Pricing the Flood Risk: Evidence from the Real Estate Market in China

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Abstract: We examine the impact of salient, short-term flood disasters on the housing market in China. Compared to the mean, the occurrence of floods decreases the housing prices by 0.006%, but increases 0.05% of transaction quantity. We find evidence that severe flood places much severe price discount on housing price. The transaction quantity in counties experienced a severe flood also significantly decrease, compared to the transactions in counties suffered a regular flood. We provide support evidence that one of the mechanisms that how floods affects housing market is public risk perception. The public risk perception is rare in regions with less floods, and the housing market thus negatively response to flood events in those regions.

Keywords: Climate Change Risk; Flood; Housing Market, China

1. Introduction

Globally, the increasing frequency, intensity, and severity of droughts, tropical cyclones, floods, and heatwaves are causing severe economic damage (Pörtner et al., 2022). Research shows that the financial market is also significantly affected by rising climate change risks (Billings et al., 2022, Dessaint and Matray, 2017, Goldsmith-Pinkham et al., 2021, Hong et al., 2019, Huynh and Xia, 2022, Jerch et al., 2020, Painter, 2020). While most studies have focus on the impacts of climate change risk on developed countries, developing countries, which remain vulnerable to the effects of climate change and have received little attention.

This paper investigates the impacts of flood risks on the local housing market in China. Utilizing unique, authoritative and comprehensive flood data, we study the impact of flood risks on housing price and transaction quantity at the county level in China. The housing market in China has been booming since the early 2000s. Tier 1 cities in China, including Beijing, Shanghai, Shenzhen, and Guangzhou, have experienced dramatic growth in housing prices, with an average growth rate of 24% per year (Fang et al., 2015, Meng et al., 2021). Housing prices in the top 35 cities in China have also increased much faster than the nationwide housing prices. Given the crucial role of housing market in Chinese economics (Glaeser et al., 2017), understanding the relationship between climate change risk and market response is of critical importance to real estate developers, homebuyers and local governments.

To roll out the impacts of multi-floods within a county, we use event study and stacked difference-in-differences (DID) approaches to estimate the impact of floods on housing market. Different from other slow-moving climate risks such as sea level rise, floods place a salient, short-term effect on housing market, which lasts for approximately 4 years. We find that, compared to housing market in counties that do not hit by a flood, the occurrence of floods decreases the housing prices by 0.006%, but increases 0.05% of transaction quantity, based on the mean value. Unlike the slow-moving climate risk of sea level rise (Bernstein et al., 2019, Painter, 2020), we find that homebuyers response to the salient risk factors of flood by significantly lower prices in inland regions, but significantly increase demands in coastal regions. Moreover, unexpected and severe floods cause more economic losses, which also play a negative impact on the housing market. Together, these results suggest that housing market in inland regions bear more negative impacts when hit by a flood. And the pattern of market response is consistent with homebuyers' risk perception toward salient, high frequency disasters (Amstad and He, 2019, Auh et al., 2022, Goldsmith-Pinkham et al., 2021, Painter, 2020).

Most closely related to this study is a series of climate change impacts on housing market. Studies have found that housing market responses to increasing risk from hurricanes, wildfires, floods, and sea level rise (Bernstein et al., 2019, Billings et al., 2022, Koo and Liang, 2022, Mulder, 2021). Bernstein et al. (2019) discover the impact of sea level risks on real estate market in the United States. Bosker et al. (2018) find that housing prices are on average 1% lower in places that are at risk of flooding. Overall, they find that the housing prices with higher climate risk suffer a price discount. Little is known about how the climate change risk affects the housing market in developing countries with large market size. Our findings contribute to the evidence that housing market significantly response to climate change risk in developing countries. Taking China as an example, we find that climate change risks create negative impacts on housing prices, but also push up transaction quantity in the affected areas.

This paper added to the literature on the studies the response of housing market to larger-scale climate shocks. Much of this literature has focused on one-off shocks (Atreya et al., 2013, Bui et al., 2022, Indaco et al., 2020, Muller and Hopkins, 2019, Votsis and Perrels, 2016, Zhang and Leonard, 2018), whereas we examine the effects of large recurrent shocks. Moreover, our data allow us to combine national coverage with localized analysis, which can provide robustness analysis with multiple heterogeneity.

Our study also shed lights on the impacts of salient, post-disaster effects on housing market. Much of the literature explore the impacts of flood risk measure by flood risk map (Bakkensen and Ma, 2020, Bosker et al., 2018, Lee, 2021, Mulder, 2021). This paper speaks directly to the impact of short-term, ex-post floods on the localized housing market in China.

In what follows, we describe the data in section 2, followed by empirical strategies in section 3. Section 4 presents the impacts of floods on housing market in China, while section 5 discusses the potential mechanism that how floods affect housing market. Section 6 concludes.

