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

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Abstract

This paper investigates the economic impacts of cleaning up heavily polluted waterways in urban neighborhoods. We exploit the Black-and-Smelly Water Program 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-Difference estimator, we find that the program mainly benefits properties within 1 mile of the cleaned-up waterways: these properties were 3.7% cheaper before the program and experienced a 2.3% market value appreciation after the program. We also show that developers building new apartment complexes near BSW sites are more likely to provide high-end units with luxury decoration and spacious layouts. In addition, we observe various service businesses thriving in the neighborhoods close to the cleaned-up waterways, indicating a revitalization of these areas. Our findings shed light on the effects of environmental programs in real estate markets and neighborhood dynamics.

JEL: Q5, R1, R3

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

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1 Introduction

In the last few decades, the rapid growth of urbanization and economy in developing countries has caused significant environmental costs, including pollution and water contamination, especially in densely populated urban areas (UNDP, 2016). As national income continues to rise, there is an increasing need for environmental regulations to control pollution emissions and clean up hazardous sites (Costa and Kahn, 2004; Zheng and Kahn, 2017; He et al., 2020). Governments worldwide have recognized this demand and are actively planning and implementing environmental programs to achieve sustainable and inclusive urban growth (Greenstone et al., 2021). However, to create effective policies, it is crucial to understand how these programs interact with neighborhood dynamics and their outcomes comprehensively.

In this paper, we study a major urban environmental program in China, the Black-and-Smelly Water Program (BSW Program thereafter), to examine its causal impacts on local housing markets and business growth. The unexpected and swiftly implemented program cleaned up the heavily polluted waterways running through the 36 most developed Chinese cities during 2016 and 2017. We find that, by improving the aesthetic amenities of these waterways, the program raised the market values of the nearby housing properties by 2.3%, and developers building new apartments near BSW sites are more likely to provide high-end units. Additionally, neighborhoods close to the treated waterways saw a growth of service business entries, which improves the service accessibility of these neighborhoods.

Despite enormous investments in water cleaning programs worldwide and long-lasting interest in understanding its economic consequences, it has been empirically challenging to identify its impacts on both the housing market and local business growth (Kuwayama and Olmstead, 2015; Keiser and Shapiro, 2019).[1] The endogenous timing and geographical 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 operation records poses a challenge in tracking neighborhood responses. The BSW Program in China, combined with detailed housing transactions and business records, provides a rare opportunity to examine these responses in the affected neighborhoods.

The BSW Program was first announced by the China State Council in late 2015. The

[1] Kullmann et al. (2018) use financing data from 140 mostly developing countries to show that 0.12% of GDP from these countries, or equivalently $35 billion per year, are spent to achieve water, sanitation, and hygiene-related targets set by the United Nations. In the US, the Clean Water Act costs $100 per person-year (Keiser and Shapiro, 2019).

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 *BSW site* if it has water transparency less than 25 cm, ammoniacal nitrogen above 8 mg/L, dissolved oxygen less than 2mg/L, or oxygen reduction potential less than 50 mV. Such waterways typically have dark colors and unpleasant odors and are therefore called "black-and-smelly waters". In the six cities for which housing transaction records are available before the beginning of the program, 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.

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

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. 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. Additionally, to obtain an unbiased estimate of the coefficients, other demand shocks since 2016 cannot confound the effects. We show the robustness of our results to a battery of possible demand factors, such as changing preferences for living close to city centers, waterways, or 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 BSW Program had a significant positive impact on housing prices in the treated regions, specifically on apartments located less than 1 mile away from the cleaned-up waterways. Prior to the program, these apartments were 3.7% cheaper compared to those located further away. After the program, we observe a notable 2.3% increase in housing prices in these areas. By quantifying the benefit of the program in terms of property value appreciation, we calculate a benefit-cost ratio of 12 for the six sampled cities. Our findings also reveal that the impact of the program was greater in neighborhoods with higher population density and housing prices in the baseline year.

We then examine the supply-side responses of the housing market to the BSW program and their implications for housing prices. Specifically, we use records of new buildings from 2010 to 2020 to investigate whether the program led to an increase in the supply of newly built apartments in neighborhoods closer to a BSW site, compared to those farther away. Our results show that there is no such increase in supply. However, we find that if real estate developers do build a new apartment complex near a BSW site, they are more likely to provide high-end units featuring luxury decoration and spacious apartment layouts after the program. This shift in the supply towards constructing high-end new apartments in the neighborhoods near the cleaned-up waterways creates downward pressure on the relative price of high-end apartments.

Finally, we show that the BSW program has a positive effect on local business growth. We find that post-program, neighborhoods close to the cleaned-up waterways attract a variety of businesses, such as recreation centers, restaurants, pharmacies, and other service providers. For example, we observe a 56% increase in the number of restaurants and 20% increase in the number of recreation centers within a 0.2-mile radius of the cleaned waterways; the effect diminishes quickly as we move away from the 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. The presence of these service businesses also makes the neighborhoods near the BSW sites more convenient and increases the local amenities available to nearby residents.

This paper contributes to several strands of literature. First, this paper is 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). Rising income in developing countries raised the 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 developing country governments to counteract the growing environmental damage (Greenstone and Hanna, 2014; Duflo et al., 2018). The existing 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.

Next, this paper contributes to an extensive literature about the impacts of pollution and pollution controls on home values and neighborhood dynamics. The existing literature has been focusing on air pollution (Chay and Greenstone, 2005; Grainger, 2012; Heblich et al., 2021; Isen et al., 2017), noise pollution (Boes and Nüesch, 2011), sewage management (Coury et al., 2022), and hazardous waste sites (Bui and Mayer, 2003; Greenstone and Gallagher, 2008; Gamper-Rabindran and Timmins, 2011; Cassidy et al., 2022), while water cleaning programs have been less studied. The only exception, to our knowledge, is Keiser and Shapiro (2019), which studies the effects of the Clean Water Act in the US on housing values. Compared to Keiser and Shapiro (2019), we study a policy that targets the densely populated urban areas in a developing country. Moreover, we uncover changes in both housing markets and local businesses using a comprehensive dataset of housing transactions and business location records.

Our paper also links to studies about the economic benefits of investment in water treatment (Alsan and Goldin, 2019; Ashraf et al., 2017; Galiani et al., 2005; Bhalotra et al., 2021; Devoto et al., 2012; Gamper-Rabindran et al., 2010; Beach, 2022). This literature highlights the health consequences of providing clean drinking water. Compared to the literature, our estimation sheds light on the aesthetic value of cleaning waterways, which has been less emphasized. To that extent, our paper also relates to studies about the environmental benefits of canals (Streiner and Loomis, 1995; Peng et al., 2019).

Finally, our empirical methodology builds upon the literature that uses the quasi-experimental hedonic method to study the values of localized public goods (Linden and Rockoff, 2008; Zhou et al., 2021; Currie et al., 2015; Gupta et al., 2022; Diamond and McQuade, 2019). The prices of transacted properties incorporate household evaluations of environmental and urban amenities (Parmeter and Pope, 2013). Therefore, estimating the property market response to local amenity changes can uncover the value of amenities, which typically do not have an explicit market. We adapt the framework to the setting of the BSW Program in China to estimate the market evaluation of clearer waterways in cities.

The rest of the paper proceeds as follows. In Section 2, we provide further details about the BSW Program. Data used in the empirical analysis are introduced in Section 3. Section 4 explains the identification strategies and displays the empirical findings. We discuss the implications of the results in Section 5. Section 6 concludes.

2 Policy Background

The BSW Program was announced in 2015 and mandates that the 36 most developed cities in China clean up heavily polluted waterways within the built-up areas by the end of 2017. The program is part of a broader initiative that seeks to combat the growing problem of water pollution, which has been exacerbated by China's rapid industrial expansion without a corresponding infrastructure development over the past few decades (Zheng and Kahn, 2017; He et al., 2020). Due to increasing public concern over water pollution, the China State Council released the Action Plan for Preventing and Treating Water Pollution in April 2015, which sets a goal of eliminating over 90 percent of heavily polluted waterways running through cities by 2020. For the 36 most developed cities, the target is even more ambitious: all polluted sites must be cleaned up by the end of 2017.[2]

As outlined in "The Guide on Polluted Urban Water Control" published in August 2015, the program involves two steps.[3] The first step is to identify all the BSW sites, which are waterway segments with transparency less than 25 cm, dissolved oxygen less than 2mg/L, oxygen reduction potential less than 50 mV, or ammoniacal nitrogen above 8 mg/L.[4] Local governments are responsible for compiling a complete list of BSW sites within their jurisdictions and submitting it to the central government for review by December 2015. Figure 1 displays the locations of the BSW sites (represented by red lines), as well as the rest of the waterways that are not included in the program (represented by blue lines). The spatial distribution of BSW sites exhibits significant cross-sectional variations both within and across cities.

