Cleaner Water, Higher Housing Prices, and Severer Inequality: Evidence from China

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Abstract

Combining water monitoring station-level administrative data and transaction-level housing price data from Shanghai, China, we investigate the impact of China's 2015 water pollution reduction policy on water pollution and housing prices. We first find that the policy significantly improved water quality of treated monitoring stations by 0.352 standard deviations. Furthermore, we find that the policy led to a 3.5% increase in the housing prices of apartments located within a 500-meter distance to the nearest treated river, but the effect disappeared for apartments located more than 500 meters away from the nearest river. Finally, we find evidence that the water reduction policy might have exacerbated the wealth inequality in Shanghai.

Keywords: water pollution; housing prices; inequality

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1. Introduction

Water quality has essential impacts on individuals' health and welfare (Galiani, Gertler, and Schargrodsky, 2005; Zhang, 2012; Zhang and Xu, 2016; Lai, 2017; Alsan and Goldin, 2019; Aggeborn and Öhman, 2021). Therefore, governments worldwide have made great efforts to improve water quality. For example, since the Clean Water Act in 1972, the U.S. has invested more than $1 trillion to abate water pollution (Keiser and Shapiro, 2019a). The Chinese government has also taken several measures to address the deterioration of water quality accompanying its fast economic growth in recent decades. As early as 2006, China's central government set water pollution reduction targets for local governments (Shi and Xu, 2018). In April 2015, the Chinese central government issued the *Action Plan on Water Pollution Prevention and Control*, which is designed to improve surface water quality.[1]

However, compared with mature evidence on the impacts of policies to reduce air pollution, there is less research on whether governments' efforts to reduce water pollution have achieved their goals and what the potential consequences are due to reduced water pollution (Greenstone et al., 2021). In this paper, we investigate the impact of China's 2015 plan to reduce water pollution and its consequences in the housing market. We focus on Shanghai, one of the two largest cities (the other one is Beijing) in China. There are several reasons for us to focus on Shanghai. First, Shanghai is the most advanced city in China, comparable to other major cities in developed countries. For example, the gross domestic product (GDP) in Shanghai was approximately 403 billion dollars in 2015, similar to that of the greater Boston metro area (approximately 379 billion dollars). The results based on Shanghai are generalizable. Second, focusing on Shanghai can mitigate the risk of estimation bias due to unobservable socioeconomic factors that might affect policy implementation in different provinces/cities and outcome variables at the same time. Third, several rivers flow through the Shanghai metro area, which provides a good context for studying this question. Fourth, we can obtain access to detailed pollution data from water quality

[1] In the remaining text, we use "surface water" and "water" interchangeably.

monitoring stations and transaction-level housing price (defined as price per square meter in our paper) data from Shanghai, which facilitates our analysis.

Based on the plan issued by the Chinese central government, Shanghai released its own action plan on water pollution prevention and control in December 2015, named the *Shanghai Action Plan on Water Pollution Prevention and Control* (the Shanghai plan or the plan hereafter). The target of the plan was to eradicate type VI water in river sections by 2020.[2] For our paper, we obtained access to water quality information on river sections where monitoring stations are located in Shanghai. The plan generates cross-monitoring station variation in terms of policy influence. That is, the monitoring stations where the water was type VI before the plan are affected more by the plan than those where the water had type I to V quality. Combining the pre- and post-policy changes and the cross-monitoring station variation in the policy influence, we can exploit a difference-in-differences (DID) strategy for identification.

We first find that the plan significantly improved water quality. Compared with untreated monitoring stations, the plan reduced the water pollution of treated monitoring stations by 0.352 standard deviations.

We then investigate the consequences of reduced water pollution by estimating the responses of housing prices to the plan, following the literature exploiting the hedonic approach (e.g., Muehlenbachs, Spiller, and Timmins, 2015; Tang, Heintzelman, and Holsen, 2018; Keiser and Shapiro, 2019a; Baldauf, Garlappi, and Yannelis, 2020; Mei et al., 2021; Cassidy, Meeks, and Moore, 2023).[3] We find that the plan had a significant effect on housing prices for apartments located within 500 meters of the nearest treated river, but the plan did not have any significant effects for those located further away. Based on this finding, we restrict our analysis to apartments located within 500 meters of the nearest river. We find that the plan led to a 3.5% increase in housing prices, which is equivalent to 5.5% of the average increase (63.5%) of the second-hand housing prices

[2] Type I to type V water can be used for various purposes, and a larger number indicates worse water quality, while type VI water refers to water that has the worst quality and loses all functions. Further details regarding China's water quality classification can be found in Section 2.1.

[3] Due to the lack of individual health outcomes, we were not able to investigate the impact of reduced water pollution on health.

in Shanghai during our sample period.

We conduct several robustness tests to justify our findings. We find that the parallel trend assumption holds and that our results are not driven by confounding events or the changes in the frequency of monitoring station reports. We also conduct permutation tests to show that our results are not driven by random factors.

In addition, we analyze the channels through which the plan increased housing prices. Our findings reveal that the plan's implementation significantly increased the number of visits by potential buyers to the apartments near treated rivers, indicating a surge in demand for these properties. Moreover, the availability of these apartments diminished, particularly those with river-facing windows. Consequently, this imbalance in supply and demand led to an increase in housing prices.

Finally, we examine the impacts of the plan on inequality. We find two pieces of evidence. First, apartment complexes with higher housing prices before the policy experienced a more substantial price increase after the policy.[4] Second, subdistricts with favorable economic conditions and proximity to the city centers before the policy saw a larger housing price increase. These findings suggest that the plan may have exacerbated wealth inequality in Shanghai.

Our paper makes the following contributions. First, although governments of countries worldwide have made great efforts to reduce water pollution, there is no consensus on whether these policies have achieved their goals. For example, Keiser and Shapiro (2019a) used a comprehensive dataset to study the impact of the 1972 U.S. Clean Water Act and found a substantial drop in water pollution concentrations after the implementation of this act. Keiser and Shapiro (2019b) summarized the existing research and concluded that water pollution has decreased in the U.S. since the implementation of different pollution reduction policies. However, Greenstone and Hanna (2014) found that water regulations had no measurable benefits in India, which

[4] Apartment complexes (known as *xiaoqv* in Chinese) refer to enclosed areas comprising multiple apartment buildings, often surrounded by walls or fences. Each apartment complex resembles a self-contained neighborhood, featuring amenities like parks, playgrounds, and sometimes shopping centers or other communal facilities. With potentially hundreds of individual apartments within each complex, these areas are densely populated. Apartment complexes are widespread in urban areas across China. In the remaining text, we use "apartment complex" and "complex" interchangeably.

was attributed to the weak institutes in developing countries. Moreover, the literature on the effect of water pollution control policies before 2010 in China found unsatisfactory policy outcomes (Kahn, Li, and Zhao, 2015; Cai, Chen, and Gong, 2016; Chen et al., 2018). This can be attributed to the tendency of local governments to reduce pollution levels in areas that receive substantial scrutiny while simultaneously allowing pollution levels to rise in areas that are less closely monitored. In contrast, we find that China's 2015 water pollution reduction action plan effectively reduced water pollution in Shanghai. Although China is also a developing country overall, Shanghai is an advanced city more similar to cities in developed countries. In addition to adding more evidence about the effectiveness of pollution reduction policies, our results imply that within developing countries, heterogeneity in policy effects exists.

Second, we add to the literature using the hedonic approach to estimate the impact of environmental policies intended to improve water quality on housing prices. For example, Leggett and Bockstael (2000) used the hedonic technique to estimate the effect of water quality improvement along the Chesapeake Bay on property values, and they found a significantly positive effect. Keiser and Shapiro (2019a) estimated the effects of grants from the 1972 U.S. Clean Water Act on housing values and found that the benefits were smaller than the grants' costs. Christensen, Keiser, and Lade (2023) found that switching from the Detroit water system to the Flint River exposed residents to dangerous levels of lead, resulting in a $30 million decrease in housing value in Flint, Michigan. We estimate the effect of water quality on housing prices in Shanghai, which provides more evidence from a less developed country.

Third, although many studies have investigated the impact of environmental policies on outcome variables such as health, worker productivity, and migration, few studies have focused on the inequality implications of these policies, and the findings are mixed. For example, Constant (2019) constructed a theoretical model to show that a stricter environmental policy can allow the economy to escape from the inequality trap if the initial inequality in human capital is not too large. Jha, Mathews, and Muller (2019) studied the impact of the Clean Air Act in the U.S. on wage inequality and found that the benefits from this policy were disproportionately distributed to the rich. They concluded that stricter environmental regulation can exacerbate income inequality. Liu et al. (2023) found that region-specific environmental policies in China can enlarge wage inequality between skilled and unskilled workers. In contrast, Cassidy, Hill, and Ma (2022) found that the Resource Conservation and Recovery Act mainly affected the lower deciles of housing prices, which narrowed inequality. In our paper, our findings suggest that the plan may exacerbate wealth inequality in Shanghai. Our results not only provide complementary evidence for the current research but also have important policy implications. China has taken many measures to address the challenge of deteriorating environments and has made considerable achievements in pollution control (Greenstone et al., 2021). However, our results suggest that pollution reduction policies might worsen inequality. Given that China is among the countries experiencing increasing inequality (Xie and Zhou, 2014; Piketty, Yang, and Zucman, 2019), our results imply that policy-makers need to comprehensively evaluate current pollution reduction policies and take unintended impacts into account in future policy-making.

The remainder of this paper is divided into the following sections. Section 2 provides background knowledge. Section 3 introduces the data used in our paper. Section 4 investigates the impact of the 2015 Shanghai plan on water pollution. Then, Section 5 studies the impact of this plan on housing prices and its implications for inequality. Finally, Section 6 concludes the paper.

2. Background

2.1. Water Pollution in China

In China, the quality of water is regulated by the *Environmental Quality Standards for Surface Water (GB 3838-2002)*, which was issued by the State Environmental Protection Administration (predecessor of the Ministry of Ecology and Environment) and the General Administration of Quality Supervision, Inspection and Quarantine on April 28, 2002.[5] The document lays out five levels of standards: type I to type V (from

[5] A Chinese version of this file can be accessed at https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/shjbh/shjzlbz/200206/t20020601_66497.shtml.

the highest to lowest quality).[6] The standards are determined by water temperature, pH value, and 22 pollutants.[7] Water that satisfies these five standards is usually called type I to type V water. In addition, water with a quality lower than type V has lost all functions and cannot be used for any purpose. For simplicity, this type of water is called type VI water.

Since the 1980s, China has experienced unprecedented economic growth. However, during the same period, the natural environment deteriorated dramatically. According to the *China Environmental Status Bulletin* issued by the Ministry of Ecology and Environment in 2002, when the current water quality standards were first implemented, among all 741 monitoring stations, 29.1% met types I to III standards, 30% met types IV and V standards, and the remaining 40.9% had quality lower than type V.[8] Such severe water pollution leads to a large loss in social welfare. It is estimated that 190 million people in China fall ill and 60,000 people die from diseases caused by water pollution every year (Tao and Xin, 2014).

The Chinese government has made great efforts to combat water pollution. The State Council issued the *Action Plan on Water Pollution Prevention and Control* in April 2015, known as the most stringent and comprehensive water pollution control act in China to date (Karplus, Zhang, and Zhao, 2021). The target of the 2015 plan for areas in Yangtze River Delta (where our sample area Shanghai is located) and Pearl River Delta was to eradicate type VI water.[9] Under the guidance of the plan, local governments released their water pollution reduction plans.

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[6] The type I standard is applied to source water or water in national nature reserves. The type II standard is applied to surface water sources in primary protection zones, habitats for rare aquatic organisms, fish and shrimp spawning grounds, and feeding grounds for young fish. The type III standard is applied to surface water sources in secondary protection zones, fish and shrimp wintering grounds, fish migratory passages, and aquaculture areas. The type IV standard is applied to industrial water and recreational water that is not directly in contact with the human body. The type V standard is applied to agricultural water and landscape water areas.

[7] They include dissolved oxygen, permanganate index, chemical oxygen demand, five-day biochemical oxygen demand, ammonia nitrogen, total phosphorus, total nitrogen, copper, zinc, fluoride, selenium, arsenic, mercury, cadmium, chromium, lead, cyanide, volatile phenol, petroleum, anionic surfactant, sulfide, and fecal coliform colonies.

[8] See page 5 in the bulletin (in Chinese). The bulletin can be found in https://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/201605/P020160526552803668343.pdf.

[9] The detail of the plan (in Chinese) can be found at https://www.gov.cn/gongbao/content/2015/content_2853604.htm.

2.2. Water Pollution Action Plan in Shanghai

As a fast-growing city, Shanghai has a high population density and severe environmental problems. Shanghai is located in a coastal plain tidal river network area. In addition to the surrounding bodies of water, such as the Yangtze River Estuary, East China Sea, and Hangzhou Bay, the inland region is primarily composed of the Huangpu River, Suzhou Creek, and their major tributaries, forming an intricate network of small and medium-sized rivers. Due to the flat terrain, the water level drop in Shanghai is relatively small (Li, Jiang, and Zhu, 2010), and it is easy for sediment and various types of garbage to settle in the riverbed. With its rapid economic development, Shanghai has suffered severe water pollution. In 2015, among all monitoring stations in Shanghai, only 14.7% met types I to III standards, 28.9% met types IV and V standards, and the remaining 56.4% had a quality lower than the type V standard.[10]

Shanghai released its action plan on water pollution prevention and control in December 2015. Consistent with the plan issued by the State Council, the target of the Shanghai plan was to eradicate type VI water by 2020.[11] To achieve the target, the Shanghai plan set up phased tasks. In particular, the Shanghai plan states that the proportion of type VI water needed to be reduced to under 15% by 2017 and finally eradicated by 2020.

Once the Shanghai plan was released, the Shanghai government promptly implemented the measures outlined in the Shanghai plan (shown in Appendix Table A1), and it immediately had an enormous impact on industrial discharge and sewage treatment. Figure 1 shows the volume of sewage treatment (shown in Panel A) and the volume of chemical oxygen demand discharge in industrial wastewater (shown in Panel B) in Shanghai from 2010 to 2020. We observed a jump in sewage treatment volume and a steep decline in industrial wastewater discharge soon after the Shanghai plan was released. Compared with 2015, the volume of sewage treatment in 2016 increased by 25.2%, and the volume of chemical oxygen demand (COD) in industrial discharge

[10] Shanghai Environmental Status Bulletin in 2015. The bulletin (in Chinese) can be found at https://sthj.sh.gov.cn/assets/html/141845.pdf.
[11] The Shanghai plan (in Chinese) can be found at https://www.shanghai.gov.cn/nw32868/20200821/0001-32868_46193.html.

decreased by 36.6%.