2. Data

2.1 Flood risk

To identify counties that expose to flood risk, we manually collect the annual peak level of control stations in national primary rivers from the *Hydrological Information Annual Report* (2008-2020), published by the Ministry of Water Resources in China. The reports also provide the warning water level of each control station. We define a flood event as the annual peak level exceeds the warning water level of that control station. We then aggregate the flood data into county-year-quarter level. The number of floods is defined as the sum of flood events within the county-year-quarter. Figure 1(B) shows the flood frequency of each station over the study period. Obviously, areas with high flood frequencies are cluster in the middle and lower reaches of Yangtze River and the Pearl River.

In some regions prone to flooding, the local governments may predict the likelihood of floods and make some adaptations to mitigate losses in flood disasters. The risk of floods in those areas thus becomes relatively lower. To address this concern, we defined unexpected flood risk as flood level exceeding the warning line by 10%, 20%, and 30%, respectively. The higher actual flood level compared to the warming line, the higher probability of it being outside of governments' exception, so as the homebuyers.

[Figure 1 around here]

2.2 Housing market in China

Housing prices are acquired from *Xitai Data*, which provides a series of housing data in China. Xitai reports average housing price, average area per transaction, and the number of transactions at a county-month scale. Considering the durations of transactions in China, we aggregate the housing data into county-quarter level, including average housing price, average area per transaction, and the number of total transactions per quarter. Figure 1(A) depicts the selected housing data in China. There are 764 counties in 72 cities in China, spanned from 2009 to 2018, resulting 32080 observations. It is clear that counties in eastern China generally carry high housing price, which also suffer more from flood risk.

To rule out impacts of other macro factors, we control for a series of city-level time-varying variables, including population, Gross Domestic Product (GDP) growth rate, the share of secondary industry to the GDP, the share of third industry to the GDP, average wage, built-up areas of each city. The data are acquired from China City Statistical Yearbook. All the price data are converted to 2018 price level.

3. Empirical Design

3.1 Event Study

To determine the appropriate empirical strategy, we test whether floods affect transactions in the housing market, and how long the effects last for. We consider an event study specification of the following type:

$$Y_{ic,t} = \sum_{\tau=-8,\tau\neq-1}^{N} \gamma_\tau I(t-F_{ic}=\tau) + \sum_{\tau=-8,\tau\neq-1}^{N} \kappa_\tau [Treat_{ic} \times I(t-F_{ic}=\tau)] + \theta X_{ct} + \gamma_{ic} + \lambda_t + \varepsilon_{ic,t} \tag{1}$$

where $Y_{ic,t}$ is the measurement of housing market, including average price and the number of transactions in county i in quarter t. F_{ic} is the year-quarter that county i experimented the first flood in the sample period from 2009 to 2018. $I(\cdot)$ is an indicator that equals one when $t-F_{ij}^{g}=\tau$ and zero otherwise. Treat is a time-constant dummy, which takes a value of one if county i experimented a flood over the study period, and takes a value of zero otherwise. X is a vector of city-level control variables, including population, GDP growth rate, the share of secondary industry, the share of third industry, average wage, and built-up areas in city c. γ_{ic} is the county fixed effects, capturing the impacts of the time-constant characteristics, such as distance to water system, distance to coastal line, elevation, and so on. And λ_t is the year-quarter fixed effects, which captures the impacts of macro time-varying variables on housing market, such as change in interest rates. $\varepsilon_{ic,t}$ is the error term. We set the event quarters to be [-8, 20] based on the literature (Beltrán et al., 2019, Bui et al., 2022).

3.2 Stacked DID Estimation

Floods, by definition, are a common, short-term effect natural disasters (Goldsmith-Pinkham et al., 2021). We first implement a generalized difference-in differences (DID) to estimate the impacts of floods on the housing market.

$$Y_{ic,t} = \alpha_0 + \beta(Treat_{ic} \times I(t - F_{ic} >= 0)) + \theta X_{ct} + \gamma_{ic} + \lambda_t + \varepsilon_{ic,t} \tag{2}$$

where $I(\cdot)$ is an indicator that equals one when $t - F_{ic} \geq 0$ and zero otherwise. All other variables' definitions are the same as in equation (1).

Figure 2 shows that the number of counties that have been flooded increase over time. The DID identification in equation (2) is thus a time-varying treatment effect. It has recently highlights potential bias in the estimation when treatment timing varies across units and periods (Callaway and Sant'Anna, 2021, de Chaisemartin and D'Haultfœuille, 2020, Goodman-Bacon, 2021, Sun and Abraham, 2021). de Chaisemartin and D'Haultfœuille (2020) show that, the traditional group and period fixed effects estimators is a "weighted average of all possible two-group/two-period DID estimators in the data." However, the "control groups" in some of those comparisons may be treated at later periods, which causes negative weights. The standard DID estimator is thus not robust to heterogeneous treatment effects. Alternative estimators are to address the potential bias (Callaway and Sant'Anna, 2021, de Chaisemartin and D'Haultfœuille, 2020, Deshpande and Li, 2019, Sun and Abraham, 2021). Given the nature of staggered events of floods by definition, we employ a stacked DID estimator to address the time-varying treatment issues, as suggested by Goodman-Bacon (2021), and Baker et al. (2022).

