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

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Motivation

- The rapid growth of urbanization and economy in developing countries has caused significant environmental costs.
- An increasing demand for cleaner environment calls for regulations to control pollution emissions and clean up hazardous sites.
- To create effective policies, it is crucial to understand how these programs interact with neighborhood dynamics.
  - A challenging empirical question given program endogeneity and data limitation

This Paper

- **Question:** How do cleaner waterways affect the local real estate market and business development?

- **Identification strategy:** Exploit the Black-and-Smelly Water Program in China as a natural experiment.
  - The program cleaned up the heavily polluted waterways running through the 36 most developed Chinese cities during 2016 and 2017.
  - Difference-in-Difference Estimation: Compare neighborhoods close to the cleaned waterways with those farther away, before and after the program.

Preview of Results

- The program mainly benefits the real estate properties within 1 mile from the cleaned waterways.
  - The market values of these properties were 3.7% lower before the program.
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- No increase in the supply of newly built apartments near the cleaned waterways.
  - New apartment complexes near the cleaned waterways more likely to have luxury decoration and spacious apartment layouts after the program.
- Various service businesses thrive in neighborhoods near the cleaned waterways.
  - 46% increase in the number of restaurants and 33% increase in the number of recreation centers within a 0.2-mile radius of the cleaned waterways.

Literature

- 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); Zheng and Kahn (2017); Ito and Zhang (2020); Greenstone and Hanna (2014); Duflo et al. (2018)
  - This paper: Highlight responses of the local housing markets and dynamics of the neighborhood
- Impacts of pollution and pollution controls on home values
  - Chay and Greenstone (2005); Grainger (2012); Heblich et al. (2021); Isen et al. (2017); Boes and Nüesch (2011); Coury et al. (2022); Bui and Mayer (2003); Greenstone and Gallagher (2008); Gamper-Rabindran and Timmins (2011); Cassidy et al. (2022); Keiser and Shapiro (2019)
  - This paper: Exploit a policy that targets the densely populated urban areas in a developing country
- 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); Streiner and Loomis (1995); Peng et al. (2019)
  - This paper: Focus on the aesthetic value of cleaning waterways

The Black-and-Smelly Water Program

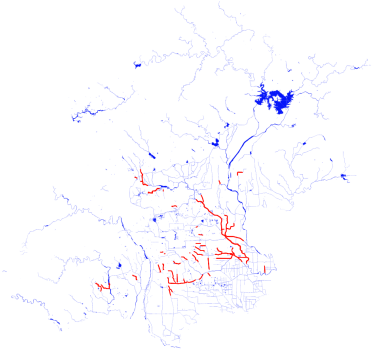
- The Black-and-Smelly Water (BSW) Program proposed in 2015 mandates that the 36 most developed cities in China clean up heavily polluted waterways within the built-up areas by the end of 2017.

- The BSWs refer to waterways with *transparency* less than 25 cm, *dissolved oxygen* less than 2 mg/L, *oxidation-reduction potential* less than 50 mV, or *ammoniacal nitrogen* above 8 mg/L.

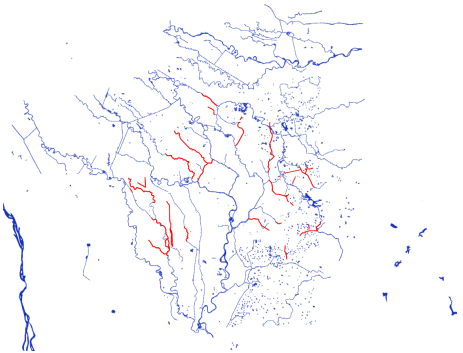
- In the six sample cities, 525 miles of waterways were cleaned in this program.
  - Beijing, Chengdu, Nanjing, Shanghai, Shenzhen, Tianjin
  - Elimination of BSWs suggested by both remote sensing analysis and monthly reports from water monitoring points. Details