With the implementation of various measures, the Shanghai Plan has made a difference in surface water quality. Figure 2 shows the surface water quality in Shanghai from 2014 to 2021. The lines on the map indicate rivers, and the shade of the line color indicates the pollution severity of this river. The darker the color, the more severe the pollution. As shown in Figure 2, since 2016, the line color has gradually become lighter, indicating a continuous reduction of pollution. At the end of 2020, type VI water was finally eradicated, meaning that the government successfully completed the phase tasks required by the plan.[12]

3. Data

In our paper, we use two sources of data: (1) surface water pollution data and (2) housing information at the transaction level. All data range from January 2014 to October 2021. All monetary values are deflated using 2014 as the base year.

3.1. Surface Water Pollution Data

Surface water pollution data are monthly and directly drawn from the 240 monitoring stations located along rivers within Shanghai. Therefore, each observation is at the monthly station level.[13] These data are released by the Shanghai Municipal Bureau of Ecology and Environment. Figure 3 shows the distribution of these monitoring stations.

The first variable we rely on is a general measurement of water quality. As we mentioned above, the water quality is divided into six types, type I to type VI. We simply assign numerical values 1, 2, 3, 4, 5, and 6 to types I, II, III, IV, V, and VI water, respectively. In this sense, higher numerical values indicate a greater degree of pollution severity. This variable is named *water pollution* in our paper.

[12] Shanghai Environmental Status Bulletin in 2020. The bulletin can be found at https://sthj.sh.gov.cn/cmsres/d8/d81b87b33c3342328911fd1b8fa15c22/850a653061787042a0f7ebfe344f8b5d.pdf.

[13] Before the policy, not all monitoring stations consistently reported pollution data on a monthly basis. A detailed discussion of this matter can be found in Section 4.4.

In addition, we apply the Probit-OLS method for assigning these values (Van Praag and Ferrer-i-Carbonell, 2008; Perez-Truglia, 2020).[14] We then normalize it to a variable with mean equal to 0 and standard deviation equal to 1. By construction, a higher value denotes greater degree of pollution severity. This variable is named *water pollution (POLS)* in our paper.

Table 1 presents the summary statistics for the aforementioned water pollution measurements. On average, *water pollution* is 4.341 and *water pollution (POLS)* is 0.

3.2. Housing Transaction Data

We collected housing transaction data from the Shanghai Agent of Lianjia Real Estate Brokerage Corporation. Lianjia, established in 2001, is a prominent real estate service company in China that covers a wide range of real estate transaction services, including second-hand, new, and rental properties. In 2019, Lianjia's market share in Shanghai reached 20%, making it the largest company in the Shanghai real estate market.[15] The dataset we collected covers all transactions involving second-hand properties that took place during our sample period. To validate the representativeness of Lianjia's second-hand property transaction data, we compared the per square meter prices of second-hand housing from Lianjia with the Shanghai Second-Hand Residential Sales Price Index published by the National Bureau of Statistics.[16] We also compared the second-hand housing transaction area from Lianjia with the corresponding statistics from the Shanghai Statistical Yearbook.[17] As shown in Appendix Figure A1, the transaction prices and areas of second-hand housing from Lianjia are consistent with the government's officially reported data, confirming the

[14] This method consists of assigning values to match the distribution of water pollution to a normal distribution. For example, if a fraction q satisfies the lowest category (type II water, as there is no type I water in our data, the lowest category is type II water), the Probit-OLS method assigns the lowest category a score of $E(z|z < q)$, where z is distributed standard normal. The resulting values for the water pollution are -2.286 (type II water), -1.102 (type III water), -0.186 (type IV water), 0.467 (type V water), and 1.359 (type VI water).

[15] The detailed information (in Chinese) can be found at https://www.thepaper.cn/newsDetail_forward_5138978.

[16] The Shanghai Second-Hand Residential Sales Price Index can be found at https://data.stats.gov.cn/easyquery.htm?cn=E0104.

[17] The Shanghai Statistical Yearbook 2022 (Table 18.7) can be found at https://tjj.sh.gov.cn/tjnj/nj22.htm?d1=2022tjnj/C1807.htm.

credibility of Lianjia's second-hand property transaction data.

The data include two types of information, one about apartments and the other about complexes where the apartments are located. The apartment information includes not only transaction prices, transaction time, listing prices, and listing time but also apartment characteristics, including housing area, directions that the windows face, the number of bedrooms, living rooms, kitchens, and bathrooms, as well as on which floor of the building the apartment is located and the total number of floors in the building. Complex-level variables include location (i.e., latitude and longitude), construction time, and number of apartments and buildings.

Since we investigate the impacts of the Shanghai plan on housing prices, we only retain apartments located no more than 500 meters away from rivers. This selection criterion will be elaborated upon in Section 5, where we demonstrate that apartments located beyond 500 meters from rivers remained unaffected by the plan. Finally, we have 120,482 transactions within our sample period.

Table 2 presents summary statistics of apartment and complex characteristics. The average housing price per square meter in our sample is RMB 42,903 (roughly USD 6,656 based on exchange rate in 2021), and the average housing area is 79.7 square meters. Approximately 96% of the apartments in the sample have a window facing south, and approximately 67% have a window facing the river. On average, buildings comprise 11 floors, with transacted apartments more commonly located on the highest (37%) and middle (35%) 1/3 of floors compared to the lowest 1/3 (28%) or basement (nearly 0%). The average numbers of bedrooms, living rooms, kitchens, and bathrooms are 2, 1, 1, and 1, respectively. Among the transacted properties, a substantial portion (97%) consists of regular residential apartments, with a small fraction (1%) being villas or designated for commercial and office use (less than 2%).

4. Impact of the Plan on Water Pollution

4.1. Empirical Strategy

As we discussed in Section 2, the target of the plan was to eradicate type VI water by 2020. The plan generated useful variation for our identification. That is, river sections classified as type VI in terms of water quality before policy implementation were targeted for extensive remediation by relevant authorities. Conversely, river sections falling within the water quality range of type I to type V before policy implementation remained unaffected by the plan. Combining cross-monitoring station variation in policy influence and the before-after policy changes, we can exploit a DID strategy to estimate the impact of the plan on water pollution.

We estimate the following equation:

$$y_{it} = \alpha_0 + \alpha_1 treat_i \times post_t + \gamma X_{it} + \delta_t + \mu_i + \varepsilon_{it} \qquad (1).$$

In Equation (1), y_{it} is a vector of variables measuring water pollution recorded by monitoring station i in year-month t, including *water pollution* and *water pollution (POLS)*. $treat_i$ is the major treatment variable. To construct $treat_i$, we calculate the average value of water pollution in 2014 for each monitoring station. $treat_i$ is equal to one if the average value is higher than five and zero otherwise. $post_t$ is a dummy variable that equals one for year-months starting from 2016 and zero otherwise. Mean value of $treat_i$ is 0.678 and the mean value of $post_t$ is 0.814 (see Table 1). The coefficient of interest is α_1, which measures the DID estimate of the water pollution reduction effect of the plan. δ_t represents year-month fixed effects that control for events affecting all stations within the same period. μ_i is the station fixed effects controlling for any station-level time-invariant factors. ε_{it} is the error term with a mean equal to zero. To address heteroskedasticity and the correlation between monitoring stations located along the same river, we calculate standard errors by clustering over rivers.[18]

As rivers are interconnected, pollutants in one river may affect the water quality of other rivers and monitoring stations. To account for this, we follow Duflo and Pande (2007) and include the interaction of the average water quality of other stations within 5,000 meters around station i in 2014 and $post_t$ in X_{it}.[19] However, some stations may not have any neighboring stations within a 5,000-meter radius. For such cases, we

[18] In our sample, there are 186 rivers.

[19] We incorporate all monitoring stations within a 5,000-meter radius, encompassing not only stations situated along the same river but also those from neighboring rivers.

assign a value of 0 to the average water quality variable and define a dummy variable that indicates whether there are any stations within 5,000 meters of station i. We incorporate the interaction of the dummy variable and $post_t$ in X_{it} as well. Summary statistics for these variables can be found in Table 1. Last, seasonal fluctuations in the water quality of rivers can occur (Ouyang et al., 2006; Duan et al., 2018), and we mitigate this by including the interaction of river dummies and month dummies in X_{it}.

4.2. Balancing Test

Since monitoring stations in the treatment group are not randomly selected, for example, they could be located in areas with more active economic activities, which might raise concerns about their comparability to those in the control group. We investigate this issue in this section.

We use three variables to measure the level of economic activity around the monitoring stations. The first variable is the nighttime light intensity (Henderson, Storeygard, and Weil, 2012). We calculate average nighttime light intensity within a 1,000-meter radius of the monitoring station in the year 2014, which is the radiance value in units of nano Watts per square cm per steradian (nanoWatt/cm^2/sr). We construct dummies to measure nightlight intensity, i.e., dummies for nightlight intensities between 0-5, 5-10, 10-15, 15-20, 20-25, 25-30, 30-35, 35-40, and above 40. The second variable is the logarithm form of the distance between the monitoring station and sites with high employment concentration (called employment centers hereafter), and the third variable is the logarithm distance between the monitoring station and the city's major residential areas. The shorter the distances, the more active the economic activities. The details of the sources of all variables in this section can be found in Appendix B.

Columns (1) and (2) in Panel A of Table 3 show the average value of the aforementioned variables for the treatment and control groups, respectively. Column (3) shows the difference. On average, monitoring stations in the treatment group have higher nighttime light intensities and are located closer to the employment centers and residential areas. The differences are all statistically significant. This is consistent with our expectation that monitoring stations in the treatment group are more likely to be located in areas with more active economic activities.

To investigate whether controlling for nighttime light intensity and the distances to the employment centers and residential areas can improve the comparability between the treatment group and control group, we first show the unconditional difference of another set of variables, including the number of restaurants, hotels, places for entertainment, convenience stores, shopping malls, various schools (including primary schools, middle schools and universities), and parks within a 1,000-meter radius of the monitoring station in 2014.[20] Column (3) in Panel B of Table 3 shows that the unconditional differences of these variables are all statistically significant. However, after we control for the variables in Panel A, the differences become insignificant. This provides evidence that controlling for the nighttime light intensity dummies and the distances to the employment centers and residential areas can improve the comparability of the treatment and control groups. Therefore, in our regression model, we also include these nighttime light intensity dummies and the distances to the employment centers and residential areas (each interacted with $post_t$).

4.3. Results

Table 4 shows the estimated impact of the plan on water pollution. In Columns (1)-(3), water pollution is assigned values from 1 to 6, with higher values indicating more severe pollution. In Columns (4)-(6), water pollution is coded using the Probit-OLS method, and then normalized to have mean 0 and standard deviation of 1. In Columns (1) and (4), we do not include any control variables other than fixed effects. In Columns (2) and (5), we control for the interaction of average water quality of other stations within 5,000 meters around the station i in 2014 and $post_t$, the interaction of a dummy variable indicating whether there are any stations within 5,000 meters of the station i and $post_t$, and the interaction of river dummies and month dummies. In Columns (3) and (6), we include all control variables.

[20] Since these variables have zero values, we do not use the logarithmic form but use the inverse hyperbolic sine of these variables, i.e., $\log\left(x + \sqrt{1 + x^2}\right)$.

The regression results in Table 4 underscore the robustness of our findings as we incorporate additional variables. The coefficients of the interaction of the treatment dummy and the post-policy dummy are all negative and statistically significant at the 1% level in all columns. Using our most preferred specification, Columns (3) and (6) show that the coefficient of the interaction term are -0.481 and -0.352 respectively. Compared with untreated monitoring stations, the plan reduces the water pollution ranking of treated monitoring stations by 0.481, or 0.352 standard deviations.[21]

In summary, the above results show that implementing the plan significantly reduced water pollution.

4.4. Robustness Checks

We conduct several robustness checks to justify our findings, which are detailed below.

Parallel Trend. One condition for the DID estimates to be valid is that the outcome variables of the treatment and control groups evolve parallelly should there be no policy. To investigate whether the condition is satisfied, we estimate the following function:

$$y_{it} = \alpha_0 + \sum_{m=-7}^{23} \alpha_m treat_i \times quarter_m + \gamma X_{it} + \delta_t + \mu_i + \varepsilon_{it} \quad (2).$$

Essentially, we replace the dummy $post_t$ with a set of year-quarter dummies $quarter_m$. m ranges from -7 to 23. The fourth quarter in 2015 is set as the benchmark ($m = 0$). Therefore, $m = -7$ indicates seven quarters before the fourth quarter in 2015 (i.e., the first quarter in 2014, which is the beginning of our sample period), and $m = 23$ indicates 23 quarters after the fourth quarter in 2015 (i.e., the third quarter in 2021, which is the end of our sample period).

We plot the estimated α_m in Figure 4, from which we can see that the coefficients before the policy are generally not significant, and their values range around zero. These

[21] We construct a dummy variable to denote whether the water is type VI water and use it as the outcome variable to estimate Equation (1). Results in Appendix Table A2 show that the plan also significantly reduced the probability for the water monitoring stations in the treatment group to have type VI water. In Appendix Table A2, we also estimate the impact of the plan on water pollution components; the results show that the plan reduced negative value of dissolved oxygen, chemical oxygen demand, biochemical oxygen demand after five days, permanganate index, total phosphorus, ammonia nitrogen, total nitrogen, cadmium, lead, cyanide, petroleum, and fecal coliform colony levels in the water. The effects on other components are not significant.

findings provide evidence that the parallel trend assumption holds. It also shows that mean reversion does not exist, otherwise the coefficients, particularly the one in the period right before the policy, are likely to be much larger than zero.

Confounding Events. There may have been other policies occurring at the same time that were correlated with the plan and affected the outcome variables as well. For example, if firms around untreated water monitoring stations (i.e., those that have better water quality than type VI) are affected by air pollution reduction policies, they might invest more in air pollution reduction, which could crowd out their investment in water pollution reduction, leading to a downward bias in our estimation.[22] To address this concern, we construct a measure of fine particulate matter ($PM_{2.5}$) intensity, which is the monthly average $PM_{2.5}$ level within the 1,000-meter neighborhood around water monitoring stations.[23] We add this variable to Equation (1), and the results are shown in Columns (1) and (4) of Table 5. We can see that the coefficients of our main variables of interest remain similar, suggesting that the possible policies to reduce air pollution do not affect our main results.