[Figure 2 around here]

Specifically, we categorize counties that experienced floods in event quarters [-8, 16] as treated counties, while counties that are not affected by any floods before the event quarters [-8, 16] as controls.[1] To construct the stacked data set, we perform the following steps. First, we create separate datasets for each of the 22 flood event-quarters *G*. We set the event quarters to be $\tau \in [-k, k]$. Event quarters are specified relative to the quarter of a flood. For example, $\tau = 0$ indicates the year-quarter when the flood hit the county. Second, we label a county as a treated county if the county is affected by a flood happened in the event-quarter *g*. Third, for each treated group *g*, we match counties that do not experience a flood before and during the event quarter of treated group *g* as controls. This ends up 22 datasets in 764 counties, and 222 counties experienced at least one flood in the event quarters [-8, 16]. Finally, we append all the 3661 treated groups into one dataset, resulting in a stacked dataset with 11,709 MCBs, and 3661 of them are treated bonds in the event months $[-k, k]$, a total of 741999 county-quarter sample. We then estimate the following equation on the stacked sample.

$$Y_{ic,t} = \alpha_0 + \beta(Treat_{ic,t}^{g} \times Post_t^{g}) + \theta X_{ct}^{g} + \gamma_{ic} + \lambda_t + \phi^{g} + \varepsilon_{ic,t}^{g} \quad (3)$$

where $Post_{ic,t}^{g}$ is a dummy variable that take a value of one if *t* is after the flood event in group *g*, and zero otherwise. All other variables' definitions are the same as in equation (1). The coefficient of β is our main interest, which capturing the causal effects of flood risk on housing market.

[1] The event quarter are determined by the results shown by equation (1) of the event study.

3.3 Summary Statistics

Table 1 summarizes the statistics of variables used in this study. Panel A reports the housing market characteristics. Averagely, the price of each transaction in the treatment counties are 906.7 thousand Yuan, which is lower than that in the control counties. The transaction quantity per quarter in treatment counties is also less than that in control counties. The average area per transaction in treatment counties, however, is larger than that in control counties. Panel B reports the summary statistics of flood at a county-level. Averagely, the county in the treatment group has been flooded in 2.75 quarters. Over 21% of floods are above 10% of the warning level, approximately 13% and 11% of floods are above 20% and 30% of the warming level, accordingly. Panel C gives the summary statistics of control variables at a city level. Averagely, the population size in treatment counties is more than that in control counties. And the economic conditions in the treatment counties are better than those in control counties, including the GDP growth rate and share of secondary industry. The wage levels in the two groups, however, are not significantly different.

[Table 1 around here]

4. Results

4.2 Evidence on the Event Quarters of Floods

Floods, by definition, are a common, short-term effect natural disasters (Goldsmith-Pinkham et al., 2021). Figure 3 provides suggestive evidence on the event quarters of floods on housing price, based on event study from equation (1). Notice that the treated and control counties exhibit parallel trends in housing prices prior to event quarter 0. Housing prices in treated counties decrease consistently after they hit by a flood. It takes eight quarters after a flood for the housing prices to become statistically negative. The negative effects disappear after 16 quarters of floods, approximately 4 years. The results provide supportive evidence that floods caused a short-term shock to housing market, which is consistent with the literature (Beltrán et al., 2019, Bui et al., 2022). We thus set the event quarters to be $\tau \in [-8,16]$ in the stacked DID specification, to identify the effects of floods on housing prices.

4.2 Effects of Floods on Housing Market

Table 3 shows the effects of floods on housing market. Columns (1)-(2) use housing price as dependent variables, while columns (3)-(4) use transaction quantity as dependent variables. We first employ a generalized DID to explore the effects of floods on housing prices. Controlling for county fixed effects and year_by_quarter fixed effects, results in column (1) show that, compared to housing prices in control counties, the housing prices in the flooded counties decrease, but the coefficient is not statistically significant. Similarly, column (3) regress transaction quantity on the occurrence of flood with the same specifications.

As we discussed previously, the occurred time of floods varies, which bias the estimation results. To address this concern, columns (2) and (4) employes a stacked DID, the results of which provides a more credit estimation on the causal effects of floods on housing market. As expected, the occurrence of floods significantly reduces housing prices by 2.9%, but substantially increases transaction quantity by 45.5%. The increase of transaction quantity in flooded counties may appear counterintuitive, by suggesting that homebuyer prefers flooded houses than non-flooded houses. In fact, it agrees with a simple economic principle that the demand increases as price decreases. Housing market in China has been boomed in the past two decades. A slight decrease in housing prices attracts potential buyers to the housing market, pushing up the transaction quantity at the end. Moreover, floods damage the nearby infrastructure, generating disamenity to the local housing market. The decrease in prices works as a filter, which transfers the flooded houses to buyers with lower income, resulting an inequality in flood risk exposure (Bakkensen and Barrage, 2018, Lindersson et al., 2023).