Program Details

Locations of the BSW Sites

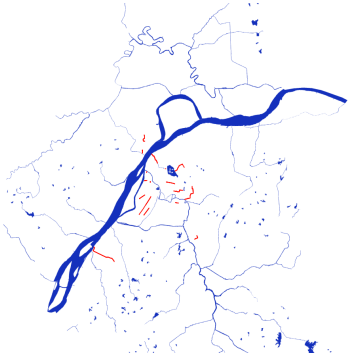


(a) Beijing



(b) Chengdu

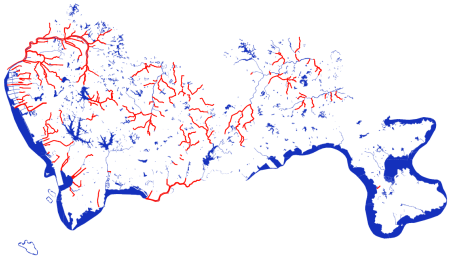
Locations of the BSW Sites, Cont'd



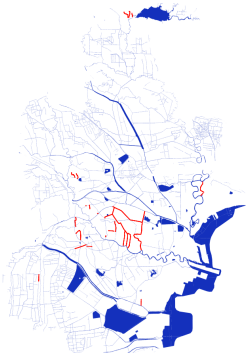
(c) Nanjing

(d) Shanghai

Locations of the BSW Sites, Cont'd



(e) Shenzhen



(f) Tianjin

Xiaotaihou River in Beijing

(a) Before the Program

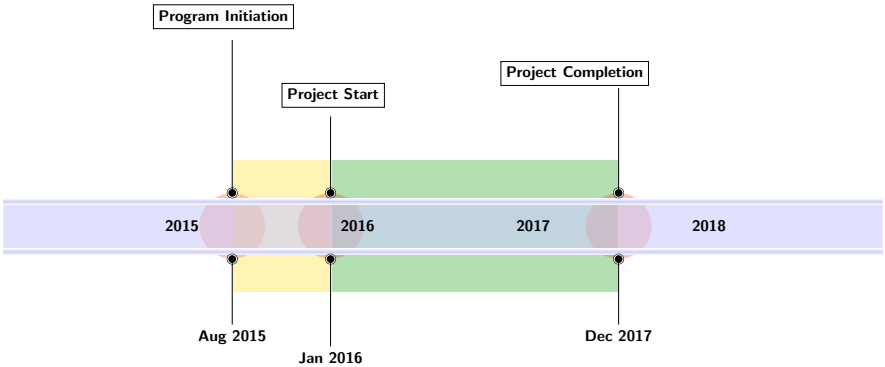
(b) After the Program

Futian River in Shenzhen

(a) Before the Program

(b) After the Program

Program Timeline



- Pre-period: Up to December 2015
- Post-period: 2016 onward
  - During the program (2016 to 2017) and after the program (2018 to 2020)

Data

- **The BSW sites**
  - Location and the pollution severity (severe or very severe)
- **Transaction records of pre-owned apartments during 2012 and 2020**
  - A representative sample that accounts for 13% of transactions in the housing market
  - Detailed apartment characteristics
    - ⋆ 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

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  - Data source: China Real Estate Index System
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- **Locations of service businesses in 2015 and 2019**
  - Data source: Gaode Map
  - Classify businesses into nine categories: recreational centers, restaurants, pharmacies, financial services, tutoring services, other services, convenience stores, grocery and supermarkets, and other retail stores

Data Representativeness | Statistics on BSW Sites | Summary Statistics

Regression Specification

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

- Difference-in-Difference Estimator
  - $\ln P_{ijkt}$: the transaction value of an apartment i in urban district j, city k, sold in year t.
  - $1_{Near,i}$ indicates whether the apartment i is located near a BSW site or not
    - ⋆ Use a distance bin analysis to flexibly identify the distance beyond which the BSW program no longer affects housing values

