The Value of Cleaner Waterways: Evidence from the Black-and-Odorous Water Program in China*

Yue Yu[1] and Qianyang Zhang[2]

[1]University of Toronto
[2]Columbia University

October 12, 2023

Abstract

This paper investigates the economic impacts of cleaning up heavily polluted waterways in urban neighborhoods. We exploit the Black-and-Odorous Water Program, a major urban environmental campaign in China, as a natural experiment to identify the causal impact of cleaner waterways on local housing prices, housing supply, and business growth. First implemented in 2016, the program remediated heavily polluted waterways in China's most developed cities. Using a difference-in-differences estimator, we find that the program mainly benefits properties within 1 mile of cleaned-up waterways: These properties had prices 3.7% lower before the program and saw a 2.3% appreciation in market value after the program. We also show that developers constructing new apartment complexes near BOW sites tend to provide high-end units with high-quality finishes and spacious layouts. Furthermore, we observe various service businesses thriving in the neighborhoods close to cleaned waterways, which indicates the revitalization of these areas. Our findings shed light on the effects of environmental programs on real estate markets and neighborhood dynamics.

JEL: Q5, R1, R3

Keywords: Water Pollution, Environmental Regulation, Real Estate Market, China

*yueyu.yu@rotman.utoronto.ca. qz2344@columbia.edu. We are grateful to Elizabeth Dhuey, Abdollah Farhoodi, Réka Juhász, David Keiser, William Strange, Shaoda Wang, and Yanos Zylberberg for helpful comments; to Simon Krause and Yuan Ren for conference discussions; and to numerous participants at conferences and seminars for helpful discussions and comments. We thank Queenie Liang and Ramtin Salamat for excellent research assistance. The usual disclaimer applies.

1 Introduction

In the last few decades, the rapid growth of urbanization and the economy in developing countries has caused significant environmental costs, including pollution and water contamination; this is especially the case in densely populated urban areas (UNDP, 2016). This environmental degradation can foster the decline of city centers, induce residential segregation, and exacerbate inequalities, deteriorating overall urban living conditions (Mieszkowski and Mills, 1993; Chay and Greenstone, 2005; Banzhaf and Walsh, 2008; Heblich et al., 2021). In response, governments worldwide are implementing environmental programs to counteract the environmental and social costs of urbanization and promote sustainability (Costa and Kahn, 2004; Zheng and Kahn, 2017; He et al., 2020; Greenstone et al., 2021). However, there remains a lack of empirical evidence regarding how these programs interact with neighborhood dynamics and whether they can effectively counteract the decline of polluted neighborhoods and contribute to resilient urban development.

In this paper, we study a large-scale urban environmental program in China, the Black-and-Odorous Water Program (BOW program hereafter), to examine its causal impacts on local housing markets and business growth. This unexpected and swiftly implemented program cleaned up heavily polluted waterways that flowed through the 36 most developed Chinese cities during 2016 and 2017. The extensive geographic coverage of the program is accompanied by substantial costs: Across the 36 cities, the program incurred a cost of approximately \$16 billion (Cao, 2019). Furthermore, as the program's initiatives were extended nationwide, the cumulative investment had reached \$157 billion by January 2020 (Ministry of Ecology and Environment, 2020). This amount is comparable to annual spending on the Clean Water Act in the US (Keiser and Shapiro, 2019) and exceeds the total annual spending required to achieve universal basic service for drinking water, sanitation, and hygiene-related targets set by the United Nations across a combination of the 140 mostly developing countries (Hutton and Varughese, 2016).

Despite enormous investments in water-cleaning programs worldwide and long-lasting interest in understanding the economic consequences, it has been empirically challenging to identify their impacts on both the housing market and local business growth (Kuwayama and Olmstead, 2015; Keiser and Shapiro, 2019). The endogenous timing and geographic coverage of many programs make it difficult to address confounding factors that impact neighborhood dynamics. Furthermore, a lack of granular data on housing transactions, real estate development, and business records poses a challenge in tracking neighborhood responses. The BOW program in China, combined with detailed housing transactions and business records, provides a rare opportunity to examine these responses in the affected neighborhoods.

The BOW program was first announced by the China State Council in late 2015. The program mandated that the local governments of the 36 most developed cities in China clean up heavily polluted waterways within their jurisdictions by the end of 2017. A section of a waterway is identified as a *BOW site* if it has water transparency of less than 25 cm, dissolved oxygen of less than 2 mg/L, oxygen reduction potential of less than 50 mV, or ammoniacal nitrogen of above 8 mg/L. Such waterways typically have a dark color and unpleasant odor and are therefore called "Black-and-Odorous waters." In the six cities for which housing transaction records are available before the beginning of the program–and are therefore included in our sample–more than 500 miles of waterways were cleaned up by the program. The program restored the heavily polluted waterways and transformed nearby river banks into new places for recreational activities and community gatherings. These waterways are never used as drinking water, and therefore the program mainly improves their aesthetic amenities and non-consumptive value.

We start by estimating the local effect of the BOW program on housing prices using a difference-in-differences estimator. Specifically, we compare the transaction prices of apartments close to BOW sites with those farther away before and after the program. As there is no consensus about the distance beyond which residents no longer benefit from a cleaned-up waterway, we adopt a distance bin approach to estimate the responses of housing prices at varying distances from a BOW site. Prior to the program, apartments closer to these polluted waterways were significantly cheaper, and this negative effect is concentrated among apartments within 1 mile. Following the program, a substantial increase in housing prices is observed among apartments less than 1 mile from a BOW site, while the effects for apartments farther away are close to zero and insignificant. Based on these two findings, we define the treated region as within 1 mile of a BOW site, and the control region as being between 1 and 2 miles from any BOW site in the central analysis.

To obtain an unbiased estimate of the average treatment effect, the key identification assumption is that without the program, the housing prices in treated and control regions should have had parallel trends throughout the study period.[1] We present evidence of parallel trends in housing prices before the start of the program, which alleviates concerns about non-comparability between treated and control regions and any anticipation of the program leading to investments in the treated areas before its implementation. Also, to obtain an unbiased estimate of the coefficient, other demand shocks since 2016 cannot confound the effects. We demonstrate the robustness of our results to a battery of possible demand factors, such as changing preferences for living close to city centers, waterways, and high-quality public schools. Furthermore, our results remain robust when taking into account differential price trends across neighborhoods within a city or changes in neighborhood characteristics beyond waterway quality.

The first main empirical finding of our study is that the BOW program has a significant positive

[1]Under the parallel trend assumption, the coefficient yields an unbiased estimate of the average treatment effect, because all sample neighborhoods receive the policy simultaneously, and all the treated units switch from untreated to treated (De Chaisemartin and d'Haultfoeuille, 2020).

impact on the housing prices of apartments located less than 1 mile from a cleaned-up waterway. We observe a significant 2.3% increase in housing prices in these areas after the program. These apartments were initially 3.7% cheaper than those located farther away, and the program eliminated most of the price gap, making it no longer significantly different from 0. We conduct a back-of-the-envelope analysis to quantify the program's benefits in terms of the appreciation in the value of residential properties, which results in a benefit-cost ratio of 12 for the six sample cities. Our findings also reveal that the impact of the program is greater in neighborhoods with higher population density and housing prices in the baseline years, as well as those near initially more severely polluted waterways.

We then examine the supply-side responses of the housing market to the BOW program and their implications for housing prices. Specifically, we use records for new buildings from 2010 to 2020 to investigate whether the program leads to an increase in the supply of newly built apartments in neighborhoods closer to a BOW site compared with those farther away. Our results show no such increase in supply. This is expected, given the scarcity of open land plots in the urban neighborhoods under study and a slow-down in construction during the study period. However, we find that if real estate developers do build a new apartment complex near a BOW site, they are more likely to provide high-end units featuring high-quality finishes and spacious apartment layouts after the program. This shift in the supply toward constructing high-end new apartments in neighborhoods near cleaned-up waterways creates downward pressure on the relative price of high-end apartments.

Finally, we show that the BOW program has a positive effect on local business growth. We find that post-program, neighborhoods close to cleaned-up waterways attract a variety of businesses, such as recreation centers and restaurants. In particular, we observe a 46% increase in the number of restaurants and a 33% increase in the number of recreation centers within a 0.2-mile radius of cleaned waterways; the effect diminishes as we move away from cleaned waterways. This influx of businesses in these areas reflects a rise in the number of visitors after the waterways were cleaned up and transformed into new recreational spots for leisure activities. We also present suggestive evidence that the increase in housing prices can be attributed more to changes in environmental amenities rather than service amenities.

This paper contributes to the literature on the economic benefits of investing in water treatment (Beach, 2022; Bhalotra et al., 2021; Alsan and Goldin, 2019; Keiser and Shapiro, 2019; Peng et al., 2019; Ashraf et al., 2017; Devoto et al., 2012; Gamper-Rabindran et al., 2010; Galiani et al., 2005; Streiner and Loomis, 1995). While the health consequences of providing clean drinking water have been better understood, the aesthetic value of cleaning waterways and its impacts on real estate and business development– which is the focus of our paper–has received scant attention. A few exceptions in the literature have examined the aesthetic value of cleaning waterways in the

US and found small effects on housing prices in nearby neighborhoods (Keiser and Shapiro, 2019; Kuwayama et al., 2022), and the value for long-distance tourists must be factored in to justify the investment in U.S. water pollution control. In contrast, our study focuses on a policy that targets densely populated urban areas in a developing country and reveals an economically significant impact on housing prices in nearby neighborhoods. Moreover, we investigate changes in both housing markets and local business activities and shed light on their interactions.

This paper is also closely related to a quickly growing literature about pollution management in developing countries (Viard and Fu, 2015; Chen et al., 2018; Li et al., 2020; He et al., 2020; Liu et al., 2021).[2] Rising income in developing countries raises demand for environmental amenities and the desire for more sustainable urbanization (Zheng and Kahn, 2017; Ito and Zhang, 2020). As a result, more and more policies and regulations have been adopted by governments in developing countries to counteract the growing environmental damage (Greenstone and Hanna, 2014; Duflo et al., 2018). This literature focuses on the role of environmental regulations in changing city-level environmental conditions and reallocating economic activities across regions. We instead highlight how environmental programs can benefit neighborhoods within a city differentially and reshape the urban landscape.

2 Policy Background

The BOW program, announced in 2015, is part of an ambitious initiative that seeks to combat the growing problem of water pollution, which has been exacerbated by China's rapid industrial expansion and the lag in pollution control infrastructure over the past few decades (Zheng and Kahn, 2017; He et al., 2020). In response to increasing public concern over water pollution, the Chinese State Council released the Action Plan for Preventing and Treating Water Pollution in April 2015, setting a goal to eliminate over 90 percent of heavily polluted waterways running through cities by 2020. This target was even more ambitious for the 36 most developed cities: all polluted sites had to be cleaned up by the end of 2017.[3]

As outlined in "The Guide on Polluted Urban Water Control" published in August 2015, the program involves two steps.[4] The first step is to identify all the BOW sites, which are waterway segments with a transparency of less than 25 cm, dissolved oxygen of less than 2 mg/L, oxygen

[2] More broadly, the study relates to an extensive literature on pollution and its impacts on housing prices, such as sewage management (Coury et al., 2022); air pollution (Chay and Greenstone, 2005; Grainger, 2012; Heblich et al., 2021; Isen et al., 2017); noise pollution (Boes and Nüesch, 2011); and hazardous waste sites (Bui and Mayer, 2003; Greenstone and Gallagher, 2008; Gamper-Rabindran and Timmins, 2011; Cassidy et al., 2022).

[3] The action plan outlined ten broad goals to address the nationwide water quality crisis, with one being the cleaning of heavily polluted waterways within urban districts. However, the action plan lacked details on policy implementation and evaluation criteria.

[4] A detailed illustration of the policy timeline is provided in Figure B.1.

reduction potential of less than 50 mV, or ammoniacal nitrogen of above 8 mg/L.[5] Local governments were asked to submit a complete list of BOW sites within their jurisdictions to the central government for review by December 2015, and the list was made public in January 2016. Figure 1 shows the locations of the BOW sites, represented by red lines, and the other waterways not included in the program, represented by blue lines. The spatial distribution of BOW sites shows significant cross-sectional variations both within and across cities.

In the second step, local governments hire specialists to design and implement clean-up projects. The designated 36 cities needed to complete all projects by the end of 2017, with the goal of ensuring that water quality no longer meet the program's BOW criteria. The clean-up methods for a BOW site vary based on the pollution sources and local ecological conditions. They typically involve three components: removing existing pollutants from the water body, preventing pollutants from entering the waterways, and restoring ecological balance. Local governments supervise these projects, ensuring that each BOW site passes a third-party examination upon completion. They are also responsible for maintaining and monitoring these waterways to avert future pollution.

To study the effects of the BOW program, we divide our study period into two periods: before the program (up to December 2015) and post the program (from January 2016 to May 2020).[6] We consider the publication of the BOW site list in January 2016 as the beginning of the program since it made clear which neighborhoods were close to a BOW site. In contrast, the Action Plan announced in April 2015 only discussed broad urban and rural environmental issues that the central government aimed to solve. Although the criteria for BOW identification were made public in August 2015, it was unclear whether local governments would adhere to the criteria from residents' perspectives. In Section 4.3.1, we show that housing prices of neighborhoods close to BOW sites did not change until 2016, which supports our phase division.

The program's announcement came as quite a shock; initially, the public was skeptical about its effects. According to (SEE and IPE, 2016), by August 2016, with one-third of the program's timeline already elapsed, many sites remained in the planning stage. This led to concerns regarding timely completion of the projects and amplified doubts about the government's commitment. However, as site treatments were implemented and the program progressed, public confidence in the program grew, especially in 2017, when the enhanced environmental aesthetics of these sites became evident (SEE and IPE, 2018). As illustrated in Figure B.2, these projects transformed heavily polluted waterways into pleasant public spaces suitable for recreational activities and community gatherings.

To guarantee that local governments meet the policy goals, the central government imple-

[5]In practice, the four criteria are highly correlated. Out of the 39 BOW sites in Chengdu, which is the only sample city with water test results publicly available, 67% of the sites met at least three of the criteria.