[Table 2 around here]

In summary, the occurrence of floods significantly reduces housing price by 2.9% but pushes up the transaction quantity by 45.5% in flooded counties. The estimate is economically significant: compared to the mean, the occurrence of floods decreases the housing prices by 0.006%, but increases 0.05% of transaction quantity.

4.2 Robustness Analysis

Even after controlling for both observables and some unobservables in the stacked DID approach, there are still some concerns regarding whether the results in Table 2 are robust in estimating the impacts of floods on housing market. One potential concern is the possibility that severe floods are typically occurred in flood-prone areas. The local governments in those areas may take some adaptations to prevent damage from floods. Using a dummy of *Treat* may bias the estimating results. We replace the *Treat* dummy by the number of floods during the event quarters in equations (2) and (3), alternatively. There are approximately 1.86 floods in the event quarters. The results in columns (2) and (4) shown that, estimated by stacked DID, the number of floods significantly reduces the housing price and pushes up the transaction quantity accordingly. Averagely, compared to counties that never experienced floods, one flood would significantly reduce the counties' housing price by 2.1%, and increase transaction quantity by 16.4%. The results remain when estimated by generalized DID, as shown in columns (1) and (3) in Table 3.

[Table 3 around here]

Another concern is that the housing market in the first-tier cities are significantly different from those in other cities, including relatively high housing price and large volume of transactions in the past two decades (Meng et al., 2021). We exclude housing markets in the first-tier cities, including Beijing, Shanghai, Guangzhou, and Shenzhen, and repeat the estimations by stacked DID. The results in Table 4 shown that, no matter measures flood risk by a dummy of Treatment or flood numbers in the event quarters, the effects of floods on housing market remain, and the coefficients are also comparable to those in Tables 2 and 3.

[Table 4 around here]

Together, these robustness tests provide strong evidence that flood risk are precisely identified and suggest a causal link between flood risks and housing market. A flood event significantly causes a reduction in housing price but an increase in transaction quantity.

4.3 Heterogeneity Analysis

We then examine how the effects of floods on housing market vary based on the flood severity. Some floods happen around a specific time every year, such as the summer season, which is more predictable than other natural disasters. Local governments take measures to mitigate economic losses during these normal floods. However, if a flood is unexpectedly severe in a city, it can impose substantial impacts on the local economy and, thus the housing market. For example, torrential rain hit Henan province on 20 July, 2021, which left 398 people dead or missing and caused an economic loss of 53 billion.[2] Pan and Qiu (2022) show that floods play a significant, negative impact on firm performance, which is mainly driven by unexpected floods. We further examine the heterogenous response of homebuyers to unexpected, severe floods. In particular, we interact the DID estimator in equation (3) by a dummy of floods over 10%, 20% and 30% of the warming level, respectively. Panel A of Table 5 reports the impacts on housing prices, and Panel B reports the impacts on transaction quantity. As expected, an unexpected, severe flood places much severe price discount on housing price. A flood over 10% of the warming level significantly reduces housing price by 10.2%, which is much larger than the baseline effects of 2.9%, reported in column (2) of Table 2. Moreover, we also find that the transaction quantity in counties experienced a severe flood, which is over 10% of the warming level, is significantly decrease by 25.8%, compared the transactions in counties suffered a regular flood. The pattens remain when

[2] Data from https://www.mem.gov.cn/gk/sgcc/tbzdsgdcbg/202201/P020220121639049697767.pdf.

we measure the severity of floods by floods over 20% and 30% of the warming level, as reported in columns (2)-(3) of Table 4, thought the magnitude of floods over 30% of warming level is not significant.

[Table 5 around here]

Salient natural disasters, such as typhoons, typically hit coastal cities, which also bring heavy rain and, ultimately, floods in those regions. On the one hand, homebuyers may measure flood risks in those areas more seriously, resulting in a lower housing price in coastal regions. On the other hand, the local economic conditions in coastal regions are typically better than counties in other regions. The local governments in coastal counties have sufficient budgets to take adaptation strategies to climate risk, including floods, which reduce the impacts on housing market in those cities. The net effects of flood risks on the housing market in coastal regions are thus unclear. The results in Table 6 shown that, the price impacts of floods on housing market in coastal regions are more than two times lower than those in inland market, but the transaction volumes are four times higher in coastal regions than those in inland regions. The results suggest that local governments in coastal regions may take adaptions strategies to climate risks, reducing damages caused by floods. Moreover, the local economic so as the housing demand in coastal regions are also better than those in inland regions.

[Table 6 around here]

5. Mechanism

The frequency of historical floods has two effects on the impacts of flood shocks on housing market. On the one hand, the damage caused by floods to housing market increase with the frequency and durations of historical floods (Beltrán et al., 2019, Kocornik-Mina et al., 2020). So the impacts of floods on regions with more historical floods are generally more significant than those on regions with less floods. On the other hand, public risk perception may change in regions with the prevalence of floods, and the housing market may already measure such risk to a greater extent (Bin and Landry, 2013, Lamond and Proverbs, 2006). That is, one of the mechanisms that how floods affect housing market is that, floods affect housing market through public risk perception, rather than the physical damages to houses.

