ABFER 2017

Behavioral Bias in Haze:
Evidence from Air Pollution and the Disposition Effect in China

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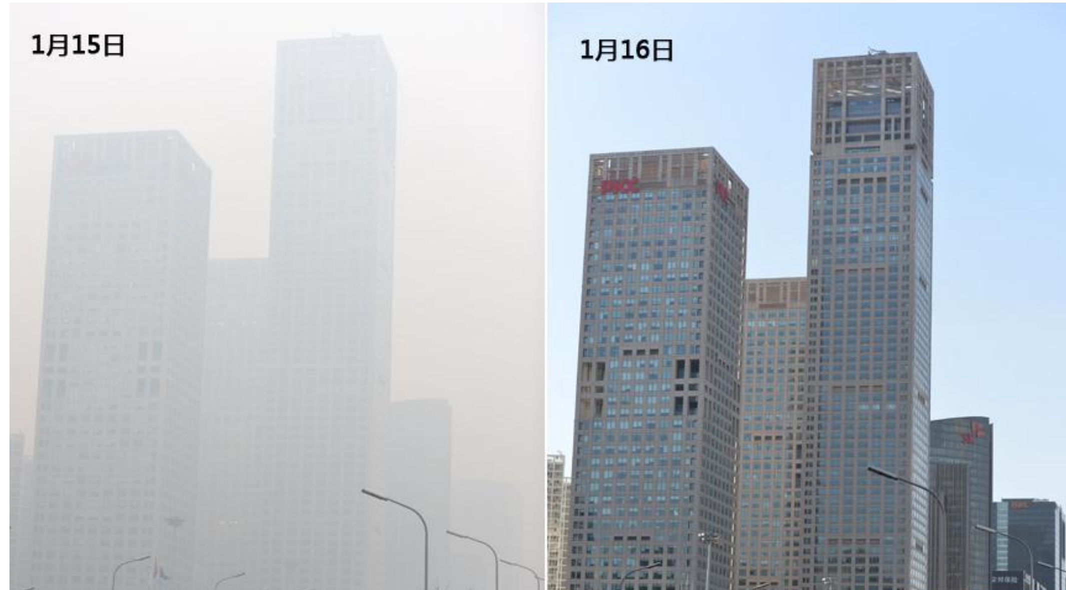
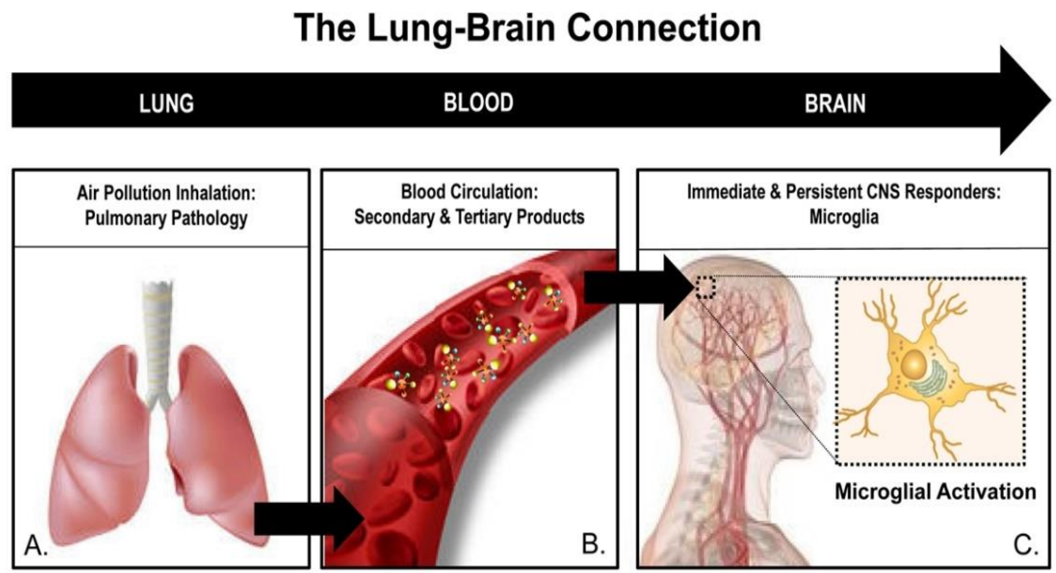
Motivation (1): Air pollution is a serious challenge