[6]For some analyses, we further divide the post-period into two sub-periods: during the program (January 2016 to December 2017) and after the program (since January 2018).

mented various monitoring strategies. First, in February 2016, the central government launched the "Urban Black-and-Odorous Water Information Platform" to publicize the progress of all BOW projects. This platform allows residents to track individual projects and voice their dissatisfaction with the outcomes.[7] Secondly, the central government sent both third-party specialists and central government officials to inspect each BOW site upon project completion.[8] Each BOW site was graded by the central government as either "good," "pass," or "fail," and these grades were made publicly available. In the six cities analyzed in this paper, nearly all BOW sites passed the examination.[9]

The program proves successful in restoring heavily polluted waterways, as studies by Wang et al. (2022), Hu et al. (2021), and Qi et al. (2020) demonstrate. These studies use satellite imagery to measure surface water quality over time. They find a clear improvement in overall water quality and the elimination of the BOWs in cities participating in the program. Additionally, monthly monitoring reports from treated waterways across our sample cities reveal a significant reduction in water pollution after the program.[10] As shown in Figure 2, the average pollution level across all the monitoring sites reduces steadily since 2016.[11]

The program's success relies heavily on tremendous investments, making it crucial to estimate the economic gains resulting from it. The cumulative investment incurred by the program exceeded 114 billion RMB (approximately $16 billion) across the 36 cities (Cao, 2019). The program's initiatives have been extended to the rest of cities and rural areas throughout China in more recent years. By January 2020, the cumulative investment in the extended program nationwide had exceeded 1,100 billion RMB (approximately $157 billion).[12] Despite the substantial investment, the program's benefits are unclear at the first stage. This paper closes the gap by investigating the effects of the BOW program on neighborhood housing prices and local business growth.

3 Data

To conduct the empirical analysis, we bring together various types of data, including information about BOW sites, the transaction records for pre-owned apartments, the supply of newly built apartments, and the addresses of all local service businesses both before and after the program.

[7] Local governments are required to review these reports and respond within seven business days.

[8] The examination of the 36 most developed cities took place in May 2018.

[9] According to the Ministry of Ecology and Environment of the People's Republic of China, 93% of BOW sites passed the examination, and the remainder were cleaned up by October 2018.

[10] It should be noted that these results are based on a limited number of monitoring stations, with uneven distribution across the cities. Beijing has 12 stations, Shanghai has 13, Shenzhen has 8, and Tianjin has 4, while the other two cities have no monitoring stations.

[11] The pollution level is an integer index that ranges from 1 to 6, and BOW sites correspond to the level of 6.

[12] Data source: the Ministry of Ecology and Environment of the People's Republic of China.

Our analysis focuses on six of the 36 most developed cities in China: Beijing, Chengdu, Nanjing, Shanghai, Shenzhen, and Tianjin. These cities are chosen because they have available apartment transaction data dating back to before 2015. Together, they represent 7% of China's population in 2010 and 15% of the national GDP in 2017. As shown in Table C.1, the sample cities have a greater share of the working population and fewer Hukou holders (and hence more temporary in-migrants). We discuss the external validity of our analysis in Section 4.3.2. The rest of this section briefly introduces each database, while more details are provided in Appendix A. Table C.3 provides summary statistics of the main variables used in Section 4.

BOW sites. Information about BOW sites is from the Institute of Public & Environmental Affairs (IPE).[13] Our sample covers 292 BOW sites, which account for 525 miles of waterways. For each BOW site, we observe its location and pollution severity before the program.[14] All the BOW sites are plotted in Figure 1, and a summary of the BOW sites by city is provided in Table C.2.

Apartment transaction records. The transaction records for pre-owned apartments were sourced from major real estate agencies in China, including Lian Jia, Mai Tian, Wo Ai Wo Jia, Zhong Yuan Di Chan, Le You Jia, and Q Fang. These agencies make the transaction records available to the public on their websites, and an external data provider collected and compiled the information into a single dataset.[15] Compared to the housing transaction records used in the existing literature that studies China's housing market, we use a much more comprehensive database that covers 13% of all pre-owned apartment transactions from 2012 to 2020 to study changes in property values over time.[16] We observe an extensive set of apartment characteristics, including the transaction price, address, floor level, floor area, the number of bedrooms, bathrooms, and living rooms, the quality of finishes, exposures, the total number of floors in that building, age of the building, and building structure.

Newly built apartment buildings. The data comes from the China Real Estate Index System (CREIS), which is provided by the China Index Academy. This database has the most comprehen-

[13] https://www.ipe.org.cn/index.html.

[14] The pollution level of a BOW site is rated as either "moderate" or "severe". To measure water quality for a segment of waterways, a series of examination spots are selected and evaluated. If two adjacent examination spots are rated as "severe", the waterway in between is rated as "severe". Next, to evaluate a particular examination spot, three tests need to be performed at different time, and at least three water samples are collected during each test. Four features are obtained for each water sample: transparency, dissolved oxygen, oxygen reduction potential, and ammoniacal nitrogen. Transparency less than 10 cm indicates severe pollution. Similarly, if a water sample has dissolved oxygen less than 0.2 mg/L, oxygen reduction potential less than -200 mV, or ammoniacal nitrogen above 15 mg/L, it indicates severe pollution in the corresponding criteria. An examination spot is classified as "severe" if either over 60% of the sample for a single indicator or at least 30% of the sample for two or more indicators meet the criteria of severe pollution.

[15] The external data provider makes the data available on the following platform: www.ershoufangdata.com.

[16] The existing literature typically uses transaction records within a short time window from a single real estate agency. A detailed discussion about the representativeness of our transaction records is provided in Appendix A.

sive records for newly built residential complexes available for sale. Our data spans from 2010 to 2020. For each newly built apartment complex, we observe the launch date, address, total number of apartments, green-space ratio, and whether it features high-end finishes or spacious layouts.

Locations of service businesses. Information about locations of service businesses is from Gaode Map.[17] For each city, we have two snapshots of all the business locations marked on the map, one in May 2015 and the other in December 2019.[18] We divide each city into hexagons with a side length of 0.3 miles and count the number of businesses by hexagon and year across nine categories: recreational centers (e.g., chess clubs, KTVs, game centers, and internet cafes), restaurants, convenience stores, pharmacies, financial services (e.g., bank branches and ATMs), tutoring services, other services (e.g., post offices, salons, laundries, photography studios, and repair shops), groceries and supermarkets, and other retail stores.

2010 Population Census. We collect demographic data from the 2010 Population Census at the level of urban district (Jiedao), which is the lowest level of census unit in the dataset.[19] The data include the total population, sex ratio, age composition, and share of Hukou holders.

4 The Impact of the BOW program on Housing Prices

To study the impact of the BOW program on housing prices, we introduce the regression specification in Section 4.1. In Section 4.2, we conduct a distance bin analysis to determine the treatment and control areas for the central specification. We then present the empirical analysis in Section 4.3, showcasing the main results and establishing their robustness across a series of alternative specifications. Lastly, a heterogeneity analysis is conducted in Section 4.4.

4.1 Regression Design

We expect that the BOW program will increase the market value of nearby housing properties, as it transforms an environmental disamenity into an amenity: By cleaning up heavily polluted waterways, the program creates new recreational areas. It is important to note that the waterways covered by the program are not used for drinking water, and their value comes solely from their aesthetic appeal.[20]

To estimate the impact on housing prices, we compare the prices of apartments near and far

[17]Gaode Map is a leading digital map provider in China that constantly updates its database by collecting street views four times a year. In addition, users can add or modify business locations on the platform after a field visit verification by the company.

[18]The data is collected by the data vendor: http://www.poi666.com/.

[19]Data source: China Data Center, University of Michigan.

[20]Drinking water in all six sample cities comes from upstream reservoirs in rural areas.

from a BOW site before and after the program.[21] The central regression specification is as follows:

$$\ln P_{ijkt} = \beta_0 + \beta_1 1_{Near,i} + \beta_2 1_{Near,i} \times \text{Post2016}_t + \tau_{kt} + X_{ijkt}\theta + \epsilon_{ijkt}. \tag{1}$$

$\ln P_{ijkt}$ is the transaction value of an apartment i in urban district j and city k sold in year t. The dummy variable $1_{Near,i}$ is used to indicate whether the apartment i is located near a BOW site or not. In Section 4.2, we conduct a bin analysis to flexibly identify the distance beyond which water pollution and the BOW program no longer affect housing values. Post2016$_t$ is a dummy variable that turns to 1 from January 2016, when the locations of the treated waterways became available to the public.[22] City time-varying effects, τ_{kt}, are always controlled for since housing markets across cities might have different dynamics over time. Additionally, we restrict the control group to apartments that are slightly farther away from the BOW sites. We double cluster the error term at the urban district level and city-year level to allow housing prices to be correlated both within the neighborhood across time and across neighborhoods within a city in a particular year.[23]

Given that the data is not structured as repeated sales, we address potential quality differences between transacted apartments across time (i.e., the composition effect) by including a comprehensive set of characteristics of the apartment in X_{ijkt}.[24] This set includes the floor area (logged), the number of bedrooms, bathrooms, and living rooms, whether the apartment has high-quality finishes or not, its exposures, the level of floor (low, middle, or high), the total number of floors in the building, the age of the building, building structure, and the urban district in which the unit is located. These control variables, along with the city time-varying effects, capture the salient features of apartments and can explain nearly 90% of the price variation. In Section 4.3.3, we examine several additional features for robustness checks, and the results are consistent with our baseline model.

Coefficients of interest include both β_1 and β_2. β_1 captures the difference in prices between apartments in the treated and control regions prior to the implementation of the program. β_2 represents the change in prices of apartments located close to the waterways targeted by the program. We consider the estimate as the short-run effect since we observe the housing market outcomes up

[21] Waterways downstream of the heavily polluted areas are included as part of the BOW site if their water quality meets the BOW criteria. For downstream waterways that aren't as polluted and thus don't meet the BOW criteria, we consider them unaffected by the program. Nonetheless, they might still become cleaner following the program's implementation. In this scenario, our approach likely underestimates the effect, offering a conservative estimate of the real estate appreciation.

[22] As an alternative specification, we estimate the price responses separately during and after the program and find that the effects are similar.

[23] We show in Section 4.3.2 that clustering the error terms in alternative ways, such as by county, results in similar standard errors as our baseline results.

[24] The dataset does not have a unique id assigned to each apartment. Our time frame also indicates that for most apartments, it is unlikely to observe multiple transactions in a short time window.

to 5 years from the program's initiation, during which the construction of new apartment buildings is limited. We present evidence to support this argument in Section 5.1.

For the coefficients to be an unbiased estimate of the average treatment effect, the key identifying assumption is that the homeowners do not fully anticipate the BOW program (Autor et al., 2014) and that housing prices in the treated and comparison regions moved in parallel without the program (De Chaisemartin and d'Haultfoeuille, 2020). This assumption is likely valid since the policy guideline was not announced until August 2015, and the list of BOW sites was only decided and made public in January 2016. We conduct an event study in Section 4.3.1 to demonstrate that parallel trends hold up to 2015 and carry out sensitivity check by relaxing parallel trends assumption in Section 4.3.3 (Rambachan and Roth, 2023). Furthermore, under the parallel trend assumption, the coefficient provides an unbiased estimate of the average treatment effect, because all the sample neighborhoods receive the policy simultaneously and the treatment group can only switch from untreated to treated (De Chaisemartin and d'Haultfoeuille, 2022).

To obtain an unbiased estimate of the coefficients, it is also important that the differential changes in housing prices between the treated and control regions are not confounded by other demand shocks since 2016. In Section 4.3.3, we explore a range of possible factors that could impact demand, such as changing preferences for living close to city centers, waterways, and high-quality public schools. Our analysis shows that after accounting for these factors, the estimated price effect remains largely unchanged. We also examine whether differences in price trends across neighborhoods within a city or changes in neighborhood characteristics beyond the quality of waterways nearby could affect housing prices differently. We show that the results are robust to these alternative specifications.

4.2 Changes in Housing Prices by Distance to BOW Sites

In this subsection, we use a flexible regression specification to estimate both the price gradient with respect to distance to the heavily polluted waterways before the program and the responses of housing prices at different distances from a BOW site after the program. In particular, we assign apartments into 0.2-mile bins according to their distances to BOW sites and run the following regression:

$$\ln P_{ijkt} = \sum_{n} \left(\beta_0^n 1_i^{\text{bin } n} + \beta_1^n 1_i^{\text{bin } n} \times \text{Post}_t \right) + \tau_{kt} + X_{ijkt}\theta + \epsilon_{ijkt}. \tag{2}$$

In the central analysis, we have 10 bins and assign apartments more than 2 miles away to the comparison group. We exclude transactions that occurred in 2016 and 2017, such that changes in the price gradient are estimated off transactions after the program completion, when households make their purchase decisions based on the realized environmental amenities.[25] The patterns barely change if we include these observations in the regression, as shown in Figure B.3. The rest of regression specification is the same as in the central regression detailed in Section 4.1.

We report the estimates of the coefficients of interests $\{\beta_1^n\}$ in Figure 3 Panel (a) and $\{\beta_0^n\}$ in Panel (b). $\{\beta_1^n\}$ represents the percentage change in the price of apartments in bin n compared with apartments more than 2 miles from any BOW site. As shown in Panel (a), apartments less than 1 mile from a BOW site had a substantial increase in housing prices after the BOW program, while the effects for apartments farther away are close to zero and insignificant. $\{\beta_0^n\}$ represents the price gradient with respect to distance from a BOW site before the program. Figure 3 Panel (b) demonstrates that apartments less than 1 mile from a BOW site had a lower price before the program. These findings, together, indicate that the heavily polluted waterways mainly negatively affect the price of apartments less than 1 mile away, and cleaning them up leads to an increase in the price of these initially negatively affected apartments.

Based on the findings above, we define the treated apartments as those within 1 mile from a BOW site and assign apartments between 1 and 2 miles from any treated waterways into the comparison group. We also consider 0.8 to 1.2 miles for robustness checks.