Some evidence suggests that continuous rainfall may result in poor water quality in rivers (Hanke et al., 2010; Passerat et al., 2011). This is because the pipes that discharge rainwater and sewage are often combined, making it challenging for sewage treatment plants to handle excess sewage during heavy rainfall. Consequently, plants may release rainwater mixed with pollutants into the river. To account for this issue, we incorporated the cumulative monthly precipitation within a 1,000-meter radius of station i in Equation (1), and the results are shown in Columns (2) and (5) of Table 5.[24] We can see that the coefficients of our main variables of interest remain similar.

Reporting Frequency Change. Prior to the policy implementation (before

[22] The air pollution control policies issued by the Chinese government during the same period, as mentioned by Karplus, Zhang, and Zhao (2021), "for example, the Action Plan on Air Pollution Prevention and Control, which was announced in September 2013 and focused on 10 key measures known as the 'Air Ten,' required early retirement of the most-polluting plants, accelerated substitution of natural gas for coal, and strengthened automobile tailpipe emissions and fuel quality standards. In 2018, the Air Ten was replaced by the Three-Year Action Plan for Winning the Blue Sky War, which set more aggressive targets for SO2, NOx, and fine particulate matter (PM2.5) by 2020".

[23] The detailed data source can be found in Appendix B.

[24] The detailed data source can be found in Appendix B.

December 2015), not all monitoring stations consistently reported pollution data on a monthly basis. Some stations reported data bi-monthly, quarterly, or semi-annually, only transitioning to monthly reporting after the policy came into effect. To investigate whether reporting frequency change could affect our estimation results, we reconstruct the sample to ensure the consistency of reporting frequency of each monitoring station before and after the policy change. For example, if a monitoring station reports data in January, March, May, July, September, and November before the policy, the data from February, April, June, August, October, and December after the policy is excluded. Results using this new sample are presented in Columns (3) and (6) of Table 5. They remained consistent with our main findings. This indicates that the change in reporting frequency does not alter the conclusions drawn in this paper.

Permutation Test. To address the concern that our results may be driven by random factors, we conduct a permutation test. In particular, we randomly assign the treatment status among the water monitoring stations, and then we re-estimate Equation (1). We repeat this process 2,000 times such that we have 2,000 coefficients of the $treat_i \times post_t$ term for each outcome variable. We plot the distribution of these coefficients in Figure 5. The dashed lines perpendicular to the x-axis represent the estimated coefficients from Columns (3) and (6) in Table 4. We can see that for either outcome variable, the dashed line lies at the far end of the distribution. Figure 5 also shows the empirical p values, all of which are smaller than 1%. These findings justify that our main findings are not driven by random factors.

5. Impact of the Plan on Housing Prices and its Implications for Inequality

5.1. Empirical Strategy

We then estimate the impact of the plan on housing prices. One difficulty is how to measure the extent to which each apartment was affected by the plan. We describe how we do it using an example (see Figure 6). To determine the treatment status of Apartment A, we first find a location (e.g., Location A) along each river that has the shortest distance from Apartment A using information on the latitude and longitude of the complex where the apartment is located.[25] We then match Apartment A to a river (say, River A), for which the distance between Apartment A and Location A on the river is the minimum. After matching apartments with rivers, we can calculate the distance from Location A to each monitoring station located on the same river; thus, we can identify the monitoring station (say, Station A) with the shortest distance to Location A on the same river. Therefore, the treatment status of Station A is assigned to Apartment A.

By doing so, we can exploit a DID strategy to estimate the impact of the plan on housing prices. The following equation is estimated:

$$\ln(Price_{act}) = \beta_0 + \beta_1 treat_c \times post_t + \eta W_{act} + \delta_t + \theta_c + \tau_{act} \qquad (3).$$

In Equation (3), $Price_{act}$ is the average housing price per square meter for apartment a located in complex c and transacted in year-month t. $treat_c$ is the treatment status for apartments located in complex c, which is defined above. $post_t$ is a dummy variable that equals one for years starting from 2016 and zero otherwise. β_1 is the coefficient of the main interest. δ_t and θ_c are year-month fixed effects and complex fixed effects, respectively. δ_t is used to control for any events occurring in the same year-month, and θ_c is used to control for any time-invariant factors within the same complex. τ_{act} is an error term with a mean equal to zero. As in Section 4.3, we calculate standard errors by clustering over rivers.

In Equation (3), we also include a vector of variables W_{act}, which include the characteristics of apartments transacted. They are housing area, a dummy for having a south-facing window, a dummy for having a river-facing window, and the number of building floors. In addition, we control for a set of fixed effects for whether the apartment is located on the highest 1/3, middle 1/3, or lowest 1/3 floors or in the basement, number of bedrooms, number of living rooms, number of kitchens, number of bathrooms, and different types of apartment usage. Finally, we include the same set of control variables of Equation (1) in W_{act}.

[25] We obtained latitude and longitude information only at the complex level, not for each individual apartment.

5.2. Results

In our paper, we restrict our analysis to apartments located within 500 meters of the nearest river. We will return to this issue later.

The estimation results of the impact of the plan on housing prices are shown in Table 6. In this table, the outcome variable is the logarithmic form of the housing price. In all columns, we control for year-month fixed effects and complex fixed effects. We can see from Column (1) that the coefficient of the interaction of the treatment dummy and post dummy is equal to 0.033 and significant at the 5% level. In Column (2), we add the logarithm of housing area. The coefficient of the interaction term is similar, equal to 0.032 and significant at the 5% level. In Column (3), we further add a dummy for having a south-facing window, a dummy for having a river-facing window, and the number of building floors (divided by 100). We can see that the coefficient of the interaction term is similar, equal to 0.033 and significant at the 5% level. In Column (4), we add more variables denoting housing characteristics, including a set of fixed effects for whether the apartment is located on the highest 1/3, middle 1/3, or lowest 1/3 floors or in the basement, number of bedrooms, number of living rooms, number of kitchens, number of bathrooms, and different types of apartment usage. The coefficient of the interaction term is 0.030 and significant at the 5% level. In Column (5), we add all control variables in Equation (3). The coefficient is equal to 0.035 and significant at the 1% level.

Using the specification in Column (5), which we favor the most, the plan increased the housing price of apartments near rivers by 3.5%. Considering Shanghai's average second-hand housing prices increased by 63.5% over our sample period (see Figure A1), the increment attributable to the plan is roughly 5.5% of the overall increase. Given that the average housing price is 35,470 yuan before the policy in the treatment group, our estimates suggest that the implementation of the plan increased the housing price by 1,241 yuan. The average housing area of apartments in treatment group is 79.5 m^2. This means that for a property in the treatment group, the implementation of the plan resulted in an appreciation of 98,660 yuan. In 2016, the average disposable income per capita in

Shanghai was 54,305 yuan.[26] Thus, property appreciation was nearly twice the average disposable income per capita.

As we mentioned above, we restrict our analysis to apartments located within 500 meters of the nearest river. We also estimate Equation (3) using apartments located within areas between 500-1,000 meters, 1,000-1,500 meters, 1,500-2,000 meters, and 2,000-2,500 meters around the nearest river. We plot the coefficients and 95% confidence intervals of the $treat_c \times post_t$ term in Appendix Figure A2. For convenience of comparison, we also plot the coefficient estimated using apartments located within 500 meters of the nearest river (i.e., that in Column (5) in Table 6). Only the coefficient using the closest apartments is significant. This means that the plan only affected the housing prices in nearby complexes. In the remaining analysis, we focus on this sample.

5.3. Robustness Checks

Parallel Trend. Essentially, we compare housing prices near the rivers affected by the plan and those near the rivers not affected by the plan. One condition is needed to ensure the validity of our identification strategy. That is, the evolution of housing prices between the treatment and control groups needs to be parallel should there be no policy change. To check whether this condition is satisfied, we estimate the following equation:

$$\ln(Price_{act}) = \beta_0 + \sum_{m=-7}^{23} \beta_m treat_c \times quarter_m + \eta W_{act} + \delta_t + \theta_c + \tau_{act} \quad (4).$$

In this equation, m is defined the same as in Equation (2). We plot the estimated coefficients β_m in Figure 7. From this figure, we can see that the estimates of coefficients are not significant before the plan, which provides evidence for the validity of the parallel trend assumption. This analysis also confirms the absence of mean reversion, as the coefficients, especially the one immediately before the policy implementation, are not significantly smaller than zero.

[26] Please refer to https://tjj.sh.gov.cn/ydsj71/20170122/0014-293195.html.

It also provides evidence that owners of apartments in the treatment group did not postpone listing the apartments in the market in anticipation of the policy implementation, otherwise we expect to observe significant effects right before the policy.

Confounding Events. In Section 4.4, we discuss the presence of concurrent air pollution reduction policies that may be correlated with the plan and could impact the outcome variables. The same issue also exists in the current context. To address this concern, we implement a similar robustness check as presented in Section 4.4. Specifically, we construct a measure of $PM_{2.5}$ intensity, which is the monthly average $PM_{2.5}$ level within the 1,000-meter neighborhood around water monitoring stations. We incorporate this variable into Equation (3), and the results are shown in Column (1) of Table 7. The coefficients of our main variables of interest remain similar, suggesting that the potential air pollution reduction policies do not significantly affect our main findings. In addition, for the same reason as in Section 4.4, continuous rainfall may result in poor water quality in rivers and have an impact on housing values. To account for this issue, we incorporated the cumulative monthly precipitation within a 1,000-meter radius of station i in Equation (3), and the results are shown in Column (2) of Table 7. The coefficients of our main variables of interest remain similar.

In addition to air pollution control policies, the opening of subway stations may be related to the plan. For example, the government may anticipate that environmental improvements will foster local economic development, thus build more subway stations nearby. Moreover, the opening of subway stations could have an impact on property prices. To address this concern, we include the number of subway stations within a 2-kilometer radius of the apartment at the time of the transaction in Equation (3). The result is presented in Column (3) of Table 7. The coefficients of our main variables of interest remain similar, suggesting that the opening of subway stations does not significantly affect our main findings.

Other Robustness Checks. In our primary setting, the treatment status of a specific apartment is determined by a single monitoring station. To assess the robustness of our findings regarding this treatment determination method, we utilize information from two monitoring stations positioned upstream and downstream of the nearest river to derive the treatment status for a particular apartment. We use the same example in Section 5.1 to illustrate how we use information from two monitoring stations. In the baseline regression, we utilize only the information from Station A to determine the treatment status for Apartment A (see Figure 6). In this robustness check, we use information from both Station A and Station B positioned upstream and downstream of Location A along River A to determine the treatment status.[27] We calculate the weighted average value of water pollution in 2014 for the two monitoring stations (inversely weighted by each monitoring station's distance to Location A). $treat_i$ is equal to one if the average value is higher than five and zero otherwise. The control variables related to the monitoring station are also constructed through the same method. The results are presented in Column (4) of Table 7. The coefficients of our main variables of interest remain similar.

Furthermore, we conduct additional regression analyses to assess the robustness of our findings. First, we exclude apartments constructed after the implementation of the plan, and the corresponding results are presented in Column (5) of Table 7. Subsequently, we focus on apartments located within 400 meters of the nearest river, and the outcomes are detailed in Column (6) of Table 7. We extend this analysis to include apartments within 600 meters of the nearest river, and these results can be found in Column (7) of Table 7. Additionally, we substitute the unit price with the total housing value as the outcome variable, and this result is displayed in Column (8) of Table 7. Notably, our main coefficients of interest remain consistent across these various specifications.

Permutation Test. To address the concern that our results may be driven by random factors, we conduct a permutation test. In particular, we randomly assign the treatment status among complexes, and then we re-estimate Equation (3). We repeat this process 2,000 times such that we have 2,000 coefficients of the $treat_c \times post_t$ term for each outcome variable. We plot the distribution of these coefficients in Figure 8. The dashed

[27] If there is only one monitoring station on the nearest river, then we use only the information of that station, which is the same as in the baseline regression.

line perpendicular to the x-axis represents the estimated coefficient from Table 6. The dashed line lies at the far end of the distribution. Figure 8 also shows the empirical p value, which is smaller than 1%. These findings confirm that our main findings are not driven by random factors.

5.4. Channels

There are several channels for the plan to affect housing prices. First, the improved water quality of rivers might increase demand for nearby apartments, which increases housing prices. Second, the effects of the supply side are not certain. On the one hand, after the water quality was improved, more apartments could be sold in the market since it was easier for the owners to sell their assets. On the other hand, the owners might have kept the apartments for their own use after the water quality of nearby rivers was improved, leading to a decrease in the supply of apartments in the housing market. Third, the characteristics of apartments in the market could be different, which could also affect housing prices. In this section, we investigate through which channels the plan affected housing prices.

Demand Side. We use the number of potential buyers' visits per day to each apartment during the period between the listing day and the sale day as a proxy for the demand for apartments. We estimate Equation (3) by using this new outcome variable. The results are shown in Table 8. Column (1) uses the whole sample, while Column (2) excludes apartments listed before the policy implementation and sold after. The coefficients of the interaction term are 0.068 in Column (1) and 0.094 in Column (2), both of which are statistically significant at the 5% level. The results reveal that there were more visits to apartments near monitoring stations affected by the policy compared with those near monitoring stations that were not affected. This suggests that the implementation of the plan increased demand for apartments.

Supply Side. We do not have the number of apartments available in the market but have only the number of transacted apartments, which is jointly determined by demand and supply. We therefore estimate the impact of the plan on the equilibrium quantity and derive the impact on the supply.

Table 9 shows the estimates of the impact of the plan on the number of transacted apartments. The outcome variable in Column (1) is the proportion of sold apartments to the total number of apartments in the complex each year, while the outcome variable in Column (2) is the number of sold apartments in each complex in each year. The coefficient of the interaction term is not significant in either column, suggesting that the implementation of the plan did not affect the number of transacted apartments.