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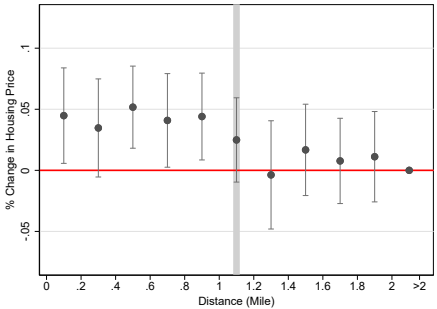
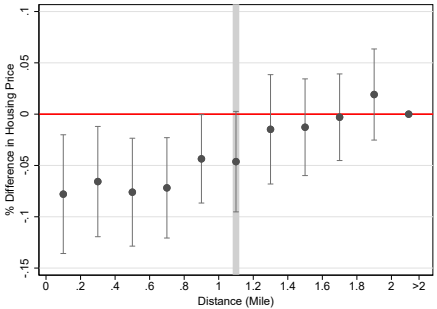
    - ⋆ Use a distance bin analysis to flexibly identify the distance beyond which the BSW program no longer affects housing values
  - Control for city time-varying effects (τ_{kt}), urban district fixed-effects (μ_j), and a comprehensive set of housing characters (X_{ijkt})
  - Double cluster the error term at the urban district level and city-year level
- Coefficients of interest: β_1 and β_2

Changes in Housing Prices by Distance to BSW Sites

- Following the program, a substantial increase in housing prices was observed among apartments less than 1 mile away from a BSW site.



(a) Price Change (%)

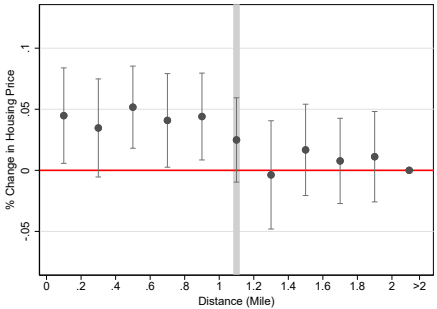


(b) Price Gradient before the Program

Details

Changes in Housing Prices by Distance to BSW Sites

- Before the program, apartments closer to these polluted waterways were significantly cheaper, and this negative effect was concentrated among apartments within 1 mile.



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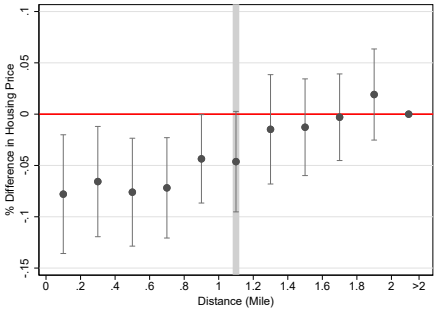
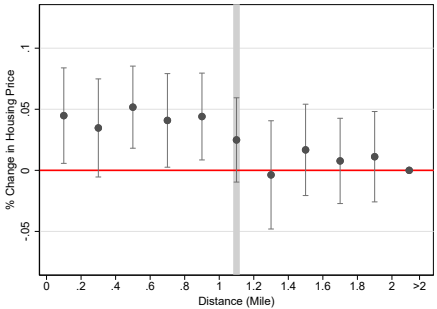


(b) Price Gradient before the Program

Details

Changes in Housing Prices by Distance to BSW Sites

- Treated region: within 1 mile from a BSW site
- Control region: between 1 and 2 miles away from any BSW site



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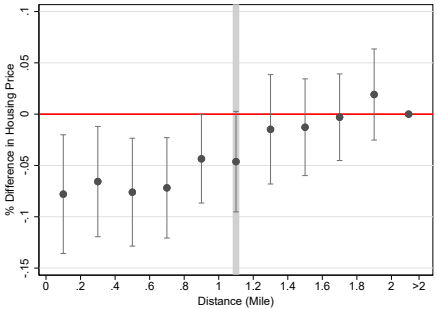
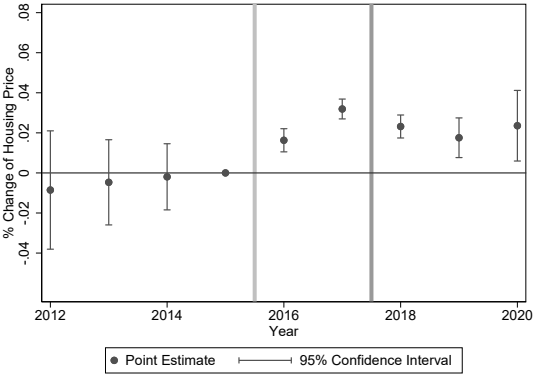


(b) Price Gradient before the Program

Details Balance Check

Changes in Housing Prices by Year

- Housing prices in the treated and control regions moved in parallel up to 2015.
- Since 2016, apartments located within 1 mile of a BSW site had significantly higher prices compared to the rest.