At the end of this subsection, we compare characteristics of apartments in the treated and comparison group using transaction records from before 2016. As shown in Table C.4, apartments in the two groups are quite similar along a variety of dimensions, including the number of bedrooms, bathrooms, exposures, floor level, total number of floors in a building, and building completion year. Next, there is only a slight distinction between the two groups in terms of the floor level, with the treated group apartments being 1% less likely to come from lower levels. Table C.4 also suggests that apartments in the treated group are smaller, less likely to have multiple living rooms and high-quality finish, and more likely to have a tower or slab structure. Despite so, the regression results remain unchanged if we control for the time-varying effects of the number of living rooms, apartment size, building structure, high-end finish, and floor level, as shown in Section 4.3.3.

4.3 Changes in Housing Prices: Difference-in-Differences Estimation

4.3.1 Event Study

Before estimating Equation 1, we conduct an event study to provide evidence of parallel trends in housing prices before the program. We use the same regression specification as in Equation 1, but estimate the effects year by year, using 2015 as the baseline year. Figure 4 indicates that up to 2015, the prices of apartments in the treated and comparison groups followed parallel trends.

[25] We also leave out apartments more than 20 miles from any BOW site, which accounts for only 0.5% of the transactions, as they are too far away and hence less comparable to the rest.

Figure 4 also reveals that, beginning in 2016, apartments within 1 mile of a BOW site experienced significantly higher prices than the rest. The immediate increase in housing values following the program's onset is because housing values reflect the present discounted value of the full range of amenities tied to a specific location. We notice a minor positive effect in 2016, followed by a sustained increase in 2017, signaling the growing confidence of residents in the program over time. Moreover, between 2018 and 2020, changes in housing prices were consistent but marginally below the effects seen in 2017.

4.3.2 Difference-in-Differences Estimation

We estimate Equation 1 and report the baseline results in Table 1, Column 1. As per the baseline estimates, apartments located less than 1 mile from the BOW sites were 3.7% cheaper than apartments that are 1 to 2 miles away before the program. It indicates that residents were avoiding living close to initially heavily polluted waterways. After the introduction of the BOW program, apartments located within 1 mile of a BOW site experienced a 2.3% increase in housing prices relative to those located 1 to 2 miles away. In Column 2, we further differentiate price responses between the period when the BOW program was in progress and the time when it was completed. We find that the effects are quite similar.

The estimated property value appreciation helps provide a benchmark for the benefit-cost ratio of the BOW program for the six sample cities. Following Keiser and Shapiro (2019), we measure the benefit of the program using the total increase in housing values of apartments within 1 mile from cleaned waterways. Given the total cost to clean up the waterways across the 6 sample cities to be 41 billion RMB, the policy's benefit-cost ratio is 12.[26] We recognize that the program brings not only property value appreciation for residential units but also other benefits that are not accounted for in the analysis. These unmeasured benefits include increased business opportunities and revenue, as well as recreational advantages for individuals living very far away (Kuwayama et al., 2022). Consequently, the benefit-cost ratio provided here represents a conservative estimate, serving as the lower bound of the actual ratio.

Our estimate is also valuable for those considering private provision of waterway clean-ups.

[26] The data on the total expenses of the program in the six cities is not directly available, so we calibrate the total investment cost using the following method. The cumulative investment incurred by the program across the 36 most developed cities was reported to be 114 billion RMB (Cao, 2019). Based on this information, we calculated the average investment per BOW site and per mile of BOW cleaned, resulting in a total investment of 41 billion RMB and 26 billion RMB for the six cities, respectively. We used the higher value of the two estimates to get a lower bound of the benefit-cost ratio. Next, we obtain a complete list of residential building complexes from An Ju Ke, a leading real estate agency in China, and identify those within 1 mile from cleaned waterways. This dataset also provides the total number of apartments in each residential building complex. Additionally, we need the market value of these apartments in 2015 to calculate their appreciation credited to the program. We use the housing transaction records in 2015 to compute the average housing price per square meter and the average floor area for each residential building complex.

While the program has expanded to other Chinese cities in recent years, governments in less developed cities often hesitate to adopt it because of the additional budget required.[27] There have been proposals to involve the private sector, including real estate companies and homeowners near these waterways, in these projects. In return, they could benefit from property value appreciation once the waterways become cleaner. The feasibility of such proposals hinges on the property value appreciation these projects generate. Since our sample is from the most developed metropolitan areas in China, the estimated change in housing prices is particularly relevant for neighborhoods with similar demographic and economic characteristics, such as population density and income levels.[28]

Finally, a t-test of the post-program price differential between the treated and control areas leads to a p-value of 0.25, indicating that, after the program, housing prices are no longer statistically different from 0. The program didn't establish a waterfront premium, likely because neighborhoods near the BOW sites traditionally housed lower-income households. This is supported by the fact that housing units close to the BOW sites tend to be smaller and less likely to feature high-quality finishes as discussed in Section 4.2. As a result, these neighborhoods are cheaper than other residential complexes even after the program.

4.3.3 Robustness Checks

To address concerns that the estimated effects may be confounded by unobserved demand shocks that vary across neighborhoods, we consider a battery of robustness checks. First, the quality of local public goods and public services, such as health care and education, play a vital role in determining housing prices. These public goods are governed by local governments at the county level and are subject to changes over time. Therefore, we further control for county time-varying effects in Table 1 Column 3 and find that the effects are close to the baseline estimates.

A related concern is that the growing demand for high-quality public schools could lead to a divergence in prices between apartment complexes located within the catchment areas of good schools and those outside. If apartments within one mile of the initially heavily polluted waterways are typically close to high-quality public schools, this alternative channel could result in a relative increase in housing prices near BOW sites. To address this concern, we adopt the approach of Zheng and Kahn (2008) and calculate the distance of each apartment to the nearest core primary and middle school.[29] We include these distances, interacted with time-varying effects,

[27] The absence of property taxes prevents governments from benefiting from property value appreciation.

[28] As shown in Table C.1, the sample townships in the six cities have a higher working population ratio and a lower percentage of Hukou holders. It is because these cities have better job opportunities and hence attract the working population from other regions. For less densely populated or less affluent neighborhoods, it is possible that the estimated price change provides an upper bound of the property value appreciation.

[29] Each apartment building belongs to a unique school catchment area, and children who live in the building have

in the regression. As shown in Table 1 Column 4, the estimates are consistent with the baseline results.

Next, to address concerns that the effects could be contaminated by changing demand for residing near the city center, we control for the time-varying effects of distance to the city center in Table 1 Column 5. In Table 1, Column 6, we provide further evidence that the observed effects are not driven by increasing demand for living near waterways over time. To do so, we estimate a triple-difference regression model that measures the differential effect of proximity to general waterways versus initially heavily polluted waterways after the implementation of the BOW program. Our findings suggest that there were no significant changes in housing prices in areas near the regular waterways, but there was a considerable increase in prices in areas where the nearby waterways were cleaned up by the program.

To address concerns that neighborhoods with different demographics may have diverging housing price trends after 2016, we incorporate urban district characteristics from 2010 interacted with year dummies in Table C.5 Column 1. These characteristics include population, sex ratio, the percentage of the population aged between 15 and 64, the percentage of the population aged above 64, and the percentage of local Hukou holders. Additionally, in Table C.5 Column 2, we control for urban district time-varying effects and hence restrict variation to come from apartments within the same urban district. This richer specification adds approximately 4000 fixed effects at the urban district-year level. Across all specifications, the results are consistent with each other.

Fifth, given that the dataset is not from repeated sales, we always include a comprehensive set of housing characteristics in the regression to control for the composition effects. In Table C.5, Column 3, we further control for the building address fixed-effects. Note that this specification no longer allows us to estimate the pre-treatment price differences between apartments in the treated and comparison region and the sample is restricted to apartments from one-third of buildings in the full sample with housing transactions before and after the program. That being said, we find the treatment effect to be consistent with the baseline results. Given the difference in housing characters in units in the treated and control regions, in Table C.5, Column 4, we control for the time-varying effects of the number of living rooms, apartment size, building structure, high-end finish, and floor level. The results remain close to the central analysis.

Sixth, we relax the strict parallel trends assumption by calculating confidence intervals for the treatment effects by year, considering different assumptions regarding the trend divergence between the treated and comparison groups (Rambachan and Roth, 2023). As depicted in Figure B.4, the coefficients for 2016 and 2017 remain significantly different from zero when we assume that

---

the right to attend the designated school. However, as in Zheng and Kahn (2008), we do not observe the designated public school for each apartment building. Therefore, we use distances to the nearest core primary school and middle school to approximate the probability of being within the catchment area of high-quality schools.

the maximum pre-treatment violations of parallel trends cannot exceed the maximal pre-treatment violation. For subsequent years, the maximum allowable deviation to achieve statistically significant effects decreases. This reduction is attributable to the enlarged identified set for later periods and the increased standard errors for coefficients in those years. A smaller maximum allowable deviation is more problematic if prominent yet unobserved demand shocks exist, systematically correlating with apartments in the treated and control regions. However, since we have accounted for the most prominent demand shocks and secular changes discussed in the literature and have demonstrated the robustness of the effects in those cases, this concern is less applicable to our study setting.

Several additional robustness checks are performed at the end of this subsection. First, we observe similar results when we include all apartments located 2 to 20 miles from any BOW sites in the comparison group, as presented in Table C.5, Column 5. Second, to address concerns about the potential impact of the Covid-19 pandemic on the housing market, we exclude apartments sold in 2020 and display the results in Table C.5, Column 6. The results also remain robust to variations in the treatment region's width, as demonstrated in Table C.5, Columns 7 and 8, where we define the treated region as 0.8 or 1.2 miles away from BOW sites and the comparison region as 0.8 to 1.6 miles away and 1.2 to 2.4 miles away, respectively. Finally, we cluster the error terms at the county level in Table C.5, Column 9, to allow housing prices across urban districts within the same county to correlate with each other, and find that it has minimal impact on the standard errors of the coefficients.

4.4 Heterogeneous Treatment Effects

In this sub-section, we explore the heterogeneity of treatment effects across neighborhoods. This analysis sheds light on which neighborhoods or waterway segments likely contribute to the most housing value appreciation. Variation in treatment effect can occur if the marginal utility brought by an environmental amenity varies across neighborhoods or if individuals with differing values for the environmental amenity provided by cleaned waterways tend to reside in different neighborhoods. We consider two characteristics in the baseline years in particular: population density and home sale prices.

To carry out the analysis, we classify urban districts into two subgroups based on whether it is below or above the median level within a city in terms of population density in 2010, average home sale prices over 2012 – 2015, and distance to the city center. We refer to them as Low-type and High-type urban districts and denote them by their corresponding subgroup, $g \in \{L, H\}$. We adapt the baseline specification in Equation 1 and estimate the following regression:

$$\begin{aligned}\ln P_{ijkt} =&\beta_0 + \beta_{\mathrm{H}} 1_{\mathrm{Near},i} \times \mathrm{Post2016}_t \times 1_{\mathrm{H},j} + \beta_{\mathrm{L}} 1_{\mathrm{Near},i} \times \mathrm{Post2016}_t \times 1_{\mathrm{L},j} \\ &+ \theta_{b(i)g(j)} + \phi_{\tau(t)g(j)} + \tau_{kt} + X_{ijkt}\theta + \epsilon_{ijkt}. \end{aligned} \tag{3}$$

We control for $\theta_{b(i)g(j)}$, the fixed effects of being located within 1 mile of a BOW site interacted with the corresponding neighborhood type.[30] We additionally control for the time-varying effects of the corresponding neighborhood type, $\phi_{\tau(t)g(j)}$, ensuring that the differential effects observed were not caused by price divergence across different types of neighborhoods.[31]

Table 2 shows the estimated β_H and β_L from Equation 3 for the two neighborhood characteristics respectively. As shown in Column 1, the positive price effects following the waterway cleanup are concentrated in urban districts that are densely populated. It is expected given that the program turns polluted waterways into new recreational open spaces, it would be valued the most in densely populated neighborhoods where open spaces are scarce. As a consequence, we expect housing prices in densely populated areas to appreciate more after a nearby BOW site gets cleaned up.

Next, we find a nearly 4% price increase after the BOW program for apartments in urban districts that are initially more expensive, as shown in Table 2, Column 2. In contrast, price effects in urban districts with low initial housing prices are close to zero and insignificant. The larger price effects in initially more expensive neighborhoods shed light on the greater willingness to pay for environmental amenity improvements from richer households.

Finally, as more polluted waterways experienced greater improvement in water quality under the program, we expect a more substantial increase in prices near more polluted waterways. We find empirical evidence in support of this conjecture. Each BOW site has been categorized as moderately polluted or severely polluted. According to Table 2 Column 3, the increase in housing prices reaches 2.8% for apartments near severely polluted waterways, nearly double the effect observed for apartments near moderately polluted waterways.

5 Real Estate and Business Development

As neighborhoods close to the treated waterways become more appealing to residents, it can create new demand for a variety of services in these revitalized communities, ranging from restaurants

[30] $\theta_{b(i)g(j)}$ represents a set of urban district heterogeneity by boundary fixed effects, equalling to one if the transacted unit i is located within 1 mile from cleaned waterways and the corresponding urban district j belongs to the subgroup g.

[31] $\phi_{\tau(t)g(j)}$ represents a set of urban district heterogeneity by post-treatment fixed effects, equalling to one if the housing transaction takes place after 2016 and the corresponding urban district j belongs to the subgroup g.

to retail shops. In this section, we examine two important sectors that can drive some of the neighborhood transformations associated with the program: real estate developers, and service and retail businesses. We study their reactions to the program and explore the interaction between their responses and changes in housing prices.

5.1 Housing Supply Responses

In this subsection, we examine the impact of the BOW program on the supply-side responses of the housing market and the subsequent implications for housing prices. Using records for new buildings from 2010 to 2020, we investigate whether there is an uptick in the supply of newly constructed residential complexes in neighborhoods closer to a BOW site, as compared with those farther away. Our findings indicate no such increase in supply. Hence, the price responses identified in the earlier section are primarily driven by the demand side. We also find that if real estate developers construct a new apartment complex near a BOW site, they tend to favor the inclusion of high-end units with luxurious finishes and spacious layouts following the program's implementation. This shift brings a relative downward pressure on the price change for existing high-end apartments.