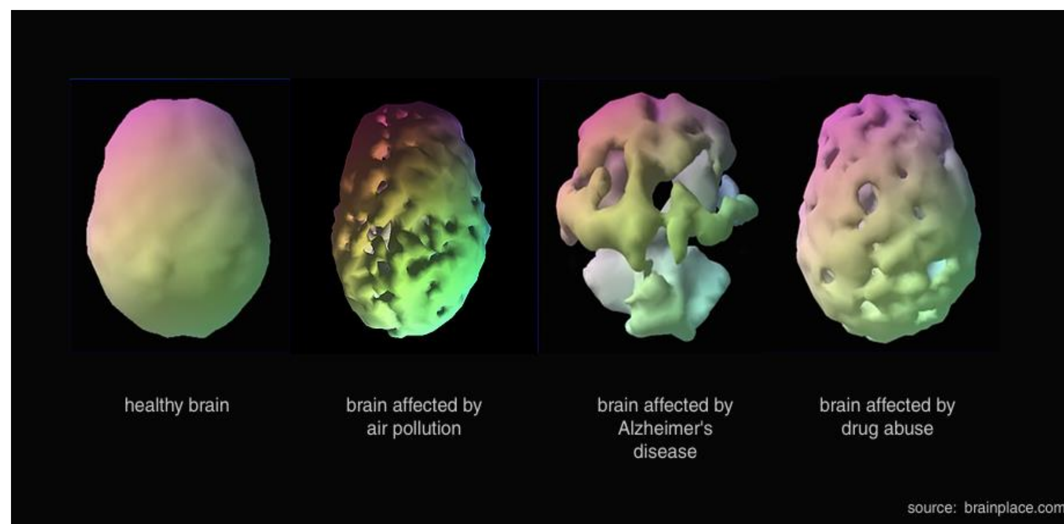
- Air Pollution is a big concern:
  - WHO (2016) regards it as "a major environmental risk to health"
  - The Economist (March 2017): "China's citizens are complaining more loudly about polluted air"
- **Pollution** and **economic activities** mutually affect each other
  - Zheng and Kahn (2013): developments lead to pollution.
  - Pollution affects **human capital efficiency** (e.g., Graff Zivin and Neidell 2013) via **education** (e.g., Currie et al, 2009; Mohai et al., 2011), **labor supply** (e.g., Hanna and Oliva 2011) and **productivity** (Graff Zivin and Neidell, 2012; Chang, Graff Zivin and Neidell, 2016a,b).
  - ➢ The influence of pollution on economic activities is more difficult to establish.



Motivation (2): air pollution affects cognitive skills

- Medical Science: air pollution could significantly damage
  - respiratory, vascular, and mortality (Pope 1989; Pope et al., 2002; Pope et al., 2011)
  - human brains/cognitive skills (Block and Calderón-Garciduenãs, 2009; Fonken et al, 2011; Mohai et al., 2011; Weuve et al., 2012)
  - Explanations from science blogs: "Under normal conditions, microglia primarily serve as the defenders of the central nervous system…But microglia can be dangerous when they are exceptionally 'angry' and are known to leave behind significant bystander damage to neighboring cells." (upper fig.)
  - Bottom fig: the SPECT scan of a brain of a person exposed to air pollution to those of Alzheimer's disease or drug abuse.





Our Intuition and major findings

- Our question: since air pollution damages cognitive skills, and since investors' trading behavior is related to brains (e.g., Frydman 2014), could air pollution increases the "cognitive bias" of investors in the market?
- Our major findings based on a very big account-level dataset:
  - Yes it does!
    - With low AQI of a city, the probability for its investors to demonstrate low disposition effect is **four times higher** than that for mid or high. Trading difference can be as high as about 4% per year
  - Yes its influence is causal!
    - Causality is identified based on Regression Discontinuity (RD) of the "**Huai-River policy**" (Almond et al., 2009; Chen et al., 2013) and Difference-in-difference (DID) tests using **sharp drops in AQI** (especially those driven by **strong winds**).
  - Yes we have more interesting results!
    - Between the two legs of the disposition effect, selling-loser is more influence by AQI. Moreover, the influence of AQI seems to be **stronger** for **younger** investors, **female** investors, **less educated** and **less experienced** investors.

➢ Air pollution may incur indirect social effect/cost via cognitive bias.

Related Literature and our contributions

- Our major contribution is three-fold: to use **account-level trading** to identified the **causal impact** of air pollution on **cognitive bias**.

➢ We contribute to the literature on environmental pollution in general and AQI in particular (e.g., on how air pollution affects stock market return: Levy and Yagil 2011; Gabriele 2016; Heyes, Neidell and Saberian, 2016; or on how AQI affects individual investors' trading profit: Huang, Xu, and Yu 2016).