Sensitivity Check

Difference-in-Difference Estimation

- Apartments located less than 1 mile away from the BSW sites were 3.7% cheaper before the program.
- Following the program, these apartments had a 2.3% increase in housing prices.

Dep. variable: lnP	(1)	(2)
$\ln 1\text{mile}_{BSW}$	-0.037**	-0.037**
	(0.015)	(0.015)
$\ln 1\text{mile}_{BSW} \times \text{Post2016}$	0.023***	
	(0.007)	
$\ln 1\text{mile}_{BSW} \times \text{During}$		0.024***
		(0.006)
$\ln 1\text{mile}_{BSW} \times \text{After}$		0.022***
		(0.008)
Observations	543,554	543,554
R-squared	0.894	0.894

Benefit-Cost Ratio | Robustness Checks | Heterogeneity

No Impacts on the Quantity of New Apartments

- The supply of newly built apartments does not significantly increase in neighborhoods closer to a BSW site than those farther away.

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- The supply of newly built apartments does not significantly increase in neighborhoods closer to a BSW site than those farther away.
  - Divide sample cities into exclusive hexagons with a side length of 0.3 miles and count the number of newly constructed apartments by cell-year
  - Regression specification:

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

	(1)	(2)
Dep. variables	$1_{\text{New Apartments}}$	IHS(Num. Units)
$\text{ln1mile}_{\text{BSW}} \times \text{Post2016}$	0.001	0.006
	(0.002)	(0.017)
Observations	104,478	104,478
R-squared	0.153	0.154

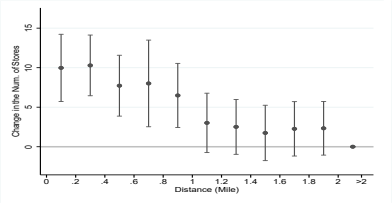
Growth in High-End Apartments

- Developers are more likely to provide high-end decoration and spacious apartment layouts after the program.

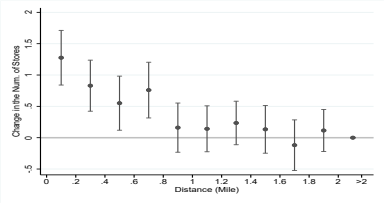
Dep. variables	(1) Luxury Decor	(2) Large Layout	(3) Green-Space Ratio
$\ln 1\text{mile}_{BSW}$	-0.053*	-0.031	1.206*
	(0.029)	(0.024)	(0.706)
$\ln 1\text{mile}_{BSW} \times \text{Year}_{2016 \text{ to } 2018}$	0.046	-0.011	-0.630
	(0.045)	(0.041)	(1.033)
$\ln 1\text{mile}_{BSW} \times \text{Year}_{2019 \text{ to } 2020}$	0.140***	0.073*	0.695
	(0.046)	(0.040)	(1.341)
Observations	2,644	2,644	2,644
R-squared	0.236	0.296	0.252

Regression Specification | Impacts on Housing Prices

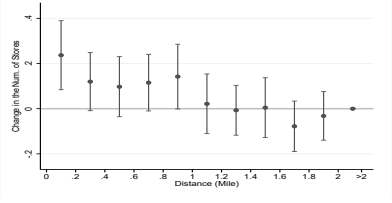
Proximity to BSW Sites and Service Business Growth



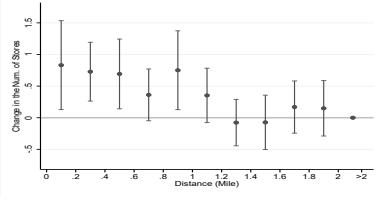
(a) Restaurants



(b) Recreation



(c) Pharmacies



(d) Convenience Stores

Regression Specification | Additional Results

Conclusion

- This paper studies the local impact of the BSW Program in China on housing markets and local business growth.
  - The market values of real estate properties within 1 mile from the cleaned waterways appreciate by 2.3% after the program.
  - Developers building new apartment complexes near these sites are more likely to provide high-end units after the program.
  - Various service businesses thrive in the neighborhoods close to the cleaned waterway.