The second step of the BSW Program involves local governments hiring specialists to design and implement clean-up projects, with the 36 most developed cities required to finish all the projects by the end of 2017. The goal of each project is to ensure that the water quality no longer falls below the program's criteria, and often involves upgrading the surrounding riverbanks. As shown in Appendix Figure 7, the program transforms heavily polluted waterways into pleasant public spaces suitable for recreational activities and community gatherings.

The methods used to clean up a BSW site vary depending on the pollution sources and local ecological conditions, but typically involve three steps: controlling source discharges and intercepting pollutants, preventing and controlling endogenous pollution,

[2]The action plan released ten broad goals related to alleviating the water quality crisis for the entire country; cleaning the heavily polluted waterways within urban districts is one of them. The action plan did not provide any detail of policy implementation or evaluation criteria.

[3]An illustration of the policy timeline is provided in Appendix Figure 6.

[4]In practice, the four criteria are closely related. Out of the 51 BSW sites in Chengdu, which is the only sample city with water test results publicly available, 65% of the sites met at least three of the criteria.

and restoring ecological balance. Local governments are responsible for supervising these projects and ensuring that each BSW site passes a third-party examination after completion. They are also responsible for maintaining and monitoring these waterways after the program to prevent future pollution.

To study the effects of the BSW 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). 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). We consider the publication of the BSW site list in January 2016 as the beginning of the program since it made clear which neighborhoods were close to a BSW 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 BSW identification were made public in August 2015, it was unclear whether local governments would adhere to the criteria from residents' perspectives. In Section 4, we show that housing prices of neighborhoods close to BSW sites did not change until 2016, which supports our phase division.

The program came out as quite a shock, and the public was skeptical about the program's effects at the beginning. As reported by (SEE and IPE, 2016), by August 2016, one-third of the program's timeline had already passed, yet many sites were still in the planning stage. This raised concerns about whether the projects would be completed on time and fueled doubts about the government's commitment to the program. However, as the program progressed and site treatments were implemented, the public's confidence in the program grew, particularly in 2017, when improvements to the environmental aesthetic of these sites became visible (SEE and IPE, 2018).

To incentivize local governments to meet the policy goal, the central government implemented various monitoring strategies. First, in February 2016, the central government established the "Urban Black-and-Smelly Water Information Platform" to publish the progress of all BSW projects. This platform enables residents to track individual projects, report the current status of a BSW site, and express dissatisfaction about the outcome.[5] Second, the central government sent both third-party specialists and central government officials to examine every BSW site after the project completion.[6] Each BSW site received a grade from the central government - either good, pass or fail - which was made publicly available. For the six cities studied in this paper, 93% of BSW sites passed

[5] Local governments are required to review these reports and respond within seven business days.
[6] The examination of the 36 most developed cities took place in May 2018.

the examination, and the remainder were cleaned up by October 2018.[7]

The program has been successful in restoring heavily polluted waterways, as shown in studies by Wang et al. (2022), Hu et al. (2021), and Qi et al. (2020), which used satellite imagery to measure surface water quality over time. They found a clear improvement in overall water quality and the elimination of the BSWs in cities participating in the program. Additionally, monthly monitoring reports from treated waterways across our sample cities also reveal a significant reduction in water pollution after the program.[8] As shown in Figure 2, the average pollution level across all the monitoring sites reduced steadily since 2016.[9]

The program's success relies heavily on tremendous investments, making it crucial to estimate the economic gains resulting from it. As of January 2020, the cumulative investment in the program nationwide has exceeded 1,100 billion RMB ($157 billion).[10] 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 BSW 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 BSW sites, the transaction records of pre-owned apartments, the supply of newly built apartments, and the locations of all local service businesses both before and after the program.

Our analysis focuses on six of the most developed metro areas in China: Beijing, Chengdu, Nanjing, Shanghai, Shenzhen, and Tianjin. These cities were 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 Appendix Table 6, 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 5.

The rest of this section briefly introduces each database, while more details are pro-

[7] The data is from the Ministry of Ecology and Environment of the People's Republic of China.

[8] It should be noted that the results are based on a limited number of monitoring stations that are unevenly distributed across the cities: Beijing has 12 stations, Shanghai has 13 stations, Shenzhen has 8 stations, and Tianjin has 4 stations.

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

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

vided in Appendix A. Appendix Table 8 provides summary statistics of the major variables used in Section 4.

BSW Sites. We collect information about BSW sites from the Institute of Public & Environmental Affairs (IPE).[11] Our sample covers 304 BSW sites, which account for 525 miles of waterways. For each BSW site, we have recorded its location and a pollution severity index before the program.[12] All the BSW sites are plotted in Figure 1, and a summary of the BSW sites by city is provided in Appendix Table 7.

Apartment Transaction Records. The transaction records of pre-owned apartments are from www.ershoufangdata.com. This website collects transaction records from multiple major real estate agencies in China, including LianJia, WoAiWoJia, ZhongYuanDiChan, MaiTian, LeYouJia, and Qfang. The existing literature (Lu, 2018; Chan et al., 2020, for example) typically uses transaction records within a short time window from a single real estate agency. In contrast, we use a much more comprehensive database that covers a time horizon from 2012 to 2020 to study changes in property values over time.[13] 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 internal decoration, 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 comprehensive records of newly built buildings available for sale. Our data spans from 2010 to 2020. For each newly built apartment building, we observe the launch date, street address, total number of apartments, green space ratio, and whether it features high-end decoration or large layouts, among other features.

Locations of service businesses. Information about locations of service businesses is from Gaode Map.[14] 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.[15] We divide each city into cells with an exclusive width of 1 km and count the number of businesses by cell

[11] http://wwwen.ipe.org.cn/MapWater/water.html?q=2.

[12] The pollution severity index is classified as either "moderate" or "severe". Specifically, an examination spot is deemed "severe" if over 60 percent of monitoring data for a single indicator or at least 30 percent of data for two or more indicators fall within the range of the corresponding BSW criteria. Next, if three adjacent examination spots are rated as "severe", the waterways in between are defined as "severe".

[13] A detailed discussion about the representativeness of our transaction records is provided in Appendix A.

[14] 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 physical verification by the company.

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

and year across eight categories: recreational centers (e.g., chess clubs, KTVs, game centers, and internet cafes), restaurants, pharmacies, financial services (e.g., bank branches and ATMs), tutoring services, other services (e.g., post offices, salons, laundries, photography studios, and repair shops), convenience stores, 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. The data include the total population, sex ratio, age composition, and share of Hukou holders.

4 Empirical Analysis

4.1 Regression Design

We expect that the BSW 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.[16]

To estimate the impact on housing prices, we compare the prices of apartments near and far from a BSW site before and after the program. 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 BSW site or not. In Section 4.2, we conduct a bin analysis to flexibly identify the distance beyond which water pollution and the BSW 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.[17] 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 further away from the BSW 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

[16] In all six sample cities, drinking water is sourced from upstream reservoirs located in nearby rural areas.

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

across time and across neighborhoods within a city in a particular year.[18]

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}.[19] This set includes the floor area (logged), the number of bedrooms, bathrooms, and living rooms, whether the apartment has a luxury decoration or not, its exposures, 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. In Section 4.3, 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 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 4.4.

For the coefficients to be unbiased, the key identifying assumption is that the homeowners do not fully anticipate the BSW Program (Autor et al., 2014) and that housing prices in the treated and comparison regions moved in parallel without the program. This assumption is likely valid since the policy guideline was not announced until August 2015, and the list of BSW sites was only decided and made public in January 2016. There was also uncertainty about the program from the residents' perspective when it first started. Additionally, in Section 4.3.1, we conduct an event study and demonstrate that parallel trends hold up to 2015.

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 4.3.2, we explore a range of possible factors that could impact demand, such as changing preferences for living close to city centers, waterways, or 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 our results are robust to these alternative

[18]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.

[19]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.

specifications.