➢ We contribute to the literature on the disposition effect (Shefrin & Statman 1985, Barberis & Xiong 2009, 2012, Ben-David & Hirshleifer 2012, Henderson 2012, Li & Yang 2013, Frydman et al. 2014, An 2016, Chang, Solomon and Westerfield 2016; Hirshleifer 2015 provides a recent survey). We show that cognitive bias may be influenced by social environment (Hirshleifer 2015)

➢ Caveat 1: due to the lack of data, we do not intend to examine the role played by different channels, such as mood/ sentiment (Kamstra et al., 2003) and neuro stimuli.

➢ Caveat 2: we use a large mutual fund investor dataset. Mutual fund investors exhibit positive disposition effect (different from Chang, Solomon and Westerfield 2016).

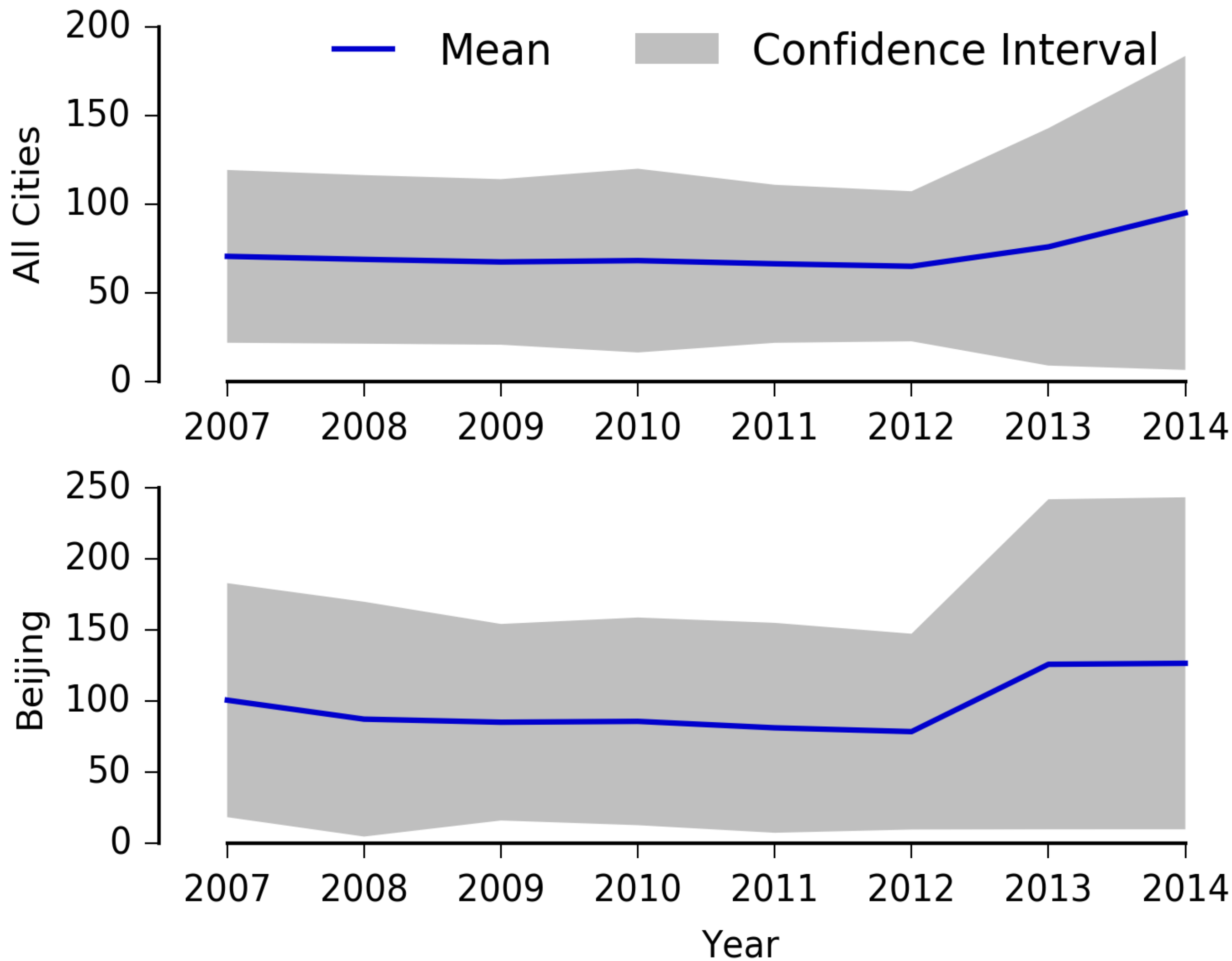
Roadmap

- ➢Data and variable
- Baseline results
- Two identification tests
- Robustness Checks