We begin by showing that there is no significant difference in the number of new apartment units supplied to the market between neighborhoods closer to a BOW site and those farther away after 2016. To carry out our empirical analysis, we divide each city into exclusive hexagons with a side length of 0.3 miles and count the number of newly built apartments by hexagon-year from 2010 to 2020.[32] We conduct a difference-in-differences estimation by comparing hexagons within 1 mile from any BOW sites with those located between 1 and 2 miles.[33] The regression specification is as follows:

$$y_{ljkt} = \beta_0 + \beta_2 1_{Near,l} \times \text{After}_t + \alpha_l + \tau_{kt} + \epsilon_{ljkt}. \tag{4}$$

For our outcome variable, we use both the count of newly built apartment units and a binary variable indicating whether at least one residential complex was completed and available for sale in the corresponding hexagon. The model controls for hexagon fixed effects (α_l) and city time-varying fixed effects (τ_{kt}), and the error terms are clustered at the urban district level and city-year level.[34]

Our analysis, presented in Table 3 Columns 1 and 2, reveals that the supply of newly built apartments does not significantly increase in neighborhoods closer to a BOW site than those far-

[32]Each hexagon has a total area of approximately 0.25 square miles.

[33]We calculate the shortest distance from the centroid of each hexagon to the nearest BOW site.

[34]We show in Table C.6 Columns 1 to 5 that the central results are robust to controlling for county time-varying effects.

ther away.[35] This result is likely due to the fact that the BOW program targets developed urban neighborhoods with limited open land for new construction.[36] This finding indicates that the growing demand for housing is the primary driver of changes in housing prices in neighborhoods close to the BOW sites.[37]

However, if real estate developers are able to construct a new residential building complex near a BOW site, they are more likely to provide high-end finishes and spacious apartment layouts after the end of the program. In particular, we conduct a difference-in-differences estimation at the level of new apartment complexes and examine whether the probability of constructing a building with high-end finishes, spacious layouts, or more green space surrounding the building changes. The regression specification is similar to Equation 1, except that each unit in the analysis is a building complex open to sale in year t.

Column 3 of Table 3 suggests an increase in the supply of apartment units with high-end finishes. To account for the typical three-year time lag from building design to market launch, we further divide the post-program period into two sub-periods: 2016 to 2018 and 2019 to 2020. We then estimate the responses in each sub-period. As shown in Column 4 of Table 3, there is a significant increase during 2019 and 2020, with a 14.0% rise in the probability of an apartment complex having high-end finishes.[38] In Columns 5 and 6, we observe an 7.3% increase in the probability of launching an apartment complex with spacious layouts in 2019 and 2020.[39] Finally, we do not find any significant changes in the green-space ratio, as shown in Columns 7 and 8 of Table 3. Overall, the findings suggest that real estate developers are anticipating an influx of higher-income families to neighborhoods adjacent to cleaned waterways and begin to provide pricier units that cater to wealthier clients.

The increasing supply of high-end new apartments can create downward pressure on the prices of existing high-end units. At the end of this subsection, we investigate the potential differences in price responses between high-end and regular housing units. We consider three proxies for high-end apartments: the presence of high-quality finishes, a spacious layout, and whether the unit was constructed in more recent years.[40] As shown in Table 4, apartments with high-quality finishes and spacious layouts and newer apartments had a less pronounced price response to the improved water

[35] We find no differential effects between the periods of 2016 to 2017 and 2018 to 2020, as shown in Table C.6, Columns 6 and 7.

[36] As shown in Table C.3, Panel B, the probability of a polygon-year having new residential complexes is as low as 2.5%.

[37] New constructions typically occur on open land, and hence do not cause any reduction in housing stocks through demolition and reconstruction.

[38] The increase is economically large, given that the pre-program probability of having an apartment complex with high-end finishes within 1 mile of the BOW sites was only 31%.

[39] This increase corresponds to a 70% growth relative to the baseline probability.

[40] We classify a unit as having a spacious layout if its floor area exceeds the median value in the sample. Next, we classify an apartment as new if it was constructed after 2000, with roughly 50% of the sample units being new.

quality.[41] This finding indicates that households with budget constraints may find it increasingly challenging to relocate to these neighborhoods, exacerbating inequality in access to environmental amenities.

5.2 Changes in Business Activities near BOW Sites

In this subsection, we show that following the program's implementation, businesses, such as recreation centers, restaurants, and pharmacies, are drawn to neighborhoods near cleaned waterways. We estimate a regression model that is similar to a bin analysis:

$$N^{w}_{lkt} = \sum_{n} \beta^{n}_{1} 1^{\text{bin } n}_{lk} \times \text{Post}_t + \alpha_l + X_{lt} + \tau_{kt} + \epsilon_{ijkt}. \tag{5}$$

Our outcome variable is the number of stores in category w, hexagon l, city k, and year t.[42] In the regression, we have ten 0.2-mile bins and include hexagons between 2 miles and 20 miles from any BOW programs in the comparison group. We control for hexagon fixed-effects (α_l), city time-varying effects (τ_{kt}), and the time-varying effects of the polynomial of the number of stores in the baseline year (X_{lt}). We use the number of stores in the baseline year in a hexagon to proxy for the presence of retail and service businesses before the program. Controlling for its interaction with year dummies allows us to address a potential upward bias if hexagons in close proximity to BOW sites display systematically different levels of activity in local commercial businesses in the baseline year, and there is an overall uptick in local commercial businesses in these commercial areas during the years 2015 and 2019.

As shown in Figure 5, we find an increase in the number of stores for various business categories close cleaned waterways. Panel (a) demonstrates a significant increase in the number of restaurants in areas close to the BOW sites. Specifically, within a 0.2-mile radius of cleaned waterways, the number of restaurants increased by 10, indicating a 46% growth compared with the baseline average. The effect becomes less pronounced as we move farther away from cleaned waterways. Additionally, we found a noteworthy increase in the number of recreational centers, with the effect being most concentrated within a 0.2-mile radius of BOW sites. Within 0.2 miles of any BOW site, there was an increase in the number of recreational centers by 1.3, implying a 33% increase compared with the baseline average. The effect also diminishes as we move away from cleaned waterways. Similar patterns were observed for pharmacies, convenience stores, tutoring

[41] They are not statistically different at 5% significance level though.

[42] We consider nine categories of stores and service businesses, including recreational centers (e.g., chess clubs, KTVs, game centers, Internet cafes), restaurants, convenience stores, pharmacies, financial services (e.g., bank branches and ATMs), tutoring services, other services (e.g., post offices, salons, laundries, photography studios, and repair shops), grocery and supermarkets, and other retail stores.

services, and other service businesses. On the other hand, we find limited responses in tutoring centers, financial services, and other retail shops. In Table 5, we conduct a difference-in-differences estimation by comparing hexagons within 1 mile of BOW sites with hexagons between 1 and 2 miles from BOW sites to summarize the average effects.[43]

The increase in service businesses near BOW sites reflects a rise in the number of visitors after the waterways were cleaned up and transformed into new recreational spots. The growth of these service businesses also improves service amenities and potentially contribute to an increase in housing prices. To investigate this mechanism, we include the number of stores surrounding a housing unit in the housing price regression, as specified in Equation 1. In particular, we count the number of stores within the same 0.3-mile hexagon where the housing unit is located.[44] This additional control variable accounts for the effects of the BOW program on housing prices through changes in the number of nearby stores. Accordingly, the residual effects of the BOW program reflect the impact attributable to the environmental amenity.

As shown in Table 6, Column 1, the residual effects are close to the central estimates. To mitigate concerns about endogenous changes in the number of stores, we utilize an instrumental variable approach in Column 2. In particular, we employ the interaction between policy treatment and a dummy variable that indicates whether the housing unit is located in a commercial area.[45] The rationale is that in commercial zones with available storefronts, there's a higher likelihood of an increase in store openings when demand grows. When using the IV approach, the residual effect is around 1.6%.[46]

Overall, the findings suggest that housing price appreciation is primarily driven by improved environmental amenities rather than service amenities. The small effect of service amenities could be explained by the high density of service amenities in the sample neighborhoods before the BOW program's introduction, and hence additional services may not significantly impact housing prices. Furthermore, foot traffic and congestion externality associated with service amenities may offset their positive effects on housing prices. It is also worth noting that the price effects apply only to residential properties, while the impacts on commercial real estate remain open questions.

In addition to retail and service businesses, we also investigate whether the creation of new parks or factory closures – potential outcomes accompanying the BOW program that could directly influence housing prices – drive the observed housing price changes. In Appendix A.2, we provide

[43] We show robustness of the results to controlling for county time-varying effects and alternative polygon shapes in Table C.7.

[44] We focus on the types of stores that show an increase near cleaned waterways in the previous analysis. Additionally, since the data for this variable is only available for 2015 and 2019, we employ linear extrapolation and set any negative values to zero.

[45] We categorize polygons that fall within the top 20th percentile for the number of stores in the baseline year as commercial areas.

[46] We need to interpret this result with caution though, as the instrumental variable is subject to weak IV biases.

evidence that the price changes are not attributable to either channel.

6 Conclusion

This paper examines the economic benefits of cleaning up heavily polluted waterways in urban neighborhoods. Using the Black-and-Odorous Water Program in China as a natural experiment, we estimate the effects of cleaner waterways on housing prices, housing supply, as well as local service businesses. Specifically, we find that the program mainly benefits real estate properties within 1 mile of cleaned waterways, which were 3.7% cheaper before the program and experienced a 2.3% market value appreciation after the program. Our results also reveal that, despite no evidence of developers shifting construction to neighborhoods close to the BOW sites, developers building new apartment complexes near these sites are more likely to provide high-end units featuring high-quality finishes and spacious layouts after the program. This finding sheds light on the potential for the program to incentivize higher-end real estate development in affected areas. Finally, we show that the program has led to the thriving of various service businesses in neighborhoods close to cleaned waterways, contributing to the revitalization of these areas.

Our findings indicate that urban environmental programs can effectively revitalize central cities in developing country cities, especially for densely populated cities with limited public space for recreational activities and growing demand for environmental amenities. Rapid urbanization often accompanies over-congestion and the deterioration of air and water quality in central cities. Our paper shows that by cleaning up the polluted waterways in urban districts, the neighborhoods close to these environmental disamenities become attractive to residents and new businesses again. Therefore, governments in developing countries may slow down or even reverse the declining trends in polluted neighborhoods by implementing such programs in cities under continued expansion.

References

Marcella Alsan and Claudia Goldin. Watersheds in child mortality: The role of effective water and sewerage infrastructure, 1880–1920. *Journal of Political Economy*, 127(2):586–638, 2019.

Nava Ashraf, Edward Glaeser, Abraham Holland, and Bryce Millett Steinberg. Water, health and wealth. Technical report, National Bureau of Economic Research, 2017.

David H Autor, Christopher J Palmer, and Parag A Pathak. Housing market spillovers: Evidence from the end of rent control in cambridge, massachusetts. *Journal of Political Economy*, 122(3): 661–717, 2014.

H Spencer Banzhaf and Randall P Walsh. Do people vote with their feet? an empirical test of tiebout's mechanism. *American economic review*, 98(3):843–863, 2008.

Brian Beach. Water infrastructure and health in us cities. *Regional Science and Urban Economics*, 94:103674, 2022.

Sonia R Bhalotra, Alberto Diaz-Cayeros, Grant Miller, Alfonso Miranda, and Atheendar S Venkataramani. Urban water disinfection and mortality decline in lower-income countries. *American Economic Journal: Economic Policy*, 13(4):490–520, 2021.

Stefan Boes and Stephan Nüesch. Quasi-experimental evidence on the effect of aircraft noise on apartment rents. *Journal of Urban Economics*, 69(2):196–204, 2011.

Linda TM Bui and Christopher J Mayer. Regulation and capitalization of environmental amenities: evidence from the toxic release inventory in massachusetts. *Review of Economics and statistics*, 85(3):693–708, 2003.

Ying Cao. Ministry of ecology and environment: A total of 114 billion yuan invested in the remediation of black and odorous water bodies, with the focus shifting to prefecture-level cities in the next two years. *China Xinhua News*, February 28 2019. URL http://www.xinhuanet.com/politics/2019-02/28/c_1210070044.htm.

Alecia W Cassidy, Elaine L Hill, and Lala Ma. Who benefits from hazardous waste cleanups? evidence from the housing market. Technical report, National Bureau of Economic Research, 2022.

Kenneth Y Chay and Michael Greenstone. Does air quality matter? evidence from the housing market. *Journal of political Economy*, 113(2):376–424, 2005.

Zhao Chen, Matthew E Kahn, Yu Liu, and Zhi Wang. The consequences of spatially differentiated water pollution regulation in china. *Journal of Environmental Economics and Management*, 88: 468–485, 2018.

Dora L Costa and Matthew E Kahn. Changes in the value of life, 1940–1980. *Journal of risk and Uncertainty*, 29(2):159–180, 2004.

Michael Coury, Toru Kitagawa, Allison Shertzer, and Matthew Turner. The value of piped water and sewers: Evidence from 19th century chicago. Technical report, National Bureau of Economic Research, 2022.

Clément De Chaisemartin and Xavier d'Haultfoeuille. Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. Technical report, National Bureau of Economic Research, 2022.

Clément De Chaisemartin and Xavier d'Haultfoeuille. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996, 2020.

Florencia Devoto, Esther Duflo, Pascaline Dupas, William Parienté, and Vincent Pons. Happiness on tap: Piped water adoption in urban morocco. *American Economic Journal: Economic Policy*, 4(4):68–99, 2012.

Esther Duflo, Michael Greenstone, Rohini Pande, and Nicholas Ryan. The value of regulatory discretion: Estimates from environmental inspections in india. *Econometrica*, 86(6):2123–2160, 2018.