Conclusion

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  - The market values of real estate properties within 1 mile from the cleaned waterways appreciate by 2.3% after the program.
  - Developers building new apartment complexes near these sites are more likely to provide high-end units after the program.
  - Various service businesses thrive in the neighborhoods close to the cleaned waterway.
- For cities under continuing expansion, urban environmental programs can effectively increase the attractiveness of heavily polluted neighborhoods to both residents and new businesses, and prevent urban decline in the long run.

THANK YOU!

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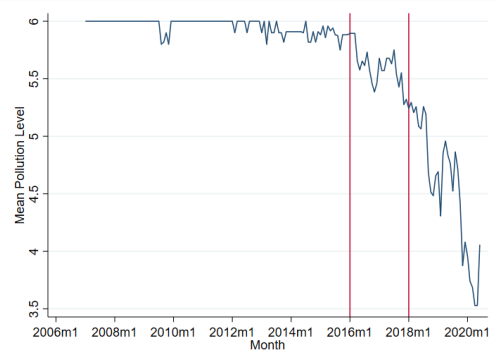
The BSW Program: More Details

- Cleaning up a BSW site involves three steps: controlling source discharges and intercepting pollutants, preventing and controlling endogenous pollution, 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.
- To incentivize local governments to meet the policy goal, the central government implemented various monitoring strategies.
  - The "Urban Black-and-Smelly Water Information Platform"
  - Third-party examination after the program
    - 93% of BSW sites passed the examination.
    - The remainder were cleaned up by October 2018.

Back

Program Outcome

- Elimination of the BSWs in cities participating in the program
  - Wang et al. (2022), Hu et al. (2021), and Qi et al. (2020)
  - Water quality measurement derived from high-resolution satellite images
- Based on monthly reports from monitoring sites at the BSW sites, water pollution continually reduced during and after the program.



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Summary Statistics: BSW Sites

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	39	18	62	104	23

Back

Summary Statistics: Main Variables

Variables	N	Mean	SD
A. Transacted Apartments			
Price ($\times 10^4$ RMB)	551,831	300.3	220.7
Distance to the Nearest BSW Site (mile)	551,831	0.894	0.551
Number of Floors	551,831	13.97	10.61
Building Completion Year	466,910	2,002	8.333
Floor Area (m^2)	551,831	81.43	37.01
Exposure:			
- *East*	522,601	0.190	0.392
- *West*	522,601	0.136	0.343
- *North*	522,601	0.382	0.486
- *South*	522,601	0.781	0.414
Floor Level:			
- *First Floor*	551,831	0.015	0.122
- *Low*	551,831	0.237	0.425
- *Middle*	551,831	0.356	0.479
- *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

Variables	N	Mean	SD
B. Supply of New Apartments			
Number of New Apartments	78,672	43.10	368.7
$1_{\text{Num. New Apartments}>0}$	78,672	0.034	0.182
% Luxury Apartments By			
- *Green Space*	2,931	34.83	9.836
- *High-end deco*	2,931	0.397	0.489
- *Large layout*	2,931	0.190	0.392
C.Store by Business Category within a $1km \times 1km$ Cell			
Recreation	7,152	4.742	9.928
Restaurants	7,152	44.756	98.018
Pharmacies	7,152	1.980	3.887
Other Services	7,152	16.378	39.991
Tutoring	7,152	4.879	11.713
Finance	7,152	5.181	12.861
Convenience Stores	7,152	21.459	38.163
Other Shopping Stores	7,152	91.761	202.353

Apartments in the Treated and Comparison Region

	Control (N = 54969)		Treatment (N = 74586)		
	Mean	SD	Mean	SD	Diff
Bathrooms	1.00	0.02	1.00	0.01	-0.00
Bedrooms	2.18	0.87	2.22	0.86	0.03
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***
Partially Furnished	0.11	0.32	0.09	0.29	-0.02**
Finely Furnished	0.23	0.42	0.21	0.41	-0.02
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 Age	2002.07	6.81	2002.89	6.43	0.82*
Building Structure-Tower	0.21	0.41	0.16	0.37	-0.05*
Building Structure-Slab	0.60	0.49	0.53	0.50	-0.07*
Building Structure-Mixed	0.19	0.39	0.31	0.46	0.12***