4.2 Changes in Housing Prices by Distance to BSW 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 to a BSW site after the program. In particular, we assign apartments into 0.2-mile bins according to their distances to BSW sites and run the following regression:

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

In the central analysis, we have 10 bins and assign apartments more than 2 miles away to the comparison group. We leave out apartments more than 20 miles away from any BSW site. We also 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. The patterns barely change if we include these observations in the regression, as shown in Appendix Figure 8. As in the central regression specification, we control for the city time-varying effects and a comprehensive set of characteristics of the apartment and double cluster the error term at the urban district level and city-year level.

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 away from any BSW site. As shown in Panel (a), apartments less than 1 mile away from a BSW site had a substantial increase in housing prices after the BSW Program, while the effects for apartments further away are close to zero and insignificant. $\{\beta_0^n\}$ represents the price gradient with respect to distance from a BSW site before the program. Figure 3 Panel (b) demonstrates that apartments less than 1 mile away from a BSW 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 BSW site in the central specification and use 0.8 to 1.2 miles for robustness checks. We assign apartments between 1 and 2 miles away from any treated waterways into the comparison group.

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

4.3.1 Event Study

Before estimating Equation 1, we conduct an event study to present evidence of parallel trends in housing prices before the program and to investigate potential dynamic price responses since the beginning of the program. We use the same regression specification as Equation 1, but we estimate the effects year by year, with 2015 as the baseline year. Figure 4 shows that until 2015, the prices of apartments in the treated and comparison groups had parallel trends. Starting in 2016, apartments located within 1 mile of a BSW site experienced significantly higher prices compared to the rest. Interestingly, we observe a small positive effect in 2016, followed by a continued increase in 2017, which indicates the residents' growing confidence in the program over time. Additionally, from 2018 to 2020, the changes in housing prices were comparable but slightly lower than the effects observed in 2017.

4.3.2 Difference-in-Difference Estimation

We start by estimating Equation 1 and report the baseline results in Table 1, Column 1. As per the baseline estimates, apartments located less than 1 mile away from the BSW 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 BSW program, apartments located within 1 mile of a BSW 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 BSW Program was in progress and the time when it was completed. We find that the effects are quite similar.

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 BSW 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.[20] We include these distances, interacted with time-varying effects, 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 BSW 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 Appendix Table 9 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 Appendix Table 9 Column 2, we control for urban district time-varying effects and hence restrict variation to come from apartments within the same urban district. 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 Appendix Table 9, 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.

Several additional robustness checks are performed at the end of this subsection. First,

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

we observe similar results when we include all apartments located 2 to 20 miles away from any BSW sites in the comparison group, as presented in Appendix Table 9, Column 4. 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 Appendix Table 9, Column 5. The results also remain robust to variations in the treatment region's width, as demonstrated in Appendix Table 9, Columns 6 and 7, where we define the treated region as 0.8 or 1.2 miles away from BSW 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 Appendix Table 9, Column 8, 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.

4.3.3 Heterogeneous Treatment Effects

In this subsection, we explore the heterogeneity of treatment effects across neighborhoods. Such variation 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 the 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 black-and-smelly waterways interacted with the corresponding neighborhood type.[21] 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

[21] $\theta_{b(i)g(j)}$ 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 the cleaned waterway and the corresponding urban district j belongs to the subgroup g.

different types of neighborhoods.[22]

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 BSW site gets cleaned up.

Next, we find a nearly 4% price increase after the BSW 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.

4.4 Housing Supply Responses

In this subsection, we examine the impact of the BSW program on the housing market's supply-side responses and their implications for housing prices. Specifically, we utilize records of new buildings from 2010 to 2020 to investigate whether there is an increase in the supply of newly constructed apartments in neighborhoods closer to a BSW site compared to those located farther away. Our findings reveal that there is no such increase in supply; however, if real estate developers construct a new apartment complex near a BSW site, they are more inclined to offer high-end units with luxury decoration and spacious layouts after the program's implementation. This shift towards constructing high-end new apartments in the areas near the cleaned-up waterways leads to relative downward pressure on the price change for high-end apartments.

We begin by showing that there is no significant disparity in the number of new apartment units supplied to the market between neighborhoods closer to a BSW site and those further away after 2016. To perform our empirical analysis, we divide each city into exclusive cells with a width of 1-km and count the number of newly constructed apartments by cell-year from 2010 to 2020. We conduct a difference-in-difference estimation by comparing cells within 1 mile from any BSW sites with those located between 1 and 2 miles.[23]

[22] $\phi_{\tau(t)g(j)}$ 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*.

[23] We calculate the distance from the centroids of each cell to the nearest BSW site.

To investigate the supply side responses of housing to the BSW program, we estimate a regression model using the number of newly built apartment units as the outcome variable. We also incorporate a binary outcome variable that indicates if there was at least one building complex that had been finished and was open for sale in the corresponding cell. The regression specification is as follows:

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

The model controls for city time-varying fixed effects and cell fixed effects, and we cluster the error terms at the urban district level and city-year level. 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 BSW site than those farther away. This result is likely due to the fact that the BSW sites are located in developed urban neighborhoods with limited open land for new construction. In fact, 77% of the cells in our regression analysis shows no new residential buildings constructed from 2010 to 2020. This finding indicates that the growing demand for housing is the primary driver of changes in housing values in neighborhoods close to BSW sites.

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

In Column 3 of Table 3, we observe an increase in the supply of condominium units with luxurious decorations. 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, we find a significant increase during 2019 and 2020, with a 12.5% rise in the probability of an apartment complex having high-end decoration. The increase is economically large, given that the pre-program probability of having an apartment complex with high-end decoration within 1 mile of the BSW sites was only 31%. In Columns 5 and 6, we observe an 8.4% increase in the probability of launching an apartment complex with large layouts in 2019 and 2020. This increase corresponds to an 80% growth relative to the baseline probability. Finally, we do not find any significant changes in the green space ratio, as shown in Columns 7 and 8 of Table 3. Altogether, the supply-side responses of luxurious building complexes and large layouts suggest that real estate developers anticipate the influx of affluent families to neighborhoods near the cleaned waterways, as these units are typically more expensive and cater to wealthier customers.

The shift towards high-end new apartments on the supply side can potentially create downward pressure on the prices of existing high-end units relative to regular housing units. We investigate the potential differences in price responses between high-end and regular housing units at the end of this subsection. We use three proxies for high-end apartments: whether the unit has luxury decoration, whether the unit features a spacious layout, and whether the unit was constructed in relatively recent years. 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. As shown in Table 4, apartments with luxury decoration and larger layouts and newer apartments had a less significant price response to the improved water quality.[24] This finding suggests that housing prices in neighborhoods became less dispersed. At the same time, it may be harder for households with budget constraints to move into these neighborhoods, which enlarges inequality in access to environmental amenities.

4.5 Changes in Business Activities near BSW Sites

In this subsection, we show that post-program, businesses such as recreation centers, restaurants, pharmacies, and other service providers are drawn to neighborhoods near the cleaned-up waterways. The presence of these business establishments makes the neighborhoods near the BSW sites more convenient and increases the local amenities available in these areas.

To study changes in the number of stores after the BSW program, we start by estimating a regression model that is similar to a bin analysis, as in Equation 5:

$$N_{lkt}^{w} = \sum_{n} \beta_1^n 1_{lk}^{\text{bin } n} \times \text{Post}_t + \alpha_l + X_{lt} + \tau_{kt} + \epsilon_{ijkt}. \tag{5}$$

Our outcome variable is the number of stores in category w, cell l, city k, and year t.[25]

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

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

In the regression, we have ten 0.2-mile bins and include grids between 2 miles and 20 miles from any BSW programs in the comparison group. We control for cell fixed-effects (α_l), city time-varying effects (τ_{kt}), and the initial number of stores interacted with year dummies (X_{lt}). We use the initial number of stores in a cell 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 grids in close proximity to BSW 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.

We present the estimation results in Figure 5. We find an increase in the number of stores for various store categories in grids in proximity to the cleaned waterways. Panel (a) shows a significant increase in the number of recreational centers, with the effect being concentrated within a 0.2-mile radius of BSW sites: Within 0.2 miles of any BSW site, we observe an increase in the number of recreational centers by 1. This implies a 20% increase given that the average number of recreational centers in each grid during the baseline year is 5. However, the effect diminishes quickly as we move away from the cleaned waterways.