Sebastian Galiani, Paul Gertler, and Ernesto Schargrodsky. Water for life: The impact of the privatization of water services on child mortality. *Journal of political economy*, 113(1):83–120, 2005.

Shanti Gamper-Rabindran and Christopher Timmins. Hazardous waste cleanup, neighborhood gentrification, and environmental justice: Evidence from restricted access census block data. *American Economic Review*, 101(3):620–24, 2011.

Shanti Gamper-Rabindran, Shakeeb Khan, and Christopher Timmins. The impact of piped water provision on infant mortality in brazil: A quantile panel data approach. *Journal of Development Economics*, 92(2):188–200, 2010.

Corbett A Grainger. The distributional effects of pollution regulations: Do renters fully pay for cleaner air? *Journal of Public Economics*, 96(9-10):840–852, 2012.

Michael Greenstone and Justin Gallagher. Does hazardous waste matter? evidence from the housing market and the superfund program. *The Quarterly Journal of Economics*, 123(3):951–1003, 2008.

Michael Greenstone and Rema Hanna. Environmental regulations, air and water pollution, and infant mortality in india. *American Economic Review*, 104(10):3038–72, 2014.

Michael Greenstone, Guojun He, Shanjun Li, and Eric Yongchen Zou. China's war on pollution: Evidence from the first 5 years. *Review of Environmental Economics and Policy*, 15(2):281–299, 2021.

Guojun He, Shaoda Wang, and Bing Zhang. Watering down environmental regulation in china. *The Quarterly Journal of Economics*, 2020.

Stephan Heblich, Alex Trew, and Yanos Zylberberg. East-side story: Historical pollution and persistent neighborhood sorting. *Journal of Political Economy*, 129(5):1508–1552, 2021.

Guoqing Hu, Donghua Chen, Congfang Liu, Yimei Xie, Saisai Liu, and Hu Li. Dynamic monitoring of urban black-odor water bodies based on gf-2 image. *Remote Sensing for Land and Resources*, 33(1):30–37, 2021.

Guy Hutton and Mili Varughese. The costs of meeting the 2030 sustainable development goal targets on drinking water, sanitation, and hygiene. 2016.

Adam Isen, Maya Rossin-Slater, and W Reed Walker. Every breath you take – every dollar you'll make: The long-term consequences of the clean air act of 1970. *Journal of Political Economy*, 125(3):848–902, 2017.

Koichiro Ito and Shuang Zhang. Willingness to pay for clean air: Evidence from air purifier markets in china. *Journal of Political Economy*, 128(5):1627–1672, 2020.

David A Keiser and Joseph S Shapiro. Consequences of the clean water act and the demand for water quality. *The Quarterly Journal of Economics*, 134(1):349–396, 2019.

Yusuke Kuwayama and Sheila Olmstead. Water quality and economics: willingness to pay, efficiency, cost-effectiveness, and new research frontiers. In *Handbook on the Economics of Natural Resources*. Edward Elgar Publishing, 2015.

Yusuke Kuwayama, Sheila Olmstead, and Jiameng Zheng. A more comprehensive estimate of the value of water quality. *Journal of Public Economics*, 207:104600, 2022.

Pei Li, Yi Lu, and Jin Wang. The effects of fuel standards on air pollution: Evidence from china. *Journal of Development Economics*, 146:102488, 2020.

Mengdi Liu, Ruipeng Tan, and Bing Zhang. The costs of “blue sky”: Environmental regulation, technology upgrading, and labor demand in china. *Journal of Development Economics*, 150: 102610, 2021.

Peter Mieszkowski and Edwin S Mills. The causes of metropolitan suburbanization. *Journal of Economic perspectives*, 7(3):135–147, 1993.

Ministry of Ecology and Environment. Record of regular press conference, January 18 2020. URL https://www.mee.gov.cn/xxgk2018/xxgk/xxgk15/202001/t20200117_760049.html.

Cong Peng, Stephen Gibbons, and Cheng Keat Tang. Valuing the environmental benefits of canals using house prices. 2019.

Keke Qi, Qian Shen, Xiaojun Luo, Jiaguo Li, Yue Yao, and Chong Yang. Remote sensing classification and recognition of blakc and odorous water in shenyang based on gf-2 image. *Remote Sensing Technology and Application*, 35(2):424–434, 2020.

Ashesh Rambachan and Jonathan Roth. A more credible approach to parallel trends. *Review of Economic Studies*, page rdad018, 2023.

SEE and IPE. Black and smelly rivers survey report i, http://www.ipe.org.cn/reports/report_18450.html. Technical report, 2016.

SEE and IPE. Black and smelly rivers survey report iii. Technical report, 2018.

Carol F Streiner and John B Loomis. Estimating the benefits of urban stream restoration using the hedonic price method. *Rivers*, 5(4):267–278, 1995.

UNDP. Undp’s support to sustainable, inclusive and resilient cities in developing world. *New York: United Nations Development Programme*, 2016.

V Brian Viard and Shihe Fu. The effect of beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics*, 125:98–115, 2015.

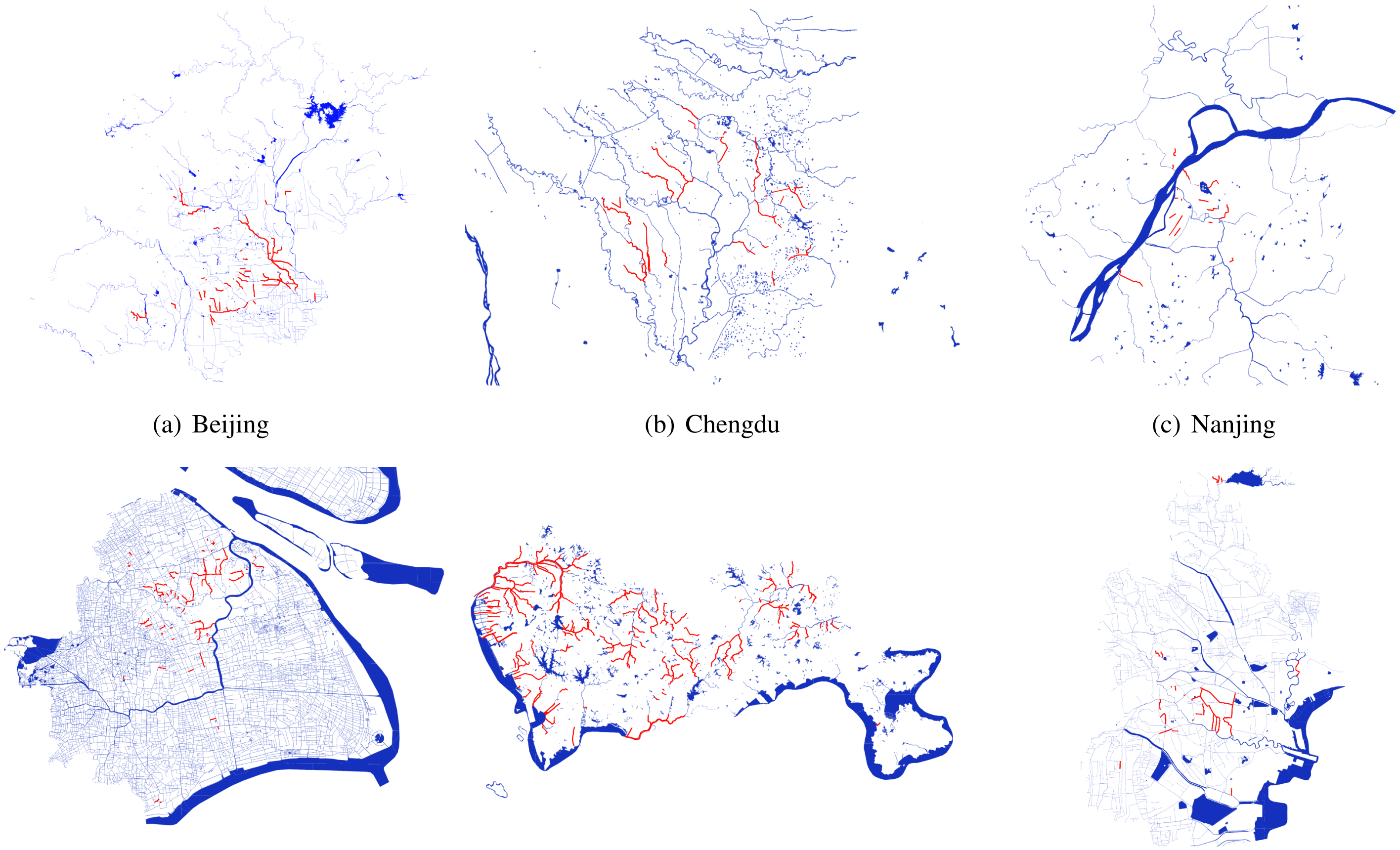
Yan Wang, Jie Yao, Pu Yang, Yu Zhang, Yanhua Sun, and Na Cui. Dynamic remote sensing monitoring and its influence factors analysis for urban black and odorous water body management and treatment in beijing, china. *Chinese Journal of Environmental Engineering*, 16(9): 3092–3101, 2022.

Siqi Zheng and Matthew E Kahn. Land and residential property markets in a booming economy: New evidence from beijing. *Journal of Urban Economics*, 63(2):743–757, 2008.

Siqi Zheng and Matthew E Kahn. A new era of pollution progress in urban china? *Journal of Economic Perspectives*, 31(1):71–92, 2017.

Figures

FIGURE 1: LOCATIONS OF BOW SITES

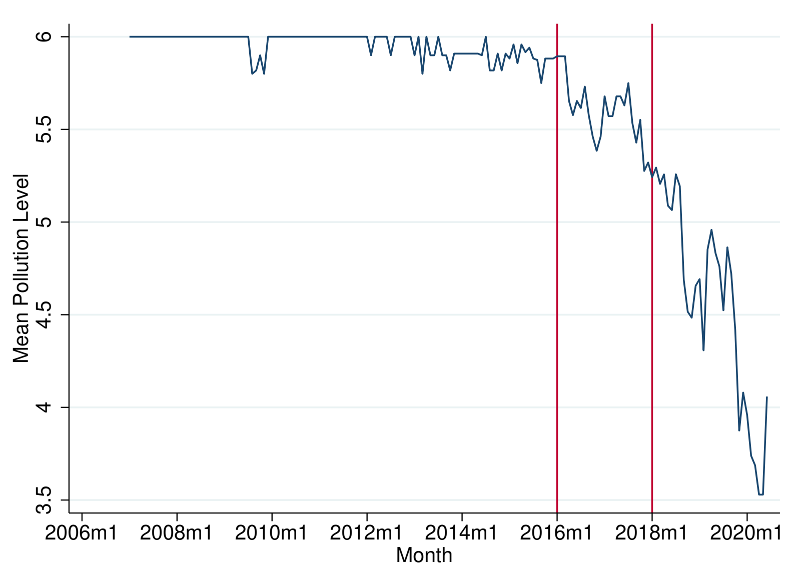


(a) Beijing (b) Chengdu (c) Nanjing

(d) Shanghai (e) Shenzhen (f) Tianjin

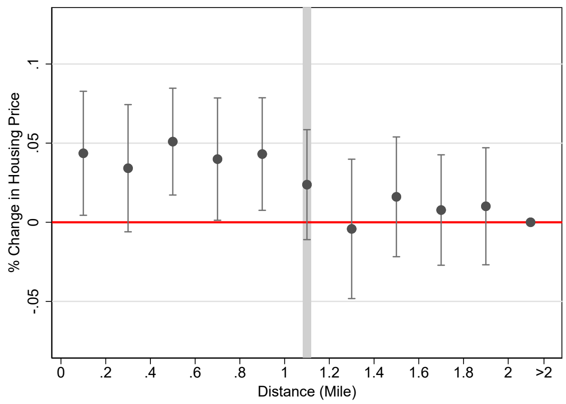
Notes: The red lines denote waterways that have been cleaned up under the BOW program, whereas the blue lines represent the remaining waterways running through each city. Data sources: Institute of Public & Environmental Affairs and Baidu Map.

FIGURE 2: CHANGES IN POLLUTION LEVEL

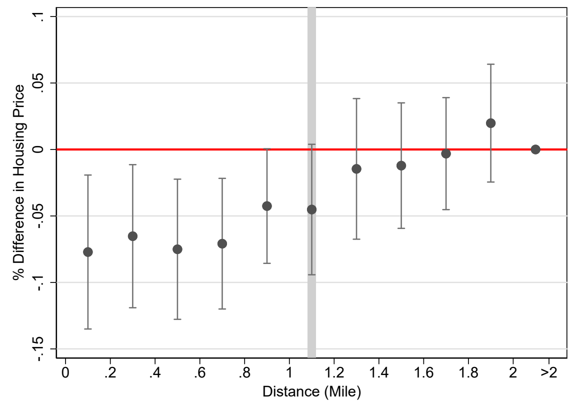


Notes: Based on the monthly data from water monitoring stations at the BOW locations, there was a consistent improvement in water quality both during and after the program. The pollution level is an integer index ranging from 1 to 6, with waterways that meet the BOW criteria corresponding to a level of 6.