Figure 4 shows that within 762 counties, 557 counties never experienced a flood, and 172 counties has experienced floods in 1-3 quarters. The number of counties with floods more than 4 quarters decrease substantially. 65 counties have experienced floods in 4-6 quarters, while only 8 counties have experienced floods more than 6 quarters. We thus define counties experienced floods less than 4 quarters over the study period as counties with less floods, while other counties are grouped as more floods. As expected, the occurrence of floods in counties with less historical floods significantly reduces the housing prices, but has no impact on housing price in counties with more historical floods. The transaction quantity in counties with more historical floods significantly decrease after hit by a recent flood. This is may be caused by the consistent floods in those regions, which reduce the housing demand accordingly (Elliott et al., 2015, Kocornik-Mina et al., 2020).

[Figure 4 around here]

[Table 7 around here]

In summary, we provide suggestive evidence that floods affect housing market through public risk perception. The public risk perception is rare in regions with less floods, and the housing market thus negatively response to floods event in those regions.

7. Conclusion

Climate change is increasing the frequency and intensity of extreme weather events, which caused damage to the local economy. But we have yet to fully understand their impacts in developing countries, which are more vulnerable to confronting climate change.

In this paper, we estimate the impacts of floods on the housing market in China. Using a stacked DID approach, we find that, compared to the mean, the occurrence of floods decreases the housing prices by 0.006%, but increases 0.05% of transaction quantity. The results are robust when we change the measurement of flood risks and exclude samples in the first-tired cities, the market conditions of which are significantly different from others. We find evidence that severe flood places much severe price discount on housing price. The transaction quantity in counties experienced a severe flood also significantly decrease, compared to the transactions in counties suffered a regular flood. We also find that the price impacts of floods on housing market in coastal regions are more than two times lower than those in inland market, but the transaction volumes are four times higher in coastal regions than those in inland regions. The potential mechanism of how floods affect housing market is public risk perception. The public risk perception is rare in regions with less floods, and the housing market thus negatively response to floods event in those regions.

This study highlights for the impact of salient flood risks on the housing market in developing countries, which are more susceptible to the climate change. With limited budgets for adaptation, these countries may face even greater losses in the future, underscoring the challenges of climate justice.

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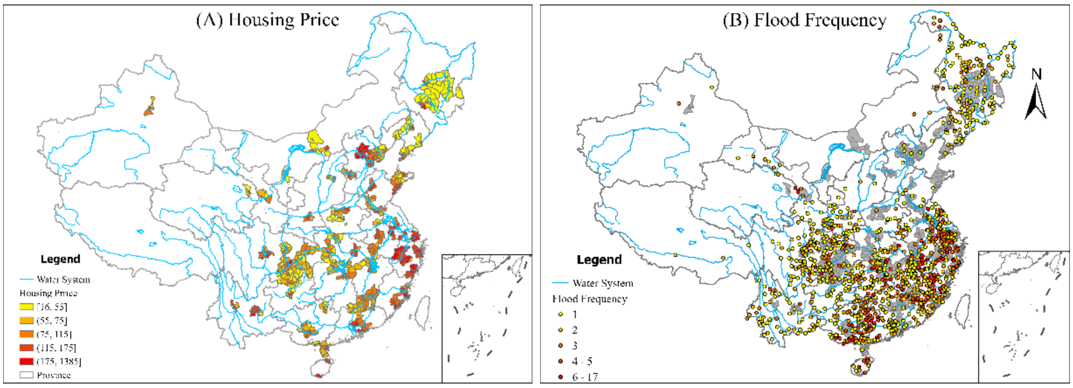

Figure 1 Housing Prices and Flood Frequency

Note: housing prices data are from Xitai, while floods data are from *Hydrological Information Annual Report* (2008-2020).

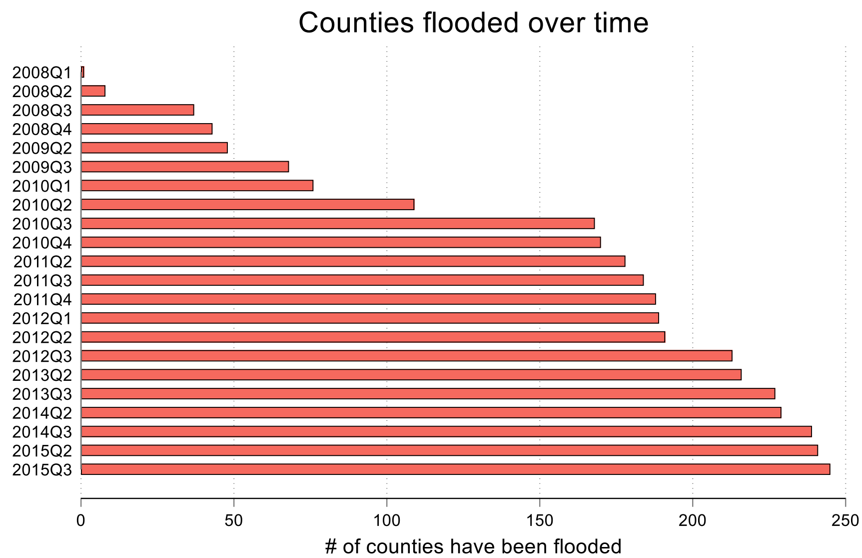

Figure 2 Timing of counties flooded.