We find an even more substantial growth of restaurants in areas close to the BSW sites. As shown in Figure 5 Panel (b), within a 0.2-mile radius of the cleaned waterways, the number of restaurants increased by 18, indicating a 56% growth in comparison to the baseline average. Although the effect diminishes more slowly compared to recreational centers, it still reduces quickly as we move away from the cleaned waterways. Similar patterns are observed for pharmacies and other service businesses, while we find limited responses in tutoring centers, financial services, convenience stores, and other retail shops. We find consistent patterns from a difference-in-difference estimation by comparing cells in 1 mile from BSW sites with cells in between 1 and 2 miles away from BSW sites, as shown in Table 5.

Local service businesses located near the BSW sites are quick to respond to foot traffic. The increase in service 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 recreational activities. The growth of these service businesses also makes it easier for people in the nearby neighborhoods to access various services, thereby enhancing the attractiveness of these areas and contributing to an increase in housing prices.

5 Discussions

Our estimates of the housing price change in neighborhoods close to the cleaned-up waterways help provide a benchmark for the cost-benefit ratio of the BSW Program. 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 the 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]

The estimated property value appreciation along with the benefit-cost ratio is useful, primarily because the program has expanded to other Chinese cities in the last few years. Governments in some less developed cities are reluctant to carry out the program because it requires an extra government budget. There have been proposals to involve the private sector, such as real estate firms, to invest in these projects. In return, real estate firms can obtain land development rights in these neighborhoods. The feasibility of such proposals hinges on the property value appreciation generated by these projects.

Given that our sample is from the most developed metro areas in China, the estimated benefits here would be most informative for cities with similar urban population density and income levels.[27] For less densely populated or less affluent neighborhoods, it is likely that the estimated price change provides an upper bound of the property value appreciation.

Next, it is worth discussing the impacts of such policies on the welfare inequality between the rich and poor. On the one hand, wealthier households benefit more from environmental amenities since they can afford to pay more to live close to these environmental amenities. On the other hand, owners of apartments close to BSW sites, who were generally less affluent before the program, acquire most of the property value appreciation after the program. Therefore, whether higher or lower-income households benefit more depends on the relative strengths of these opposite channels.

Finally, our findings suggest that there may have been or may be ongoing residential sorting following the implementation of the BSW Program. We observe that newly constructed apartment buildings in proximity to cleaned-up waterways typically have better

[26]The data on the total expenses of the program in the six cities is not available, so we estimated the total investment cost. The cumulative investment incurred by the program across the 36 most developed cities was reported to be 114 billion RMB (Cao, February 28, 2019). Based on this information, we calculated the average investment per BSW site and per mile of BSW cleaned, resulting in a total investment of 41 billion RMB and 26 billion RMB for the six cities, respectively. To estimate a lower bound of the benefit-cost ratio, we used the higher value of the two estimates.

[27]As shown in Table 6, the sample townships in the six cities have a higher working population ratio and a much lower percentage of Hukou holders. It is because these cities have lots of opportunities and hence attract the working population from other regions.

internal decoration and more spacious layouts. This implies that real estate developers are targeting more affluent households for these properties. Additionally, the increase in service businesses in these areas may also attract wealthier households, who value proximity to service businesses more. Together, these findings provide indirect evidence of an influx of wealthier households into neighborhoods close to the cleaned-up waterways.

6 Conclusion

This paper examines the economic benefits of cleaning up heavily polluted waterways in urban neighborhoods. Using the Black-and-Smelly 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 the cleaned-up 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 BSW sites, developers building new apartment complexes near these sites are more likely to provide high-end units featuring luxury decoration 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 the cleaned-up 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. It can cause an urban decline as wealthier residents flee to suburban neighborhoods with a more appealing environment (Mieszkowski and Mills, 1993). The neighborhood sorting may intensify residential segregation between rich and poor and endanger inter-generational mobility (Chetty et al., 2016). 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.

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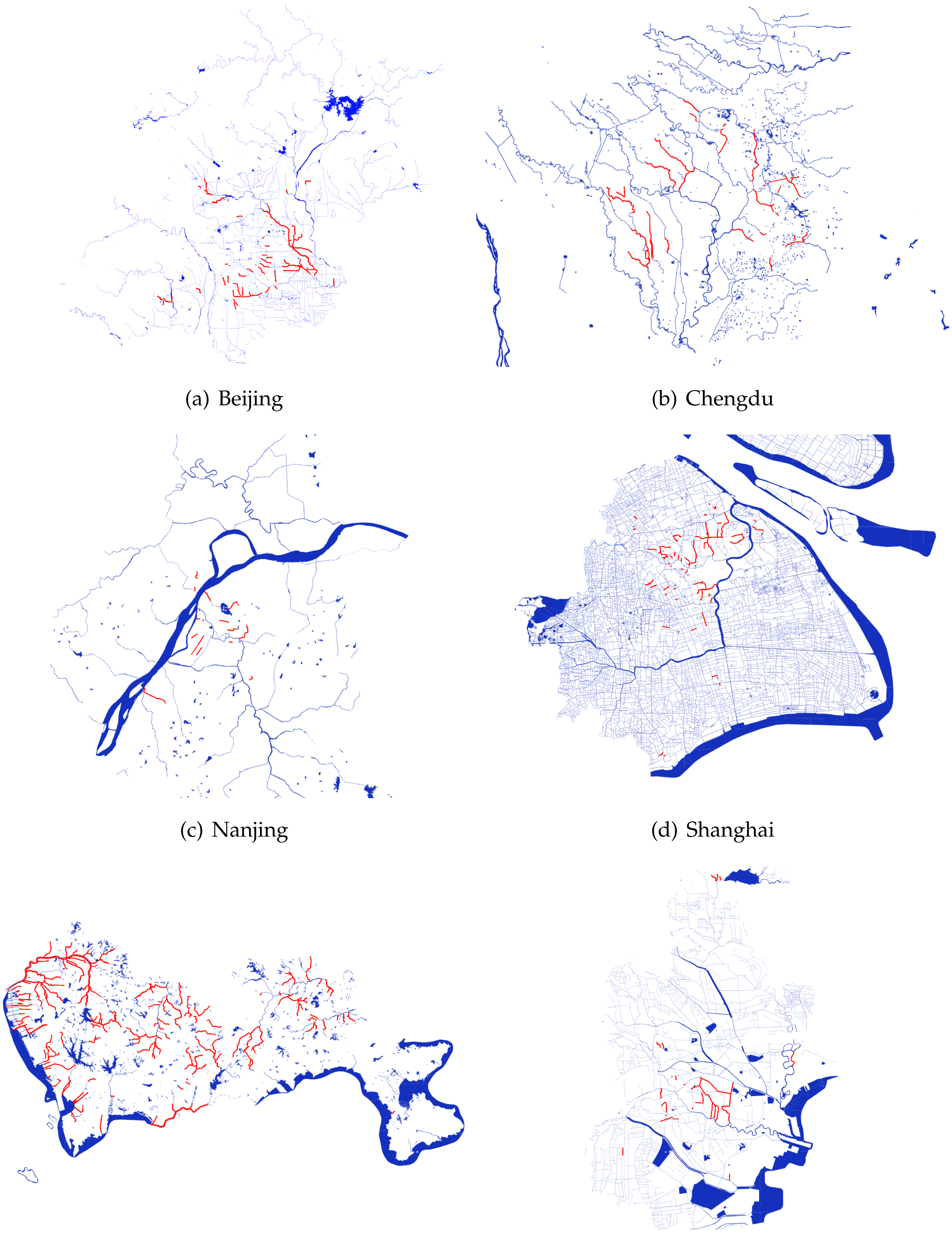
Figures