FIGURE 3: CHANGES IN HOUSING PRICES BY DISTANCE FROM BOW SITES



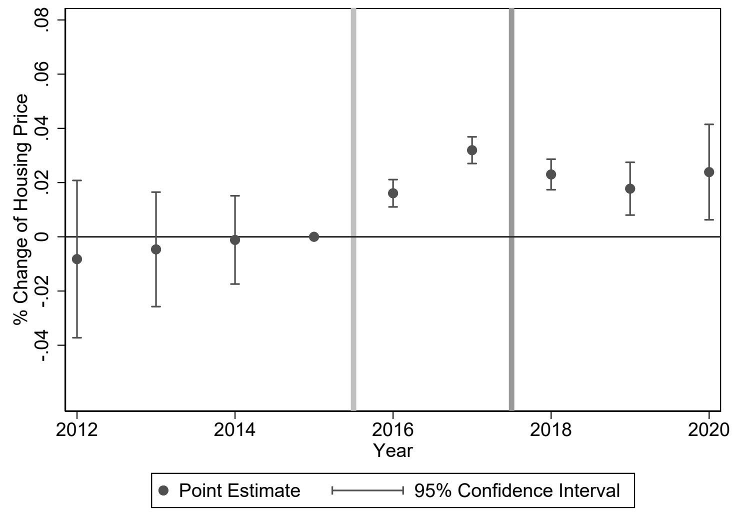
(a) Price Change (%)



(b) Price Gradient before the Treatment

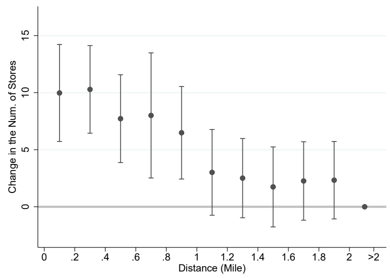
Notes: This figure shows that apartments located less than 1 mile from a BOW site experienced a significant increase in housing prices following the BOW program. In contrast, the effects on apartments located farther away are negligible and statistically insignificant. Panel (b) displays the price gradient with respect to distance from a BOW site and suggests that apartments within a 1-mile radius of a BOW site had a lower price before the program. We categorize apartments into equal-width bins according to their proximity to the nearest BOW site and run the following regression: $\ln P_{ijkt} = \sum_n \left(\beta_0^n 1_{\text{bin } n} + \beta_1^n 1_{\text{bin } n} \times \text{Post}_t\right) + \tau_{kt} + X_{ijt}\theta + \epsilon_{ijkt}$. We then plot the coefficients $\left\{\beta_1^n\right\}$ onto Panel (a) and the coefficients $\left\{\beta_0^n\right\}$ onto Panel (b). We set the bin width at 0.2 miles and group apartments located more than 2 miles away as the comparison group. Coefficient β_1^n represents the percentage change in housing prices for apartments in bin n compared with those more than 2 miles from a BOW site after the end of the program. We control for a comprehensive set of housing characteristics, urban district fixed effects, and city time-varying effects and double-cluster the error terms at both the urban district and city-year levels.

FIGURE 4: EVENT STUDY

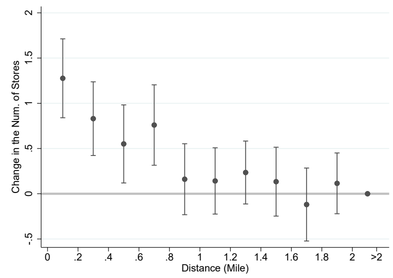


Notes: This figure shows that up to 2015, housing prices of apartments within 1 mile of a BOW site followed parallel trends to those of apartments located farther away; from 2016 onwards, apartments within this 1-mile radius had significantly higher prices compared with those 1 to 2 miles away. We estimate the effect of the BOW program on housing prices year by year and plot the coefficient estimates onto the graph. We use 2015 as the benchmark year for comparisons. Each coefficient represents whether, compared with 2015, the transacted apartments within 1 mile of a BOW site have systematically different price compared with those between 1 to 2 miles from a BOW site. We control for a comprehensive set of housing characteristics, urban district fixed effects, and city time-varying effects, and double-cluster the error terms at both the urban district and city-year levels.

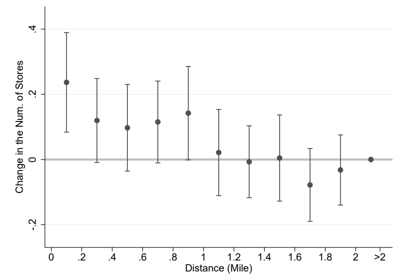
FIGURE 5: RETAIL AND SERVICE BUSINESS GROWTH BY DISTANCE FROM BOW SITES



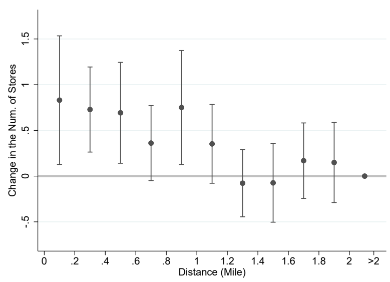
(a) Restaurants



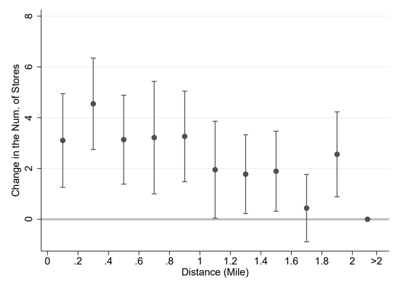
(b) Recreation



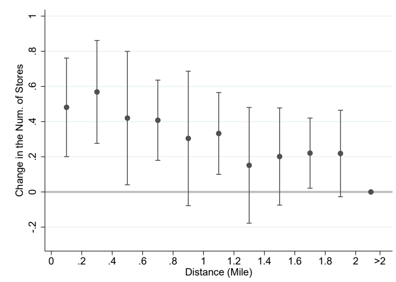
(c) Pharmacies



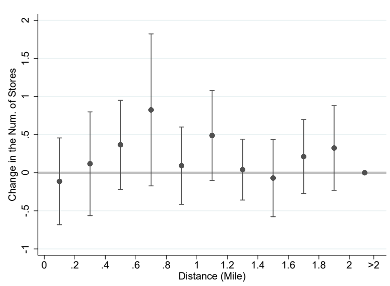
(d) Convenience Stores



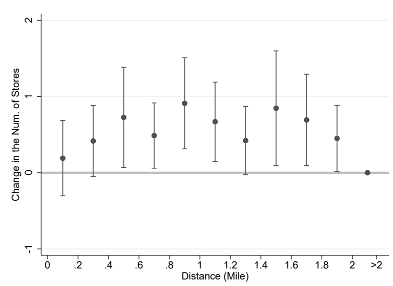
(e) Other Services



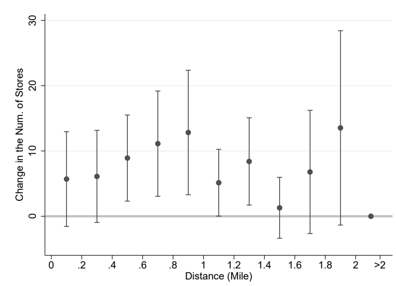
(f) Tutoring



(g) Finance



(h) Groceries and Supermarkets



(i) Other Retail Stores

Notes: The figure shows a localized increase in the number of various types of stores in neighborhoods that are located near cleaned waterways. Specifically, we observe a substantial increase in the number of restaurants and recreation centers within a 0.2-mile radius of cleaned waterways, and this positive effect declines as we move farther away from cleaned waterways. Similar patterns are observed for pharmacies, convenience stores, tutoring centers, and other services. Other services include post offices, salons, laundries, photography studios, and repair shops. Finally, we do not find such type of response for financial services, groceries and supermarkets, and other retail stores.

Tables

TABLE 1: DIFFERENCE-IN-DIFFERENCES ESTIMATION

Dep. variable: lnP	(1)	(2)	(3)	(4)	(5)	(6)
$In1mile_{BOW}$	-0.037**	-0.037**	-0.035**	-0.037**	-0.035***	-0.044***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.015)
$In1mile_{BOW} \times Post2016$	0.023***		0.019***	0.023***	0.021***	0.031***
	(0.006)		(0.004)	(0.006)	(0.006)	(0.009)
$In1mile_{BOW} \times During$		0.024***				
		(0.006)				
$In1mile_{BOW} \times After$		0.022***				
		(0.007)				
$In1mile_{waterways}$						0.005
						(0.029)
$In1mile_{waterways} \times Post2016$						-0.007
						(0.024)
Observations	543,554	543,554	543,554	543,554	543,554	881,453
R-squared	0.893	0.893	0.896	0.894	0.894	0.897

Notes: This table shows that the implementation of the BOW program leads to a 2.3% increase in housing prices for apartments located within 1 mile of a BOW site. We always control for a comprehensive set of housing characteristics, urban district fixed effects, and city time-varying effects in our analysis. Standard errors double-clustered at the urban district and city-year levels are in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 2: HETEROGENEOUS PRICE RESPONSES BY NEIGHBORHOOD CHARACTERISTICS

Dep. variable: lnP	(1)	(2)	(3)
$\text{In1mile}_{\text{BOW}}\times$Post2016$\times$Low Pop Density	0.002		
	(0.020)		
$\text{In1mile}_{\text{BOW}}\times$Post2016$\times$High Pop Density	0.024***		
	(0.008)		
$\text{In1mile}_{\text{BOW}}\times$Post2016$\times$Low Housing Price		0.013	
		(0.014)	
$\text{In1mile}_{\text{BOW}}\times$Post2016$\times$High Housing Price		0.029***	
		(0.008)	
$\text{In1mile}_{\text{BOW}}\times$Post2016$\times$Moderate Pollution			0.018*
			(0.010)
$\text{In1mile}_{\text{BOW}}\times$Post2016$\times$Severe Pollution			0.030***
			(0.008)
Observations	543,554	543,554	543,554
R-squared	0.894	0.894	0.894

Notes: This table indicates that price effects are most pronounced for apartments in densely populated areas and neighborhoods with high housing prices, as shown in Columns 1 and 2. Additionally, there's a greater increase in housing prices near waterways that were initially more polluted, as shown in Columns 3. We categorize townships into two groups based on whether their population density in 2010 and average housing prices from 2012 to 2015 are below or above the city's median levels. We always control for a comprehensive set of housing characteristics, urban district fixed effects, and city time-varying effects in our analysis. Standard errors double-clustered at the urban district and city-year levels are in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Supply of New Apartment Complexes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. variables	$1_{\text{New Apartments}}$	Num. Units	Luxury Decor		Spacious Layout		Green-Space Ratio	
$\text{In1mile}_{\text{BOW}}$			-0.053*	-0.053*	-0.031	-0.031	1.209*	1.206*
			(0.029)	(0.029)	(0.024)	(0.024)	(0.706)	(0.706)
$\text{In1mile}_{\text{BOW}} \times \text{Post2016}$	0.001	0.006	0.085**		0.024		-0.084	
	(0.002)	(0.017)	(0.037)		(0.034)		(0.924)	
$\text{In1mile}_{\text{BOW}} \times \text{Year}_{\text{2016 to 2018}}$				0.046		-0.011		-0.630
				(0.045)		(0.041)		(1.033)
$\text{In1mile}_{\text{BOW}} \times \text{Year}_{\text{2019 to 2020}}$				0.140***		0.073*		0.695
				(0.046)		(0.040)		(1.341)
Observations	104,478	104,478	2,644	2,644	2,644	2,644	2,644	2,644
R-squared	0.153	0.154	0.235	0.236	0.295	0.296	0.252	0.252

Notes: This table shows that the supply of newly built apartments does not increase significantly in neighborhoods closer to a BOW site compared with those farther away. However, if real estate developers do build a new apartment complex near a BOW site, they are more likely to provide high-end finishes and more spacious layouts after the program. Robust standard errors double-clustered at the urban district and city-year levels are in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 4: HETEROGENEOUS PRICE RESPONSES BY HOUSING CHARACTERISTICS

Dep. variable: lnP	(1)	(2)	(3)
$\text{In1mile}_{\text{BOW}} \times \text{Post2016} \times \text{Regular Finish}$	0.023***		
	(0.006)		
$\text{In1mile}_{\text{BOW}} \times \text{Post2016} \times \text{High-quality Finish}$	0.000		
	(0.000)		
$\text{In1mile}_{\text{BOW}} \times \text{Post2016} \times \text{Small}$		0.030**	
		(0.011)	
$\text{In1mile}_{\text{BOW}} \times \text{Post2016} \times \text{Large}$		0.017*	
		(0.009)	
$\text{In1mile}_{\text{BOW}} \times \text{Post2016} \times \text{Old}$			0.047***
			(0.016)
$\text{In1mile}_{\text{BOW}} \times \text{Post2016} \times \text{New}$			0.020**
			(0.009)
Observations	543,554	543,554	463,754
R-squared	0.893	0.894	0.894

Notes: This table shows that apartments with high-quality finishes, larger layouts, and recent construction have a less significant price response to the improved water quality. We define a unit as having a spacious layout if its floor area exceeds the sample median, and we classify an apartment as "new" if it was constructed after 2000. We always control for a comprehensive set of housing characteristics, urban district fixed effects, and city time-varying effects in our analysis. Standard errors double-clustered at the urban district and city-year levels are in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 5: IMPACTS OF THE BOW PROGRAM ON RETAIL AND SERVICE BUSINESSES

Dep. variables	(1) Restaurants	(2) Recreation	(3) Pharmacy	(4) Convenience Stores	(5) Other Services	(6) Tutoring	(7) Finance	(8) Groceries and Supermarkets	(9) Other Stores
$\text{In1mile}_{\text{BOW}} \times \text{Post2016}$	5.535***	0.568***	0.147***	0.442**	1.550**	0.231**	0.138	-0.045	3.029
	(1.307)	(0.136)	(0.040)	(0.173)	(0.605)	(0.109)	(0.213)	(0.183)	(3.133)
Observations	18,992	18,992	18,992	18,992	18,992	18,992	18,992	18,992	18,992
R-squared	0.916	0.905	0.947	0.971	0.886	0.968	0.909	0.961	0.914

Notes: This table shows that after the implementation of the BOW program, there is an increase in a variety of stores, such as restaurants and recreational centers, within a 1-mile radius of BOW sites. We always control for hexagon fixed effects, city time-varying effects, and the time-varying effects of a polynomial of the number of stores in the baseline year of 2015. Robust standard errors clustered at the urban district level are in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 6: EFFECTS OF STORE INCREASE ON HOUSING PRICES

Dep variable: lnP	(1)	(2)
$\text{In1mile}_{\text{BOW}} \times \text{Post2016}$	0.023***	0.016**
	(0.006)	(0.007)
Num. Stores	-0.002	0.041*
	(0.002)	(0.023)
Observations	543,554	543,554
R-squared	0.893	0.738
Specification	OLS	IV
F-stat		8.75