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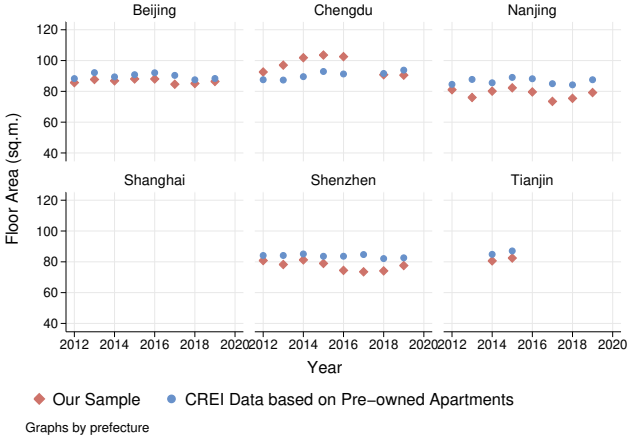
Representativeness of the Housing Transaction Records

- The average floor area of the transacted apartments in our data is very close to the counterpart in the China Real Estate Information.



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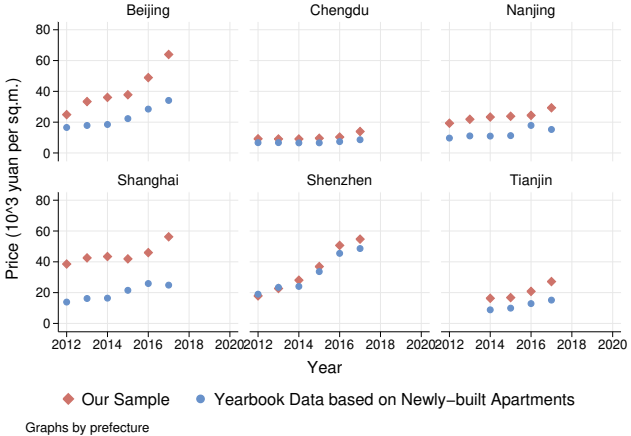
Representativeness of the Housing Transaction Records, Cont.

- The trend of the average price of the pre-owned apartments closely follows that of the newly built apartments in all the six cities.



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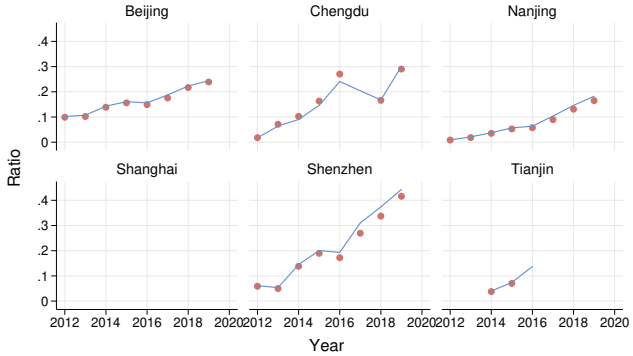
Sample Coverage



Graphs by prefecture

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Details on the Regression Design

- Regression specification

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

  - Ten 0.2-mile bins and assign apartments 2 to 20 miles away to the comparison group.
  - $\{\beta_1^n\}$ represents the percentage change in the price of apartments in bin n compared with apartments more than 2 miles away from any BSW site
  - $\{\beta_0^n\}$ represents the price gradient with respect to distance from a BSW site before the program

- Exclude transactions that occurred in 2016 and 2017, such that changes in the price gradient are estimated off transactions after the program completion
  - Patterns barely change when including these observations in the regression. Figures

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Difference-in-Difference Estimation, Robustness Checks

- Results are not driven by demand shocks, such as changing preferences for living close to waterways, city centers, or high-quality public schools.
  - A triple-difference regression model that measures the differential effect of proximity to general waterways versus initially heavily polluted waterways in the post period

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  - Quality of local public goods and public services
  - Changes in neighborhood dynamics

