The Effect of Risk Information on Housing Prices in Taiwan*

Tzu-Chang Forrest Cheng† Tai-Chi Wang‡ Jian-Da Zhu§

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Abstract

This research uses a difference-in-differences framework to investigate the effect of new risk information on housing prices in Taiwan. The results show that this information changed individuals' subjective risk perceptions, so that housing prices in the highest-risk areas dropped, but only temporarily in the first three months after the disclosure. This information effect happened for those apartments lacking certain earthquake-resistant characteristics. In addition, we investigate the dynamics of the effect around the boundary. We demonstrate that individuals were able to form continuous risk beliefs based on discrete information, and the housing prices dropped more sharply for apartments located closer to the center of the highest-risk area. Furthermore, individuals had updated their risk beliefs differently for apartments with different levels of earthquake resistance. For apartments with the least earthquake resistance, the immediate price drops were larger, and the housing prices returned to normal more slowly, relative to the safer apartments. Most notably, the effect did not disappear at all for those apartments with the least earthquake resistance that were also located in the center of the highest-risk area.

Keywords: information disclosure; risk perception; housing market; soil liquefaction risk
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†Department of Economics, National Central University.

‡National Center for High-performance Computing.

§Corresponding author. Email: jdzhu@ntu.edu.tw. Department of Economics, National Taiwan University.

1 Introduction

Housing prices can be determined by many factors, one of which is risk perceptions of natural disasters, because those disasters, such as earthquakes or floods, could entirely destroy a house, albeit with a small probability. Although it is hard to directly measure how individuals evaluate the risk of natural disasters when purchasing real estate, the literature uses changes in housing prices before and after major natural disasters or releases of new risk information, to capture changes in risk perception.[1] Some studies indicate that this effect might not be persistent, but based on a temporary change in subjective risk beliefs. In addition, information disclosed by the government might only have a discrete hazard map, while the risk measure is continuous, and tends to only contain general information, and not specific details for certain types of houses. Therefore, this research extends the current literature to answer the following questions: (1) Does such risk information affect individuals' risk perceptions persistently or temporarily? (2) Based on the same information, do individuals' risk perceptions of houses vary with their earthquake-resistant qualities? (3) How does discrete risk information affect people's risk perceptions over time?

On February 6, 2016, an earthquake of 6.6 magnitude on the Richter scale hit the Meinong District of Kaohsiung City in Taiwan. The 2016 Meinong earthquake caused an apartment building to collapse in Tainan, leading to 117 deaths.[2] The government subsequently released, for the first time, on March 14, 2016, a risk map of soil liquefaction, to help people understand the risks to their own houses. Figure 1 shows the soil liquefaction risk map for the Taipei metropolitan area, with four levels (colors) of risk potential: high (red), moderate (yellow), low (green), and no risk (light blue). In addition, the soil liquefaction risk was reported frequently by the media after the earthquake. Figure 2 shows that the total number of news articles related to liquefaction rose in February and peaked in March 2016, when the information was first disclosed, but dropped back dramatically to an ignorable level three months later.[3]

[1] This method relies on a relevant assumption that individuals have homogeneous risk perception, so we follow this assumption in this research. However, we will discuss the other possibility with heterogeneous agents in Section 7. We thank the anonymous referee for pointing out this possible channel.

[2] Although the cause of this building's collapse was not soil liquefaction, people started to worry about soil liquefaction because it is likely to increase the risk of buildings collapsing after earthquakes. Therefore, the government promised to reveal the soil liquefaction risks of potential areas within one month of the incident.

[3] The data were collected from the United Daily News Group, one of the mainstream news media channels in Taiwan.

Since the timing of the earthquake and the information disclosure is very close, the effects should be considered simultaneously. We attempt to decompose the effect into the earthquake effect and the effect of the information disclosure in Section A of the online appendix. However, the results suggest that the earthquake caused no significant effect on housing prices during the period between the earthquake and the disclosure of the risk map. Therefore, in this research, we focus on the effect of the information disclosure on housing prices in the Taipei metropolitan area, based on a difference-in-differences framework. We also extend the analysis to the boundary between each risk area to see whether individuals were able to shape continuous risk beliefs based on the discrete information.

Both the housing transaction data and the liquefaction risk map for Taiwan can provide two helpful features for studying the information effect on housing prices. First, the housing transaction data come from administrative data collected by the government, including comprehensive information on all real estate transactions, such as the exact date of the transaction and the latitude and longitude of each piece of real estate.[4] The exact date of a transaction allows us to identify the immediate information effect following the disclosure, and the locations of houses combined with the risk map let us precisely measure the distance from the boundary and analyze the effect close to the boundary. Second, the liquefaction risk map provides a natural control group (the no-risk area) for the analysis.[5] Because liquefaction risk only occurs in sandy soil with a high groundwater level, there is no liquefaction risk in some higher-altitude areas outside of the Taipei Basin. This allows us to compare housing prices in different risk areas with those in the no-risk area before and after the disclosure of the risk map.

The results show that housing prices in the high-risk area dropped significantly, by 3.33%, in the first three months following the disclosure, relative to those in the no-risk area, and there was no effect for the moderate- and low-risk areas. This information effect was temporary, and housing prices had returned to their original levels three months later. Furthermore, this effect only showed up for apartments with less earthquake resistance, such as those without elevators, and older apartments built before 1999; there was no effect for the "safe" apartments. In addition, we do not observe a housing-price discontinuity on the boundary between each risk area, which shows that individuals were able to form continuous risk beliefs, even though

[4]Based on legal requirements, each real estate transaction in Taiwan has to be registered within 30 days of the transfer of ownership.

[5]We provide detailed evidence to show the validity of the control group in Section B of the online appendix.

they received discrete information from the government. Within the high-risk area, housing prices dropped more sharply for apartments located closer to the center of the high-risk area. Facing the same risk information, individuals had updated their risk beliefs differently for apartments with different levels of earthquake resistance. For those apartments with the least earthquake resistance, the immediate price drops were larger, and the housing prices returned to normal more slowly, than for the safer apartments. The effect remained in place, persisting, for those apartments with the least earthquake resistance that were also located in the center of the high-risk area.

Four implications can be drawn from the above results. First, the information disclosure only changed individuals' subjective risk probabilities, which also returned to normal quickly. Second, people only changed their beliefs for houses that were actually at risk or less earthquake resistant. Third, people were able to form their beliefs as a continuous risk measure, even though the disclosed risk map was discrete. Fourth, the temporary information effects varied across different levels of earthquake resistance, and also vanished at different speeds.

Our paper makes three additions to the literature. First, we show that the information effect on risk perceptions could be temporary, like the effect of massive disasters. As long as the probability of risk events is small enough, we might only observe the effect through changes in people's subjective beliefs. Second, given the same piece of risk information, the temporary effects for apartments with different qualities of earthquake resistance might vary, both in terms of the immediate shock and the speed with which the shock vanishes. Tanaka and Zabel (2018) show that the temporary effect might vary with the distance from the source of risk, and we further extend this spatial dimension to the quality dimension for houses. Third, to the best of our knowledge, our paper is the first to demonstrate that people can form continuous risk beliefs very quickly based on discrete information on a map. The results show that there is no price discontinuity across the boundary of the risk map, and the risk beliefs for different locations for which the same risk information is given differ.

The remainder of this paper is structured as follows. Section 2 presents the related literature. Section 3 provides the hypotheses to be tested. Section 4 describes the details of the data. Section 5 explains the identification strategy and shows the empirical models. Section 6 reports the empirical results. Section 7 discusses alternative explanations and concludes the paper.

2 Literature Review

In this section, we first introduce the literature related to the effects of massive disasters and information disclosure. Then we present the studies which mention the heterogeneous effects on different houses or around the boundary.

Some of the literature uses housing price differentials across regions with various risk levels to evaluate people's risk perceptions of natural disasters, such as earthquakes (Nakagawa, Saito and Yamaga, 2007) and floods (Bin and Polasky, 2004). Because some unobserved effects correlated with risk levels could create estimation bias, recent studies use panel data and apply the difference-in-differences method to compare price differentials before and after disclosure of risk information. Information disclosure usually produces a persistent price differential for houses in risky areas (Brookshire et al., 1985; Moulton, Sanders and Wentland, 2018; Votsis and Perrels, 2016; Billings and Schnepel, 2017), because people form new beliefs following the disclosure. Votsis and Perrels (2016) show that housing prices in flood-prone areas indicated by a flood-risk map drop significantly after the disclosure of the map. This suggests that people are usually not aware of, or underestimate the risk of, natural disasters before the release of risk information. If people do update or change their risk beliefs, the negative effect on housing prices in the risk areas is usually permanent after the new information has been released.

Another stream of literature examines how housing prices react to huge natural disasters, given the existing risk information. Both persistent and temporary effects can be found (Naoi, Seko and Sumita, 2009; Bin and Landry, 2013; Boes, Nüesch and Wüthrich, 2015; Gibbons et al., 2016; Tanaka and Zabel, 2018; Hsu et al., 2020). Naoi, Seko and Sumita (2009) show that price differentials due to location within a quake-prone area become significantly larger soon after an earthquake event. Bin and Landry (2013) find a similar effect for flood risk; however, the price differential tends to diminish over time. If the price differential is created by a change in subjective risk beliefs, and not a change in the actual risk, this information effect could disappear once subjective risk beliefs return to normal. Tanaka and Zabel (2018) show that housing prices in the United States decreased by around 10-20% in the two-kilometer radius around nuclear power plants after the Fukushima nuclear crisis in 2011. Although the nuclear crisis in Japan did not change the risk of nuclear power plants in the United States, a temporary change in subjective risk beliefs generated a temporary change in price differentials for the risky areas. The authors show that housing prices returned to their original levels within a year.

Furthermore, previous literature finds that people have different risk beliefs about apartments in the same area that have different characteristics. Nakagawa, Saito and Yamaga (2007) show that houses in risky areas that were built prior to the amendment of the Building Standard Law have larger price discounts than those built afterwards. Hidano, Hoshino and Sugiura (2015) also find that, compared to older apartments, prices of new apartments are less affected by seismic risk information because they were built under stricter regulations.

In addition, the literature usually uses the distance from the source of the risk to measure the level of risk. Tanaka and Zabel (2018) find that prices of houses within a two-kilometer radius of a nuclear power plant drop by more than those of houses two to four kilometers away from a plant. Although risk is continuous, based on distance from the source, revealed risk maps could be discrete, which creates the boundary of risk areas. Hidano, Hoshino and Sugiura (2015) use a spatial two-dimensional regression discontinuity design to study the effect of seismic hazard risk information on housing prices. Interestingly, they find significant price discounts around the boundary between the high- and low-risk areas.

3 Hypothesis Development

In our study, the effects of an earthquake and the disclosure of risk information need to be considered simultaneously because the soil liquefaction risk map was revealed about one month after the earthquake. Because the information about the soil liquefaction risk was being revealed for the first time in Taiwan, people could only construct their risk beliefs based on it. However, people's subjective probabilities of rare events happening could have been increased by the tremendous tragedy that occurred after the earthquake.