Since we have already shown that the implementation of the plan increased housing prices and attracted greater demand, our finding that the equilibrium quantity did not change suggests that the supply of apartments near rivers in the housing market could decrease under the assumption that the demand curve is downward sloping and the supply curve is upward sloping.[28]

Housing Characteristics. Although we show above that the number of transacted apartments did not change because of the plan, it could be possible that the characteristics of the transacted apartments were different. We investigate this issue in this section. To do so, we estimate Equation (3) but replace housing prices with different housing characteristics. The results are shown in Table 10. The coefficients of the interaction term are not significant for the majority of housing characteristics. One of the significant coefficients is for the dummy for having a river-facing window, which is equal to -0.023 and significant at the 5% level. One possible explanation could be that after the water quality was improved, the owners of the apartments with windows facing the river were more willing to live in the apartments such that the supply of such apartments was reduced in the markets. The other significant coefficient is for the number of bedrooms. This means that apartments in the treatment group with more bedrooms were easily transacted after the policy.

In summary, we find that the implementation of the plan attracted greater demand for apartments, but the supply decreased. Moreover, the decrease in the supply is mainly

[28] An alternative interpretation of our findings could be that the supply of apartments listed in the second-hand housing market was inelastic, resulting in higher prices as demand increased, while the equilibrium quantity remained unchanged. However, this possibility is less likely to be true because the yearly number of listed apartments in the second-hand housing market has varied between 1,443 and 24,694 during our sample period, with a standard deviation of 8,830.

due to the decrease in apartments with windows facing the river.

5.5. Implications for Inequality

In this section, we discuss the impacts of the plan on wealth inequality. Housing property is the most important type of wealth for Chinese families. According to the China Household Wealth Survey Report (2018), housing property accounted for 66.35% of family wealth in China in 2017.[29] Therefore, any fluctuations in real estate prices could have a substantial impact on wealth distribution and wealth inequality among Chinese households. In this section, we investigate how the water pollution reduction policy affected wealth inequality in Shanghai.

First, we construct a dummy variable, denoted as $high_c$, which measures whether the complex's pre-policy housing prices were above the median. To create the variable $high_c$, we use properties transacted before the implementation of the plan and regress the total housing value of each apartment on the housing area and year-month fixed effects. We keep the residuals and calculate the mean of residuals for each complex. If the mean of the residuals for each complex is higher than the median, then $high_c = 1$; otherwise, $high_c = 0$. By using the residuals instead of the total housing value or the housing price, we can partial out the time effect and the effect of housing area and capture only the quality of each complex in $high_c$. Then, we estimate the following equation:

$$\ln(Price_{act}) = \beta_0 + \beta_1 treat_c \times post_t \times high_c + \beta_2 treat_c \times post_t + \beta_3 post_t \times high_c + \eta W_{act} + \delta_t + \theta_c + \tau_{act} \quad (5).$$

In Equation (5), all variables except $high_c$ are the same as in Equation (3). We use the same sample in Table 6 to estimate Equation (5), and the result is reported in Table 11. The results show that the price of apartments located in complexes with high pre-policy housing prices increased more after the plan.

Second, we use data from the 2010 population census of China to calculate the average building area per capita and the employment rate for each subdistrict in

[29] The Chinese version of the report can be found at https://www.gov.cn/xinwen/2018-12/28/content_5352858.htm.

Shanghai.[30] We use our property transaction data to calculate the proportion of treatment apartments to total apartments for each subdistrict in Shanghai. We show the relationship of these variables in Figure 9. Panel A in Figure 9 shows the relationship between the proportion of treatment apartments to total apartments and the average building area per capita, while Panel B shows the relationship between the proportion of treatment apartments to total apartments and the employment rate. As we can see, for subdistricts with larger average building areas per capita and higher employment rates, the proportion of policy-influenced apartments is higher. This means that in subdistricts with better economic conditions in 2010 (proxied by larger building areas and higher employment rates), there was a greater proportion of houses experiencing price increases after the policy was implemented. In addition, in Table 3, we show that the areas surrounding the monitoring stations of the treatment group exhibit more favorable economic conditions and are also in closer proximity to the employment centers and residential zones. This also means that areas with favorable economic conditions and in closer proximity to the city centers experienced greater increases in housing prices after the plan.

In summary, these findings suggest that the plan resulted in further widening of wealth inequality in Shanghai.

6. Conclusions

In this paper, we investigate the impact of China's 2015 water pollution reduction policy on water pollution and housing prices using data from Shanghai. We find that the implementation of the policy significantly reduced water pollution. Then, we estimate the impact of the policy on housing prices, and we find that the policy had a significantly positive impact on housing prices for apartments located within 500 meters of the river. Further analysis shows that the impact on housing prices occurred through increased demand and reduced supply of apartments after the policy. Finally,

[30] In urban areas of China, a prefecture-level city comprises three different levels of administrative divisions. The highest level is the district, which is a lower-level administrative division within a prefecture-level city, such as Huangpu District in Shanghai. One level below that is the subdistrict, for example, Waitan Subdistrict in Huangpu District, Shanghai. The lowest level is the complex.

we find that the impact was larger for apartments with higher prices before the policy, which implies that the water pollution reduction policy might have had an unintended consequence in increasing wealth inequality.

China has faced increasingly severe challenges from the deterioration of the environment during the process of its fast economic growth. The Chinese government has invested heavily in pollution reduction. Our paper provides evidence supporting the effectiveness of pollution reduction policies. However, our results also show that pollution reduction policies might have an unintended effect on increasing wealth inequality. This implies that policy-makers need to take this effect into account in the evaluation of current pollution reduction policies or the making of future policies.

In our paper, we find that a water pollution reduction policy was effective in reducing water pollution. This result is not consistent with that of Greenstone and Hanna (2014), who showed that a water pollution reduction policy was not effective using Indian data. The inconsistency may be because we focus on data from Shanghai, one of the most advanced cities in China and similar to cities in developed countries. Exploring whether the water pollution policy had different effects in less developed areas and the potential reasons requires broader data and further study.

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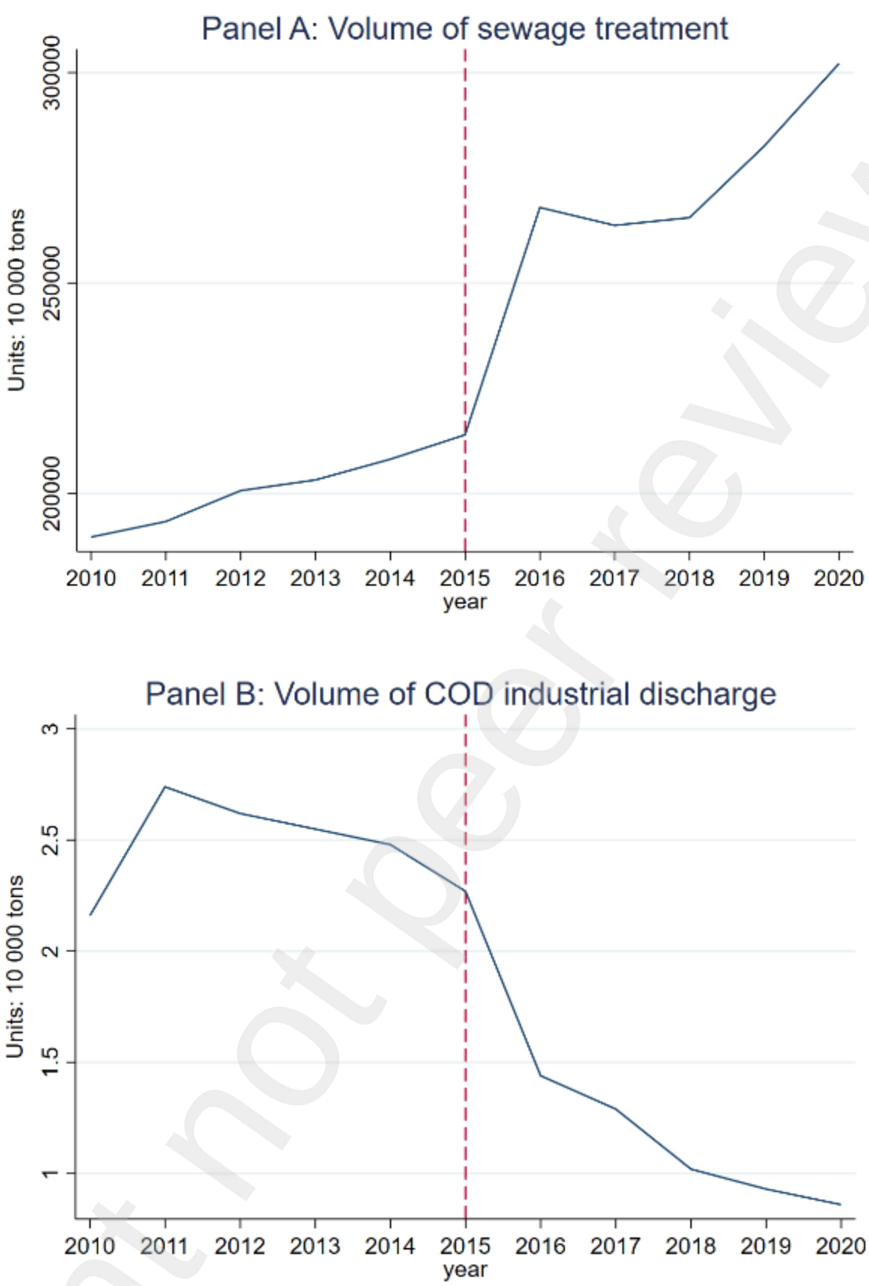
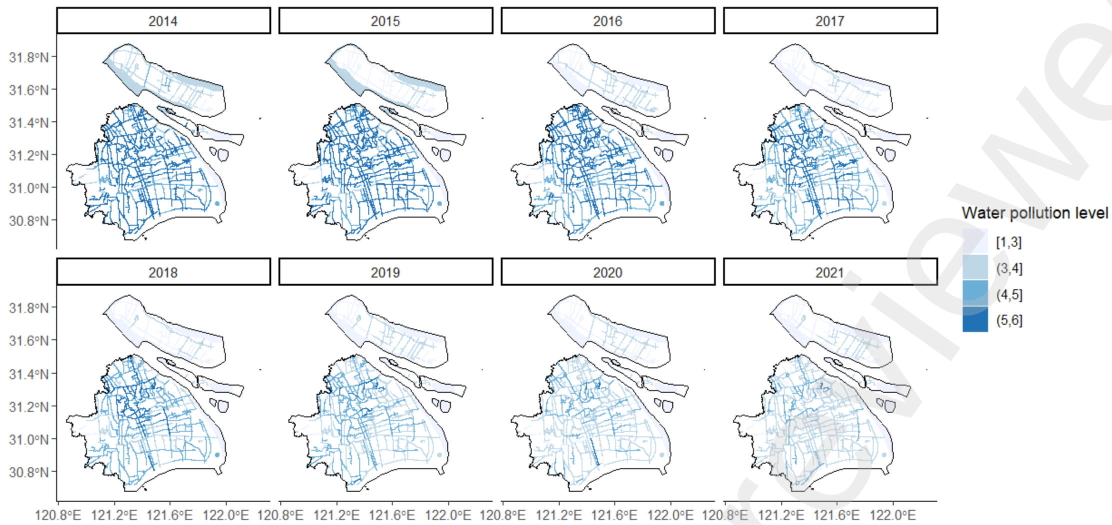
Figure 1. Volume of Sewage Treatment and COD Industrial Discharge in Shanghai



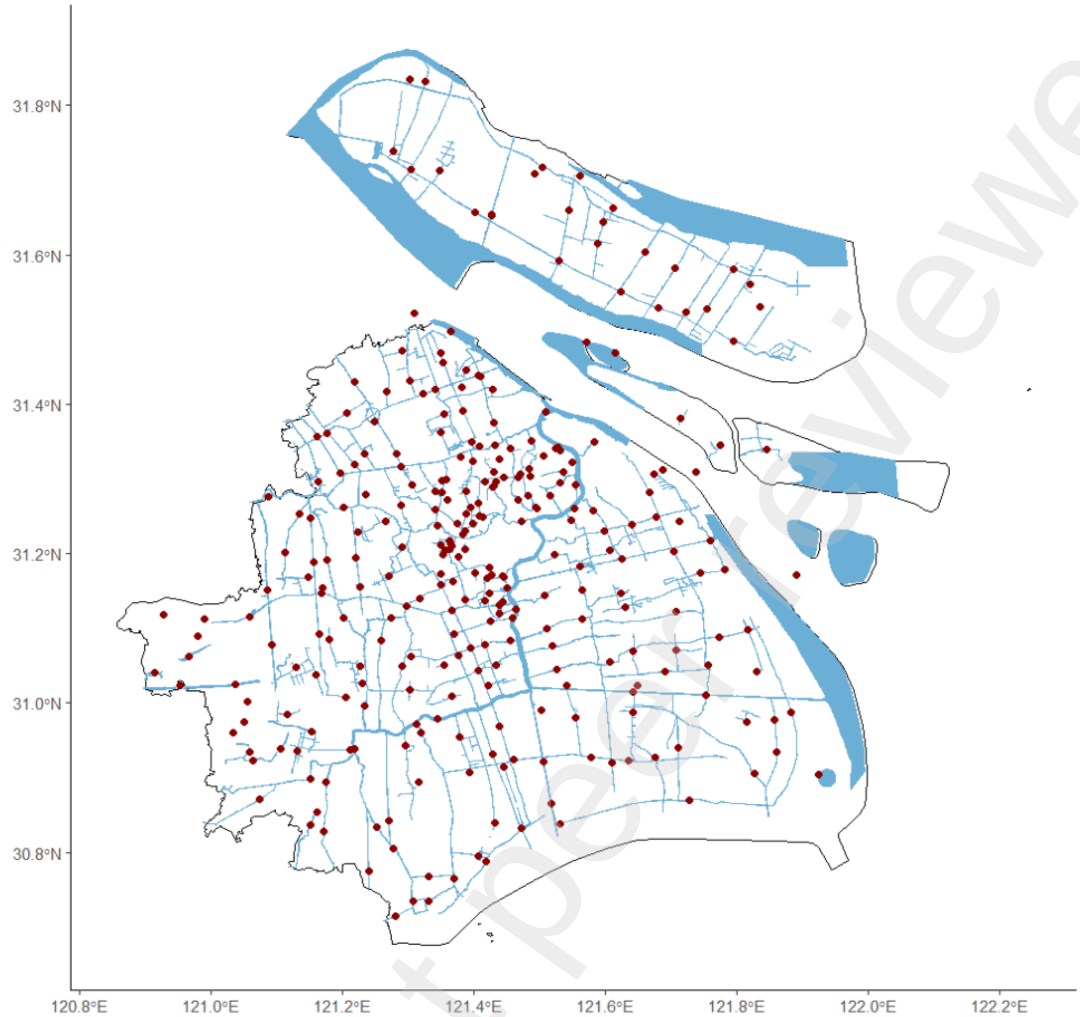
Note: This figure shows the volume of sewage treatment (Panel A) and the volume of chemical oxygen demand (COD) discharge in industrial wastewater (Panel B) in Shanghai from 2010 to 2020. The data source is the Shanghai Statistical Yearbook 2021.