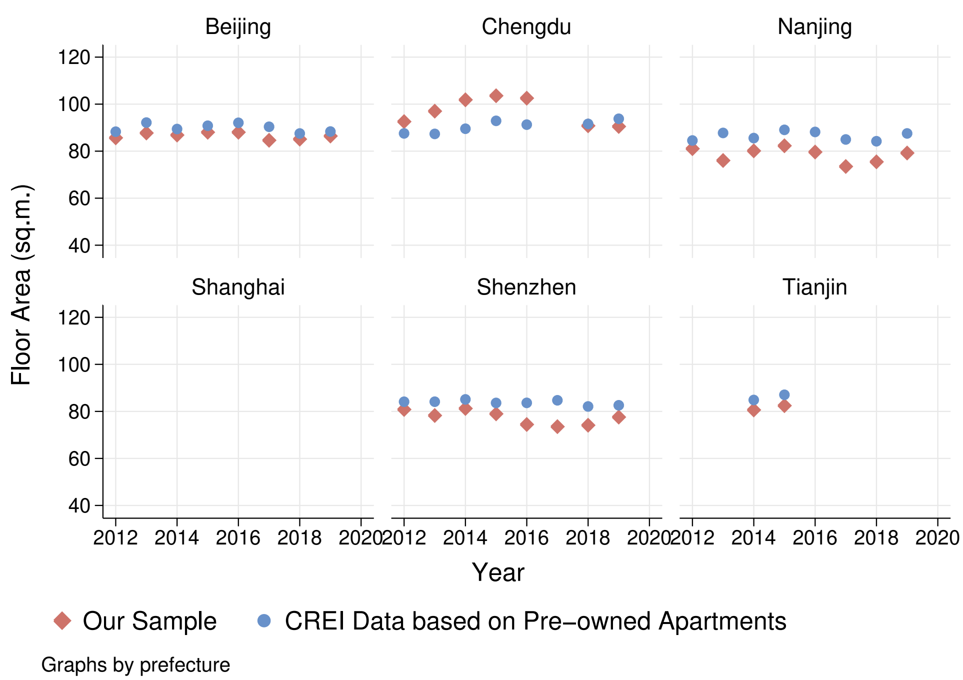
Notes: This table provides suggestive evidence that housing price appreciation is mainly driven by improved environmental amenity. The regression specifications are the same as specified in Equation 1, except that we control for the number of stores around a housing unit. We conduct an OLS estimation in Column 1 and an IV estimation in Column 2, using the interaction between policy treatment and a dummy indicator on whether the housing unit is located in a commercial area as the instrumental variable. Robust standard errors are in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A Data Appendix

A.1 Representativeness of the Apartment Transaction Records

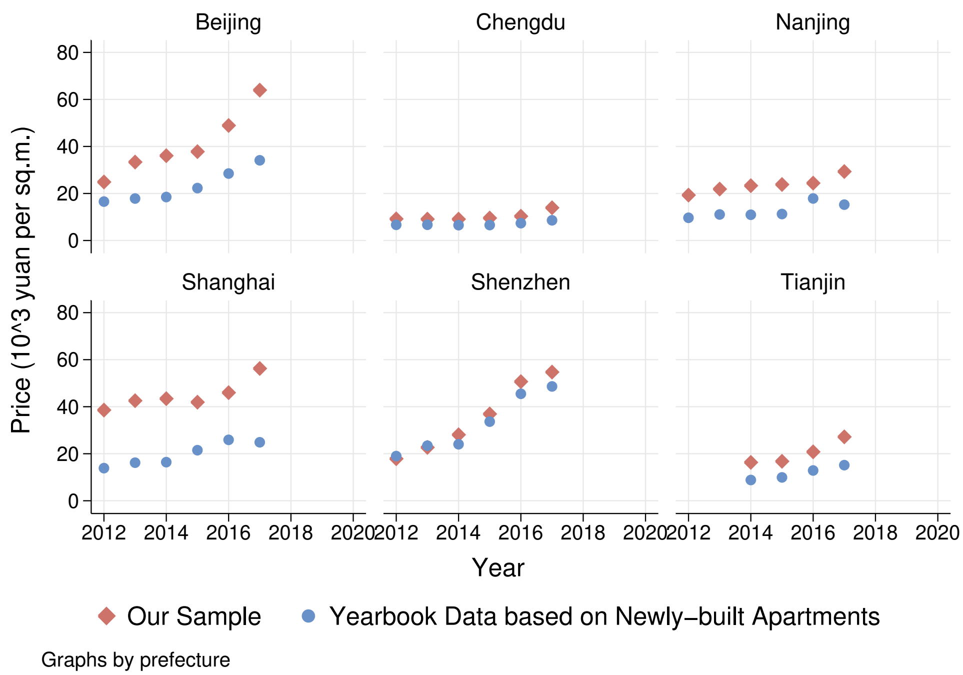
In this subsection, we examine the representativeness of the transaction records for pre-owned apartments. We begin by highlighting that the average floor area of transacted apartments in our dataset closely aligns with the corresponding values in the China Real Estate Information (CREI), as depicted in Figure A.1. CREI, maintained by the State Information Center, provides data on the total number of pre-owned apartments sold and registered with the government bureau, along with their respective floor areas. This allows us to compute the average floor area of a transacted pre-owned apartment for each city-year and plot it against figures derived from our transaction records. It's important to note that data for Shanghai and Tianjin for the years 2012, 2013, and 2016 to 2018 are absent in CREI.

FIGURE A.1: COMPARISON OF AVERAGE FLOOR AREA



Next, we show that the price trend for pre-owned apartments closely mirrors that of newly built units across all six cities, as illustrated in Figure A.2. The average price of pre-owned apartments is calculated by dividing the total transaction values by the total floor areas involved in these transactions. Data for newly constructed apartment prices are sourced from the China Real Estate Statistics Yearbooks (2012 to 2017). Notably, in Beijing and Shanghai, newly constructed apartments are often located further from the city center compared with transacted pre-owned units. This location difference explains the higher average prices of pre-owned apartments relative to the newly constructed ones in these cities.

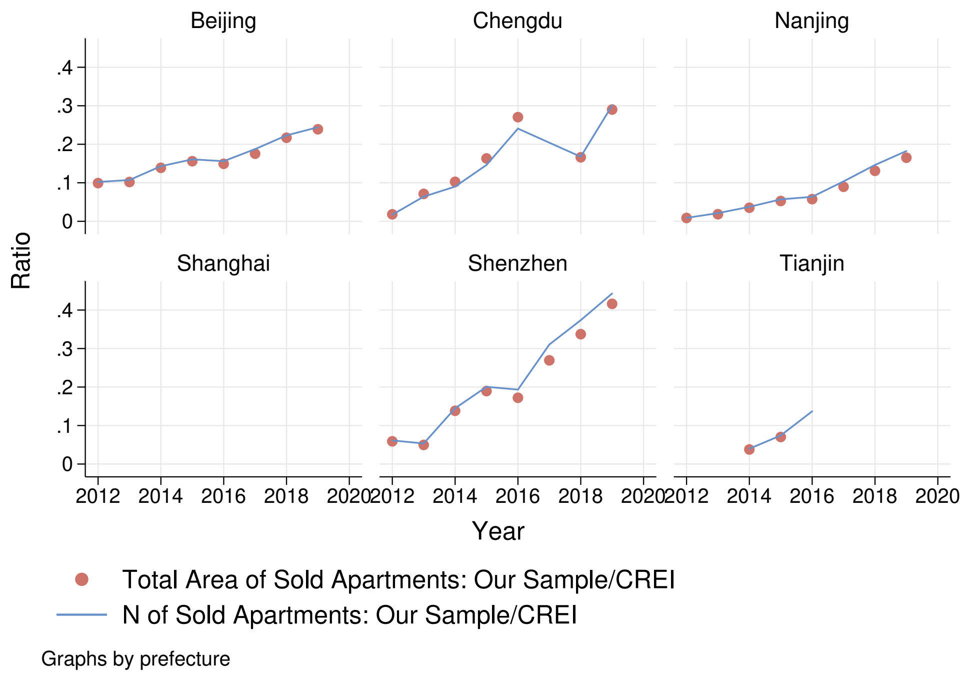
FIGURE A.2: PRICE TREND COMPARISON



Our sample covers 12.8% of all pre-owned apartment transactions in the sample cities between 2012 and 2018, with an improving sample coverage over time.[47] We also calculate the sample coverage by city-year and plot the data in Figure A.3, and observe similar trends across all six cities. This trend is attributable to the continuous expansion of the prop-tech agencies, our primary data source. The reliability of our data remains intact as long as our data provides a representative snapshot of the broader population, as indicated by metrics like average apartment prices and average floor areas.

[47] Sample coverage is defined as the ratio of the transaction volume in our dataset to the transaction volume documented in CREI. Our analysis excludes official records for Shanghai and Tianjin for 2012 and 2017 due to their unavailability in CREI.

FIGURE A.3: SAMPLE COVERAGE



A.2 Other Mechanisms

In this subsection, we explore two alternative mechanisms that may accompany water clean-up projects and potentially influence housing prices. The first mechanism involves local governments complementing water clean-up efforts with park construction, resulting in an emergence of new parks near cleaned-up waterways. These new parks can also contribute to the rise in housing prices. To test this hypothesis, we identify all places of interest designated as parks on Gaode Map in 2015 and 2019. We then examine whether there is any increase in the number of parks near cleaned waterways, employing the regression specified in Equation 5. However, as presented in Table A.1, Column 1, our result does not indicate any systematic increase.

Next, despite that the six sample cities are mostly service sector oriented, they still house factories, some of which may contribute to water pollution. Local governments have the authority to shut them down, which could have direct impact on housing prices in adjacent neighborhoods. To test this mechanism and its implications on housing prices, we identify all factories using Gaode Map and estimate the program's impact on the number of factories near cleaned waterways. As shown in Table A.1 Columns 2 and 3, there is a positive effect in Shenzhen and null effects in the remaining cities.

In light of these findings, we revisit our housing price regression, this time excluding Shenzhen,

TABLE A.1: ALTERNATIVE MECHANISMS

	(1)	(2)	(3)	(4)	(5)
Dep. variables	Num. Parks	Num. Factories		lnP	
In1mile$_{BOW}$ × Post2016	0.013	-0.006	0.591***	0.020**	0.023***
	(0.017)	(0.012)	(0.123)	(0.009)	(0.007)
Num. Factories					-0.013***
					(0.004)
Observations	18,992	14,664	4,328	410,389	543,554
R-squared	0.784	0.981	0.913	0.896	0.894
Sample	All	No Shenzhen	Shenzhen	No Shenzhen	All

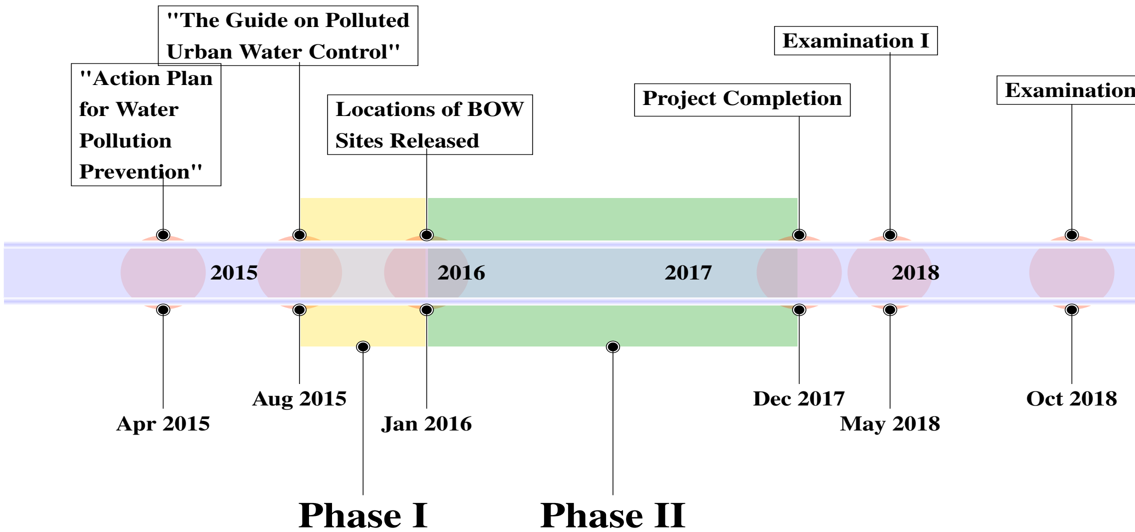
Notes: The regression specifications in Columns 1 to 3 follow Equation 5, while the regression specifications in Columns 4 and 5 follow Equation 1. Robust standard errors are in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

and as shown in Column 4, the estimated price changes closely align with our baseline values. This result confirms that changes in the number of factories cannot not be the driver of the observed housing price change. In Column 5, we employ an alternative regression specification by directly controlling for the number of factories surrounding a housing unit and find that the estimated price change stay close to the baseline.[48] This finding further confirms that change in housing prices cannot be driven by changes in the number of factories surrounding.

[48] In particular, we control the number of factories in the same 0.3-mile hexagon as where the housing unit locates at. Since the variable is only available in 2015 and 2019, we employ linear extrapolation and reassign negative values to zero.

B Appendix Figures

FIGURE B.1: PROGRAM TIMELINE



Notes: This figure displays the important milestones for the BOW program. A comprehensive overview of the program timeline is provided in Section 2.