We expect that the two mixed effects could have led people to update their risk perceptions, so housing price decreases in risky areas can reflect changes in individuals' risk perceptions. However, this information effect could be temporary or persistent, depending on whether the subjective risk probabilities are changing over time. In addition, apartments with less earthquake resistance may have larger price discounts than those with more. Accordingly, we propose the following as our first hypothesis.

Hypothesis 1. *Housing price decreases in risky areas could be temporary or persistent, and they might vary across apartments with different levels of earthquake resistance.*

The disclosed risk of soil liquefaction in our study is divided into four risk levels, but individuals might create continuous risk beliefs based on the discrete information. Around the boundary between two different risk areas, risk beliefs should not be discontinuous, because individuals should have the same risk beliefs for two apartments close to each other, even if one is located in the higher and one in the lower risk area. Although they may be labeled with different risk potential, the apartments may be too close to be treated as having different risk levels. Therefore, the discontinuous information provided by the government should not have a discontinuous effect on housing prices, especially in the long run.

Furthermore, inside the same risk-potential area, individuals can generate continuous risk beliefs based on relative distances from the centers of high-risk areas. Taking two apartments located in a high-risk area as an example, one may be located near the boundary with a moderate-risk area, the other close to the center of the high-risk area. The actual risk for the former is lower than that for the latter, and the risk difference between them will increase the further away from one another they are located. Although they are labeled with the same risk potential, we should expect the price of the apartment at the center of the high-risk area to have a larger price discount than the other.

Based on the previous two arguments, individuals are likely to update their risk beliefs based on information about the riskiness and relative locations of apartments, so the following hypothesis can be proposed:

Hypothesis 2. *Near the boundary between two different risk areas, housing prices should not be discontinuous if risk is treated as a continuous measure. Also, inside the risky area, price discounts should be larger for apartments located closer to the center of the risky area.*

4 Data

This study uses data on housing transactions and the map of the soil liquefaction risk in the Taipei metropolitan area, which includes Taipei City and New Taipei City.[6]

[6]There are two reasons to focus on the Taipei metropolitan area. First, most of the real estate transactions in Taiwan are conducted in this area. Second, the soil liquefaction risk map that was released on March 14, 2016 covered this area.

4.1 Housing Transactions

The housing transaction data collected from the Real Estate Transaction Registration Database consist of comprehensive information on each real estate transaction, from January 1, 2014, to August 31, 2017. Properties involved in real estate transactions could include one or multiple items, such as lands, buildings, or parking lots, but we limit our sample to those sales that included at least one building (81.97% of the initial sample). Furthermore, we focus on residential properties, apartments (68.37% of the initial sample) and studios[7] (6.40%). We also exclude non-market transactions and sales of furnished apartments (35.87% of the initial sample) because the prices in those transactions could contain some unobserved factors that are difficult to control.[8] Finally, we exclude transactions with extreme values for the housing characteristics (1.5% of the initial sample).[9]

The housing transaction data include information on the transaction price, the transaction date (the specific date on the contract), the location of the building (latitude and longitude), and other housing characteristics as listed in Table 1. For each transaction, we further collect information on the location, including zoning regulations and the distances to the nearest subway station, elementary school, junior high school, senior high school, and university. Table 1 reports summary statistics on the types of apartments, housing characteristics, location information, and risk information for all the transactions. Around 58% of the sample are apartments with elevators, 30% are apartments without elevators, and 12% are studios. The apartments without elevators were typically built longer ago. Overall, the average building age is 21.19 years, and the average price per square meter is 140,100 New Taiwan Dollars (NTD). 75% of the transactions are located in residential zones, and the average distance from the nearest subway station is less than one kilometer.

[7]The studio is listed as a category from the database. Because we cannot further distinguish whether a studio has an elevator or not, we keep this as an independent category.

[8]The transaction data include detailed notes for each sale. We exclude transactions between friends or relatives, acquisitions by the government, and any with specific notes indicating that any unobserved factors might affect the price.

[9]We drop transactions with missing information on floor, where the number of buildings is greater than three, the number of parking lots is great than three, the size of the land is larger than 100 square meters, and where the gross floor area is smaller than 20 square meters or larger than 500 square meters.

4.2 Map of Soil Liquefaction Risk

The soil liquefaction risk map was released by the Central Geological Survey on the Soil Liquefaction Potential Inquiry System.[10] Figure 1 shows the map of soil liquefaction risk in the Taipei metropolitan area. The risk is classified into three levels (colors) on the map,[11] high (red), moderate (yellow), and low (green), and the remaining light blue areas are the no-risk areas. Using the geocoding software QGIS, each transaction can be exactly pinpointed on the map based on its latitude and longitude, allowing us to associate the risk with each transaction.

The bottom panel of Table 1 shows that most of the transactions are located in low-risk areas (54.9% of the sample), with 12.4% and 22.3% of the sample located in high- and moderate-risk areas, respectively. Table 2 displays how the housing characteristics and information vary across the different risk areas before and after the disclosure. Because most of the high-risk areas are located in the center of the Taipei Basin, which is also the downtown area of the city, the average price in the high-risk areas before the disclosure is 177,100 NTD per square meter, the highest of all the areas. The average price in the no-risk areas is the lowest, at 118,900 NTD per square meter. However, the average age of the buildings in the high-risk areas before the disclosure is 22.67 years, the oldest of all the areas. Regarding the zoning areas, around 51.8% of the transactions in the high-risk areas are located in commercial zones, but most of the transactions in the other risk areas are located in residential zones.

After the disclosure, housing prices drop in all the areas. Notably, the average price in the high-risk areas decreases by around 10,000 NTD per square meter, the largest of all the areas. However, all the other housing characteristics do not change too much in each risk area.

5 Empirical Models

We use difference-in-differences as an identification strategy to compare housing prices in the no-risk area (control group)[12] and the areas with different levels of risk (treatment groups) before and after the disclosure of the

[10] https://www.moeacgs.gov.tw/2016.htm

[11] The classification of risk levels is based on the potential liquefaction index, P_L, assessed by the Central Geological Survey. A property is considered at high risk if $P_L > 15$, at moderate risk if $5 \leq P_L \leq 15$, and at low risk if $0 < P_L < 5$. Instead of reporting the P_L index, the government only announced the three levels of risk.

[12] We discuss the validity of the control group in Section B of the online appendix, especially for arguing that the substitution effect between the risky and no-risk areas is not significant.

risk map. Housing prices in the no-risk area should not be affected by the risk map, making it the control group in the difference-in-differences setup. We assume that housing prices would have exhibited the same movement in the no-risk and risky areas in the absence of any disclosure, when controlling for housing characteristics and any other regional factors that might affect the housing prices.

Because Figure 2 shows that the number of news articles related to soil liquefaction was much higher in the first three months after the disclosure of the map, we first divide the sample period into pre- and post-disclosure periods, and subsequently split the post-disclosure period into three sub-periods: from the disclosure to June 2016 ($Post^1 = 1$), July to December 2016 ($Post^2 = 1$), and January to August 2017 ($Post^3 = 1$). All the model specifications in this paper include the interactions between the treatment and the three post-disclosure dummies to capture the dynamic effect over time.

We use two frameworks to study the effect of the disclosure of the risk map on housing prices. First, we use the housing transactions within one kilometer of the boundaries (almost all the transactions in the risk areas plus those transactions in the no-risk area that are close to the boundary between the no-risk and low-risk areas) to test Hypothesis 1. The treatment effects across different risk levels can be directly identified by comparing the changes in the housing prices in the different risk areas with those in the no-risk area, so the following baseline model is considered:

$$\begin{aligned}\log(P_{ijt}) = \beta_0 + X_{ijt}\boldsymbol{\beta} + \sum_{s=L,M,H} \delta^s Risk_i^s \\ + \sum_{s=L,M,H}\sum_{k=1}^{3} \gamma^{sk} Risk_i^s \times Post_t^k + f_j + \theta_t + \lambda_j \times t + u_{ijt},\end{aligned} \tag{1}$$

where P_{ijt} and X_{ijt} are the transaction price and housing characteristics for apartment i in town j at time t. $Risk_i^s$ is a dummy indicating whether apartment i is located in one of the three risk areas: high ($s = H$), moderate ($s = M$), and low ($s = L$). We also include the township fixed effects (f_j), year-by-month fixed effects (θ_t), and different time trends among different towns ($\lambda_j \times t$). The robust standard errors are clustered at the township level. We use the same framework for apartments with different earthquake-resistant characteristics to further explore the heterogeneous information effect.

Second, to test Hypothesis 2, we restrict the sample to observations near each boundary. However, according to the graphical analysis in Section 6.2, the effect only exists around the boundary between the high- and moderate-risk areas. Therefore, we only focus on this part to conduct the regression analysis. We divide each risk area into three sub-areas: within 200 meters of, 200-400 meters from, and more than 400 meters from the boundary, as shown in Figure 3, with $Area^1$ treated as the control group because it is the one with the least risk. The treatment effects can be identified based on the changes in housing prices in different areas relative to those in $Area^1$ after the disclosure of the risk map, so the following regression model is used:

$$\begin{aligned}\log(P_{ijt}) &= \beta_0 + X_{ijt}\boldsymbol{\beta} + \sum_{s=2}^{6}\delta^s Area^s \\ &+ \sum_{s=2}^{6}\sum_{k=1}^{3}\gamma^{sk} Area^s \times Post^k + f_j + \theta_t + \lambda_j \times t + u_{ijt}, \qquad (2)\end{aligned}$$

where γ^{sk} are the main coefficients for the information effect.

More specifically, the price differences between $Area^3$ and $Area^4$ before and after the disclosure can directly indicate whether the risk is continuous around the boundary. Also, the information effects in $Area^4$, $Area^5$, and $Area^6$ can be observed to test the effect inside the high-risk area. If people update their risk beliefs based on relative distances from the centers of risky areas, we should observe the largest effect in $Area^6$. Finally, we also use the price changes for apartments with different earthquake-resistant characteristics, in these five areas, relative to those in $Area^1$ to explore the heterogeneous effect in Hypothesis 1.

6 Empirical Results

6.1 Effect of Information on Risk Perceptions

The main estimates, $\hat{\gamma}^{sk}$, reported in column (4) of Table 3, capture the information effects on housing prices over different periods. For the first three months after the disclosure, all the coefficients are negative, with a decreasing pattern from low-risk areas to high-risk areas. Relative to the housing prices in the no-risk areas, prices in the high-risk areas dropped significantly, by 3.33%, but prices in the moderate- and low-risk areas only show small and statistically insignificant negative effects, of 1.56% and 1.06%, respectively. This finding indicates an immediate price drop, in accordance with risk perception adjustments, during the first three months after the disclosure.

However, the information effect on housing prices in the high-risk area dissipates three months later, showing the temporary effect predicted in

Hypothesis 1. This information might only change people's subjective assessments of the probability of liquefaction risk, with these subjective probabilities returning to their prior levels soon afterwards. The literature usually finds temporary effects coming after tremendous disasters (Tanaka and Zabel, 2018; Bin and Landry, 2013); however, we further show that information disclosure can also create a temporary effect as long as the chances of the liquefaction causing a building collapse are small enough to only change individuals' subjective probabilities.