Figure 2. Surface Water Quality in Shanghai from 2014 to 2021



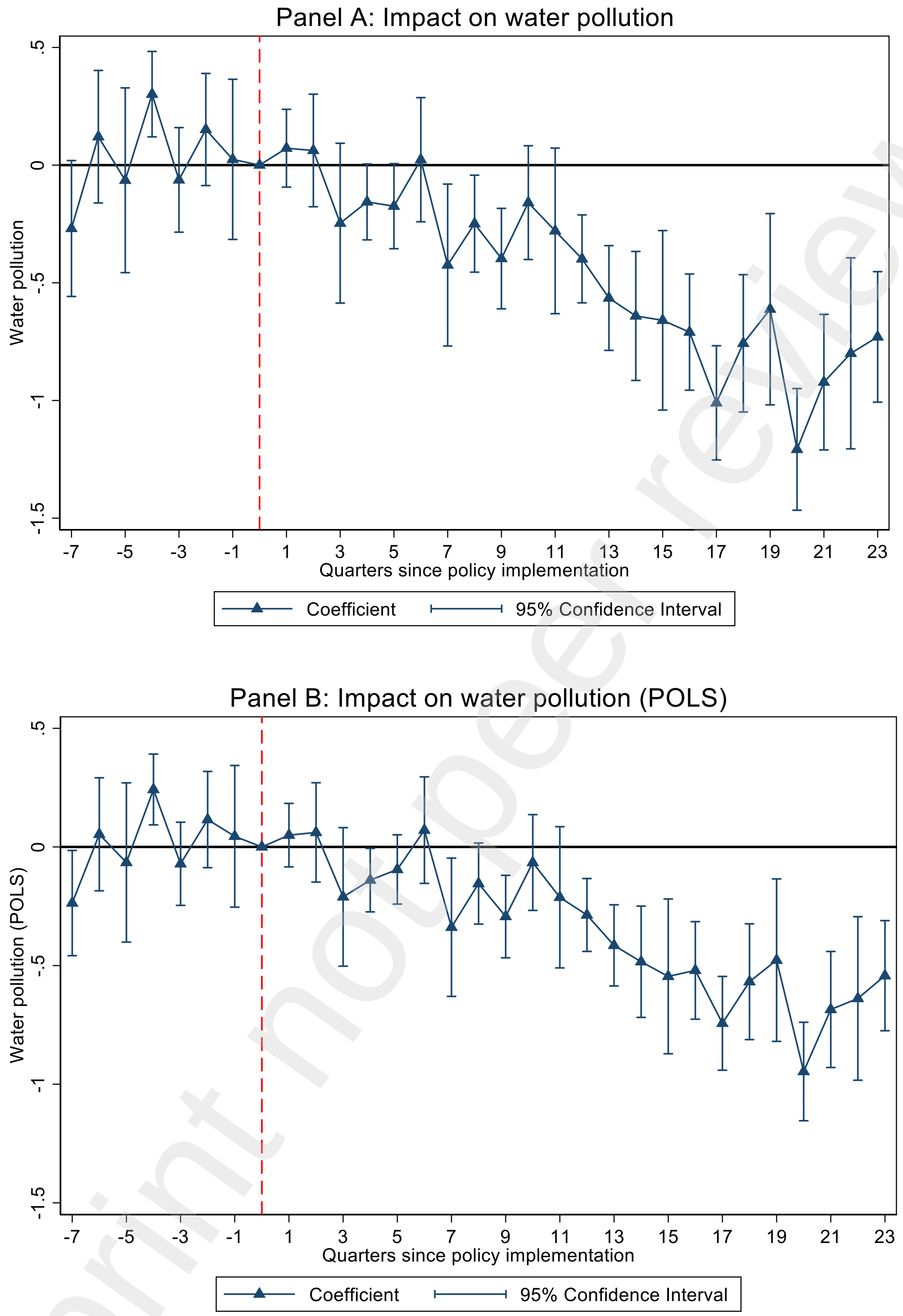
Note: This figure shows the surface water quality in Shanghai from 2014 to 2021. The lines on the map indicate river sections, and the shade of the line color indicates the pollution severity of this river section. The darker the color is, the more severe the pollution. The data source is the Shanghai Municipal Bureau of Ecological Environment.

Figure 3. Distribution of Water Monitoring Stations



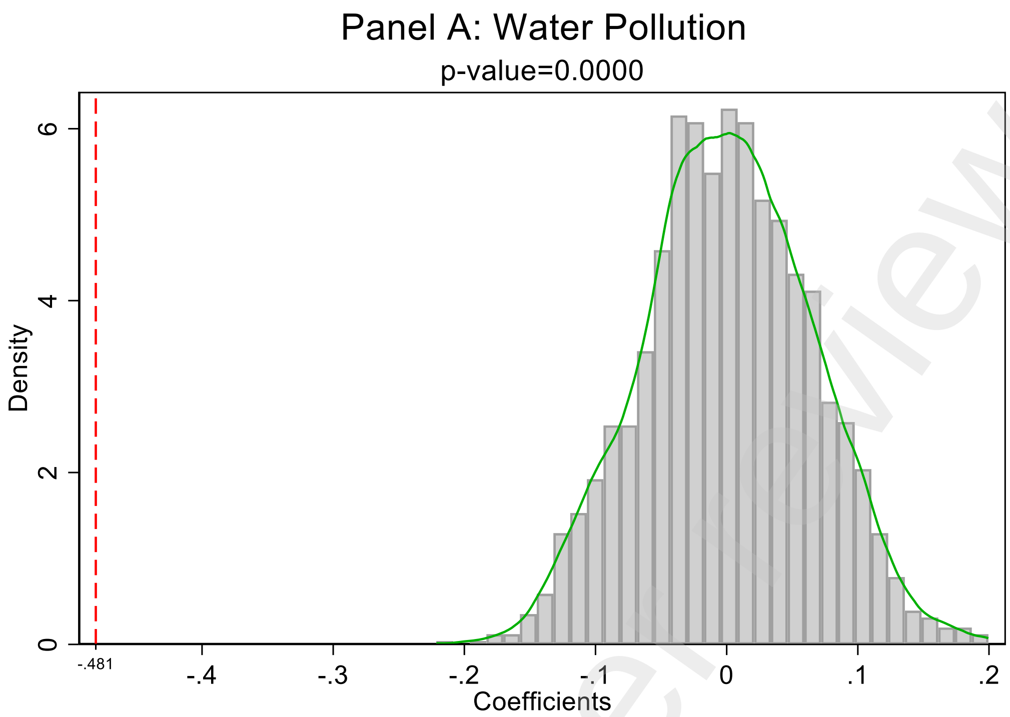
Note: This figure shows the map of Shanghai surface water monitoring stations. The blue lines on the map indicate river sections, and the red dots indicate the surface water monitoring stations. The data source is the Shanghai Municipal Bureau of Ecological Environment.

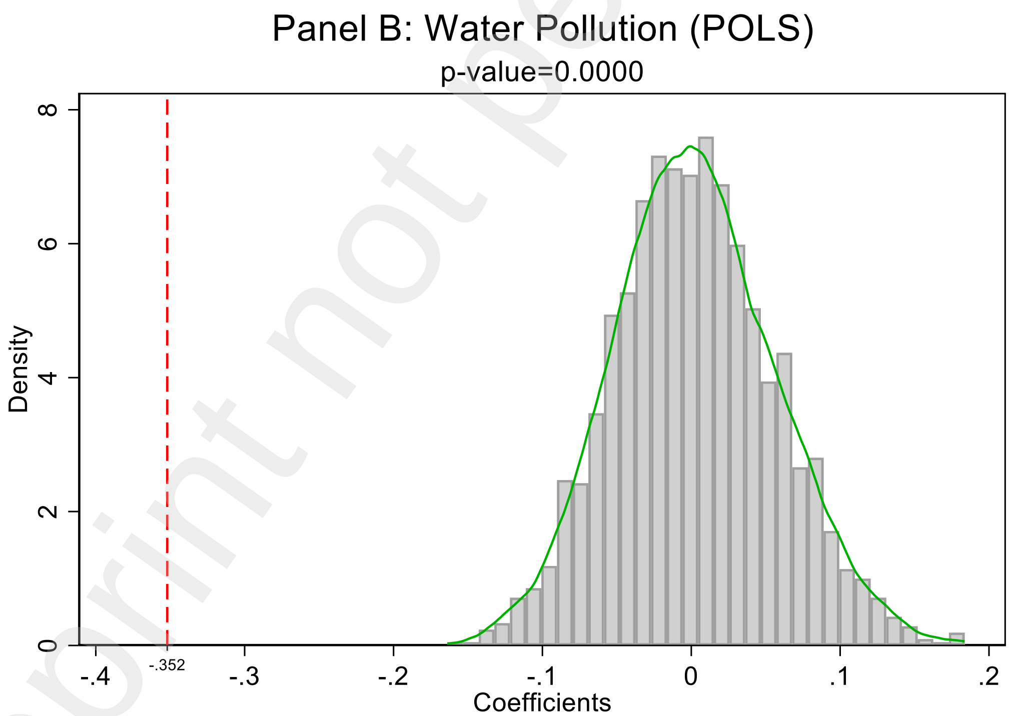
Figure 4. Test for Parallel Trends of Water Quality



Note: We replace the interaction term *Treat*×*Post* with interactions between *Treat* and indicators for quarters relative to the policy implementation, and the figures above plot the estimated coefficients of these interactions. The control variables used in this parallel trend test are the same as those in Columns (3) and (6) of Table 4. The fourth quarter in 2015 is set as the benchmark. On the x-axis, -7 indicates seven quarters before the fourth quarter in 2015 (i.e., the first quarter in 2014, which is the beginning of our sample period), and 23 indicates 23 quarters after the fourth quarter in 2015 (i.e., the third quarter in 2021, which is the end of our sample period).

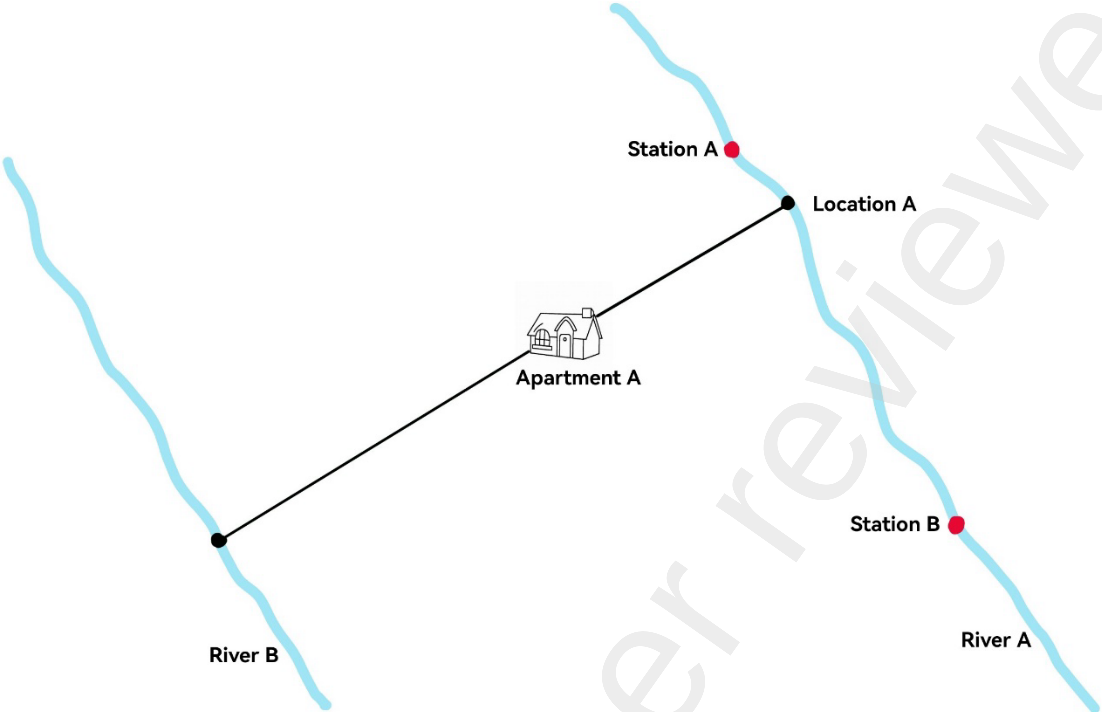
Figure 5. Permutation Test





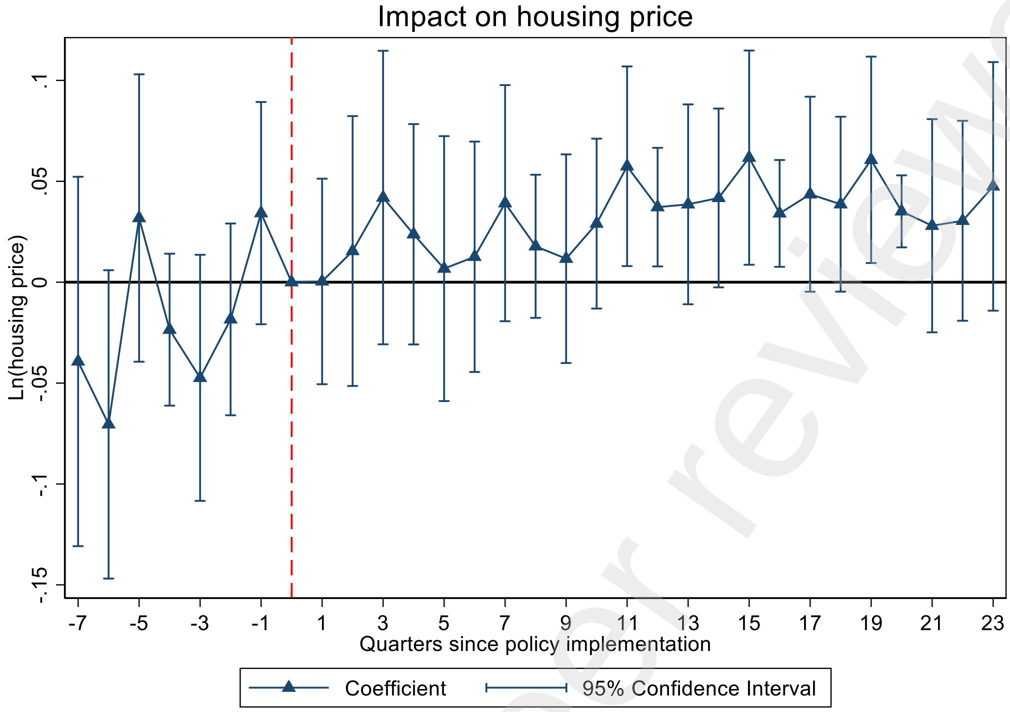
Note: *Water pollution (POLS)* is normalized Probit-OLS transformation of *water pollution*. We randomly assign the treatment status among the water monitoring stations and re-estimate Equation (1). This process is repeated 2,000 times such that we have 2,000 coefficients of the *Treat*×*Post* term for each outcome variable. The figures above plot the distribution of these coefficients. The dashed lines perpendicular to the x-axis represent the estimated coefficients from Columns (3) and (6) in Table 4.