FIGURE B.2: EXAMPLES OF BOW SITES

(a) Xiaotaihou River, Beijing, Before the Program

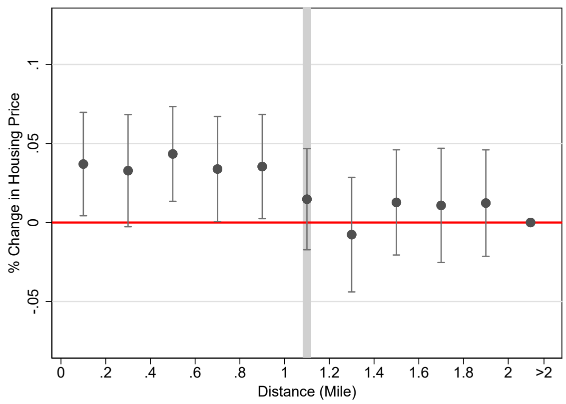
(b) Xiaotaihou River, Beijing, After the Program

(c) Futian River, Shenzhen, Before the Program

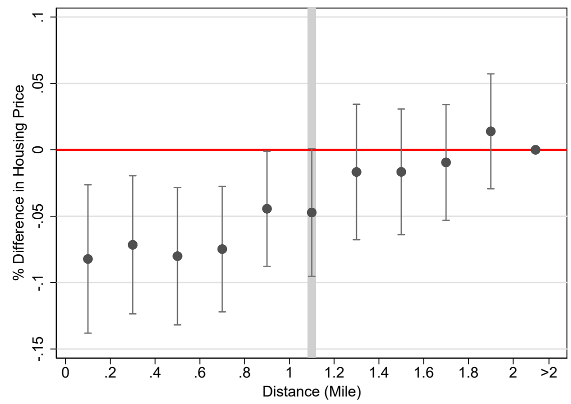
(d) Futian River, Shenzhen, After the Program

Notes: This figure shows that the program transforms heavily polluted waterways into pleasant public spaces suitable for recreational activities and community gatherings. The photos are from SEE and IPE (2018) and the Ministry of Ecology and Environment of the People's Republic of China.

FIGURE B.3: CHANGES IN HOUSING PRICES BY DISTANCE TO A BOW SITE, ROBUSTNESS CHECK



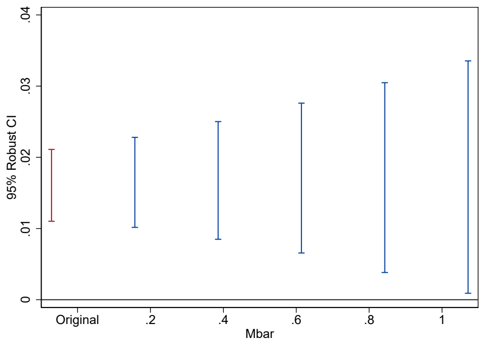
(a) Price Change (%)



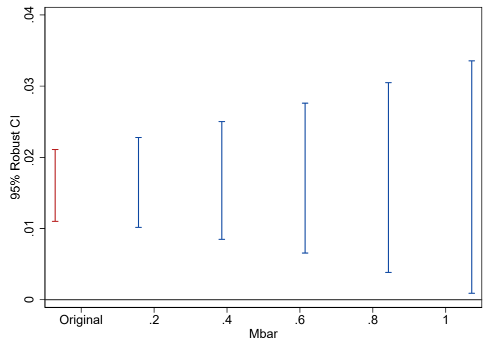
(b) Price Gradient before the Treatment

Notes: This figure demonstrates that the results from the bin analysis remain nearly unchanged when including transactions made in 2016 and 2017. The rest of regression specifications are identical to the central specification.

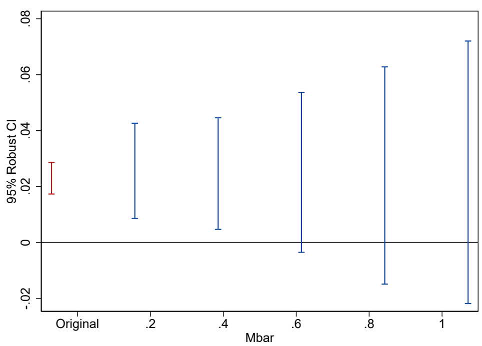
Figure B.4: Year-by-Year Effects: Sensitivity Analysis



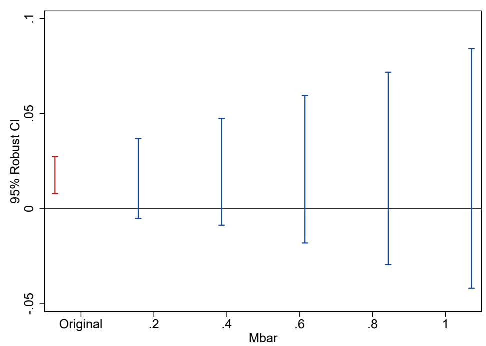
(a) 2016



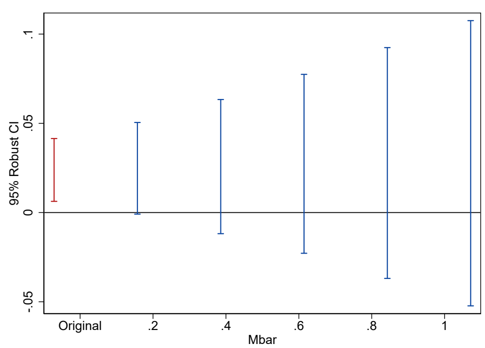
(b) 2017



(c) 2018



(d) 2019



(e) 2020

Notes. This figure presents confidence intervals for the treatment effects by year, considering various assumptions regarding the trend divergence between the treated and comparison groups (Rambachan and Roth, 2023). We employ the relative magnitude method and make two main observations. For 2016 and 2017, the coefficients are significantly different from zero when we relax the parallel trends assumption and instead assume that the maximum pre-treatment violations of parallel trends cannot exceed the maximal pre-treatment violation. For subsequent years, the maximum allowable deviation to obtain statistically significant effects becomes smaller. This occurs due to the enlarged identified set for later periods and the increased standard errors for coefficients in those years during estimation.

C Appendix Tables

TABLE C.1: COMPARISON OF SAMPLE CITIES WITH THE REST IN CHINA

	Sample Cities	36 Most Developed Cities	All in China
% Male	52.0	51.3	51.2
% Age 0-14	9.1	12.4	16.6
% Age 15-64	82.5	78.8	74.5
% Age 65 and Over	8.4	8.7	8.9
% Hukou holders	46.1	62.9	79.2
Urban population density (per km^2)	9566	9008	7569

Notes: This table illustrates that the sample cities have a higher proportion of the working population, a lower number of Hukou holders, and a higher urban population density. Data regarding population demographics are sourced from the 2010 Census, while urban population density data is obtained from the 2010 China Urban Construction Statistical Yearbook.

TABLE C.2: SUMMARY STATISTICS OF BOW SITES ACROSS CITIES

City	Beijing	Chengdu	Nanjing	Shanghai	Shenzhen	Tianjin
Total Length (mile)	136	54	36	22	195	82
% Severely Polluted	34.3	45.1	28.5	16.6	74.1	10.8
Number of Sites	46	39	18	62	104	23

Notes: This table reports the number of BOW sites, the total miles of waterways cleaned, and the percentage of BOW sites identified as severely polluted for each sample city. A continuous section of waterway that meet the BOW criteria is defined as one BOW site.

TABLE C.3: SUMMARY STATISTICS

VARIABLES	N	Mean	SD
A. Transacted Apartments			
Price ($\times 10^4$ RMB)	543,556	304.1	230.1
Distance to the Nearest BOW Site (miles)	543,556	0.888	0.548
Number of Bedrooms	526,575	2.134	0.871
Number of Bathrooms	526,575	1.006	0.0902
Number of Living Rooms	526,575	1.122	0.722
Floor Area (sqare meters)	543,556	81.47	37.10
High-quality Finish	543,556	0.248	0.432
Exposure - South	514,425	0.779	0.415
Exposure - West	514,425	0.137	0.343
Floor Level - High	510,013	0.351	0.477
Floor Level - Middle	510,013	0.380	0.485
Floor Level - Low	510,013	0.269	0.444
Number of Floors	488,485	15.57	10.03
Building Completion Year	463,755	2,002	8.170
Building Structure - Tower	543,556	0.136	0.343
Building Structure - Slab	543,556	0.474	0.499
Building Structure - Mixed	543,556	0.186	0.389
B. Supply of New Apartments			
Number of New Aapartments	104,478	30.85	312.2
$1_{\text{Num. New Aapartments}} > 0$	104,478	0.0251	0.157
High-quality Finish	2,931	0.397	0.489
Spacious Layout	2,931	0.190	0.392
Green Space Ratio	2,931	34.83	9.836
C. Number of Stores by Business Category			
Restaurants	19,534	37.27	85.13
Recreation	19,534	3.756	8.169
Pharmacies	19,534	1.681	3.435
Convenience Stores	19,534	10.15	18.51
Other Services	19,534	13.87	35.41
Tutoring	19,534	3.966	9.871
Finance	19,534	4.414	13.50
Groceries and Supermarkets	19,534	6.836	17.98
Other Stores	19,534	78.02	193.2

Table C.4: Apartments in the Treated and Comparison Region: Balance Check

	Control (N = 54969)		Treatment (N = 74586)		
	Mean	SD	Mean	SD	Diff
Number of Bedrooms	2.18	0.87	2.22	0.86	0.03
Number of Bathrooms	1.00	0.02	1.00	0.01	-0.00
Number of Living Rooms	1.26	0.71	1.08	0.82	-0.19***
Floor Area (square meter)	93.66	41.36	84.91	36.17	-8.75***
High-quality Finish	0.20	0.40	0.16	0.37	-0.04*
Exposure - South	0.79	0.41	0.75	0.43	-0.03
Exposure - West	0.14	0.35	0.13	0.33	-0.01
Floor Level - High	0.32	0.47	0.31	0.46	-0.01
Floor Level - Middle	0.35	0.48	0.35	0.48	-0.00
Floor Level - Low	0.27	0.44	0.25	0.43	-0.01***
Number of Floors	15.96	9.63	16.20	9.95	0.24
Building Completion Year	2002.07	6.67	2002.83	6.40	0.76
Building Structure - Tower	0.19	0.39	0.13	0.33	-0.06***
Building Structure - Slab	0.53	0.50	0.41	0.49	-0.12***
Building Structure - Mixed	0.17	0.37	0.24	0.43	0.07***

Notes: In this table, we compare apartments in the treated and comparison regions across a comprehensive set of characteristics. Apartments in both groups exhibit nearly identical features along many dimensions, including the number of bedrooms, bathrooms, exposures, floor level, total number of floors in a building, and building completion year. The table also shows three distinctions between the treated and control groups. Firstly, apartments in the treated group are less likely to have multiple living rooms compared with those in the comparison group, and correspondingly, there is a 9-square-meter difference in floor area between the two groups. Secondly, the treated group is more likely to have a mixed building structure and less likely to have a tower or slab structure. Finally, apartments in the treated group are slightly less likely to have high-quality finishes. The error terms are clustered at urban district: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE C.5: DIFFERENCE-IN-DIFFERENCES: ROBUSTNESS CHECKS

Dep. variable: lnP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
In1mile$_{BOW}$	-0.039***	-0.034**		-0.036**	-0.043***	-0.037**			-0.037**
	(0.014)	(0.014)		(0.014)	(0.015)	(0.015)			(0.016)
In1mile$_{BOW}$ $\times$ Post2016	0.022***	0.019***	0.013*	0.021***	0.031***	0.022***			0.023**
	(0.006)	(0.005)	(0.007)	(0.006)	(0.009)	(0.006)			(0.009)
In0.8mile$_{BOW}$							-0.038**		
							(0.016)		
In0.8mile$_{BOW}$ $\times$ Post2016							0.015**		
							(0.007)		
In1.2mile$_{BOW}$								-0.048***	
								(0.014)	
In1.2mile$_{BOW}$ $\times$ Post2016								0.022**	
								(0.010)	
Observations	540,141	543,440	407,906	543,554	881,075	508,661	472,364	610,546	543,554
R-squared	0.894	0.899	0.952	0.894	0.897	0.894	0.897	0.894	0.893

Notes: This table shows that the estimates of price changes of apartments close to BOW sites are robust to alternative regression specifications. Robust standard errors are in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE C.6: HOUSING SUPPLY RESPONSES: ROBUSTNESS CHECKS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Num.	Luxury	Large	Green-Space		Num.
Dep. variables	$1_{\text{New Apartments}}$	Units	Decor	Layout	Ratio	$1_{\text{New Apartments}}$	Units
$\text{In1mile}_{\text{BOW}}$			-0.075***	-0.047*	0.766		
			(0.028)	(0.027)	(0.677)		
$\text{In1mile}_{\text{BOW}} \times \text{Post2016}$	0.000	0.004					
	(0.002)	(0.017)					
$\text{In1mile}_{\text{BOW}} \times \text{Year}_{\text{2016 to 2018}}$			0.044	-0.021	-0.144	0.001	0.009
			(0.042)	(0.047)	(1.186)	(0.002)	(0.018)
$\text{In1mile}_{\text{BOW}} \times \text{Year}_{\text{2019 to 2020}}$			0.158***	0.116**	0.897	0.000	0.003
			(0.059)	(0.045)	(1.666)	(0.003)	(0.020)
County time-varying effects	Y	Y	Y	Y	Y		
City time-varying effects						Y	Y
Observations	104,467	104,467	2,505	2,505	2,505	104,467	104,467
R-squared	0.161	0.161	0.345	0.402	0.370	0.153	0.154

Notes: Columns 1 to 5 in this table demonstrate the robustness of the results related to housing supply responses when controlling for county time-varying effects. Next, columns 6 and 7 in this table reveal no differential effects between the periods 2016 to 2018 and 2019 to 2020. Robust standard errors are in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE C.7: IMPACTS OF THE BOW PROGRAM ON LOCAL BUSINESS PERFORMANCE: ROBUSTNESS

Dep. variables	(1) Restaurants	(2) Recreation	(3) Pharmacy	(4) Convenience Stores	(5) Other Services	(6) Tutoring	(7) Finance	(8) Groceries and Supermarkets	(9) Other Stores
$\text{In1mile}_{\text{BOW}} \times \text{Post2016}$	5.349***	0.435***	0.143***	0.618***	1.721***	0.263***	0.183	0.068	3.497
	(1.221)	(0.128)	(0.040)	(0.181)	(0.612)	(0.100)	(0.167)	(0.181)	(3.786)
Observations	18,990	18,990	18,990	18,990	18,990	18,990	18,990	18,990	18,990
R-squared	0.919	0.912	0.949	0.973	0.889	0.970	0.916	0.962	0.916

Notes: This table shows that the regression results are almost the same when controlling for county time-varying effects. Robust standard errors are in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.