To further study the information effects across apartments with different earthquake-resistant characteristics, we use the same regression model as in equation (1), but divide the sample into three sub-groups based on three different dimensions: type of apartment, housing age, and year built.[13]

Table 4 presents the results for different types of apartments: those with elevators, those without elevators, and studios. The coefficient on $Risk^H \times Post^1$ in column (2) shows that the prices of apartments without elevators dropped by 5.97% during the first three months following the disclosure of the risk map, whereas the effects were insignificant for the other two types of apartments. This result is consistent with the fact that apartments without elevators were typically built longer ago, and therefore featured fewer earthquake-resistant measures. In addition, apartments without elevators might not have deep foundations, making them more likely to be affected by soil liquefaction after earthquakes. In column (2), we also find a decreasing pattern through the three different risk levels in the first three months, and the information effect disappears three months later in the case of the high-risk areas.

Table 5 shows the results for apartments of different ages: 0-15, 15-30, and 30-50 years old. The results indicate that the prices for the apartments that were more than 30 years old dropped by 7.71% during the three months following the disclosure of the risk map, but for the other two groups there were insignificant effects on prices. This suggests that people only changed their subjective beliefs about older houses in the market, because these might be less earthquake resistant and be more likely to collapse after earthquakes. Similarly, temporary effect lasted only three months, and a decreasing pattern through the different risk levels can be observed in column (3).

Since apartments built after 2000 are believed to have better earthquake-

[13]The housing age is calculated as the transaction year minus the construction year, but the year built is based only on the construction year.

resistant features in Taiwan,[14] we divide the sample into three groups, based on year built: before 1999, 2000-2010, and after 2011. Table 6 shows that only for those apartments built before 1999 is there a significant negative effect on prices, of around 3.16%, in the first three months. However, we find no effect for any apartments built after 2000, indicating that individuals only updated their subjective beliefs about those perceived-to-be-unsafe apartments.

Overall, the results in Tables 4, 5, and 6 show that apartments lacking earthquake-resistant characteristics or with a higher soil liquefaction risk have larger price differentials than other apartments, which is consistent with Hypothesis 1 and the previous literature's findings (Nakagawa, Saito and Yamaga, 2007; Hidano, Hoshino and Sugiura, 2015). The results further show that the price differentials across apartments with different features only showed up temporarily, in the first three months.

6.2 The Information Effect around the Boundary

To further examine Hypothesis 2, we now focus on each boundary.[15] We first present the graphical evidence, and then apply a difference-in-differences framework around the boundary to produce empirical results.

First, we focus on the boundary between the high- and moderate-risk areas. We apply a hedonic regression model, controlling all the housing characteristics, township fixed effects, year-by-month fixed effects, and different time trends among different towns, while leaving the risk information out of the model. The average residuals, calculated within every 20 meters, are plotted on Figure 4. The x-axis represents the distance to the boundary between the high- and moderate-risk areas, with positive (negative) numbers in the high (moderate) risk areas. Figure 4(a) presents the average residuals before the disclosure of the risk map, showing that there is no

[14] On September 21, 1999, an earthquake, known as the 921 earthquake, measured at 7.3 on the Richter scale, struck Taiwan, killing 2,347 and damaging more than 100,000 buildings. The damage was the greatest of any earthquake in Taiwan's history. The government revised the seismic design code after that and imposed a higher standard on buildings built after January 1, 2000.

[15] If we can transform a two-dimensional map into a line, we can directly draw the price pattern from the no-risk area to the high-risk area and examine the changes after the disclosure to test Hypothesis 2 for all the risk areas simultaneously. However, it is difficult to do this transformation since the distance between any of the two boundaries could vary on a two-dimensional map. For instance, we pick two locations, A and B, in the moderate risk area. Location A could be far away from the two boundaries (one is between the high- and moderate-risk areas, and the other one is between the moderate- and low-risk areas), but location B could be close to these two boundaries simultaneously. Since the sum of distances from the two boundaries could be different between locations A and B, it is unable to fix the distance between these two boundaries on a line.

price variation with respect to liquefaction risk. Because the liquefaction risk map was being revealed for the first time in Taiwan, we would not expect any price discontinuity across the boundary, or any decreasing patterns toward the centers of the high-risk areas before the disclosure. Furthermore, the residuals stay roughly at the same level in both moderate- and high-risk areas.

Figures 4(b), 4(c), and 4(d) show the average residual plots relative to those before the disclosure. Interestingly, in Figure 4(b), there was a clear price discount pattern toward the centers of the high-risk areas during the first three months following the disclosure, which suggests that people formed continuous risk beliefs within the high-risk areas, consistent with the second part of Hypothesis 2. Despite the existence of information discontinuities, it is worth mentioning that there are no price discontinuities across the boundaries, which supports the first part of Hypothesis 2. The price discounts along the distance to the boundary gradually bounced back three months later, as shown in Figure 4(c) (July to December 2016) and Figure 4(d) (January to August 2017).

Next, we apply the same framework to check the other two boundaries, as shown in Figures A1 and A2 in the online appendix. The results show that there are no price discontinuities across these two boundaries; however, we do not observe any price discount pattern toward the high-risk areas. It seems that the information effect only exists around the boundary between the high- and moderate-risk areas, which is consistent with our previous findings that housing prices only dropped in the high-risk area. In the regression-based analysis, we only focus on the sample around the boundaries between the high- and moderate-risk areas.

The column (4) in Table 7 shows that the effects on housing prices in the high-risk areas, $Area^4$, $Area^5$, and $Area^6$, are all negative relative to the baseline, and the magnitude becomes larger as apartments are located closer to the center of a high-risk area, which is consistent with Hypothesis 2. Compared with the baseline ($Area^1$), prices in the center of the high-risk area ($Area^6$) dropped by 12.1%, which is much larger than the average effect across the high-risk area, of 3.33%, reported in Table 3. In addition, this temporary effect in the center of the high-risk area lasted until the end of 2016 ($Post^2$), with housing prices 5.75% (significant at only 10%) lower than the baseline.

Now looking at whether the risk beliefs differ across the boundary due to the discontinuity of information, the results show that prices in the first three months in $Area^4$ (high-risk area) and $Area^3$ (moderate-risk area) dropped by only 2.54% (significant at only 10%) and 1.63% (insignificant), respectively. This suggests that the market was slightly disturbed by the information discontinuity for a very short period, but this noise disappeared in the following periods, $Post^2$ and $Post^3$. Thus, the evidence demonstrates that, although the information is discrete, people were able to produce a continuous risk measure quickly.

To further study whether the findings vary depending on the different earthquake-resistant features of the apartments, we next consider the same model as in equation (2) but divide the sample into three sub-groups, by type of apartment, housing age, and year built. We summarize the results here but put all the detailed results in the online appendix.[16]

We find that apartments with different qualities did see heterogeneous effects immediately after the disclosure of the risk map, and these effects then decayed at different speeds. For those apartments with the least earthquake resistance, such as older apartments without elevators, the immediate price drops were relative larger, and the speeds with which the prices returned to normal were very slow. For instance, prices for apartments without elevators dropped by 29.6% in the first three months, which is the largest effect in this study. In addition, prices for apartments with elevators and for studios also dropped, by 6.34% and 16.2%, respectively. Although new apartments have better earthquake-resistant features, individuals did change their risk beliefs about those safer apartments in the area with the highest risk. Then three months later, there is no significant effect for apartments with elevators, which indicates that individuals updated their subjective risk beliefs back to the original levels quickly. However, for the apartments without elevators, price differentials continued until August 2017, with a price drop of 14.5% remaining between January and August 2017. The results indicate that individuals can update their risk beliefs based on both the locations and the different qualities of houses.

6.3 Testing for Parallel Trend Assumption

The validity of the difference-in-differences method is built on the parallel price paths before the information disclosure across risk areas. Importantly, unobserved heterogeneity in demographics or risk perceptions among risk areas could potentially fail the parallel-trend assumption, thus threaten-

[16]In the online appendix, Figure A3 summarizes the information effect on housing prices in the central part of the high-risk areas ($Area^6$), relative to the control group ($Area^1$). All the regression results can be found in Tables A1, A2, and A3.

ing our identification strategy.[17] To examine whether the parallel-trend assumption holds in this context, we exploit the sample before hazard disclosure, starting from January 2014 to March 2016. We use the model in equation (3) by further including the interaction terms with four dummies that indicate different periods before the disclosure of the risk map: from January 2016 to the disclosure date ($Prior^0$), from July 2015 to December 2015 ($Prior^{-1}$), from January 2015 to June 2015 ($Prior^{-2}$), and from July 2014 to December 2014 ($Prior^{-3}$). The baseline period is from January 2014 to June 2014 ($Prior^{-4}$). The regression model is as follows:

$$\log(P_{ijt}) = \beta_0 + X_{ijt}\boldsymbol{\beta} + \sum_{s=L,M,H} \delta^s Risk_i^s + \sum_{s=L,M,H} \sum_{k=1}^{3} \gamma^{sk} Risk_i^s \times Post_t^k$$
$$+ \sum_{s=L,M,H} \sum_{k=-3}^{0} \gamma^{sk} Risk_i^s \times Prior_t^k + f_j + \theta_t + \lambda_j \times t + u_{ijt}. \tag{3}$$

Figure 5 shows the main estimates, $\hat{\gamma}^{sk}$, from equation (3). The insignificant coefficients for $k = -3, -2, -1$, and 0 in each figure show that there were no housing price differences across the different risk areas before the disclosure of the risk map.

7 Discussion and Conclusion

To sum up, we find that housing prices in the high-risk areas dropped significantly, by 3.33%, in the first three months following the disclosure of the liquefaction risk map, relative to those in the no-risk area, and there was no effect for the moderate- and low-risk areas. This information effect on housing prices was temporary, and it diminished quickly and became insignificant after three months. This effect also only showed up for the apartments lacking certain earthquake-resistant features, namely apartments without elevators, apartments more than 30 years old, and apartments built before 1999.

Around each boundary, we first find that individuals can form continuous risk beliefs even if they receive discrete information from the government. Second, within the high-risk areas, housing prices dropped more sharply for those apartments located closer to the center of the high-risk areas. Third, individuals updated their risk beliefs differently for apartments with different features indicating earthquake resistance. For apartments with the least earthquake resistance, the immediate price drops were larger, and

[17]We thank the editor for pointing out possible factors that might invalidate the parallel-trend assumption.

the housing prices returned to normal more slowly, relative to the most earthquake-resistant ones.

However, several alternative channels may also explain our findings on the transient discount of housing prices. First, the availability heuristic proposed by Tversky and Kahneman (1974), in which people tend to use information that comes to mind quickly and easily when making decisions, can roughly explain our findings. The pattern of news dissemination in Figure 2 is closely consistent with the price dynamics we observed in this study, which is in line with the prediction from the behavioral model with the availability heuristic. However, we also find that the effect remained in place for some apartments, which might suggest a caveat for the behavioral explanation.