Figure 6. Graph Example



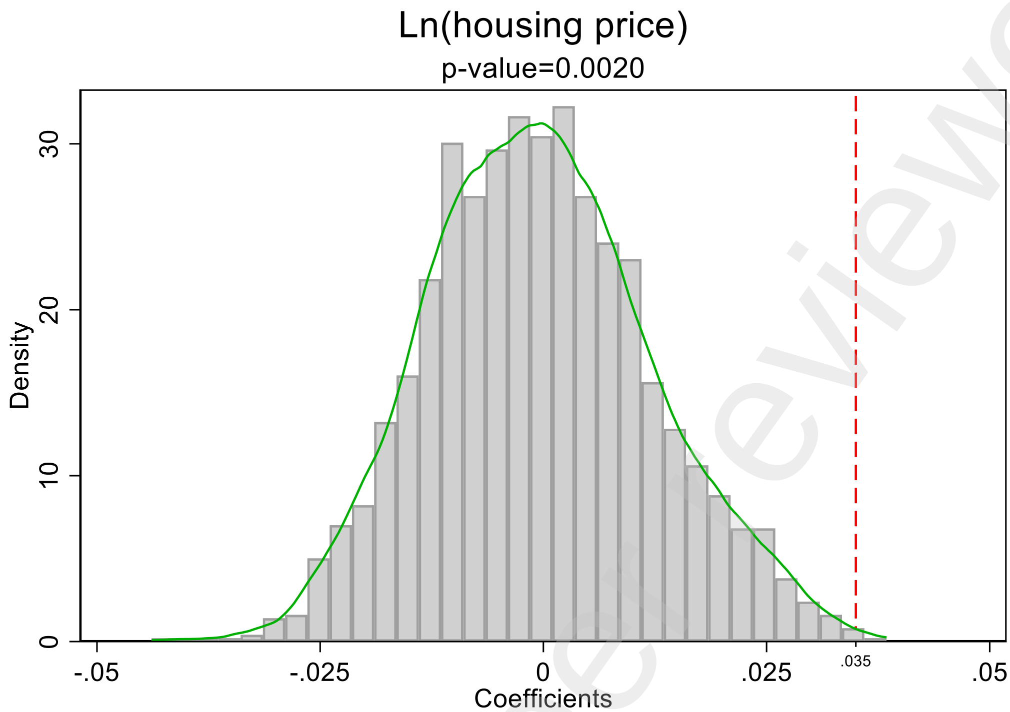
Note: A graph example to show how we assign the treatment status for each apartment. To determine the treatment status of Apartment A, we first find a location (e.g., Location A) along each river that has the shortest distance from Apartment A using information on the latitude and longitude of the complex where the apartment is located. We then match Apartment A to a river (say, River A), for which the distance between Apartment A and Location A on the river is the minimum. After matching apartments with rivers, we can calculate the distance from Location A to each monitoring station located on the same river; thus, we can identify the monitoring station (say, Station A) with the shortest distance to Location A on the same river. Therefore, the treatment status of Station A is assigned to Apartment A.

Figure 7. Test for Parallel Trends of Housing Prices



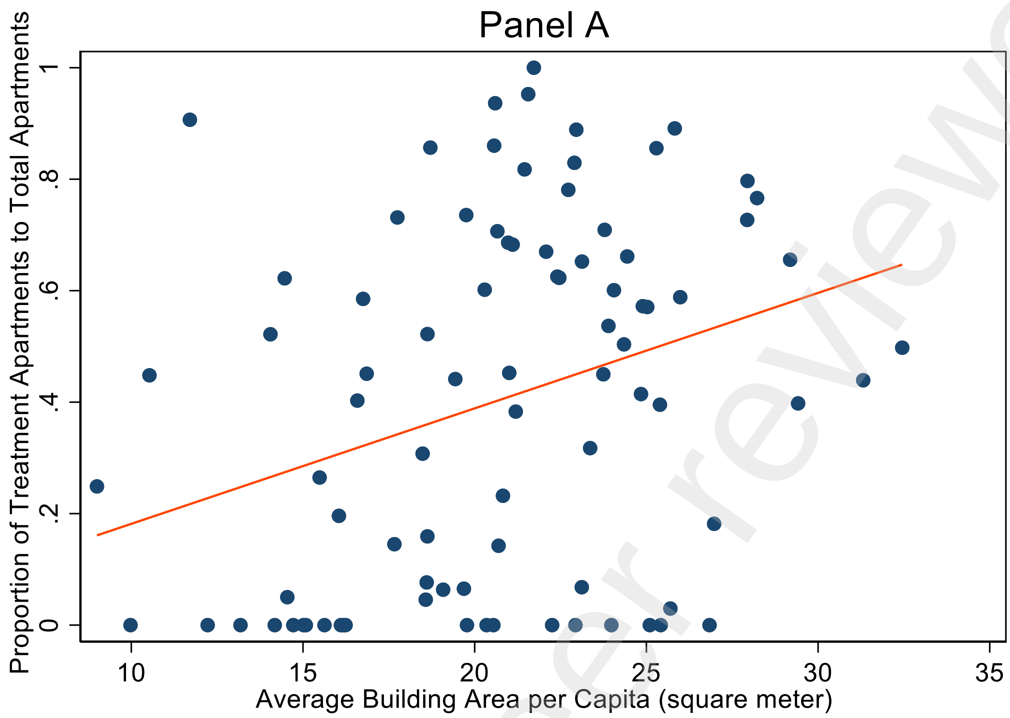
Note: We replace the interaction term *Treat*×*Post* with interactions between *Treat* and indicators for quarters relative to the policy implementation, and the figure above plots the estimated coefficients and confidence intervals of these interactions. The control variables used in this parallel trend test are the same as those in Column (5) of Table 6. The fourth quarter in 2015 is set as the benchmark. On the x-axis, -7 represents seven quarters before the fourth quarter in 2015 (i.e., the first quarter in 2014, which is the beginning of our sample period), and 23 indicates twenty-three quarters after the fourth quarter in 2015 (i.e., the third quarter in 2021, which is the end of our sample period).

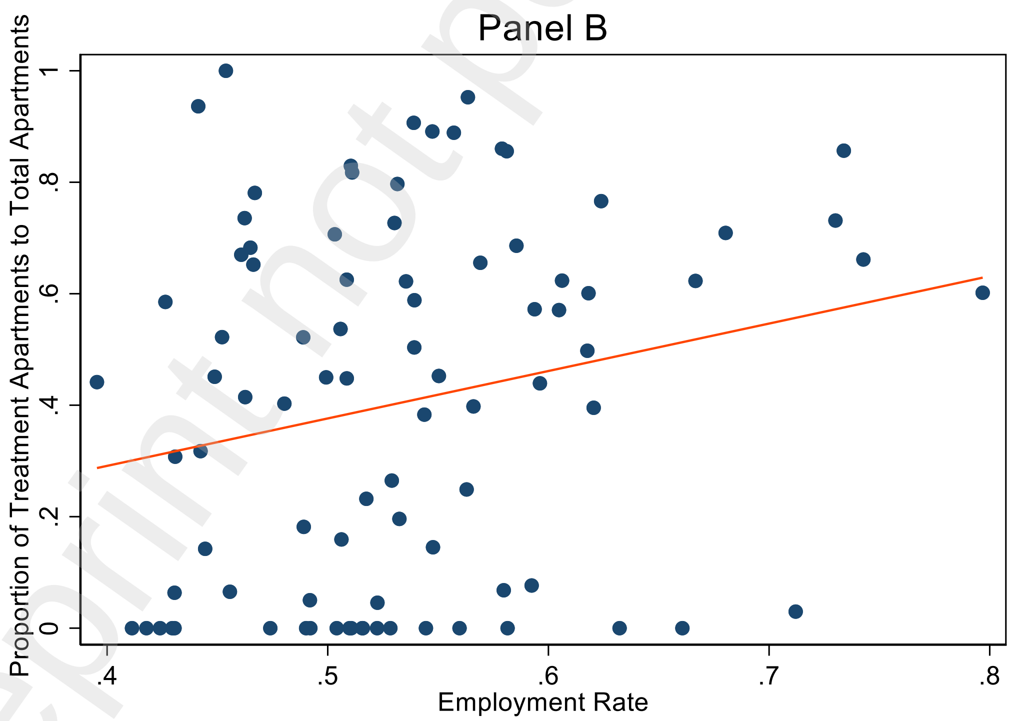
Figure 8. Permutation Test for the Impact of Housing Prices



Note: We randomly assign the treatment status among the complexes and re-estimate Equation (3). This process is repeated 2,000 times such that we have 2,000 coefficients of the *Treat*×*Post* term. The figure above plots the distribution of these coefficients. The dashed line perpendicular to the x-axis represents the estimated coefficient from Column (5) in Table 6.

Figure 9. Proportion of Treatment Apartments to Total Apartments, Average Building Area per Capita and Employment Rates at the Subdistrict Level





Note: The average building area per capita and the employment rate for each subdistrict are calculated from the 2010 population census of China. The proportion of treatment apartments to total apartments for each subdistrict is calculated from our property transaction data.

Table 1. Variable Definitions and Sample Statistics for Surface Water Pollution (N=18,701)

Variable	Definition	Mean	S.D.
Water pollution	Water quality classification, represented by values 1, 2, 3, 4, 5, and 6, with higher values indicating more severe pollution.	4.341	1.198
Water pollution (POLS)	Based on the following classifications: "Type I, II, III, IV, V, and VI water." These six categories are assigned values using Probit-OLS method, and then the variable is standardized to have mean 0 and standard deviation 1. Higher values denote more severe pollution.	-0.000	1.000
Treat	A dummy variable representing whether the monitoring station is in the treatment group.	0.678	0.467
Post	Takes the value 1 for the years 2016 and after, and takes the value 0 for the years 2014-2015.	0.814	0.389
Average water quality of nearby stations	Average water quality of other stations within 5,000 meters around the station in 2014. If there is no other surrounding station, a value of 0 is assigned.	4.926	1.479
Surrounding stations	A dummy variable indicating whether there is a station within 5,000 meters around the station, yes=1, otherwise=0.	0.938	0.240

Note: All variables are at the monthly station level. Definitions, means, and standard deviations are reported. The data sources are described in Section 3.1.

Table 2. Variable Definitions and Sample Statistics for Properties within 500 Meters of Rivers (N=120,482)

Variable	Definition	Mean	S.D.
Housing price	Housing price (units: RMB/m^2, adjusted to 2014 RMB using the CPI from the National Bureau of Statistics of China).	42,903.039	17,176.764
Treat	A dummy variable representing whether the apartment is in the treatment group.	0.866	0.340
Post	Takes the value 1 for the years 2016 and after, and takes the value 0 for the years 2014-2015.	0.889	0.314
Housing area	Residential area (units: m^2).	79.735	39.497
Having a south-facing window	Presence of a south-facing window.	0.963	0.190
Having a river-facing window	Presence of a river-facing window.	0.669	0.471
Number of building floors	Number of floors in the building.	10.969	7.918
Highest floor	The apartment is located on the highest 1/3 floors of the building=1, otherwise=0.	0.367	0.482
Middle floor	The apartment is located on the middle 1/3 floors of the building=1, otherwise=0.	0.349	0.477
Lowest floor	The apartment is located on the lowest 1/3 floors of the building=1, otherwise=0.	0.283	0.451
Basement	The apartment is located in the basement of the building=1, otherwise=0.	0.000	0.012
Number of bedrooms	Number of bedrooms.	2.003	0.781
Number of living rooms	Number of living rooms.	1.364	0.594
Number of kitchens	Number of kitchens.	0.974	0.160
Number of bathrooms	Number of bathrooms.	1.183	0.462
Villa	The department is a villa=1, otherwise=0.	0.011	0.105
Regular dwelling	The department is a regular dwelling=1, otherwise=0.	0.972	0.165
Commercial property	Apartment for commercial and office use=1, otherwise=0.	0.017	0.129
Average water quality of nearby stations	Average water quality of other stations within 5,000 meters around the station in 2014. If there is no other surrounding station, a value of 0 is assigned.	5.484	0.664
Surrounding stations	A dummy variable indicating whether there is a station within 5,000 meters around the station, yes=1, otherwise=0.	0.990	0.099

Note: All variables are at the property transaction level. Definitions, means, and standard deviations are reported. The data sources are described in Section 3.2.

Table 3. Balancing Test (All Variables use Values from 2014).

