |
| Panel B: HDB | | | | | | |
| Unit price (S$/m$^2$) | 5700 | 5306.530 | 1252.793 | 6433 | 4558.022 | 1093.064 |
| Building age | 5700 | 36.142 | 12.126 | 6433 | 29.302 | 10.771 |
| Floor level | 5700 | 8.762 | 5.565 | 6433 | 7.999 | 5.331 |
| Area (m$^2$) | 5700 | 85.558 | 24.075 | 6433 | 101.500 | 25.296 |
| Distance to MRT station (km) | 5700 | 0.677 | 0.507 | 6433 | 0.635 | 0.349 |
| Distance to bus stop (km) | 5700 | 0.128 | 0.065 | 6433 | 0.127 | 0.068 |
| Distance to top 30 primary school (km) | 5700 | 1.239 | 0.724 | 6433 | 1.396 | 1.187 |
| Distance to CBD (km) | 5700 | 4.946 | 2.744 | 6433 | 10.021 | 4.142 |

This table shows summary statistics of the private property sample and the HDB sample. Treatment indicates transactions in SLR areas, i.e., areas projected to be submerged on the topography map shown by the Prime Minister. Control indicates tractions in non-SLR areas and within 500 m radiuses of treated transactions.

**Supplementary Table 2 Robustness check: control group changed**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Private property | | HDB | |
| | ln(unit price) | ln(unit price) | ln(unit price) | ln(unit price) |
| $treat_j \times after_t$ | -0.005 | -0.006 | -0.028*** | -0.029*** |
| | (0.003) | (0.004) | (0.003) | (0.003) |
| Property attributes | √ | √ | √ | √ |
| Location attributes | √ | √ | √ | √ |
| Year-month FE | √ | √ | √ | √ |
| Project-aftercool FE | √ | √ | | |
| 4-digit location FE | √ | | √ | |
| 6-digit location FE. | | √ | | √ |
| Observations | 42,759 | 42,545 | 38,270 | 38,100 |
| R-squared | 0.961 | 0.966 | 0.851 | 0.935 |

The dependent variable is the log of the unit transaction price. Each column represents one regression at the transaction level. Columns (1) to (2) report results of the private property sample, and columns (3) and (4), the HDB sample. Both two samples include property transactions between 2018 to August 2021. Dummy variable $treat_j$ takes value 1 if the transacted property locates in SLR areas, and takes 0 if within 2000 m buffer of SLR areas. Dummy variable $after_t$ takes value 1 if the transaction was completed after the announcement, i.e., Aug 18 in 2019. Property attributes, location attributes, year-month fixed effects, location fixed effects (4-digit FE or 6-digit FE) are controlled. We also control project-aftercool (indicating transactions after 2018 Singapore cooling measures) fixed effects for the private property sample. Robust standard errors shown in parentheses are clustered at the postal code level. *** p<0.01, ** p<0.05, * p<0.1.

**Supplementary Table 3 Robustness check: identified by flood ratio**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Private property | | HDB | |
| | ln(unit price) | ln(unit price) | ln(unit price) | ln(unit price) |
| $floodratio_j \times after_t$ | 0.001 | 0.002 | -0.036*** | -0.037*** |
| | (0.002) | (0.002) | (0.003) | (0.002) |
| Property attributes | √ | √ | √ | √ |
| Location attributes | √ | √ | √ | √ |
| Year-month FE | √ | √ | √ | √ |
| Project-aftercool FE | √ | √ | | |
| 4-digit location FE | √ | | √ | |
| 6-digit location FE. | | √ | | √ |
| Observations | 49,544 | 49,257 | 70,953 | 70,617 |
| R-squared | 0.962 | 0.967 | 0.858 | 0.932 |

The dependent variable is the log of the unit transaction price. Each column represents one regression at the transaction level. Columns (1) to (2) report results of the private property sample, and columns (3) and (4), the HDB sample. Both two samples include property transactions between 2018 to August 2021. Dummy variable $floodratio_j$ is defined as 1 if the transacted property locates in the grid with the flood ratio higher than 30%, otherwise, 0. Dummy variable $after_t$ takes value 1 if the transaction was completed after the announcement, i.e., Aug 18 in 2019. Property attributes, location attributes, year-month fixed effects, location fixed effects (4-digit FE or 6-digit FE) are controlled. We also control project-aftercool (indicating transactions after 2018 Singapore cooling measures) fixed effects for the private property sample. Robust standard errors shown in parentheses are clustered at the postal code level. *** p<0.01, ** p<0.05, * p<0.1.

**Supplementary Table 4 Falsification test: false shock on Aug 18, 2018**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Private property | | HDB | |
| | ln(unit price) | ln(unit price) | ln(unit price) | ln(unit price) |
| $treat_j \times after_t$ | 0.003 | -0.012 | 0.007 | 0.005 |
| | (0.011) | (0.013) | (0.007) | (0.006) |
| Property attributes | √ | √ | √ | √ |
| Location attributes | √ | √ | √ | √ |
| Year-month FE | √ | √ | √ | √ |
| Project-aftercool FE | √ | √ | | |
| 4-digit location FE | √ | | √ | |
| 6-digit location FE. | | √ | | √ |
| Observations | 9,000 | 8,575 | 3,119 | 2,754 |
| R-squared | 0.965 | 0.973 | 0.884 | 0.960 |

The dependent variable is the log of the unit transaction price. Each column represents one regression at the transaction level. Columns (1) to (2) report results of the private property sample, and columns (3) and (4), the HDB sample. Both the two samples include property transactions in 2018. Dummy variable $treat_j$ takes value 1 if the transacted property located in SLR areas, and takes 0 if within 500 m buffer of SLR areas. Dummy variable $after_t$ takes value 1 if the transaction was completed after the false date, i.e., Aug 18 in 2018. Property attributes, location attributes, year-month fixed effects, location fixed effects (4-digit FE or 6-digit FE) are controlled. We also control project-aftercool (indicating transactions after 2018 Singapore cooling measures) fixed effects for the private property sample. Robust standard errors shown in parentheses are clustered at the postal code level. *** p<0.01, ** p<0.05, * p<0.1.