Second, housing insurance can help individuals secure their properties in the long run. Although price discounts act as a self-insurance mechanism, through which individuals move to safety (Brookshire et al., 1985), individuals might switch to purchasing market insurance, since self-insurance and market insurance are substitutes (Ehrlich and Becker, 1972). Gallagher (2014) shows that the insurance take-up rate increased after floods but gradually declined to baseline over years. Therefore, this possible channel can be verified if we can observe the detailed insurance take-up rate during this period. However, it is beyond the scope of this paper and may serve as a promising avenue for future research.

Third, sorting by heterogeneous agents can also fit our findings. Using the change of housing prices across risk areas to capture the path of risk perception updating needs the assumption of homogeneous agents. However, the estimated coefficient from the hedonic approach may depart from the marginal willingness to pay when heterogeneous agents reside in the market (Tanaka and Zabel, 2018; Bakkensen, Ding and Ma, 2019). Allowing for heterogeneity in agents in the housing market, Kuminoff and Pope (2014) indicate that, when an exogenous shock to non-market goods or services occurs, agents would sort themselves along with characteristics of houses accordingly. In our context, liquefaction risk is the non-market good, and sorting driven by the heterogeneous risk beliefs would emerge in the form of migration across liquefaction risk areas. It then changes the composition of buyers and sellers in the high-risk area before and after the risk map disclosure. However, we do not have the information about the buyers and sellers in our sample, so this study cannot exclude the possibility that our findings are driven by agents with heterogeneous risk perceptions, especially over time.

Besides the alternative explanations, the results have three important policy implications for the government. First, the government does not need to worry about the information effect on housing prices in this efficient market because only the prices of apartments with the least earthquake resistance were affected for a long time. For the "safe" apartments, some small disturbances occurred in the very short term, but then housing prices returned quickly to their original levels. Second, the government could target the apartments with the least earthquake resistance when considering policies such as urban-renewal programs. Third, Ehrlich and Becker (1972) argue that individuals are more likely to use the market insurance against rare losses than self-insurance when both options are available; therefore, the government could introduce a policy related to housing insurance to help housing insurers to solve this issue of uncertain risk.

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Figures and Tables

Figure 1: Map of Soil Liquefaction Risk in the Taipei Metropolitan Area

This figure shows a map of the soil liquefaction risk in the Taipei metropolitan area. The red areas with plus signs are the high-risk areas; the yellow areas with diamonds represent the moderate-risk areas; the green areas with small dots are the low-risk areas. In the remaining light blue area with no markers there is no liquefaction risk. The dark blue shows rivers.

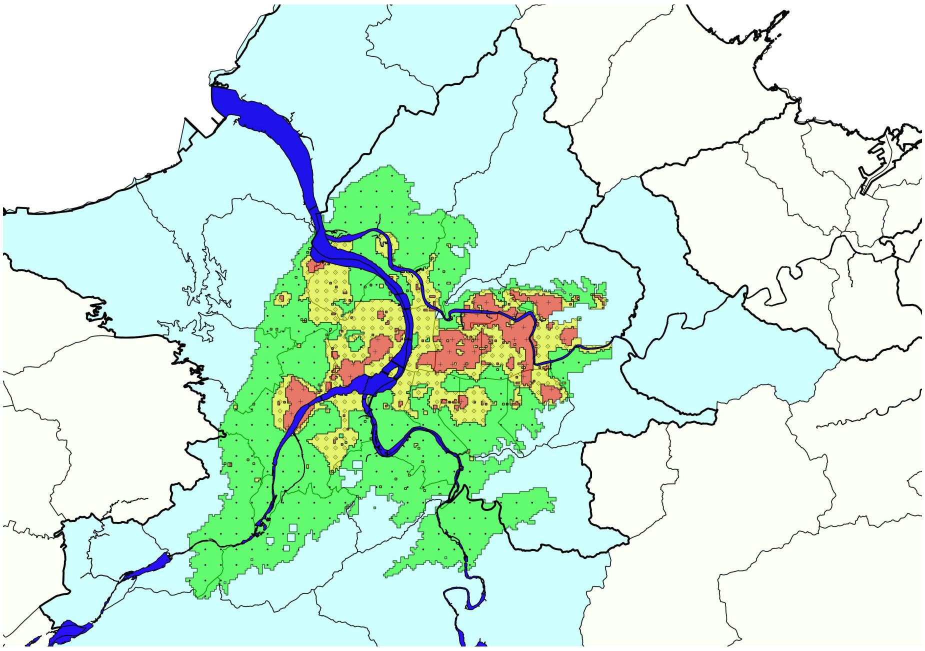


Figure 2: Number of News Articles

This figure shows the monthly data for the number of news articles with the keyword "soil liquefaction". The data were collected from an online news database (http://www.udndata.com/ndapp/Index) owned by the United Daily News Group, one of the mainstream news media channels in Taiwan.

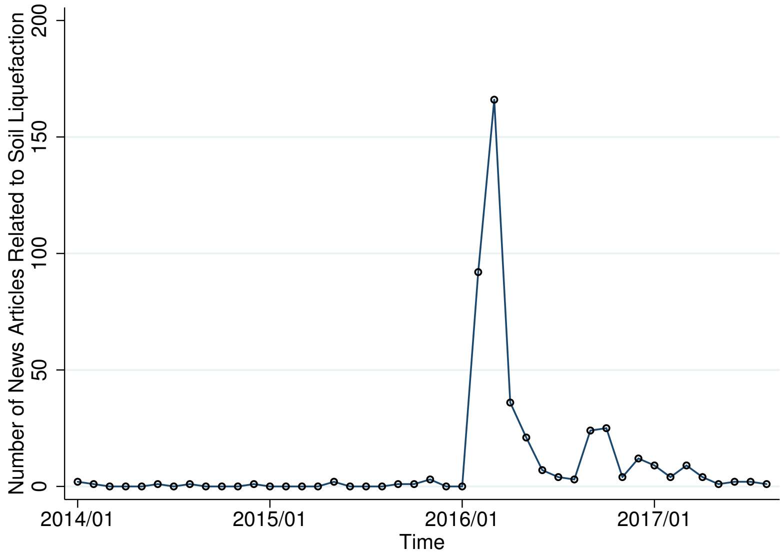


Figure 3: Identification Illustration Near the Boundary

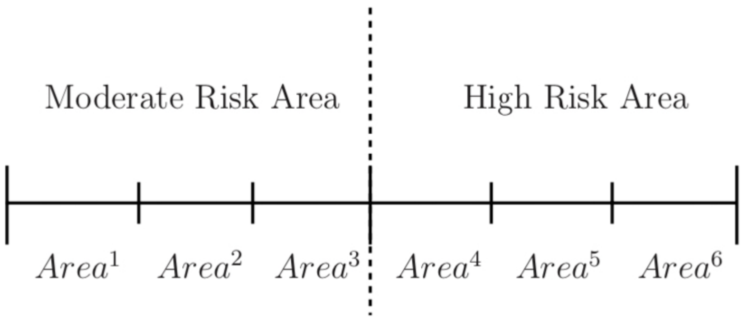
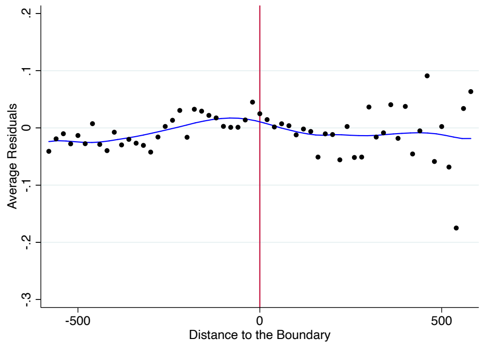
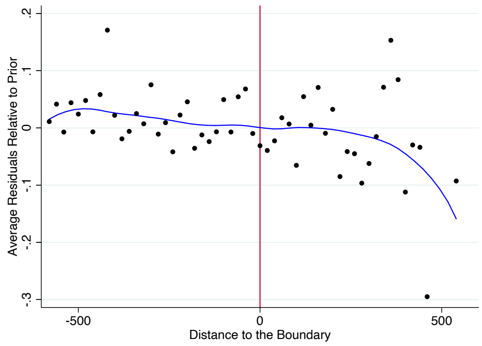


Figure 4: Residual around the Boundary between the High- and Moderate-Risk Areas

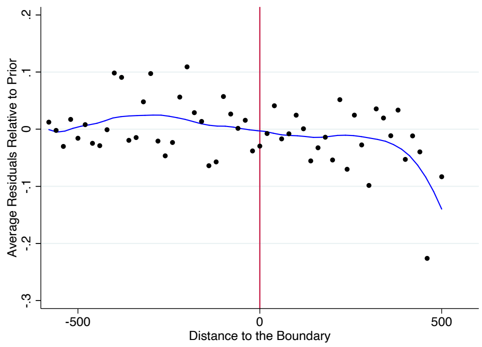
(a) $Prior$



(b) $Post^1 - Prior$



(c) $Post^2 - Prior$



(d) $Post^3 - Prior$

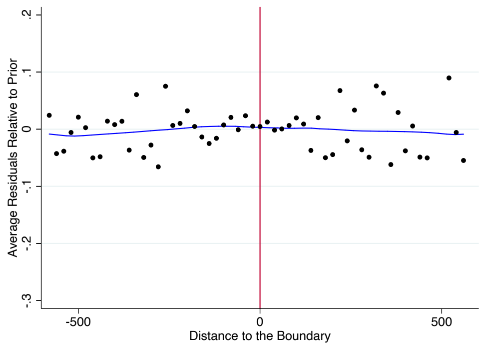
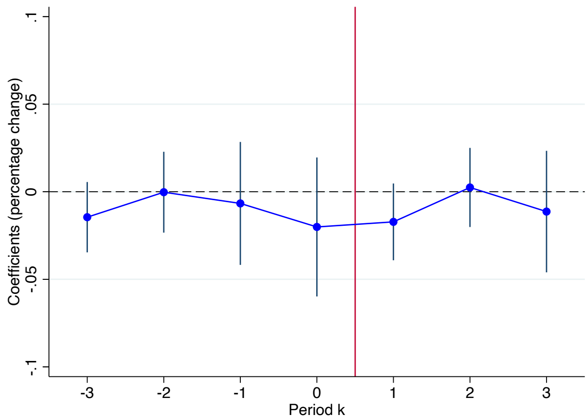
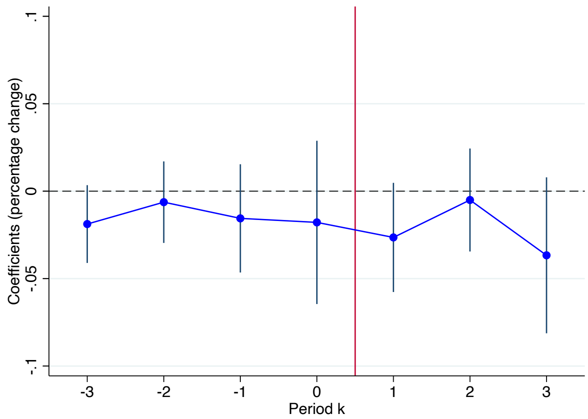


Figure 5: Testing for Parallel Assumption

(a) Low-Risk v.s. No-Risk (γ^{Lk})



(b) Moderate-Risk v.s. No-Risk (γ^{Mk})



(c) High-Risk v.s. No-Risk (γ^{Hk})

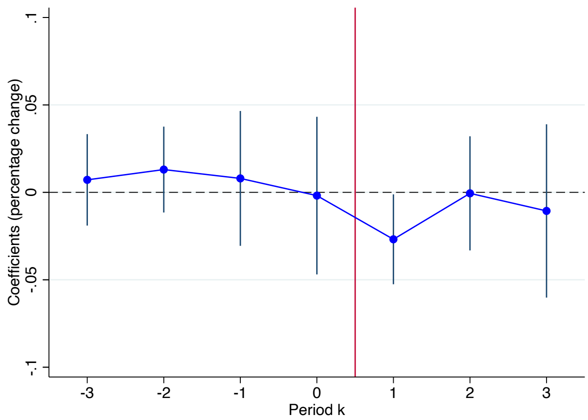


Table 1: Summary Statistics

This table shows summary statistics for types of apartments, housing characteristics, location information, and risk information for all the transactions conducted from January 2014 to August 2017 in the Taipei metropolitan area (both Taipei City and New Taipei City).