Variable	Treatment group (1)	Control group (2)	Unconditional diff. (3)	Conditional diff. (4)
Panel A: Key control variables				
Dummy for light intensity between 0-5	0.049	0.395	-0.346***	
	(0.216)	(0.492)	(0.063)	
Dummy for light intensity between 5-10	0.073	0.171	-0.098**	
	(0.261)	(0.379)	(0.048)	
Dummy for light intensity between 10-15	0.152	0.132	0.021	
	(0.361)	(0.340)	(0.047)	
Dummy for light intensity between 15-20	0.104	0.053	0.051	
	(0.306)	(0.225)	(0.037)	
Dummy for light intensity between 20-25	0.146	0.066	0.081**	
	(0.355)	(0.250)	(0.040)	
Dummy for light intensity between 25-30	0.146	0.066	0.081**	
	(0.355)	(0.250)	(0.040)	
Dummy for light intensity between 30-35	0.152	0.053	0.100***	
	(0.361)	(0.225)	(0.038)	
Dummy for light intensity between 35-40	0.110	0.039	0.070**	
	(0.314)	(0.196)	(0.033)	
Dummy for light intensity larger than 40	0.067	0.026	0.041	
	(0.251)	(0.161)	(0.027)	
Ln(distance from the employment centers)	2.696	3.230	-0.534***	
	(0.888)	(0.732)	(0.119)	
Ln(distance from the residential areas)	2.085	2.805	-0.721***	
	(1.024)	(0.879)	(0.145)	
Panel B: Other characteristics (All take the inverse hyperbolic sine form)				
Number of restaurants	3.275	1.779	1.496***	0.329
	(2.002)	(1.742)	(0.282)	(0.239)
Number of hotels	1.796	0.906	0.890***	0.132
	(1.381)	(1.202)	(0.200)	(0.175)
Number of entertainment places	2.036	1.126	0.910***	0.176
	(1.510)	(1.142)	(0.191)	(0.179)
Number of convenience stores	2.584	1.454	1.130***	0.287
	(1.507)	(1.404)	(0.211)	(0.188)
Number of shopping malls	0.586	0.256	0.330***	0.049
	(0.755)	(0.534)	(0.085)	(0.090)
Number of schools	1.199	0.636	0.563***	0.118
	(1.208)	(0.853)	(0.141)	(0.123)
Number of parks	0.589	0.192	0.398***	0.096
	(0.918)	(0.552)	(0.097)	(0.097)
Observations	164	76		

Note: This table reports the summary statistics of the treatment and control samples. Panel A shows the comparison of key control variables between the treatment and control groups. Panel B compares the treatment and control groups in terms of various economic development variables in 2014, both before and after controlling for the key control variables. Columns 1 and 2 show the means and standard deviations. Column 3 reports the unconditional differences between the treatment and control groups. Column 4 reports the conditional differences of these characteristics of a regression on the treatment dummy controlling for the key control variables. The standard errors are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 4. Impact of the Water Pollution Reduction Policy on Water Pollution

	(1)	(2)	(3)	(4)	(5)	(6)
Variable		Water pollution			Water pollution (POLS)	
Treat × Post	-0.687***	-0.491***	-0.481***	-0.512***	-0.358***	-0.352***
	(0.077)	(0.062)	(0.061)	(0.063)	(0.046)	(0.047)
Observations	18,701	18,701	18,701	18,701	18,701	18,701
R-squared	0.637	0.689	0.691	0.639	0.691	0.692
Other controls	NO	Partial	YES	NO	Partial	YES
Year-month FE	YES	YES	YES	YES	YES	YES
Station FE	YES	YES	YES	YES	YES	YES
Mean of dept. var.	4.341	4.341	4.341	-0.000	-0.000	-0.000

Note: (1) *Treat* is a dummy variable representing the assignment of monitoring stations to either the treatment group (*Treat*=1) or the control group (*Treat*=0). To construct *Treat*, we calculate the average value of water quality in 2014 for each monitoring station. *Treat* is equal to one if the average value is higher than five and zero otherwise. *Post* is a dummy variable that equals one for year-months starting from 2016 and zero otherwise.

(2) In columns 1-3, water pollution is assigned values from 1 to 6, with higher values indicating more severe pollution. In columns 4-6, water pollution is coded using the Probit-OLS method, and then normalized to have mean 0 and standard deviation of 1.

(3) Other controls include the interaction of average water quality of other stations within 5,000 meters around the station in 2014 and *Post*, the interaction of a dummy variable indicating whether there are any stations within 5,000 meters of the station and *Post*, the interaction of river dummies and month dummies, the interactions of the nightlight intensity dummy variables and *Post*, the interactions of the logarithm distance to employment centers and *Post*, and the interactions of the logarithm distance to residential areas and *Post*. In columns 1 and 4, we do not include any variables from "Other controls." In columns 2 and 5, we control for the interaction of average water quality of other stations within 5,000 meters around the station in 2014 and *Post*, the interaction of a dummy variable indicating whether there are any stations within 5,000 meters of the station and *Post*, and the interaction of river dummies and month dummies. In columns 3 and 6, we include all variables from "Other controls."

(4) Standard errors in parentheses are calculated by clustering over rivers. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 5. Robustness Checks for the Impact of the Plan on Water Pollution

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Water pollution			Water pollution (POLS)		
Treat × Post	-0.477***	-0.474***	-0.461***	-0.348***	-0.346***	-0.338***
	(0.061)	(0.052)	(0.062)	(0.046)	(0.039)	(0.048)
Observations	18,523	18,095	12,858	18,523	18,095	12,858
R-squared	0.685	0.692	0.715	0.686	0.694	0.714
PM2.5	YES	NO	NO	YES	NO	NO
Rain	NO	YES	NO	NO	YES	NO
Other controls	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES
Station FE	YES	YES	YES	YES	YES	YES
Mean of dept. var.	4.358	4.366	4.381	0.0154	0.0212	0.0277

Note: (1) *Treat*, *Post* and *Other controls* are the same as the definitions in Table 4.

(2) In columns 1-3, water pollution is assigned values from 1 to 6, with higher values indicating more severe pollution. In columns 4-6, water pollution is coded using the Probit-OLS method, and then normalized to have mean 0 and standard deviation of 1.

(3) Columns 1 and 4 control for the monthly average PM2.5 level within the 1,000-meter neighborhood around water monitoring stations. Columns 2 and 5 control for the cumulative monthly precipitation within a 1,000-meter radius of the station. In columns 3 and 6, we delete data from certain months for some monitoring stations to ensure that the monitoring frequency for these stations remains consistent over the years. For example, if a monitoring station reports data in January, March, May, July, September, and November before the policy, the data from February, April, June, August, October, and December after the policy is excluded.

(4) Standard errors in parentheses are calculated by clustering over rivers. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 6. Impact of the Plan on Housing Prices

	(1)	(2)	(3)	(4)	(5)
Variable			Ln(housing price)		
Treat × Post	0.033**	0.032**	0.033**	0.030**	0.035***
	(0.015)	(0.014)	(0.014)	(0.015)	(0.013)
Ln(housing area)		-0.131***	-0.135***	-0.244***	-0.243***
		(0.009)	(0.009)	(0.011)	(0.011)
Having a south-facing window			0.061***	0.062***	0.061***
			(0.006)	(0.005)	(0.005)
Having a river-facing window			0.003	0.000	-0.000
			(0.002)	(0.002)	(0.002)
Number of building floors/100			0.008	0.019	0.019
			(0.047)	(0.034)	(0.035)
Observations	120,482	120,482	120,482	120,482	120,482
R-squared	0.923	0.928	0.929	0.934	0.936
Other housing characteristics	NO	NO	NO	YES	YES
Other controls	NO	NO	NO	NO	YES
Year-month FE	YES	YES	YES	YES	YES
Complex FE	YES	YES	YES	YES	YES
Mean of dept. var.	10.59	10.59	10.59	10.59	10.59

Note: (1) Other housing characteristics include a set of fixed effects for whether the apartment is located on the highest 1/3, middle 1/3, or lowest 1/3 floors or in the basement, number of bedrooms, number of living rooms, number of kitchens, number of bathrooms, and type of apartment usage.
(2) Other controls include the interaction of the average water quality of other stations within 5,000 meters around the corresponding monitoring station in 2014 and *Post*, the interaction of a dummy variable indicating whether there are any stations within 5,000 meters of the corresponding monitoring station and *Post*, the interaction of the corresponding river dummies and month dummies, the interactions of the corresponding monitoring station's nightlight intensity dummy variables and *Post*, and the interactions of distances to the employment centers and residential areas and *Post*. The corresponding monitoring station is the station assigned to the apartment used to determine the treatment status.
(3) Standard errors in parentheses are calculated by clustering over rivers. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 7. Robustness Checks for the Impact of the Plan on Housing Prices

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(housing price)							Ln(total housing value)
Treat × Post	0.035***	0.035**	0.035***	0.022*	0.036**	0.035**	0.033**	0.036**
	(0.012)	(0.014)	(0.013)	(0.012)	(0.014)	(0.016)	(0.014)	(0.014)
Observations	120,468	120,079	120,482	120,482	119,453	98,972	140,522	120,433
R-squared	0.936	0.936	0.936	0.935	0.935	0.936	0.935	0.969
Housing characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES	YES	YES
Complex FE	YES	YES	YES	YES	YES	YES	YES	YES
Mean of dept. var.	10.59	10.59	10.59	10.59	10.59	10.58	10.59	5.656

Note: (1) Column 1 controls for monthly average PM2.5 levels within the 1,000-meter neighborhood around water monitoring stations. Column 2 controls for the cumulative monthly precipitation within a 1,000-meter radius of the station. Column 3 controls for the number of subway stations within a 2-kilometer radius of the apartment at the time of the transaction. Column 4 uses information from two monitoring stations positioned upstream and downstream of the nearest river to derive the treatment status for a particular apartment. Column 5 excludes apartments constructed after *the plan*'s implementation. Column 6 focuses on apartments located within 400 meters of the nearest river. Column 7 focuses on apartments located within 600 meters of the nearest river. Column 8 uses the total housing value as the outcome variable.

(2) Housing characteristics include housing area, a dummy for having a south-facing window, a dummy for having a river-facing window, and the number of building floors. In addition, they include a set of fixed effects for whether the apartment is located on the highest 1/3, middle 1/3, or lowest 1/3 floors or in the basement, number of bedrooms, number of living rooms, number of kitchens, number of bathrooms, and type of apartment usage.

(3) Other controls include the interaction of the average water quality of other stations within 5,000 meters around the corresponding monitoring station in 2014 and *Post*, the interaction of a dummy variable indicating whether there are any stations within 5,000 meters of the corresponding monitoring station and *Post*, the interaction of the corresponding river dummies and month dummies, the interactions of the corresponding monitoring station's nightlight intensity dummy variables and *Post*, and the interactions of distances to the employment centers and residential areas and *Post*. The corresponding monitoring station is the station assigned to the apartment used to determine the treatment status.

(4) Standard errors in parentheses are calculated by clustering over rivers. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 8. Impact of the Plan on the Number of Visits per Day

	(1)	(2)
Variable	Number of visits per day	
Treat × Post	0.068**	0.094**
	(0.027)	(0.040)
Observations	120,103	88,976
R-squared	0.274	0.230
Housing characteristics	YES	YES
Other controls	YES	YES
Year-month FE	YES	YES
Complex FE	YES	YES
Mean of dept. var.	0.300	0.405

Note: (1) We use the number of potential buyers' visits per day to each apartment during the period between the listing day and the sale day as a proxy for the demand for apartments. Column 1 uses the whole sample, while Column 2 excludes apartments listed before the policy implementation and sold after.

(2) *Housing characteristics* and *Other controls* are the same as the definitions in Table 7.

(3) Standard errors in parentheses are calculated by clustering over rivers. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 9. Impact of the Plan on the Number of Transacted Apartments

Variable	(1) Proportion of transaction volume	(2) Volume of transactions
Treat × Post	-0.000	-0.286
	(0.000)	(0.610)
Observations	49,646	49,698
R-squared	0.246	0.602
Other controls	YES	YES
Year FE	YES	YES
Complex FE	YES	YES
Mean of dept. var.	0.00409	2.682

Note: (1) All variables are at the yearly complex level. The outcome variable of Column 1 is the proportion of apartments sold to the total number of apartments in the complex each year. The outcome variable of Column 2 is the number of sold apartments in each complex each year.

(2) Other controls include the interaction of the average water quality of other stations within 5,000 meters around the corresponding monitoring station in 2014 and *Post*, the interaction of a dummy variable indicating whether there are any stations within 5,000 meters of the corresponding monitoring station and *Post*, the interactions of the corresponding monitoring station's nightlight intensity dummy variables and *Post*, and the interactions of distances to the employment centers and residential areas and *Post*. The corresponding monitoring station is the station assigned to the apartment used to determine the treatment status.

(3) Standard errors in parentheses are calculated by clustering over rivers. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 10. Impact of the Plan on the Characteristics of Transacted Apartments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Ln(housing area)	Having a south-facing window	Having a river-facing window	Highest floors	Middle floors	Lowest floors	Number of bedrooms
Treat × Post	-0.003	-0.010	-0.023**	0.003	0.008	-0.009	0.023***
	(0.004)	(0.007)	(0.010)	(0.015)	(0.018)	(0.015)	(0.009)
Observations	120,482	120,482	120,482	120,482	120,482	120,482	120,482
R-squared	0.932	0.334	0.803	0.092	0.079	0.092	0.817
Housing characteristics	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES
Year/month FE	YES	YES	YES	YES	YES	YES	YES
Complex FE	YES	YES	YES	YES	YES	YES	YES
Mean of dept. var.	4.282	0.963	0.669	0.367	0.349	0.283	2.003

	(8)	(9)	(10)	(11)	(12)	(13)
Variable	Number of living rooms	Number of kitchens	Number of bathrooms	Villa	Regular dwelling	Commercial property
Treat × Post	0.000	-0.002	-0.007	0.000	0.000	-0.000
	(0.010)	(0.005)	(0.009)	(0.001)	(0.001)	(0.000)
Observations	120,482	120,482	120,482	120,482	120,482	120,482
R-squared	0.672	0.088	0.740	0.908	0.936	0.954
Housing characteristics	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES
Year/month FE	YES	YES	YES	YES	YES	YES
Complex FE	YES	YES	YES	YES	YES	YES
Mean of dept. var.	1.364	0.974	1.183	0.0111	0.972	0.0169

Note: (1) *Housing characteristics* and *Other controls* are the same as the definitions in Table 7. The only difference is that when the outcome variable is a certain characteristic, the *Housing characteristics* in that column no longer include that characteristic.