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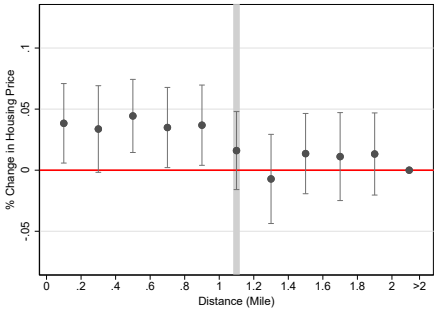
- Results are not confounded by potential changes in other neighborhood characters
  - Quality of local public goods and public services
  - Changes in neighborhood dynamics
- Results are robust to alternative regression specifications
  - Include all apartments located 2 to 20 miles away in the control group
  - Exclude apartments sold in 2020
  - Define the treated region as 0.8 or 1.2 miles away from BSW sites and the control region as 0.8 to 1.6 miles away and 1.2 to 2.4 miles away, respectively
  - Cluster the error term at more aggregate level

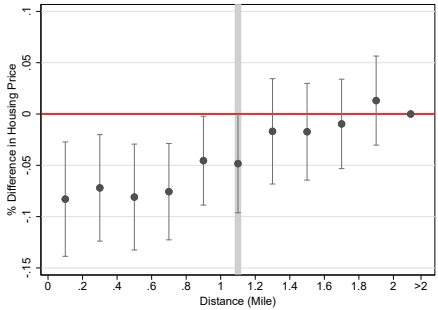
Table 1 Table 2

Price Change by Distance to BSW Sites, Robustness

- Patterns robust to including transactions from 2016 and 2017



(a) Price Change (%)



(b) Price Gradient before the Program

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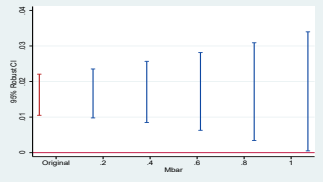
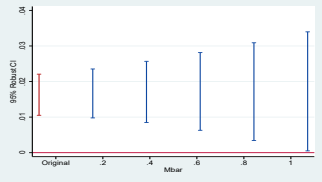
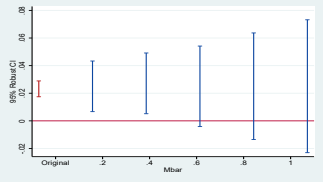
Year-by-Year Effects: Sensitivity Analysis



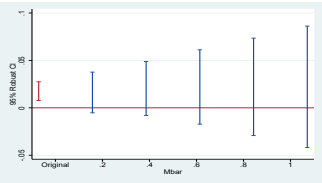
(c) 2016



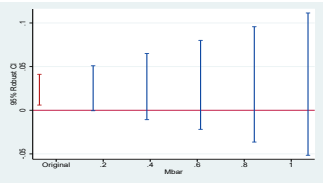
(d) 2017



(e) 2018



(f) 2019



(g) 2020

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Changes in Housing Prices, Robustness Checks

Dep. variable: lnP	(1)	(2)	(3)	(4)
$\ln 1\text{mile}_{BSW}$	-0.035**	-0.037**	-0.035***	-0.044***
	(0.014)	(0.014)	(0.013)	(0.015)
$\ln 1\text{mile}_{BSW} \times \text{Post2016}$	0.019***	0.023***	0.022***	0.032***
	(0.004)	(0.006)	(0.006)	(0.009)
$\ln 1\text{mile}_{waterways}$				0.004
				(0.029)
$\ln 1\text{mile}_{waterways} \times \text{Post2016}$				-0.006
				(0.025)
Observations	543,554	543,554	543,554	881,453
R-squared	0.896	0.895	0.895	0.897

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Changes in Housing Prices, Robustness Checks

Dep. variable: lnP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln 1mile_{BSW}$	-0.037**	-0.034**		-0.043***	-0.037**			-0.037**
	(0.015)	(0.014)		(0.015)	(0.015)			(0.016)
$\ln 1mile_{BSW} \times Post2016$	0.023***	0.019***	0.013**	0.032***	0.022***			0.023**
	(0.007)	(0.005)	(0.007)	(0.009)	(0.006)			(0.009)
$\ln 0.8mile_{BSW}$						-0.038**		
						(0.016)		
$\ln 0.8mile_{BSW} \times Post2016$						0.015*		
						(0.007)		
$\ln 1.2mile_{BSW}$							-0.048***	
							(0.014)	
$\ln 1.2mile_{BSW} \times Post2016$							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

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Heterogeneous Price Responses by Neighborhood Characters

- Larger effects in more densely populated and more expensive urban districts
- Larger effects near the most severely polluted waterways