Variables (N=45,998)	Mean	Std. Dev.	Min	Max
Types of Apartments				
Apartments (with elevators)	0.578	0.494	0	1
Apartments (without elevators)	0.299	0.458	0	1
Studios	0.123	0.329	0	1
Housing characteristics				
Housing age (years)	21.19	12.83	0	49.92
Unit price (thousand NTD per square meter)	140.1	60.30	28.63	859.6
Total price (million NTD)	15.30	12.36	1.300	208
Size of floor area (square meters)	109.0	56.32	20.02	497.2
Floor on which unit is located	6.051	4.562	1	42
Number of floors for building	10.42	6.212	1	46
Located on first floor	0.0649	0.246	0	1
Reinforced concrete	0.914	0.280	0	1
Parking lot	0.297	0.457	0	1
With compartment	0.965	0.183	0	1
With guard or not	0.648	0.478	0	1
Number of bedrooms	2.448	1.050	0	5
Number of living rooms	1.581	0.605	0	2
Number of bathrooms	1.481	0.613	0	4
Location Information				
Residential zone	0.748	0.434	0	1
Commercial zone	0.194	0.395	0	1
Industrial zone	0.00115	0.0339	0	1
Distance to the nearest (meters)				
subway station	891.4	747.8	5.408	5,164
elementary or junior high school	398.7	224.7	6.957	2,148
senior high school	775.4	519.8	14.96	3,743
university	1,806	1,101	39.17	5,029
Risk information				
Located in				
high-risk area	0.124	0.329	0	1
moderate-risk area	0.223	0.417	0	1
low-risk area	0.549	0.498	0	1
no-risk area	0.104	0.305	0	1

Table 2: Summary Statistics by Risk Area

	Risk Potential							
	High		Moderate		Low		No Risk	
Variables	Before	After	Before	After	Before	After	Before	After
Housing characteristics								
Housing age (years)	22.67	23.01	21.33	20.84	20.91	21.62	19.44	20.04
	(13.27)	(14.67)	(13.25)	(14.60)	(12.26)	(12.77)	(11.19)	(11.95)
Unit price (thousand NTD per square meter)	177.1	167.1	151.7	149.8	134.3	128.2	118.9	115.9
	(61.97)	(53.65)	(66.93)	(64.28)	(56.18)	(54.17)	(51.99)	(49.96)
Total price (million NTD)	16.29	16.94	16.21	16.38	14.84	14.96	13.92	14.22
	(13.65)	(14.56)	(12.71)	(12.72)	(11.29)	(13.07)	(11.51)	(12.02)
Size of floor area (square meters)	91.03	99.66	107.5	110.9	109.7	114.2	114.8	119.6
	(58.92)	(65.36)	(57.26)	(57.99)	(52.75)	(56.20)	(55.78)	(58.60)
Floor on which unit is located	6.186	6.537	5.757	6.227	6.087	6.267	5.457	5.713
	(3.939)	(4.323)	(4.286)	(4.784)	(4.752)	(4.836)	(4.019)	(4.161)
Number of floors for building	10.30	11.09	9.838	10.84	10.56	10.72	9.628	9.954
	(4.887)	(5.653)	(5.735)	(6.634)	(6.614)	(6.502)	(5.358)	(5.953)
Located on the first floor	0.0460	0.0495	0.0689	0.0569	0.0667	0.0604	0.0935	0.0770
	(0.210)	(0.217)	(0.253)	(0.232)	(0.249)	(0.238)	(0.291)	(0.267)
Reinforced concrete	0.929	0.877	0.912	0.855	0.918	0.914	0.955	0.940
	(0.257)	(0.328)	(0.284)	(0.352)	(0.274)	(0.280)	(0.208)	(0.237)
Parking lot	0.206	0.253	0.278	0.318	0.293	0.317	0.372	0.391
	(0.404)	(0.435)	(0.448)	(0.466)	(0.455)	(0.465)	(0.483)	(0.488)
With compartment	0.945	0.934	0.956	0.951	0.975	0.969	0.980	0.974
	(0.228)	(0.248)	(0.206)	(0.216)	(0.156)	(0.174)	(0.140)	(0.160)
With guard or not	0.702	0.715	0.602	0.633	0.633	0.646	0.708	0.709
	(0.458)	(0.452)	(0.490)	(0.482)	(0.482)	(0.478)	(0.455)	(0.454)
Number of bedrooms	1.984	2.078	2.392	2.376	2.558	2.556	2.526	2.518
	(1.132)	(1.167)	(1.097)	(1.085)	(0.994)	(0.984)	(0.998)	(0.993)
Number of living rooms	1.297	1.378	1.523	1.550	1.637	1.662	1.648	1.653
	(0.663)	(0.661)	(0.639)	(0.627)	(0.572)	(0.563)	(0.559)	(0.557)
Number of bathrooms	1.303	1.352	1.465	1.462	1.513	1.516	1.529	1.539
	(0.609)	(0.640)	(0.629)	(0.647)	(0.596)	(0.602)	(0.599)	(0.616)

Note: The standard deviations for each group are shown in parentheses.

Table 2: (Continued) Summary Statistics by Risk Area

	Risk Potential							
	High		Moderate		Low		No Risk	
Variables	Before	After	Before	After	Before	After	Before	After
Type of Apartments								
Apartments (with elevators)	0.564	0.560	0.563	0.588	0.574	0.597	0.588	0.592
	(0.496)	(0.496)	(0.496)	(0.492)	(0.495)	(0.491)	(0.492)	(0.492)
Apartments (without elevators)	0.214	0.205	0.311	0.285	0.322	0.309	0.302	0.295
	(0.410)	(0.404)	(0.463)	(0.452)	(0.467)	(0.462)	(0.459)	(0.456)
Studios	0.222	0.234	0.127	0.127	0.105	0.0941	0.110	0.113
	(0.415)	(0.424)	(0.333)	(0.333)	(0.306)	(0.292)	(0.313)	(0.317)
Location Information								
Residential zone	0.427	0.438	0.713	0.672	0.831	0.829	0.799	0.780
	(0.495)	(0.496)	(0.452)	(0.469)	(0.374)	(0.377)	(0.401)	(0.414)
Commercial zone	0.518	0.504	0.232	0.284	0.125	0.124	0.0551	0.0674
	(0.500)	(0.500)	(0.422)	(0.451)	(0.330)	(0.329)	(0.228)	(0.251)
Industrial zone	0.000261	0	0.000738	0.00114	0.00130	0.00228	0.000619	0
	(0.0162)	(-)	(0.0272)	(0.0338)	(0.0360)	(0.0477)	(0.0249)	(-)
Distance to the nearest (meters)								
subway stations	448.7	465.5	617.5	627.2	996.9	1006.7	1426.4	1399.5
	(238.5)	(239.6)	(324.0)	(322.6)	(713.6)	(729.3)	(1281.7)	(1269.7)
elementary or junior high school	355.4	355.3	374.3	363.2	400.2	397.6	509.3	503.2
	(152.8)	(156.2)	(192.9)	(190.7)	(215.5)	(220.0)	(336.7)	(338.1)
senior high school	604.2	634.3	720.9	733.8	751.2	763.2	1185.1	1174.2
	(306.9)	(308.3)	(393.0)	(381.1)	(478.3)	(512.8)	(824.7)	(841.9)
university	1569.4	1615.2	2342.5	2255.4	1724.8	1756.0	1344.5	1366.8
	(940.2)	(932.3)	(1307.0)	(1313.2)	(1007.1)	(1033.9)	(784.1)	(810.8)

Note: The standard deviations for each group are shown in parentheses.

Table 3: Difference-in-Differences

Variables	(1) log(Price)	(2) log(Price)	(3) log(Price)	(4) log(Price)
Compared to no-risk area,				
$Risk^L \times Post^1$	-0.0368	-0.0177	-0.0111	-0.0106
	[0.0277]	[0.0165]	[0.0106]	[0.0107]
$Risk^M \times Post^1$	-0.0199	-0.00470	-0.00923	-0.0156
	[0.0320]	[0.0207]	[0.0126]	[0.0139]
$Risk^H \times Post^1$	-0.0683**	-0.0272	-0.0275***	-0.0333***
	[0.0271]	[0.0160]	[0.00872]	[0.00816]
Compared to no-risk area,				
$Risk^L \times Post^2$	-0.0212	0.00734	0.00947	0.00919
	[0.0191]	[0.0118]	[0.00897]	[0.00907]
$Risk^M \times Post^2$	0.0438	0.0332	0.0147	0.00601
	[0.0348]	[0.0283]	[0.0134]	[0.0138]
$Risk^H \times Post^2$	-0.0446	0.00267	0.00161	-0.00722
	[0.0283]	[0.0271]	[0.0171]	[0.0185]
Compared to no-risk area,				
$Risk^L \times Post^3$	-0.000445	-0.00292	-0.00403	-0.00444
	[0.0250]	[0.0211]	[0.0169]	[0.0184]
$Risk^M \times Post^3$	0.0229	-0.00330	-0.0126	-0.0254
	[0.0384]	[0.0282]	[0.0183]	[0.0207]
$Risk^H \times Post^3$	0.0225	-0.00422	-0.00717	-0.0176
	[0.0311]	[0.0302]	[0.0229]	[0.0308]
Observations	45,998	45,998	45,995	45,995
R-squared	0.087	0.646	0.788	0.788
Township fixed effects	No	Yes	Yes	Yes
Year-by-month fixed effects	No	Yes	Yes	Yes
Housing characteristics	No	No	Yes	Yes
Time trend × township	No	No	No	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Difference-in-Differences by Type of Apartment