(2) Standard errors in parentheses are calculated by clustering over rivers. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

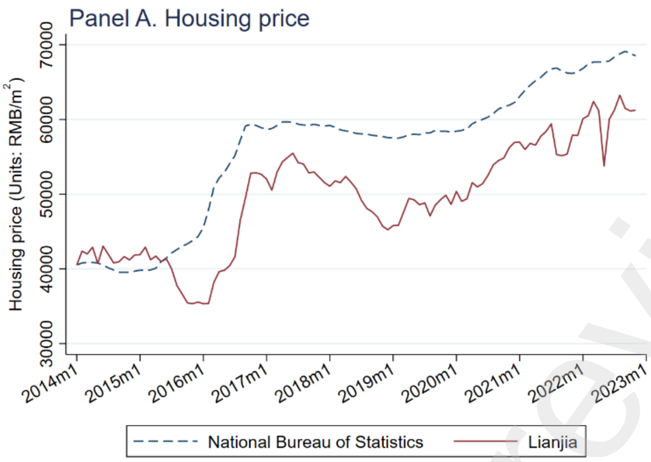
Table 11. Heterogeneous Effect of the Plan on Housing Prices

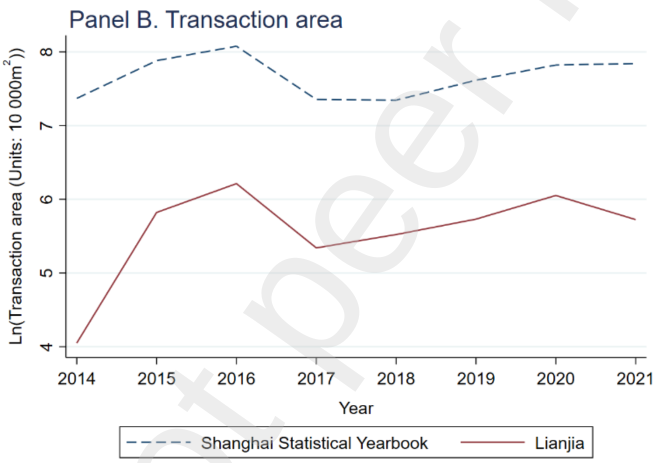
	(1)
Variable	Ln(housing price)
Treat × Post × High	0.043**
	(0.020)
Treat × Post	-0.000
	(0.010)
Post × High	-0.072***
	(0.019)
Observations	100,481
R-squared	0.929
Housing characteristics	YES
Other controls	YES
Year-month FE	YES
Complex FE	YES
Mean of dept. var.	10.62

Note: (1) *Housing characteristics* and *Other controls* are the same as the definitions in Table 7. *High* is a dummy variable indicating whether the complex in which the apartment is located had housing prices exceeding the median before the plan.
(2) Standard errors in parentheses are calculated by clustering over rivers. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Appendix A

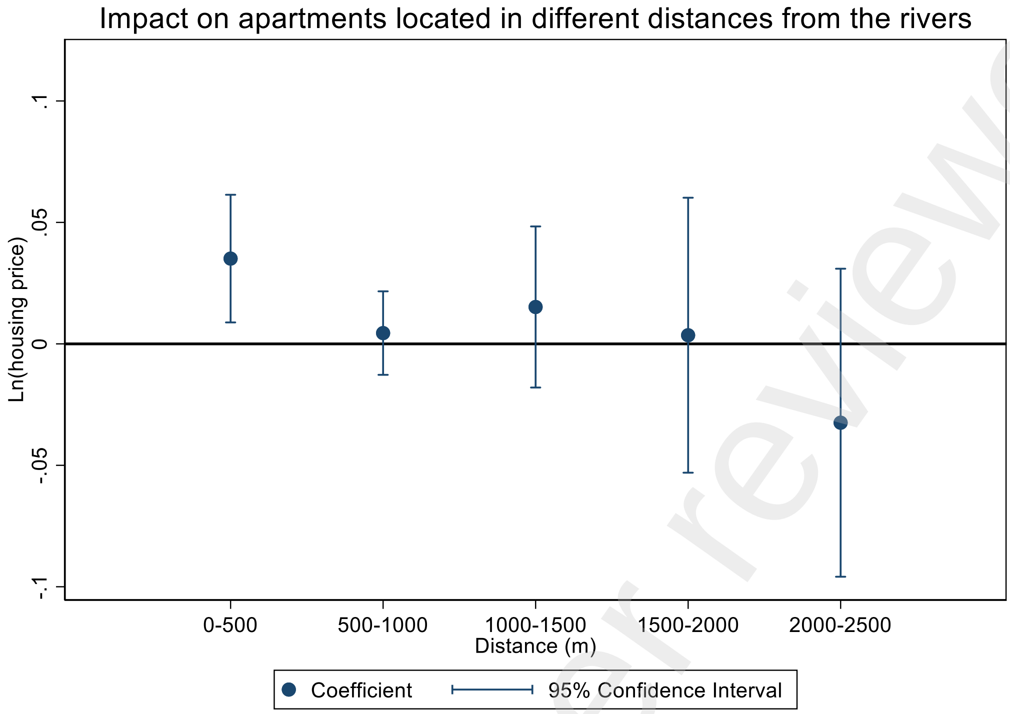
Figure A1. Representativeness of Lianjia Data





Note: We calculated the per square meter prices of second-hand housing per month from Lianjia, which is the red solid line shown in Panel A. Since the Price Index published by the National Bureau of Statistics is a monthly price index whereby the previous month's price is set at 100, we used Lianjia's per square meter prices in January 2014 as the baseline. We multiplied this baseline price by the Price Index to calculate the housing price, which is the blue dashed line shown in Panel A. We also calculated the log of second-hand housing transaction area per year from Lianjia (the red solid line shown in Panel B) and compared them with the corresponding statistics from the Shanghai Statistical Yearbook (the blue dashed line shown in Panel B).

Figure A2. Impact of the Plan on Apartments at Different Distances from the Rivers



Note: We estimate Equation (3) using apartments located within areas between 0-500 meters, 500-1,000 meters, 1,000-1,5000 meters, 1,500-2,000 meters, and 2,000-2,500 meters around the nearest river. The coefficients and 95% confidence intervals of the interaction term *Treat* × *Post* for each sample are shown in the above figure.

Table A1. Shanghai Plan and Detailed Measures

Shanghai plan	Detailed measures
Guarantee the safety of potable water.	Develop and oversee water sources; Mitigate environmental risks associated with water sources; Enhance the quality of drinking water.
Enhance water environmental infrastructure.	Enhance urban sewage and sludge treatment capacity; Establish sewage collection networks; Build municipal pollution control infrastructure; Develop sponge cities.
Address agricultural and rural pollution.	Prevent and mitigate pollution stemming from animal husbandry and nonpoint source pollution in agriculture; Enhance rural environmental management.
Optimize industrial structure and spatial arrangement.	Refine industrial structure; Optimize the spatial layout of industries; Bolster efforts to prevent and control water pollution in industrial agglomeration zones.
Prevent and control pollution in rivers, lakes, coastal areas, and groundwater.	Implement comprehensive river management; Advance the ecological preservation of rivers and lakes; Intensify efforts to prevent and control pollution in coastal waters, ships, ports, and groundwater.
Enhance innovation in the comprehensive management system.	Institute a responsibility assessment system; Reinforce the water ecological space control system and the total pollutant control system; Implement rigorous water resource management; Enhance information disclosure and social oversight mechanisms.
Enhance the capacity for water environment supervision.	Monitor drinking water sources, groundwater, surface water bodies, marine environments, and pollution sources; Establish a water environment information-sharing mechanism
Enhance legal pollution control measures.	Enhance environmental legal standards; Bolster environmental oversight and law enforcement; Implement a system for managing pollutant source discharge permits.
Boost scientific and technological support.	Enhance technological research; Expedite the adoption of new technologies; Reinforce research on environmental standards.
Promote innovative and diverse investment mechanisms.	Promote and guide the involvement of private sector investment; Augment government capital expenditure.

Table A2. Impact of the Plan on Water Pollution Components

Variable	(1) Type VI water	(2) NDO	(3) COD	(4) BOD5	(5) PI	(6) TP
Treat × Post	-0.365***	-0.711***	-1.608***	-0.387**	-0.635***	-0.109***
	(0.026)	(0.143)	(0.350)	(0.164)	(0.122)	(0.012)
Observations	18,701	18,701	18,644	18,631	18,701	18,689
R-squared	0.542	0.745	0.493	0.481	0.536	0.526
Other controls	YES	YES	YES	YES	YES	YES
Year/month FE	YES	YES	YES	YES	YES	YES
Station FE	YES	YES	YES	YES	YES	YES
Mean of dept. var.	0.244	-5.264	16.84	3.753	4.587	0.229

Variable	(7) NH3-N	(8) TN	(9) Cu	(10) Zn	(11) Fluoride	(12) Se
Treat × Post	-1.113***	-1.367***	-11.119	-9.416	-746.034	1.902
	(0.113)	(0.158)	(8.653)	(38.036)	(505.764)	(1.340)
Observations	18,701	18,219	10,501	10,498	10,265	10,052
R-squared	0.661	0.685	0.332	0.374	0.750	0.600
Other controls	YES	YES	YES	YES	YES	YES
Year/month FE	YES	YES	YES	YES	YES	YES
Station FE	YES	YES	YES	YES	YES	YES
Mean of dept. var.	1.285	3.495	44.83	135.9	4358	3.187

Variable	(13) As	(14) Hg	(15) Cd	(16) Cr	(17) Pb	(18) Cyanide
Treat × Post	2.401	0.056	-0.566*	2.974	-5.043*	-4.716*
	(2.809)	(0.065)	(0.301)	(2.648)	(2.947)	(2.802)
Observations	10,266	10,077	10,075	10,048	10,286	10,043
R-squared	0.678	0.398	0.358	0.564	0.452	0.512
Other controls	YES	YES	YES	YES	YES	YES
Year/month FE	YES	YES	YES	YES	YES	YES
Station FE	YES	YES	YES	YES	YES	YES
Mean of dept. var.	22.05	0.195	0.458	20.62	5.862	18.81

Variable	(19) VP	(20) Petroleum	(21) AS	(22) Sulfide	(23) FC
Treat × Post	-1.655	-199.511*	-8.670	-10.272	-45.984**
	(2.562)	(110.432)	(70.820)	(19.828)	(23.203)
Observations	17,965	18,048	10,045	10,172	9,510

R-squared	0.266	0.575	0.487	0.334	0.312
Other controls	YES	YES	YES	YES	YES
Year/month FE	YES	YES	YES	YES	YES
Station FE	YES	YES	YES	YES	YES
Mean of dept. var.	12.34	360.7	352.4	44.05	14.86

Note: (1) *Treat*, *Post* and *Other controls* are the same as the definitions in Table 4.

(2) Type VI water in Column 1 is a dummy variable with one denoting type VI water and 0 otherwise. The outcome variables in columns 2-23 are negative values of dissolved oxygen (NDO), chemical oxygen demand (COD), 5-day biochemical oxygen demand (BOD5), permanganate index (PI), total phosphorus (TP), ammonia nitrogen (NH3-N), total nitrogen (TN), copper (Cu), zinc (Zn), fluoride (Fluoride), selenium (Se), arsenic (As), mercury (Hg), cadmium (Cd), chromium (Cr), lead (Pb), cyanide (Cyanide), volatile phenol (VP), petroleum (Petroleum), anionic surfactant (AS), sulfide (Sulfide), and fecal coliform colony (FC). The units for NDO, COD, BOD5, PI, and TP are mg/L. The units for NH3-N, TN, Cu, Zn, fluoride, Se, As, Hg, Cd, Cr, Pb, cyanide, VP, petroleum, AS, and sulfide are 10^{-4} mg/L. The unit for FC is 10^{4} units/L. For all these variables, higher values denote more severe pollution.

(3) Standard errors in parentheses are calculated by clustering over rivers. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Appendix B

In our paper, we also use other variables, including the average nighttime light intensity within a 1-km radius of the monitoring station in 2014, the distance between the monitoring station and the city's employment centers, the distance between the monitoring station and the city's major residential areas, the number of nearby restaurants, hotels, places for entertainment, convenience stores, shopping malls, various schools (including primary schools, middle schools and universities) and parks within a 1-km radius of the monitoring station in 2014, monthly average PM2.5 levels within a 1-km radius of the monitoring station, and the cumulative monthly precipitation within a 1-km radius of the monitoring station. Below, we discuss some relevant details of the data source and variable construction.

The average nighttime light intensity. We obtained annual nighttime light intensity data (Annual VNL V2) from the Earth Observation Group of NOAA (National Oceanic and Atmospheric Administration), where scientists processed Visible Infrared Imaging Radiometer Suite (VIIRS) data to screen out ephemeral sources of light, such as aurora, fires and gas flares, and to mask background (nonlight) noise (Elvidge et al., 2021; Gibson et al., 2021). We calculate the average nighttime light intensity within a 1-km radius of the monitoring station in 2014, which is the radiance value in units of nano Watts per square cm per steradian (nanoWatt/cm2/sr).

The number of nearby restaurants, hotels, places for entertainment, convenience stores, shopping malls, various schools (including primary schools, middle schools and universities) and parks. We obtained location information of interest from Baidu Map (a Chinese version of Google Maps) in Shanghai in 2014. For each category, restaurants, hotels, places for entertainment (e.g., karaoke parlors (KTVs), board game clubs, gymnasiums and game centers), convenience stores, shopping malls, various schools (including primary schools, middle schools and universities) and parks, we count the number of businesses within a 1-km radius of the monitoring station.

PM2.5. We measured the monthly average PM2.5 levels in the area within the 1-km neighborhood around each monitoring station between 2014 and 2021. The monthly PM2.5 data are from the China High Air Pollutants (CHAP) dataset in units of μg/m3.

These data are generated from big data (e.g., ground-based measurements, satellite remote sensing products, atmospheric reanalysis, and model simulations) using artificial intelligence by considering the spatiotemporal heterogeneity of air pollution (Wei et al., 2021).

Precipitation. The precipitation data are from the National Science and Technology Infrastructure Platform - National Earth System Science Data Center, in units of 0.1 mm (Peng et al., 2019). We aggregate the monthly precipitation within a 1-km radius of the monitoring station.

The distance between the monitoring station and the city's employment centers and the distance between the monitoring station and the city's major residential areas. We use public transportation card data from April 1, 2015, to April 30, 2015, in Shanghai. We use data from weekday morning peak hours to identify the top 16 subway stations in Shanghai with the highest passenger exit volume and the top 19 stations with the highest passenger entry volume. We designate the top 16 stations with the highest passenger exit volume as the employment centers of Shanghai and the top 19 stations with the highest passenger entry volume as the major residential areas in Shanghai. We calculate the respective shortest distances between each monitoring station and the 16 subway stations in the employment centers, as well as the 19 stations in the residential areas. These distances are defined as "the distance between the monitoring station and the employment centers" and "the distance between the monitoring station and the major residential areas". The data source is the 2015 "Youzu Cup" Shanghai Open Data Innovation Application Competition, and more information about the data can be found at https://zhuanlan.zhihu.com/p/540392168.