FIGURE 1: LOCATIONS OF BSW SITES



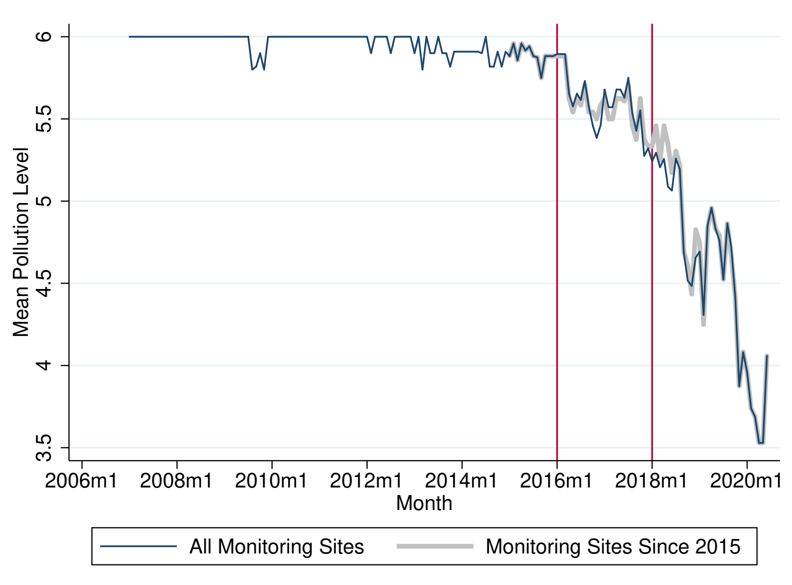
(a) Beijing (b) Chengdu

(c) Nanjing (d) Shanghai

(e) Shenzhen (f) Tianjin

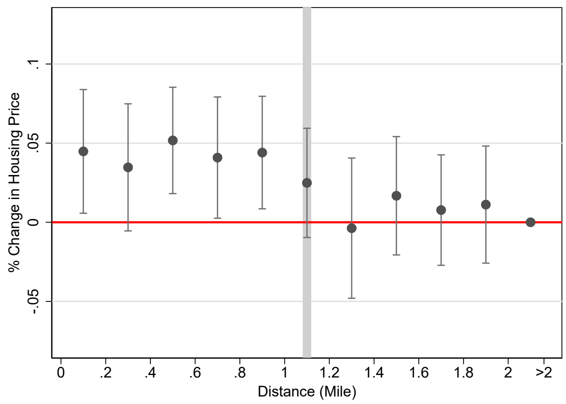
Notes: The red lines represent waterways cleaned up under the BSW Program, while blue lines represent the rest of the waterways that run through each city. Data sources: Institute of Public & Environmental Affairs (IPE) and Baidu Map.

FIGURE 2: CHANGES IN POLLUTION LEVEL

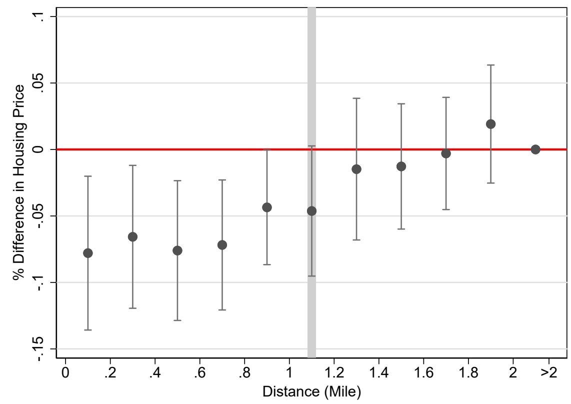


Notes: Based on the monthly monitoring data collected from the monitoring sites around the BSW sites, water pollution reduced continually during and after the program.

FIGURE 3: CHANGES IN HOUSING PRICES BY DISTANCE TO A BSW SITE



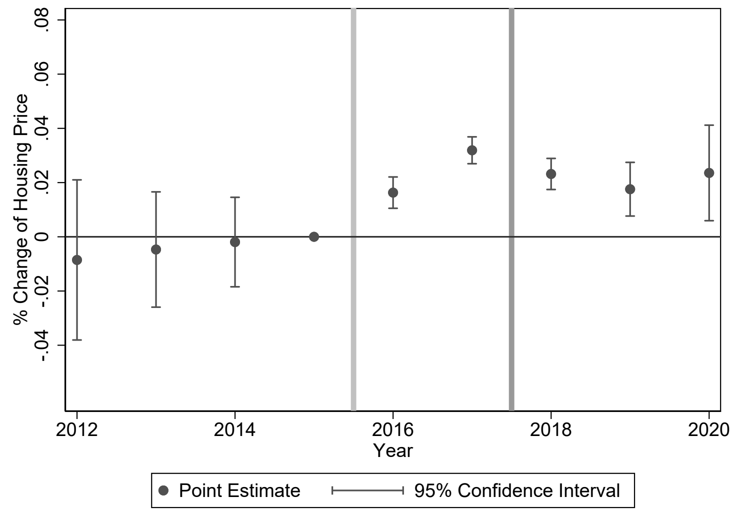
(a) Price Change (%)



(b) Price Gradient before the Treatment

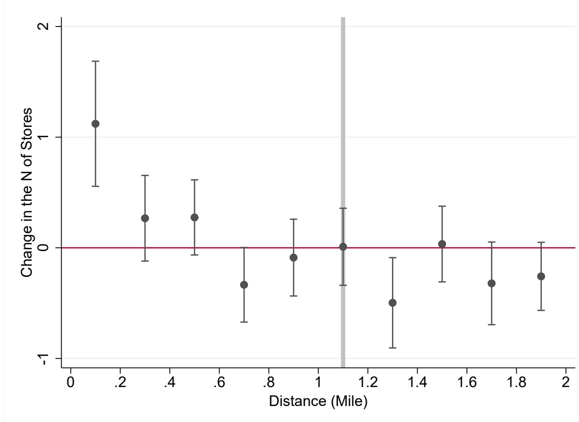
Notes: This figure shows that apartments less than 1 mile away from a BSW site had a substantial increase in housing prices after the BSW Program, while the effects for apartments further away are close to zero and insignificant. Panel b shows the price gradient with respect to distance from a BSW site and also suggests that apartments less than 1 mile away from a BSW site had a lower price before the program. We classify apartments into equal-width bins according to their distances to the closest BSW 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 $\{\beta_1^n\}$ onto Panel (a) and the coefficients $\{\beta_0^n\}$ onto Panel (b). We specify 0.2 mile as bin width and assign apartments more than 2 miles away to the comparison group. Correspondingly, coefficient β_1^n represents the percentage change of housing prices of apartments in bin n relative to those more than 2 miles away from a BSW site after 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 the urban district level and city-year level.

FIGURE 4: EVENT STUDY

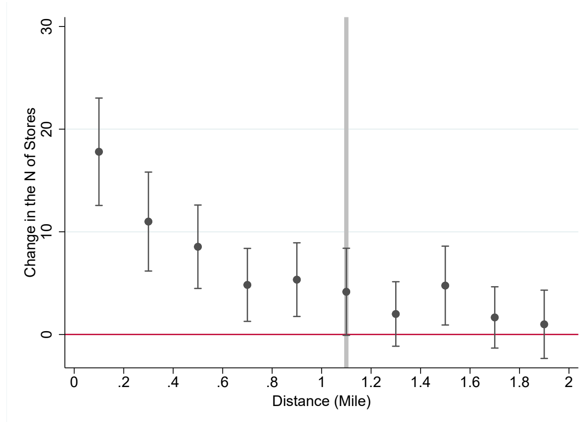


Notes: This figure shows that up to 2015, housing prices of apartments within 1 mile from a BSW site are in parallel trends with apartments further away; starting from 2016, apartments within 1 mile from a BSW site have significantly higher prices comparing to apartments 1 to 2 miles away. We estimate the impact of the BSW Program on housing prices year by year and plot the coefficient estimates onto the graph. The benchmark year for comparison is 2015. Each coefficient represents that compared to 2015, whether transacted apartments less than 1 mile from a BSW site have systematically different price compared to transacted apartments 1 to 2 miles away from a BSW 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 the urban district level and city-year level.