	Type of Apartment		
	Apartments with Elevators	Apartments without Elevators	Studios
Variables	(1)	(2)	(3)
Compared to no-risk area,			
$Risk^L \times Post^1$	0.00215	-0.0199	-0.0322*
	[0.0167]	[0.0126]	[0.0174]
$Risk^M \times Post^1$	0.00247	-0.0335	-0.0243
	[0.0179]	[0.0204]	[0.0240]
$Risk^H \times Post^1$	-0.0116	-0.0597**	-0.0382*
	[0.0148]	[0.0276]	[0.0193]
Compared to no-risk area,			
$Risk^L \times Post^2$	0.0192	0.00819	0.0180
	[0.0138]	[0.00834]	[0.0181]
$Risk^M \times Post^2$	0.0194	0.00954	-0.000606
	[0.0186]	[0.0183]	[0.0222]
$Risk^H \times Post^2$	0.0122	-0.0234	-0.00639
	[0.0206]	[0.0319]	[0.0210]
Compared to no-risk area,			
$Risk^L \times Post^3$	0.00937	-0.00464	-0.0365
	[0.0200]	[0.0134]	[0.0397]
$Risk^M \times Post^3$	-0.0128	-0.0135	-0.0547
	[0.0201]	[0.0183]	[0.0397]
$Risk^H \times Post^3$	0.00176	-0.0251	-0.0561
	[0.0369]	[0.0240]	[0.0369]
Observations	26,566	13,754	5,675
R-squared	0.806	0.734	0.782
Township fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Time trend × township	Yes	Yes	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Difference-in-Differences by Housing Age

	Housing Age (Years Old)		
	0-15	15-30	30-50
Variables	(1)	(2)	(3)
Compared to no-risk area,			
$Risk^L \times Post^1$	-0.0104	0.0201	-0.0570**
	[0.0211]	[0.0184]	[0.0217]
$Risk^M \times Post^1$	-0.00993	0.0195	-0.0635**
	[0.0226]	[0.0182]	[0.0298]
$Risk^H \times Post^1$	-0.0189	-0.00587	-0.0771***
	[0.0182]	[0.0181]	[0.0250]
Compared to no-risk area,			
$Risk^L \times Post^2$	0.0139	0.00983	0.0113
	[0.0159]	[0.0109]	[0.0257]
$Risk^M \times Post^2$	0.00646	0.0187	0.00896
	[0.0258]	[0.0164]	[0.0295]
$Risk^H \times Post^2$	0.0114	0.0238*	-0.00255
	[0.0291]	[0.0136]	[0.0304]
Compared to no-risk area,			
$Risk^L \times Post^3$	0.0189	0.00238	-0.0224
	[0.0306]	[0.0130]	[0.0187]
$Risk^M \times Post^3$	-0.0167	-0.000655	-0.0200
	[0.0330]	[0.0160]	[0.0193]
$Risk^H \times Post^3$	0.0107	-0.00549	-0.0293
	[0.0509]	[0.0228]	[0.0183]
Observations	15,054	16,348	14,593
R-squared	0.811	0.797	0.753
Township fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Time trend × township	Yes	Yes	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Difference-in-Differences by Year Built

	Year Built		
	Before 1999	2000-2010	After 2011
Variables	(1)	(2)	(3)
Compared to no-risk area,			
$Risk^L \times Post^1$	-0.00819	-0.0191	0.0335
	[0.0125]	[0.0116]	[0.0305]
$Risk^M \times Post^1$	-0.0126	-0.0238	0.0194
	[0.0156]	[0.0181]	[0.0240]
$Risk^H \times Post^1$	-0.0316**	-0.0196	-0.0393
	[0.0125]	[0.0143]	[0.0262]
Compared to no-risk area,			
$Risk^L \times Post^2$	0.0113	0.00771	0.0398
	[0.00814]	[0.00988]	[0.0399]
$Risk^M \times Post^2$	0.0135	-0.0129	0.0144
	[0.0115]	[0.0221]	[0.0443]
$Risk^H \times Post^2$	-0.000141	0.00385	0.00995
	[0.0149]	[0.0164]	[0.0466]
Compared to no-risk area,			
$Risk^L \times Post^3$	-0.00893	0.0279	0.0184
	[0.0128]	[0.0192]	[0.0511]
$Risk^M \times Post^3$	-0.0157	0.0106	-0.0329
	[0.0154]	[0.0292]	[0.0432]
$Risk^H \times Post^3$	-0.0185	-0.00435	0.00134
	[0.0195]	[0.0336]	[0.0662]
Observations	30,577	9,684	5,734
R-squared	0.767	0.836	0.748
Township fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Time trend × township	Yes	Yes	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Difference-in-Differences around Boundary

Variables	(1) log(Price)	(2) log(Price)	(3) log(Price)	(4) log(Price)
Compared to $Area^1$				
$Area^2 \times Post^1$	-0.00704	-0.0228	-0.00542	-0.00856
	[0.0286]	[0.0231]	[0.0122]	[0.0131]
$Area^3 \times Post^1$	-0.0119	-0.0451	-0.0149	-0.0163
	[0.0340]	[0.0340]	[0.0181]	[0.0156]
$Area^4 \times Post^1$	-0.0509	-0.0360	-0.0213	-0.0254*
	[0.0339]	[0.0269]	[0.0134]	[0.0124]
$Area^5 \times Post^1$	-0.0930***	-0.0694**	-0.0363*	-0.0446**
	[0.0291]	[0.0297]	[0.0177]	[0.0208]
$Area^6 \times Post^1$	-0.0848	-0.160***	-0.112***	-0.121***
	[0.0634]	[0.0260]	[0.0182]	[0.0152]
Compared to $Area^1$				
$Area^2 \times Post^2$	-0.0115	0.0227	0.0468**	0.0424**
	[0.0744]	[0.0495]	[0.0190]	[0.0194]
$Area^3 \times Post^2$	-0.103	-0.0488	0.0105	0.00724
	[0.0691]	[0.0521]	[0.0137]	[0.0149]
$Area^4 \times Post^2$	-0.150*	-0.0470	0.00162	-0.00639
	[0.0738]	[0.0592]	[0.0190]	[0.0247]
$Area^5 \times Post^2$	-0.153**	-0.0613	-0.000837	-0.0142
	[0.0716]	[0.0625]	[0.0205]	[0.0318]
$Area^6 \times Post^2$	0.0332	0.0272	-0.0424**	-0.0575*
	[0.0799]	[0.0622]	[0.0166]	[0.0286]
Compared to $Area^1$				
$Area^2 \times Post^3$	-0.0833	-0.0136	0.00888	-0.00234
	[0.0660]	[0.0400]	[0.0154]	[0.0171]
$Area^3 \times Post^3$	-0.114	-0.0422	0.00535	-0.00394
	[0.0758]	[0.0432]	[0.0241]	[0.0244]
$Area^4 \times Post^3$	-0.0818	-0.0284	0.00565	-0.00446
	[0.0581]	[0.0485]	[0.0225]	[0.0336]
$Area^5 \times Post^3$	-0.0788	-0.0207	0.0155	-0.00374
	[0.0547]	[0.0408]	[0.0198]	[0.0326]
$Area^6 \times Post^3$	0.0705	0.0713	-0.0308	-0.0519
	[0.0618]	[0.0549]	[0.0239]	[0.0392]
Observations	15,960	15,960	15,958	15,958
R-squared	0.093	0.634	0.797	0.798
Township fixed effects	No	Yes	Yes	Yes
Year-by-month fixed effects	No	Yes	Yes	Yes
Housing characteristics	No	No	Yes	Yes
Time trend × township	No	No	No	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix

A Effects of the Earthquake and the Information Disclosure

To decompose the effect into the earthquake effect and the effect of risk map disclosure, we use the same regression model as in equation (1), and further include a dummy variable $Post^0$, indicating the period from February 6, 2016, to March 14, 2016, and the interaction between the period dummy and the dummy variables for risk areas. The results are shown in Table A4. Since the risk information is disclosed after March 14, 2016, we first create a dummy variable, $Risk$, for all the risk areas. The coefficient on $Risk \times Post^0$ in column (2) shows that, relative to the no-risk area, there is no significant price change in risky areas after the earthquake. If we split the risk areas into three risk levels, the coefficients in column (3) are also insignificant, which indicates that the earthquake caused no significant effect on housing prices during the period between the earthquake and the disclosure of the risk map.

B Validity of the Control Group

In this section, we argue the validity of our control group in this study. Under our difference-in-differences framework, the control group should not be affected by the disclosure of the risk map. However, people could substitute houses in the no-risk area for those in risky areas, which might inflate the estimated effect of risk information. If the substitution patterns exist, we will expect that number of transactions and housing prices in the no-risk area should both increase. Therefore, we focus on the sample in the no-risk area and examine the quantity and price changes in the following subsections.

B.1 Quantity Analysis

Due to the seasonality of the housing market, the number of transactions, shown in Figure A4, moves in a similar pattern each year. To examine the effect of risk information on the number of transactions in the no-risk area, we focus on the sample from 2014 to 2016 in the no-risk area and use the observations before the disclosure as the control group. The following model is estimated:

$$Q_{jmy} = \beta_0 + \beta_1 Post + \sum_k \tau^k \left(I_k \times Post\right) + f_j + \eta_m + \psi_y + \lambda_j \times t + u_{ijt},$$

where Q_{jmy} is the number of transactions in town j for month m in year y, and $Post$ is a dummy variable that indicates the period after the disclosure (March 2016). I_k is the indicator that refers to the month after the disclosure. We also include the township fixed effects (f_j), month fixed effects (η_m), year fixed effects (ψ_y), and different time trends among different towns ($\lambda_j \times t$).

The results shown in Table A5 indicate that the quantity in the no-risk area does not change significantly after the disclosure of risk information, especially during the first three months following the disclosure. If we extend the period of interaction terms to the end of the year, Figure A5 displays the quantity patterns between treatment and control groups. To sum up, we do not observe any significant quantity increase in the no-risk area after the disclosure.

B.2 Price Analysis

Since there is no seasonality in housing prices, we can not follow the same framework in the previous quantity analysis. We first focus on the sample in the no-risk area from November 2015 to July 2016 (four months before and after March 2016), and then consider the following model:

$$\log(P_{ijt}) = \beta_0 + X_{ijt}\boldsymbol{\beta} + \sum_{k=2}^{40} D_{kt} + f_j + u_{ijt},$$

where D_{kt} is a set of dummy variables to indicate each week, and f_j is the township fixed effects. Instead of year-by-month fixed effects and all the time trends, we include a set of dummy variables for each week to capture the price pattern over this period. The results are shown in Figure A6. The 15th week refers to the timing of the earthquake, and the 20th week is the timing of the information disclosure. Overall, housing prices do not change significantly during this period.