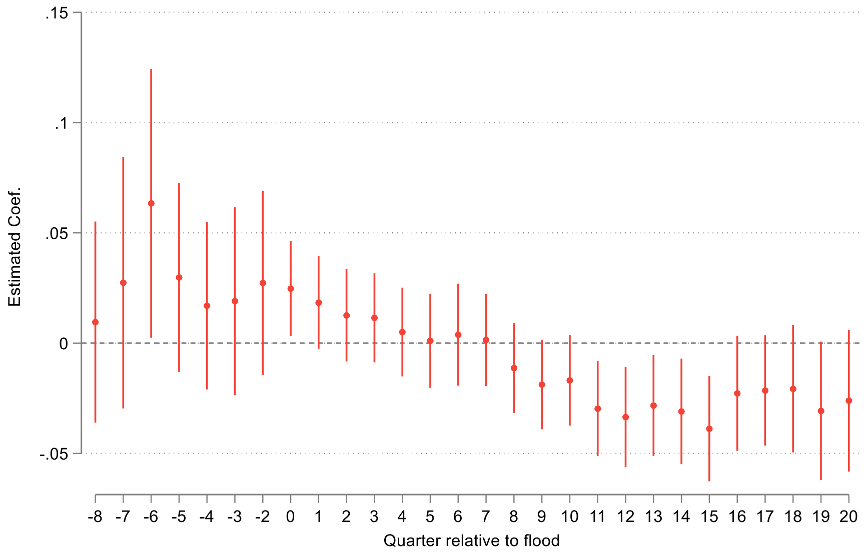

Figure 3 Effects of floods on housing price

Note: This figure shows the coefficients κ_τ ($\tau \in [-8, 20]$) by equation (1), taking $\tau = -1$ as the reference quarter.

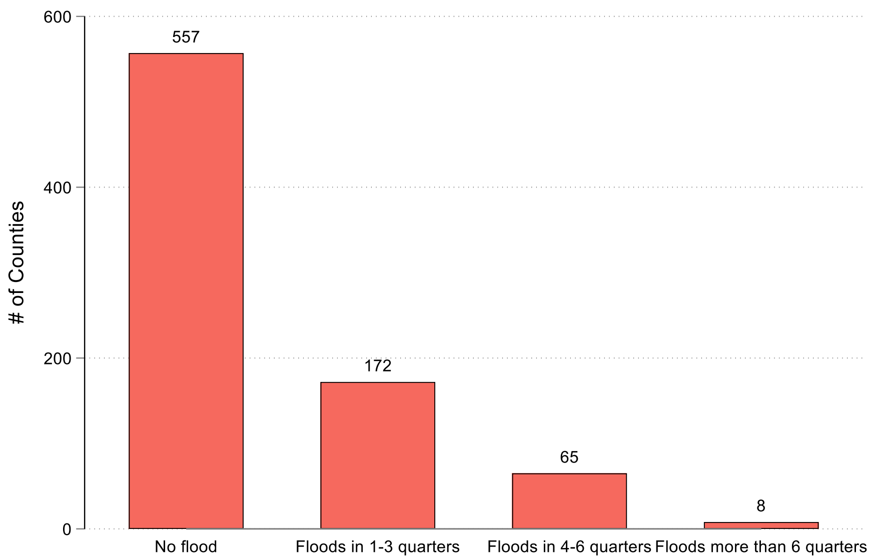

Figure 4 The floods frequency of counties

Table 1 Summary Statistics

This table reports the summary statistics. Treatment group is counties that hit by floods throughout the study period of 2008 – 2018, and counties never hit by floods are regarded as control groups. Panel A report the descriptive analysis of housing transactions at a county level, including the average transaction price, the transaction quantity in a given county-quarter level, and the average transactions area. Panel B report the descriptive analysis of flood. Post is a dummy which tales a value of one if the transaction year-quarter is after a flood hit the county. # of quarters with floods is the number of quarters that is hit by floods throughout the study period from 2009 to 2018. Flood over 10% of WL is a dummy if the flood level is over 10% of the warming level, flood over 10% of WL is a dummy if the flood level is over 20% of the warming level, and flood over 30% of WL is a dummy if the flood level is over 30% of the warming level. Panel C report the city variables, including population, GDP growth rate, the share of secondary industry, the share of third industry, the average wage, and the built-up areas.