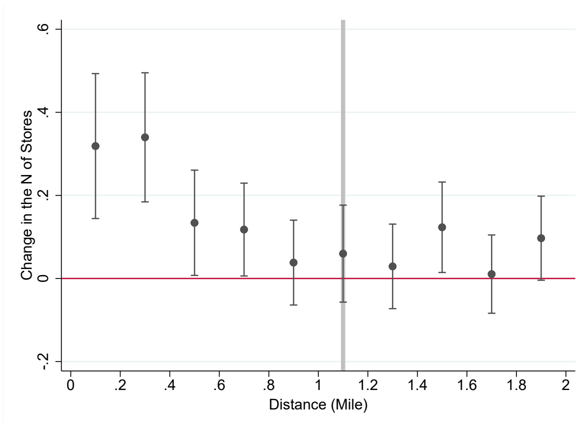
FIGURE 5: SERVICE BUSINESS GROWTH IN RELATION TO PROXIMITY TO BSW SITES



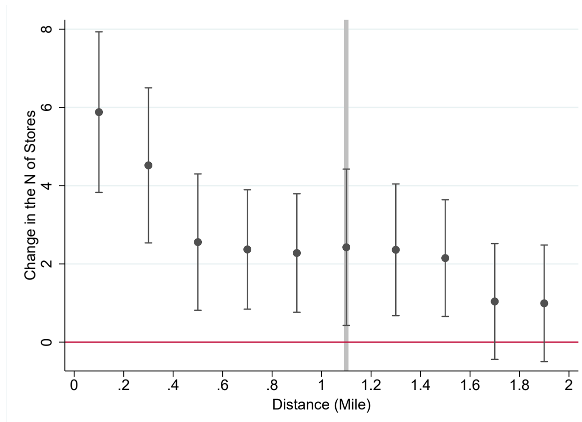
(a) Recreation



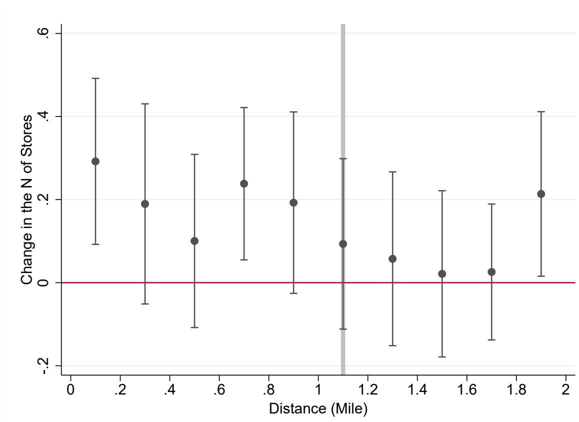
(b) Restaurants



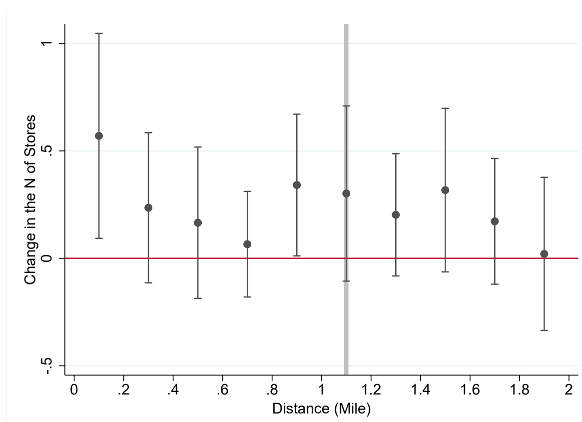
(c) Pharmacies



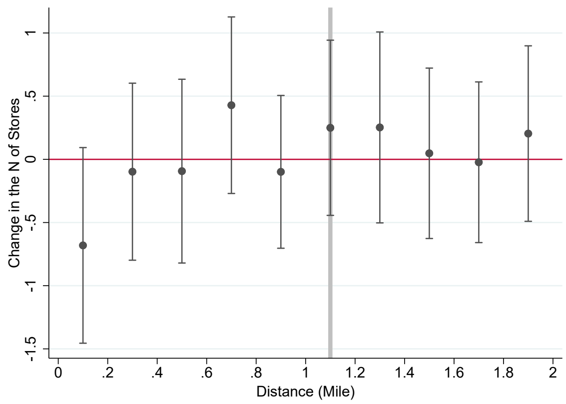
(d) Other Services



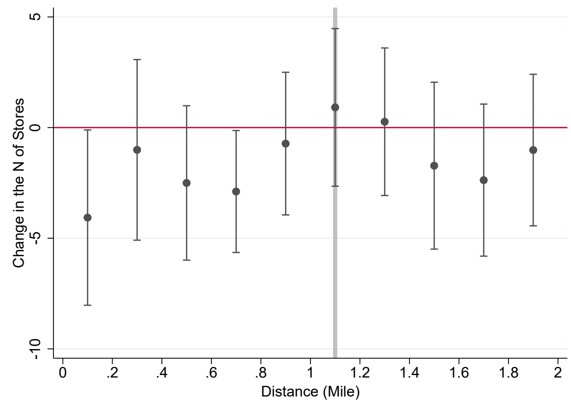
(e) Tutoring



(f) Finance



(g) Convenience Stores



(h) Other Shopping 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, there is a significant increase in the number of recreation centers, with the effect being concentrated within a 0.2-mile radius of BSW sites. We also observe a substantial increase in the number of restaurants within a 0.2-mile radius of the cleaned waterways, but this positive effect declines rapidly as we moved further away from the waterways. Similar patterns are observed for pharmacies and other service businesses. Service businesses include post offices, salons, laundries, photography studios, and repair shops. We do not find similar patterns for tutoring centers, financial services, convenience stores, and other retail shops.

Tables

TABLE 1: DIFFERENCE-IN-DIFFERENCE RESULTS

Dep. variable: lnP	(1)	(2)	(3)	(4)	(5)	(6)
$In1mile_{BSW}$	-0.037**	-0.037**	-0.035**	-0.037**	-0.035***	-0.044***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.015)
$In1mile_{BSW} \times$Post2016	0.023***		0.019***	0.023***	0.022***	0.032***
	(0.007)		(0.004)	(0.006)	(0.006)	(0.009)
$In1mile_{BSW} \times$During		0.024***				
		(0.006)				
$In1mile_{BSW} \times$After		0.022***				
		(0.008)				
$In1mile_{waterways}$						0.004
						(0.029)
$In1mile_{waterways} \times$Post2016						-0.006
						(0.025)
Observations	543,554	543,554	543,554	543,554	543,554	881,453
R-squared	0.894	0.894	0.896	0.895	0.895	0.897

Notes: This table shows that the implementation of the BSW Program resulted in a 2.3% increase in housing prices for apartments located within 1 mile of any BSW site. It's important to note that before the program, these apartments were 3.7% cheaper, suggesting that residents were avoiding living close to heavily polluted waterways. 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 level and city-year level 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)
$\text{In1mile}_{BSW} \times \text{Post2016} \times \text{Low Pop Density}$	0.001	
	(0.020)	
$\text{In1mile}_{BSW} \times \text{Post2016} \times \text{High Pop Density}$	0.028***	
	(0.008)	
$\text{In1mile}_{BSW} \times \text{Post2016} \times \text{Low Housing Price}$		0.005
		(0.010)
$\text{In1mile}_{BSW} \times \text{Post2016} \times \text{High Housing Price}$		0.036***
		(0.008)
Observations	548,404	545,560
R-squared	0.895	0.894

Notes: This table shows that price effects are mainly driven by apartments that are located in densely populated areas and in areas where housing prices are high in the baseline years. We classify townships into different groups based on whether it is below or above the median level within a city in terms of population density in 2010 and average housing price level over 2012 – 2015. We always control for a comprehensive set of housing characteristics, urban district fixed effects, and city time-varying effects in our analysis. Standard errors are double-clustered at the urban district level and city-year level 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		Large Layout		High Green Plot Ratio	
$\text{In1mile}_{\text{BSW}}$			-0.045	-0.046	-0.034	-0.034	1.156	1.152
			(0.029)	(0.029)	(0.024)	(0.024)	(0.725)	(0.726)
$\text{In1mile}_{\text{BSW}} \times \text{Post2016}$	-0.000	0.001	0.073*		0.038		-0.285	
	(0.003)	(0.021)	(0.037)		(0.033)		(0.940)	
$\text{In1mile}_{\text{BSW}} \times \text{Year}_{\text{2016 to 2018}}$				0.036		0.006		-0.890
				(0.045)		(0.039)		(1.080)
$\text{In1mile}_{\text{BSW}} \times \text{Year}_{\text{2019 to 2020}}$				0.124**		0.084**		0.576
				(0.047)		(0.040)		(1.335)
Observations	78,364	78,364	2,627	2,627	2,627	2,627	2,627	2,627
R-squared	0.178	0.178	0.240	0.241	0.295	0.296	0.249	0.250

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

TABLE 4: HETEROGENEOUS PRICE RESPONSES BY HOUSING CHARACTERS

Dep. variable: lnP	(1)	(2)	(3)
$\text{In1mile}_{\text{BSW}} \times \text{Post2016} \times \text{Regular Decor}$	0.023**		
	(0.009)		
$\text{In1mile}_{\text{BSW}} \times \text{Post2016} \times \text{Luxury Decor}$	0.009		
	(0.008)		
$\text{In1mile}_{\text{BSW}} \times \text{Post2016} \times \text{Small}$		0.031**	
		(0.012)	
$\text{In1mile}_{\text{BSW}} \times \text{Post2016} \times \text{Large}$		0.017*	
		(0.009)	
$\text{In1mile}_{\text{BSW}} \times \text{Post2016} \times \text{Old}$			0.045**
			(0.017)
$\text{In1mile}_{\text{BSW}} \times \text{Post2016} \times \text{New}$			0.021**
			(0.010)
Observations	435,554	543,554	463,754
R-squared	0.900	0.894	0.895