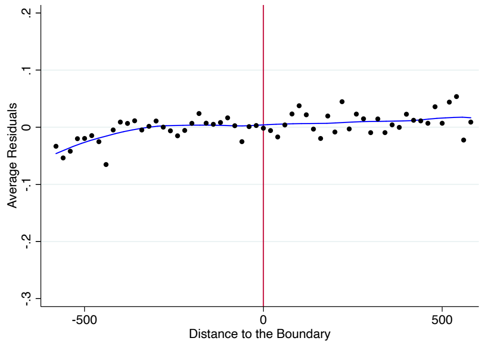
Furthermore, we use the same sample and apply the following regression to examine the effect of risk information on housing prices in the no-risk area:

$$\log(P_{ijt}) = \beta_0 + \beta_1 Post_t + X_{ijt}\boldsymbol{\beta} + f_j + \lambda_j \times t + u_{ijt},$$

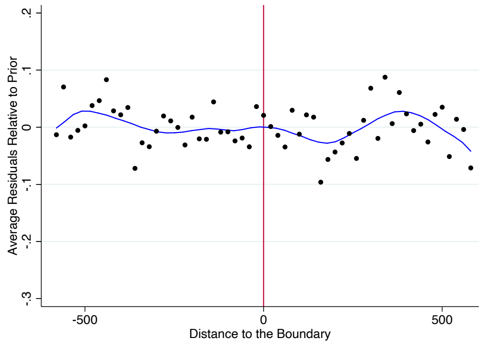
where $Post_t$ is a dummy variable that indicates the period after the disclosure, and the coefficient on $Post_t$ represents the overall price effect after

Figure A1: Residual around the Boundary between the Moderate- and Low-Risk Areas

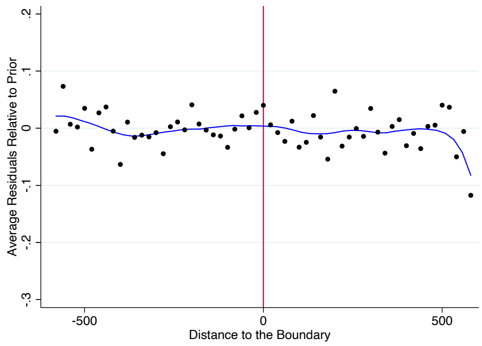
(a) *Prior*



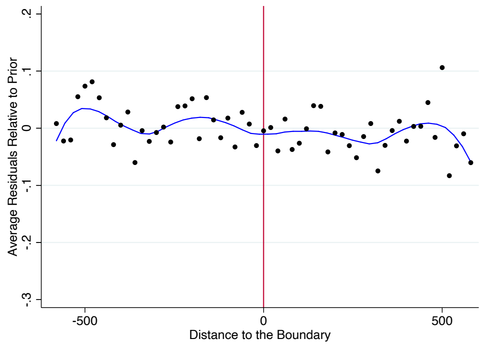
(b) $Post^1 - Prior$



(c) $Post^2 - Prior$



(d) $Post^3 - Prior$



the disclosure. We also include the township fixed effects (f_j), and different time trends among different towns ($\lambda_j \times t$). The results in Table A6 indicate that housing prices do not change significantly after the disclosure, which shows that housing prices in the no-risk area are not affected by the risk map.

To sum up, based on the price and quantity analyses, we do not find a significant change both in housing prices and transactions in the no-risk area after the disclosure of risk information; therefore, we may fairly conclude that the no-risk area is valid to serve as the control group in this study.

C Additional Figures and Tables

Figure A2: Residual around the Boundary between the Low- and No-Risk Areas

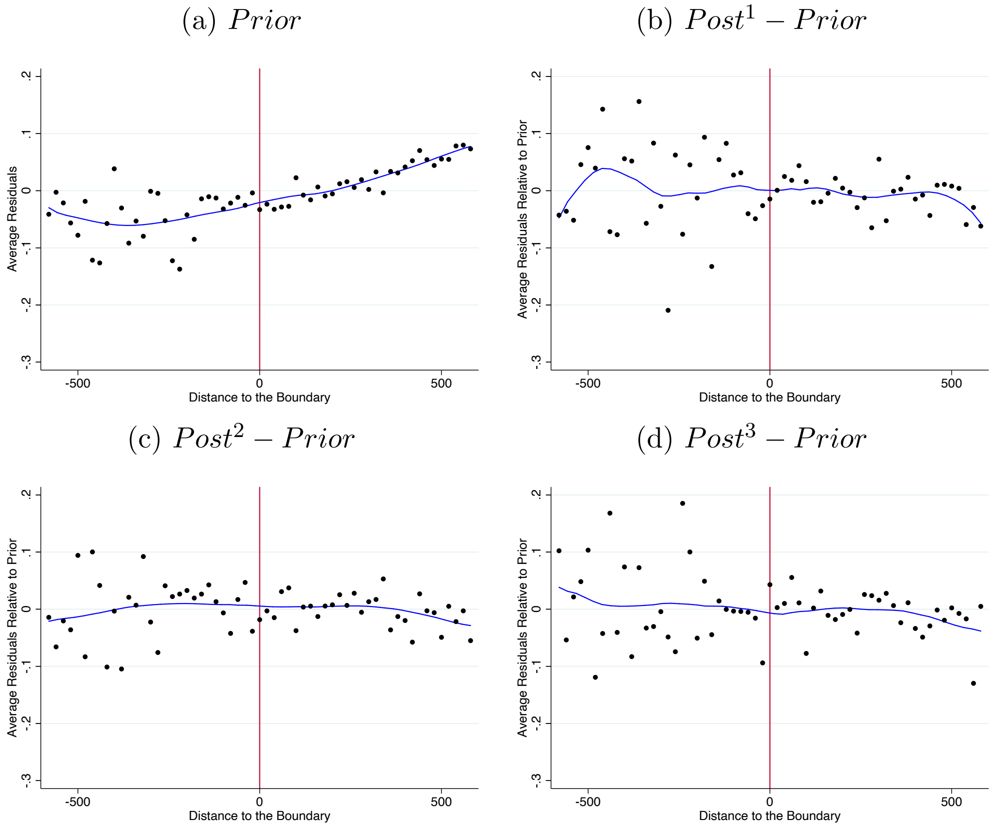
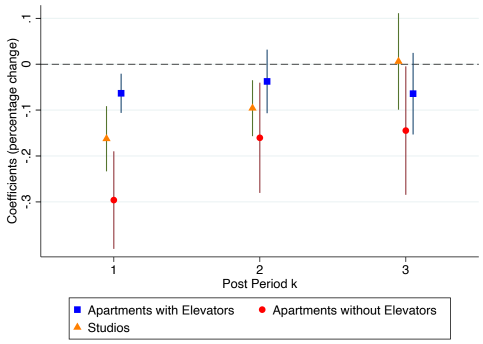
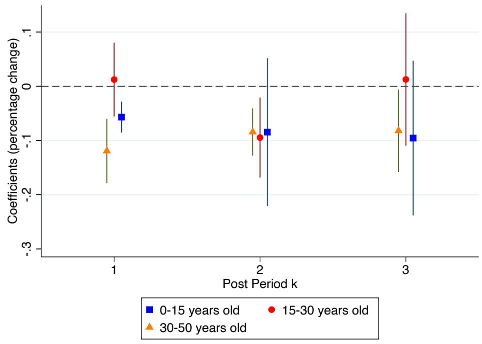


Figure A3: Heterogeneous Information Effect around the Boundary

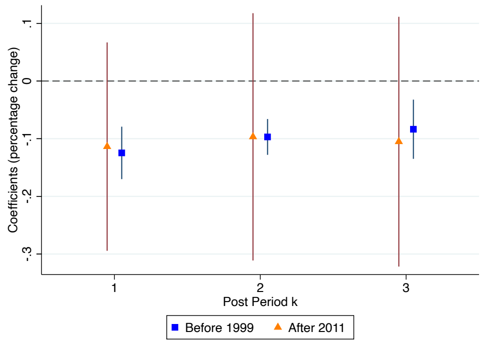
(a) By Type of Apartment ($\hat{\gamma}^{6k}$)



(b) By Housing Age ($\hat{\gamma}^{6k}$)



(c) By Year Built[a] ($\hat{\gamma}^{6k}$)



[a]Since there are no observations in the sample that have construction year within 2000-2010 and that are located in $Area^6$ during periods $Post^2$ and $Post^3$, we do not present the coefficients for this group in the figure.