Dep. variable: lnP	(1)	(2)	(3)
$\ln 1mile_{BSW} \times Post2016 \times$ Low Pop Density	0.000		
	(0.020)		
$\ln 1mile_{BSW} \times Post2016 \times$ High Pop Density	0.029***		
	(0.008)		
$\ln 1mile_{BSW} \times Post2016 \times$ Low Housing Price		0.005	
		(0.010)	
$\ln 1mile_{BSW} \times Post2016 \times$ High Housing Price		0.036***	
		(0.008)	
$\ln 1mile_{BSW} \times Post2016 \times$ Moderate Pollution			0.016*
			(0.010)
$\ln 1mile_{BSW} \times Post2016 \times$ Severe Pollution			0.028***
			(0.008)
Observations	548,404	545,560	550,753
R-squared	0.896	0.894	0.895

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Implications on Housing Prices

- The shift towards high-end new apartments on the supply side creates downward pressure on the prices of existing high-end units relative to regular units.

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

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The Benefit-Cost Ratio

- Benefit of the program: 489 billion RMB
  - The total increase in housing values of apartments within 1 mile from the cleaned waterways
  - Assume no indirect impact on housing prices more than 1 mile from the cleaned waterways
  - Ignored profit increase of service businesses
- Cost of the program for the six sample cities: 41 billion RMB
  - Calibrated based on the cumulative investment incurred by the program across the 36 most developed cities
- The conservative method generates a ratio of 12.

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Features of New Apartments: Regression Specification

- If real estate developers do construct a new building complex near a BSW site, are they more likely to provide high-end units after the program?

Features of New Apartments: Regression Specification

- If real estate developers do construct a new building complex near a BSW site, are they more likely to provide high-end units after the program?
- Regression at the level of new building complexes:

$$y_{bjkt} = \beta_0 + \beta_1 1_{Near,b} + \beta_2 1_{Near,b} \times \text{Year}_{2016-2018} + \beta_3 1_{Near,b} \times \text{Year}_{2019-2020} + \alpha_j + \tau_{kt} + \epsilon_{ljkt}$$

  - y_{bjkt}: A dummy variable indicating whether building b in urban district j, city k, launched to the market in year t has a particular feature
    - ⋆ Consider three features: high-end decoration, large layouts, and more green space
  - Divide the post-program period into two sub-periods: 2016 to 2018 and 2019 to 2020
    - ⋆ Account for the typical three-year time lag from building design to market launch

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Service Business Growth: Regression Specification

- Regression specification

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

  - N_{ijkt}^{m}: the number of stores in category w, cell l, city k, and year t.
  - 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})

Service Business Growth: Regression Specification

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  - N_{ijkt}^{m}: the number of stores in category w, cell l, city k, and year t.
  - 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 consider nine categories of stores and service businesses:
    - restaurants
    - recreational centers (e.g., chess clubs, KTVs, game centers, Internet cafes)
    - pharmacies
    - convenience stores
    - 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
    - other retail stores

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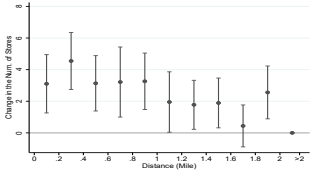
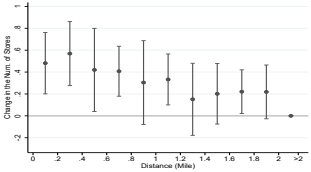
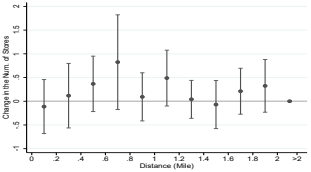
Service Business Growth, Cont.



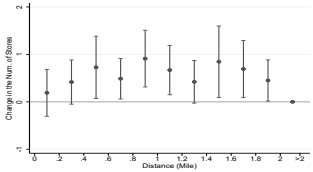
(h) Other Services



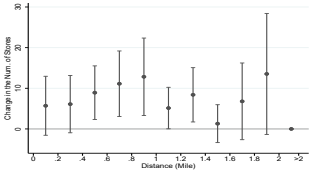
(i) Tutoring



(j) Finance



(k) Groceries and Supermarkets



(l) Other Retail Stores

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