Variable	Treatment			Control			Mean differences
	N	Mean	SD	N	Mean	SD	
Panel A: Housing Transactions							
Price (CMY)	8074	90.67	89.84	19085	103.8	125.2	-13.09***
Sale quantity	8226	4513	7914	19433	5682	10308	-1168.85***
Average area (sq m)	8074	115.0	27.18	19085	107.7	22.34	7.36***
Year	8226	2014	2.780	19433	2014	2.809	0.14
Quarter	8226	2.514	1.118	19433	2.514	1.117	0.00
Panel B: Flood							
Post Flood	9800	0.817	0.387	22280	0	0	0.82***
# of Quarters with Floods	9800	2.747	1.896	22280	0	0	2.75***
Floods over 10% of WL	9800	0.208	0.406	22280	0	0	0.21***
Floods over 20% of WL	9800	0.131	0.338	22280	0	0	0.13***
Floods over 30% of WL	9800	0.113	0.316	22280	0	0	0.11***
Panel C: City Characteristics							
Population (10 thousand)	8182	858.1	674.6	19090	755.3	568.7	102.81***
GDP growth rate (%)	7191	10.15	2.973	16932	10.10	3.420	0.05
Share of secondary industry (%)	7211	46.10	7.928	16968	45.17	9.256	0.93***
Share of third industry (%)	7175	46.30	10.04	16921	47.99	10.98	-1.69***
Average wage (CMY/month)	8094	58404	20179	18957	58401	20868	2.88
Built-up areas (sq km)	7800	360.3	340.0	18232	380.9	350.5	-20.58***

Table 2 The impacts of floods on housing market.

This table report the baseline results. Regressions in columns (1) and (3) are estimated by a generalized DID, while columns (2) and (4) are estimated by stacked DID. The dependent variable in columns (1)-(2) are log(price), and the dependent variables in columns (3)-(4) are log(quantity). Treatment takes a value of one if a county has been hit by floods throughout the study period, and takes a value of zero otherwise. Post is a dummy variable which take a value of one if the transaction quarter is after the flood quarter, and take a value of zero otherwise. Area is the average transaction area. City level control variables include population, GDP growth rate, the share of secondary industry, the share of third industry, the average wage, and the built-up areas. All regressions include county fixed effects, year_by_quarter fixed effects. Regressions in columns (2) and (4) further include stacked group fixed effects. Standard errors in parentheses in columns (1) and (3) are clustered by county level, while those in columns (2) and (4) are cluster by stacked group level. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Price	(2) Price	(3) Quantity	(4) Quantity
Treatment×Post	-0.032	-0.029***	0.216*	0.455***
	(0.020)	(0.005)	(0.114)	(0.024)
Log(area)	1.059***	1.054***	-0.311***	0.027
	(0.040)	(0.002)	(0.113)	(0.044)
Observations	22,185	516,102	22,214	47,802
R-squared	0.945	0.948	0.909	0.911
County unit	790	790	790	245
Estimation	Generalized DID	Stacked DID	Generalized DID	Stacked DID
County FE	Yes	Yes	Yes	Yes
Year_by_Quarter FE	Yes	Yes	Yes	No
Stacked group FE	No	Yes	No	Yes

Table 3 Robustness I: Different measurement of flood risk

This table replaces the measurement of flood risk by the number of floods within the event quarters [-16,16]. Regressions in columns (1) and (3) are estimated by a generalized DID, while columns (2) and (4) are estimated by stacked DID. The dependent variable in columns (1)-(2) are log(price), and the dependent variables in columns (3)-(4) are log(quantity). City level control variables include population, GDP growth rate, the share of secondary industry, the share of third industry, the average wage, and the built-up areas. All regressions include county fixed effects, year_by_quarter fixed effects. Regressions in columns (2) and (4) further include stacked group fixed effects. Standard errors in parentheses in columns (1) and (3) are clustered by county level, while those in columns (2) and (4) are cluster by stacked group level. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Price	(2) Price	(3) Quantity	(4) Quantity
# of Floods	-0.027***	-0.021***	0.084**	0.164***
	(0.008)	(0.004)	(0.038)	(0.028)
Observations	22,214	516,102	22,214	516,102
R-squared	0.946	0.948	0.909	0.909
County unit	790	790	790	790
Estimation	Generalized DID	Stacked DID	Generalized DID	Stacked DID
County FE	Yes	Yes	Yes	Yes
Year_by_Quarter FE	Yes	Yes	Yes	Yes
Stacked group FE	No	Yes	No	Yes

Table 4 Robustness II: Strict sample

This table uses sample excluding housing prices in the first-tier cities, including Beijing, Shanghai, Guangzhou and Shenzhen. The dependent variables in columns (1) and (3) are housing prices, while dependent variables in columns (2) and (4) are transaction quantity. City level control variables include population, GDP growth rate, the share of secondary industry, the share of third industry, the average wage, and the built-up areas. All regressions include county fixed effects, year_by_quarter fixed effects and stacked group fixed effects, estimated by stacked DID. Standard errors in parentheses are cluster by stacked group level. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Price	(2) Quantity	(3) Price	(4) Quantity
Treatment×Post	-0.024***	0.216***		
	(0.005)	(0.027)		
# of Floods			-0.016***	0.141***
			(0.004)	(0.028)
Observations	486,962	486,962	486,962	486,962
R-squared	0.933	0.908	0.933	0.908
County unit	736	736	736	736
Estimation	Stacked DID	Stacked DID	Stacked DID	Stacked DID
County FE	Yes	Yes	Yes	Yes
Year_by_Quarter FE	Yes	Yes	Yes	Yes
Stacked Group FE	Yes	Yes	Yes	Yes

Table 5 The heterogeneity effects of flood severity on housing market.