Notes: This table shows that apartments that feature luxury decoration, larger layouts, and were constructed more recently had a less significant price response to the improved water clarity. We classify a unit as having a large layout if its floor area is above sample median and we classify an apartment to be 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 level and city-year level are in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 5: IMPACT OF BSW PROGRAM ON LOCAL BUSINESS PERFORMANCE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. variables	Recreation	Restaurants	Pharmacy	Other Services	Tutoring	Finance	Convenience Stores	Other Stores
$\text{In1mile}_{\text{BSW}} \times \text{Post2016}$	0.295**	5.445***	0.088**	1.177**	0.089	0.064	-0.353	-1.764
	(0.130)	(1.358)	(0.039)	(0.537)	(0.062)	(0.112)	(0.234)	(1.219)
Observations	14,248	14,248	14,248	14,248	14,248	14,248	14,248	14,248
R-squared	0.948	0.944	0.962	0.927	0.987	0.969	0.986	0.987

Notes: This table shows that neighborhoods located less than 1 mile from any BSW site experienced an increase in recreational centers, restaurants, pharmacies, and other services following the implementation of the BSW program. In contrast, there were only minor changes in the number of tutoring centers, financial services, convenience stores, and other retail shops in these neighborhoods. We always control for cell fixed effects, city time-varying effects, and the time-varying effects of the number of stores in the baseline year of 2015. Robust standard errors clustered at the urban district level are in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A Appendix Data

A.1 Representativeness of the Apartment Transaction Records

In this subsection, We discuss the representativeness of the transaction records of the pre-owned apartments. We start by showing that the average price of pre-owned apartments based on our data closely tracks the official records of the average price of newly built apartments, as shown in Appendix Figure 9 (a). The average price of pre-owned apartments is defined as the ratio of the total transaction values to the total floor areas sold in these transactions. The official records of newly built apartment transactions come from China Real Estate Statistics Yearbooks (2012 to 2017). The trend of the average price of the pre-owned apartments closely follows that of the newly built apartments in all the six cities. In Beijing and Shanghai, the newly built apartments are much further away from the city center than the transacted pre-owned apartments. That explains why in these two cities, the average price of the pre-owned apartments is higher than that of the newly built apartments.

The second evidence is that the average floor area of the transacted apartments in our data is very close to the counterpart in the China Real Estate Information (CREI), as shown in Appendix Figure 9 (b). CREI is a database maintained by the State Information Center.[28] It reports the total number of pre-owned apartments sold and registered in the government bureau and the corresponding floor areas. Therefore, we can calculate the average floor area of a transacted pre-owned apartment for each city-year, and compare it with the data calculated based on our transaction records.[29]

Next, our sample covers 12.79% of total transactions of pre-owned apartments in the sample cities during 2012 and 2018 and the sample coverage improves over time.[30] Furthermore, we calculate the sample coverage by city-year and plot the data in Appendix Figure 10. This is because the real estate agencies, where our data comes from, first launched their businesses around early 2010s in a few most developed cities.[31] It does not create any bias as long as our data always provides a representative sample of the population data, demonstrated by the average apartment prices and the average floor areas of an apartment.

[28] http://www.crei.cn/.

[29] The data for Shanghai and Tianjin (2012, 2013, 2016 to 2018) is missing in CREI.

[30] The sample coverage is defined as the ratio of transaction volume captured by our data to the transaction volume reported in CREI. We exclude Shanghai from the analysis as the official records for Shanghai is missing in CREI.

[31] Compared to traditional real estate companies, they have both physical stores and online platforms.

B Appendix Figures

FIGURE 6: PROGRAM TIMELINE

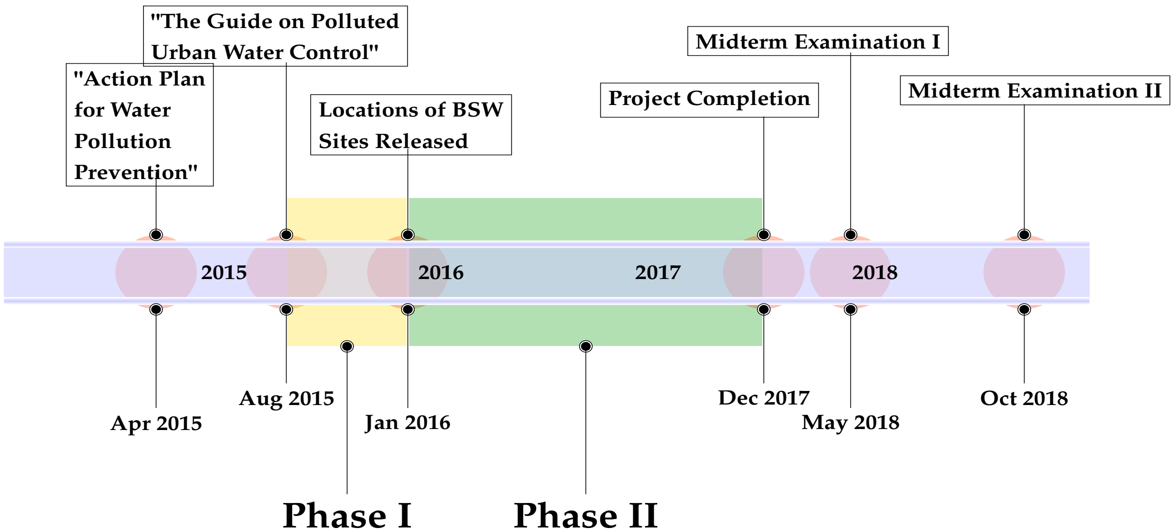


Figure 7: Examples of BSW Sites

(a) Xiaotaihou River, Beijing, Before the Program

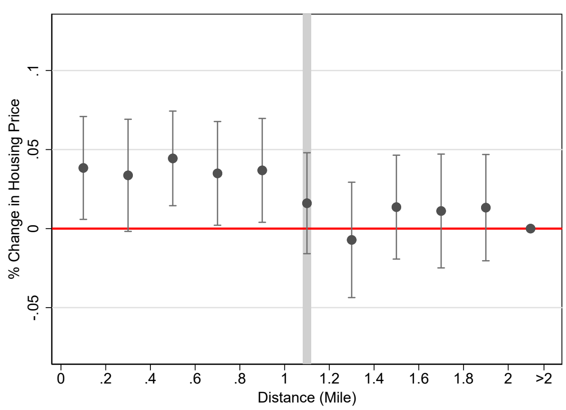
(b) Xiaotaihou River, Beijing, After the Program

(c) Futian River, Shenzhen, Before the Program

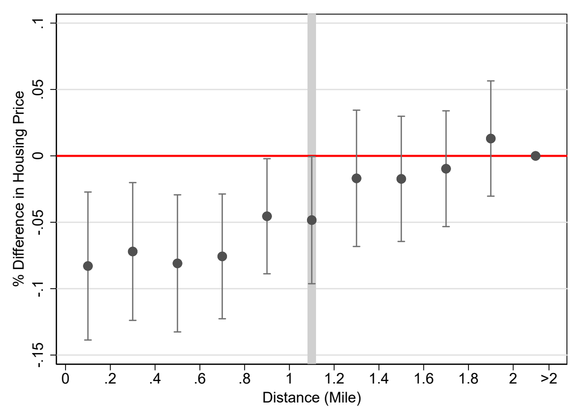
(d) Futian River, Shenzhen, After the Program

Notes: The photos are from SEE and IPE (2018) and the Ministry of Ecology and Environment of the People's Republic of China.