Figure A4: Number of Housing Transactions in No-Risk Area

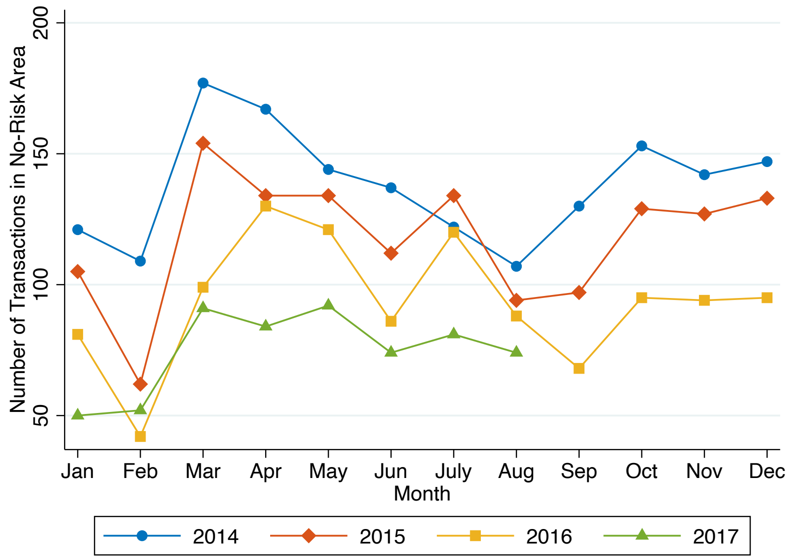


Figure A5: Estimates for Quantity Difference-in-Differences in No-Risk Area

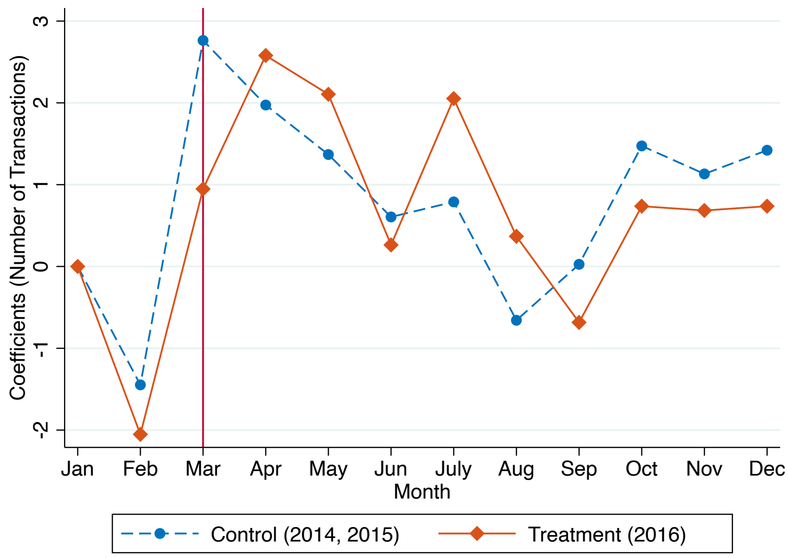


Figure A6: Housing Prices in No-Risk Area

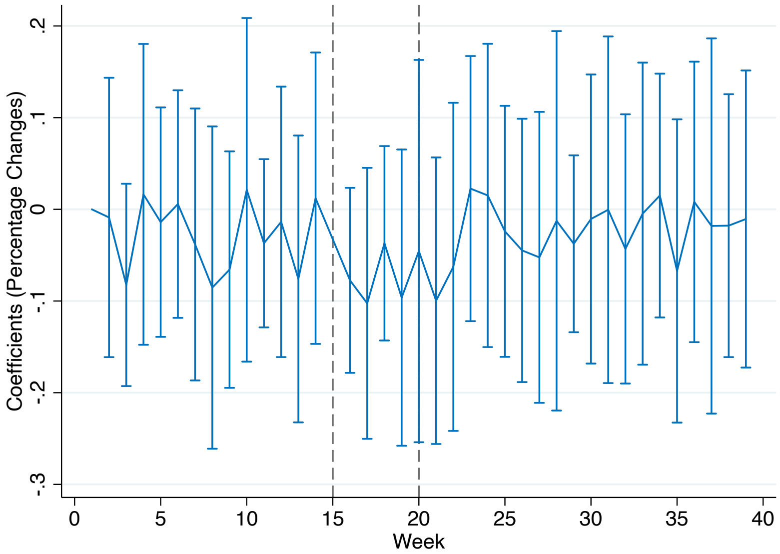


Table A1: Difference-in-Differences around Boundary by Type of Apartment

	Type of Apartment		
	Apartments with Elevators	Apartments without Elevators	Studios
Variables	(1)	(2)	(3)
Compared to $Area^1$			
$Area^2 \times Post^1$	0.0112	-0.0370	-0.0977**
	[0.0156]	[0.0245]	[0.0424]
$Area^3 \times Post^1$	-0.000294	-0.0326	-0.00271
	[0.0154]	[0.0265]	[0.0390]
$Area^4 \times Post^1$	-0.00992	-0.0579*	-0.0238
	[0.0158]	[0.0310]	[0.0254]
$Area^5 \times Post^1$	-0.0457*	-0.0511	-0.0636**
	[0.0251]	[0.0433]	[0.0290]
$Area^6 \times Post^1$	-0.0634***	-0.296***	-0.162***
	[0.0203]	[0.0506]	[0.0335]
Compared to $Area^1$			
$Area^2 \times Post^2$	0.0437*	0.0256	0.0177
	[0.0240]	[0.0376]	[0.0348]
$Area^3 \times Post^2$	0.00130	0.00523	0.0473
	[0.0194]	[0.0302]	[0.0386]
$Area^4 \times Post^2$	-0.00605	-0.0328	0.0269
	[0.0232]	[0.0460]	[0.0274]
$Area^5 \times Post^2$	-0.00806	-0.0466	0.00287
	[0.0350]	[0.0532]	[0.0253]
$Area^6 \times Post^2$	-0.0375	-0.160**	-0.0959***
	[0.0329]	[0.0572]	[0.0288]
Compared to $Area^1$			
$Area^2 \times Post^3$	0.00612	-0.0257	-0.00581
	[0.0198]	[0.0255]	[0.0597]
$Area^3 \times Post^3$	0.00326	-0.0293	0.00621
	[0.0250]	[0.0369]	[0.0401]
$Area^4 \times Post^3$	0.0111	-0.0321	-0.0276
	[0.0286]	[0.0466]	[0.0411]
$Area^5 \times Post^3$	0.0176	-0.0630	0.00213
	[0.0423]	[0.0390]	[0.0462]
$Area^6 \times Post^3$	-0.0642	-0.145**	0.00604
	[0.0422]	[0.0666]	[0.0496]
Observations	9,068	4,304	2,586
R-squared	0.798	0.780	0.742
Township fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Time trend × township	Yes	Yes	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Difference-in-Differences around Boundary by Housing Age

	Housing Age (Years Old)		
	0-15	15-30	30-50
Variables	(1)	(2)	(3)
Compared to $Area^1$			
$Area^2 \times Post^1$	-0.0460**	0.0310	-0.0301
	[0.0201]	[0.0304]	[0.0239]
$Area^3 \times Post^1$	-0.0469***	0.00792	-0.00804
	[0.0154]	[0.0230]	[0.0339]
$Area^4 \times Post^1$	-0.0288**	-0.00769	-0.0359
	[0.0135]	[0.0235]	[0.0261]
$Area^5 \times Post^1$	-0.0825*	-0.0354	-0.0125
	[0.0427]	[0.0282]	[0.0367]
$Area^6 \times Post^1$	-0.0569***	0.0124	-0.119***
	[0.0135]	[0.0321]	[0.0282]
Compared to $Area^1$			
$Area^2 \times Post^2$	0.00830	0.0381	0.0437
	[0.0439]	[0.0226]	[0.0303]
$Area^3 \times Post^2$	-0.0110	0.00341	0.00995
	[0.0298]	[0.0177]	[0.0185]
$Area^4 \times Post^2$	-0.000287	0.0266	-0.00928
	[0.0367]	[0.0231]	[0.0258]
$Area^5 \times Post^2$	-0.0217	-0.00460	-0.000461
	[0.0493]	[0.0292]	[0.0140]
$Area^6 \times Post^2$	-0.0846	-0.0946**	-0.0844***
	[0.0643]	[0.0348]	[0.0207]
Compared to $Area^1$			
$Area^2 \times Post^3$	-0.0242	0.0216	-0.0272
	[0.0291]	[0.0191]	[0.0177]
$Area^3 \times Post^3$	-0.0108	0.0163	-0.0420*
	[0.0344]	[0.0252]	[0.0224]
$Area^4 \times Post^3$	0.0158	-0.00227	-0.0573*
	[0.0382]	[0.0300]	[0.0305]
$Area^5 \times Post^3$	0.00812	0.0158	-0.0504*
	[0.0568]	[0.0229]	[0.0280]
$Area^6 \times Post^3$	-0.0955	0.0126	-0.0821**
	[0.0673]	[0.0577]	[0.0362]
Observations	5,334	4,910	5,714
R-squared	0.825	0.808	0.757
Township fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Time trend × township	Yes	Yes	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Difference-in-Differences around Boundary by Year Built

	Year Built		
	Before 1999	2000-2010	After 2011
Variables	(1)	(2)	(3)
Compared to $Area^1$			
$Area^2 \times Post^1$	0.00269	-0.0256	-0.00783
	[0.0157]	[0.0210]	[0.0170]
$Area^3 \times Post^1$	-0.00169	-0.0421**	-0.0266
	[0.0215]	[0.0193]	[0.0375]
$Area^4 \times Post^1$	-0.0266	-0.00641	-0.0786***
	[0.0157]	[0.0206]	[0.0247]
$Area^5 \times Post^1$	-0.0144	-0.118**	-0.0305
	[0.0184]	[0.0419]	[0.0284]
$Area^6 \times Post^1$	-0.125***	-0.0771***	-0.114
	[0.0216]	[0.0212]	[0.0829]
Compared to $Area^1$			
$Area^2 \times Post^2$	0.0439**	0.0298	0.0487
	[0.0170]	[0.0237]	[0.0547]
$Area^3 \times Post^2$	0.00812	0.0192	0.00129
	[0.0161]	[0.0277]	[0.0627]
$Area^4 \times Post^2$	-0.0111	0.0328**	-0.00315
	[0.0224]	[0.0143]	[0.0492]
$Area^5 \times Post^2$	-0.0146	-0.0331	0.0660*
	[0.0227]	[0.0346]	[0.0358]
$Area^6 \times Post^2$	-0.0970***		-0.0968
	[0.0148]		[0.0984]
Compared to $Area^1$			
$Area^2 \times Post^3$	-0.00707	-0.0265	0.00602
	[0.0164]	[0.0313]	[0.0455]
$Area^3 \times Post^3$	-0.0154	-0.0407	0.0314
	[0.0214]	[0.0385]	[0.0575]
$Area^4 \times Post^3$	-0.0303	-0.0484	0.0600
	[0.0302]	[0.0333]	[0.0418]
$Area^5 \times Post^3$	-0.0175	-0.0373	0.0582
	[0.0282]	[0.0410]	[0.0571]
$Area^6 \times Post^3$	-0.0836***		-0.105
	[0.0244]		[0.0994]
Observations	10,445	3,184	2,329
R-squared	0.771	0.846	0.842
Township fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Time trend × township	Yes	Yes	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Earthquake Effects

Variables	(1) log(Price)	(2) log(Price)	(3) log(Price)
Compared to no-risk area,			
$Risk \times Post^0$		0.0245	
		[0.0189]	
$Risk^L \times Post^0$			0.0207
			[0.0205]
$Risk^M \times Post^0$			0.0370
			[0.0247]
$Risk^H \times Post^0$			0.0179
			[0.0239]
Compared to no-risk area,			
$Risk^L \times Post^1$	-0.0106	-0.00997	-0.0100
	[0.0107]	[0.0106]	[0.0106]
$Risk^M \times Post^1$	-0.0156	-0.0149	-0.0144
	[0.0139]	[0.0139]	[0.0139]
$Risk^H \times Post^1$	-0.0333***	-0.0326***	-0.0327***
	[0.00816]	[0.00805]	[0.00830]
Compared to no-risk area,			
$Risk^L \times Post^2$	0.00919	0.00986	0.00981
	[0.00907]	[0.00888]	[0.00889]
$Risk^M \times Post^2$	0.00601	0.00678	0.00731
	[0.0138]	[0.0137]	[0.0137]
$Risk^H \times Post^2$	-0.00722	-0.00646	-0.00645
	[0.0185]	[0.0184]	[0.0184]
Compared to no-risk area,			
$Risk^L \times Post^3$	-0.00444	-0.00371	-0.00375
	[0.0184]	[0.0183]	[0.0183]
$Risk^M \times Post^3$	-0.0254	-0.0246	-0.0240
	[0.0207]	[0.0206]	[0.0206]
$Risk^H \times Post^3$	-0.0176	-0.0168	-0.0167
	[0.0308]	[0.0306]	[0.0305]
Observations	45,995	45,995	45,995
R-squared	0.788	0.788	0.788
Township fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Time trend x township	Yes	Yes	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Quantity Difference-in-Differences in No-Risk Area

Variables	(1) Quantity	(2) Quantity	(3) Quantity
Post	0.254	0.254	0.254
	[0.614]	[0.614]	[0.623]
March $\times$ *Post*	-1.768	-1.768	-1.768
	[1.095]	[1.095]	[1.111]
April $\times$ *Post*	0.654	0.654	0.654
	[1.032]	[1.032]	[1.046]
May $\times$ *Post*	0.785	0.785	0.785
	[0.758]	[0.758]	[0.769]
June $\times$ *Post*	-0.294	-0.294	-0.294
	[0.662]	[0.662]	[0.672]
Mean of the quantity		6.12	
Observations	684	684	684
R-squared	0.813	0.813	0.835
Township fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Time trend	No	Yes	Yes
Time trend $\times$ township	No	No	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Price Analysis in No-Risk Area

Variables	(1) log(Price)	(2) log(Price)	(3) log(Price)
Post	0.00888	0.00397	0.00242
	[0.0182]	[0.0271]	[0.0268]
Observations	935	935	935
R-squared	0.844	0.844	0.848
Township fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Time trend	No	Yes	Yes
Time trend $\times$ township	No	No	Yes

Note: Robust standard errors in brackets are clustered at the township level. *** p<0.01, ** p<0.05, * p<0.1.