This table reports the heterogeneous effects of flood severity on housing market. Panel A uses logarithmic value of Price as the dependent variable, while Panel B uses logarithmic value of Quantity as the dependent variable. All regressions are estimated by stacked DID. *Floods over k% of WL* is a dummy variable which takes a value of one if the flood level is above the *k*% of the warming level (WL), *k* = 10, 20 and 30, respectively. All regressions include county fixed effects, year_by_quarter fixed effects. Standard errors in parentheses are cluster by stacked group level. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) 10% over the WL	(2) 20% over the WL	(3) 30% over the WL
Panel A: Dependent variable = log(Price)			
Treatment×Post	-0.006	-0.021***	-0.024***
	(0.007)	(0.006)	(0.006)
Floods over *k*% of WL	0.063***	0.001	0.012
	(0.012)	(0.012)	(0.018)
Treatment×Post×Floods over *k*% of WL	-0.102***	-0.062***	-0.046***
	(0.011)	(0.007)	(0.007)
Observations	516,102	516,102	516,102
R-squared	0.948	0.948	0.948
County unit	790	790	790
Estimation	Stacked DID	Stacked DID	Stacked DID
County FE	Yes	Yes	Yes
Year_by_Quarter FE	Yes	Yes	Yes
Stacked group FE	Yes	Yes	Yes
Panel B: Dependent variable = log(Quantity)			
Treatment×Post	0.322***	0.290***	0.280***
	(0.027)	(0.028)	(0.027)
Floods over *k*% of WL	0.052	-0.106	-0.273**
	(0.043)	(0.081)	(0.100)
Treatment×Post×Floods over *k*% of WL	-0.258***	-0.211**	-0.118
	(0.049)	(0.086)	(0.095)
Observations	516,102	516,102	516,102
R-squared	0.909	0.909	0.909
County unit	790	790	790
Estimation	Stacked DID	Stacked DID	Stacked DID
County FE	Yes	Yes	Yes
Year_by_Quarter FE	Yes	Yes	Yes
Stacked group FE	Yes	Yes	Yes

Table 6 The heterogeneous effects of floods in coastal and inland regions

This table split the full samples into counties in coastal regions and counties in inland regions. Coastal region refers to counties located in provinces of Liaoning, Hebei, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan and Guangxi, while inland region refers to counties in the other provinces. The dependent variables in columns (1) and (3) are housing prices, while dependent variables in columns (2) and (4) are transaction quantity. City level control variables include population, GDP growth rate, the share of secondary industry, the share of third industry, the average wage, and the built-up areas. All regressions include county fixed effects, year_by_quarter fixed effects and stacked group fixed effects, estimated by stacked DID. Standard errors in parentheses are cluster by stacked group level. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Price Coastal Region	(2) Price Inland Region	(3) Quantity Coastal Region	(4) Quantity Inland Region
Treatment×Post	-0.016*	-0.037***	0.589***	0.141***
	(0.009)	(0.007)	(0.044)	(0.021)
Observations	191,458	324,644	191,458	324,644
R-squared	0.950	0.941	0.911	0.909
County unit	288	502	288	502
Estimation	Stacked DID	Stacked DID	Stacked DID	Stacked DID
County FE	Yes	Yes	Yes	Yes
Year_by_Quarter FE	Yes	Yes	Yes	Yes
Stacked group FE	Yes	Yes	Yes	Yes

Table 7 Mechanism: Uncertainty in flood risks

This table report the mechanism of flood risk on housing market. The dependent variable in columns (1)-(2) are log(price), grouped by flood frequency. And the dependent variables in columns (3)-(4) are log(quantity), grouped by flood frequency. Less flood refers to the frequency of floods hit a given county is less than 4 times throughout the study period, while more floods are counties with the frequency of 4 times and more. All regressions are estimated by stacked DID. Each regression includes county fixed effects, year_by_quarter fixed effects. Standard errors in parentheses are cluster by stacked group level. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Price Less flood	(2) Price More flood	(3) Quantity Less flood	(4) Quantity More flood
Treatment×Post	-0.031***	-0.010	0.314***	-0.060**
	(0.006)	(0.007)	(0.024)	(0.027)
Observations	505,609	10,493	505,609	10,493
R-squared	0.948	0.919	0.909	0.914
County unit	717	73	717	73
Estimation	Stacked DID	Stacked DID	Stacked DID	Stacked DID
County FE	Yes	Yes	Yes	Yes
Year_by_quarter FE	Yes	Yes	Yes	Yes
Stacked group FE	Yes	Yes	Yes	Yes