Figure 8: Changes in Housing Prices by Distance to a BSW Site, Robustness Check

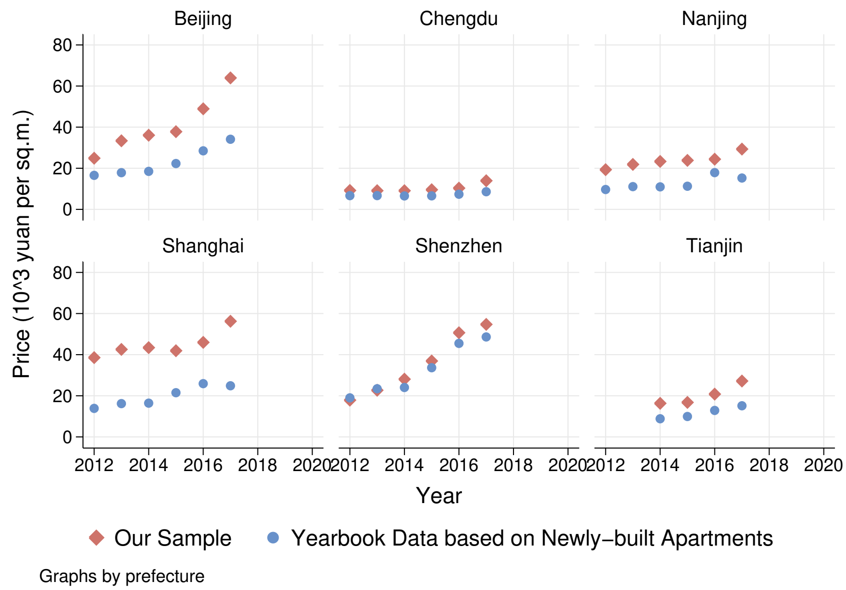


(a) Price Change (%)

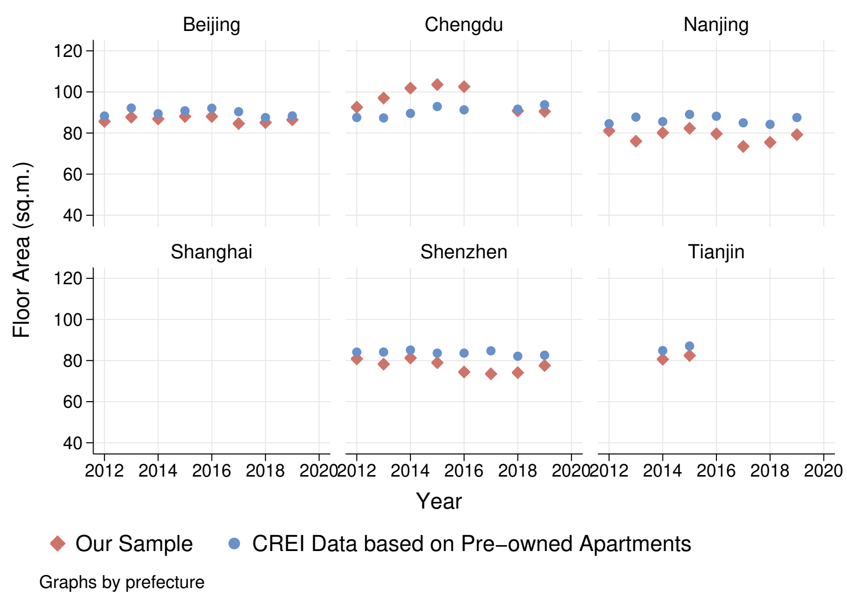


(b) Price Gradient before the Treatment

FIGURE 9: COMPARISON OF TRANSACTION DATA IN OUR SAMPLE WITH OFFICIAL RECORDS

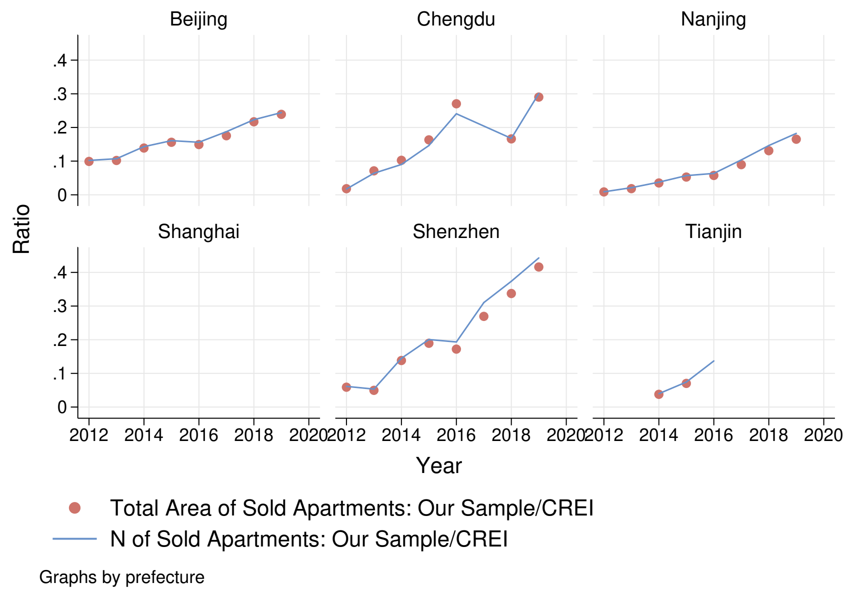


(a) Average Price



(b) Average Floor Area

FIGURE 10: PRE-OWNED APARTMENT TRANSACTIONS COVERED BY OUR DATA



C Appendix Tables

Table 6: 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

Table 7: Waterways Included in the BSW Program

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 Projects	46	51	18	62	104	23

TABLE 8: SUMMARY STATISTICS

Variables	N	Mean	SD	Variables	N	Mean	SD
A. Transacted Apartments				**B. Supply of New Apartments**			
Price ($\times 10^4$ RMB)	551,831	300.3	220.7	Number of New Apartments	78,672	43.10	368.7
Distance to the Nearest BSW Site (mile)	551,831	0.894	0.551	$1_{\text{Num. New Apartments}>0}$	78,672	0.034	0.182
				% Luxury Apartments By			
Number of Floors	551,831	13.97	10.61	- *Green Space*	2,931	34.83	9.836
Building Completion Year	466,910	2,002	8.333	- *High-end deco*	2,931	0.397	0.489
Floor Area (m^2)	551,831	81.43	37.01	- *Large layout*	2,931	0.190	0.392
Exposure:				**C.Store by Business Category within a $1km \times 1km$ Cell**			
- *East*	522,601	0.190	0.392	Recreation	7,152	4.742	9.928
- *West*	522,601	0.136	0.343	Restaurants	7,152	44.756	98.018
- *North*	522,601	0.382	0.486	Pharmacies	7,152	1.980	3.887
- *South*	522,601	0.781	0.414	Other Services	7,152	16.378	39.991
Floor Level:				Tutoring	7,152	4.879	11.713
- *First Floor*	551,831	0.015	0.122	Finance	7,152	5.181	12.861
- *Low*	551,831	0.237	0.425	Convenience Stores	7,152	21.459	38.163
- *Middle*	551,831	0.356	0.479	Other Shopping Stores	7,152	91.761	202.353
- *High*	551,831	0.310	0.462				
- *Penthouse*	551,831	0.020	0.139				
Building Structure:							
- *Concrete Slab*	551,831	0.136	0.343				
- *Tower*	551,831	0.475	0.499				
- *Concrete Slab and Tower*	551,831	0.186	0.389				
- *Others*	551,831	0.000	0.021				
Internal Design:							
- *Unfurnished*	551,831	0.029	0.168				
- *Partially Furnished*	551,831	0.159	0.366				
- *Finely Furnished*	551,831	0.248	0.432				
- *Others*	551,831	0.366	0.482				

TABLE 9: DIFFERENCE-IN-DIFFERENCE: ROBUSTNESS CHECKS

Dep. variable: lnP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$In1mile_{BSW}$	-0.037**	-0.034**		-0.043***	-0.037**			-0.037**
	(0.015)	(0.014)		(0.015)	(0.015)			(0.016)
$In1mile_{BSW} \times Post2016$	0.023***	0.019***	0.013**	0.032***	0.022***			0.023**
	(0.007)	(0.005)	(0.007)	(0.009)	(0.006)			(0.009)
$In0.8mile_{BSW}$						-0.038**		
						(0.016)		
$In0.8mile_{BSW} \times Post2016$						0.015*		
						(0.007)		
$In1.2mile_{BSW}$							-0.048***	
							(0.014)	
$In1.2mile_{BSW} \times Post2016$							0.023**	
							(0.010)	
Observations	543,554	543,440	407,906	881,075	508,661	472,364	610,546	543,554
R-squared	0.894	0.899	0.953	0.898	0.894	0.897	0.894	0.894

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