Data and variables (1): Account coverage

- A unique proprietary dataset with complete account-level information for all (retail) investors in one large **mutual fund family** in China.
  - 773,198 valid investment accounts (all 31 provinces and more than 200 cities) trading seven equity funds; From 2007 to 2015.
  - Our geographic and account coverage is by far the largest.

Data and variables (2): AQI in recent China



Data and variables (3): the Disposition Effect

- City-level Disposition Effect is constructed as follows (in spirit of Ben-David and Hirshleifer 2012):

1. We start from **individual accounts**:
   - For each account in each day: a given fund will be classified as a **winners/loser** if the current price of the fund (NAV) is higher/lower than the historical cost of existing shares.
   - Each sell-trade can be classified as selling winner/loser (or neither).
2. We then **aggregate** the probability of selling **at the city level**.
   - Probability of selling winners (**PSW**) is defined for each city as the fraction of winners sold by all investors in the city across all funds.
   - Probability of selling losers (**PSL**) is defined similarly.
3. City-level Disposition Effect (**Bias**): **PSW-PSL**
   - Statistics (level) similar to Ben-David and Hirshleifer (2012).

Roadmap

- Data and variable
- ➢Baseline results
- Two identification tests
- Robustness Checks

Baseline results (1):

Portfolio analysis via double sorting on AQI and Disposition Effect

B1: Tercile Values of AQI/Disposition Effect (in paranthesis) and the Fraction of Observation

	Disp_Low (-0.407%)	Disp_Mid (0.020%)	Disp_High (0.977%)
AQI_Low (49.439)	22.56%	5.08%	5.68%
AQI_Mid (74.573)	5.96%	20.37%	6.99%
AQI_High (116.622)	4.81%	7.86%	20.69%

B2: Trading Performance of High-High and Low-Low AQI-associated Disposition Groups

	(1) Raw Return(bp)	(2) arket-adjusted Return(b	(3) 3-factor-model-adjusted Return(bp)	(4) Benchmark-adjusted Return(bp)
Low-Low	0.670	0.901	1.773	3.784
	(0.51)	(1.33)	(2.98)***	(2.48)**
High-High	-5.987	-0.823	0.399	0.026
	(-5.82)***	(-1.70)*	(0.76)	(0.02)
High-High minus Low-Low	-6.657	-1.724	-1.374	-3.758
	(4.02)***	(2.08)**	(1.71)*	(2.00)**

1. Most observations are on diagonal elements, confirming that AQI and Disp is highly correlated
2. E.g., with low AQI, the probability of low bias is **four times** higher than that for mid or high

2. Focusing on the diagonal elements, a one-stdev increase in AQI is associated with a 60%-stdev increase in the disposition effect (moving from Low-Low to High-High).

3. LL outperforms HH. Trading difference between LL and HH can be as high as 8.97%, 4.2%, 3.4% per year for benchmark-adjusted, market-adjusted, and three-factor-adjusted return, respectively.

Baseline results (2): regression analysis

$$Trading\ Bias_{j,t} = \alpha_0 + \alpha_1 \times AQI_{j,t} + \alpha_2 \times X_{j,t} + \delta_t + \theta_j + \varepsilon_{j,t}$$

Table 2: The Impact of Air Quality on Trading Bias: Baseline Analysis

	(1)	(2)	(3)	(4)
	Disposition Effect			
Log_AQI	0.023***	0.029**	0.038**	0.038**
	(2.79)	(2.13)	(2.05)	(2.05)
Log_GDP				-0.068
				(-1.21)
Log_pop				0.032
				(1.16)
Log_num_domestic_firm				0.036
				(0.71)
Log_gov_income				0.035
				(1.09)
Constant	0.100***	0.166***	0.115	0.337
	(2.84)	(2.83)	(1.38)	(0.44)
City Fixed Effect	No	Yes	Yes	Yes
Time Fixed Effect	No	No	Yes	Yes
No. of Obs	144,238	144,238	144,238	144,238
R-Sqr	0.00	0.00	0.02	0.02

1. We observe a positive relationship between AQI and the Disposition Effect in regression as well

Roadmap

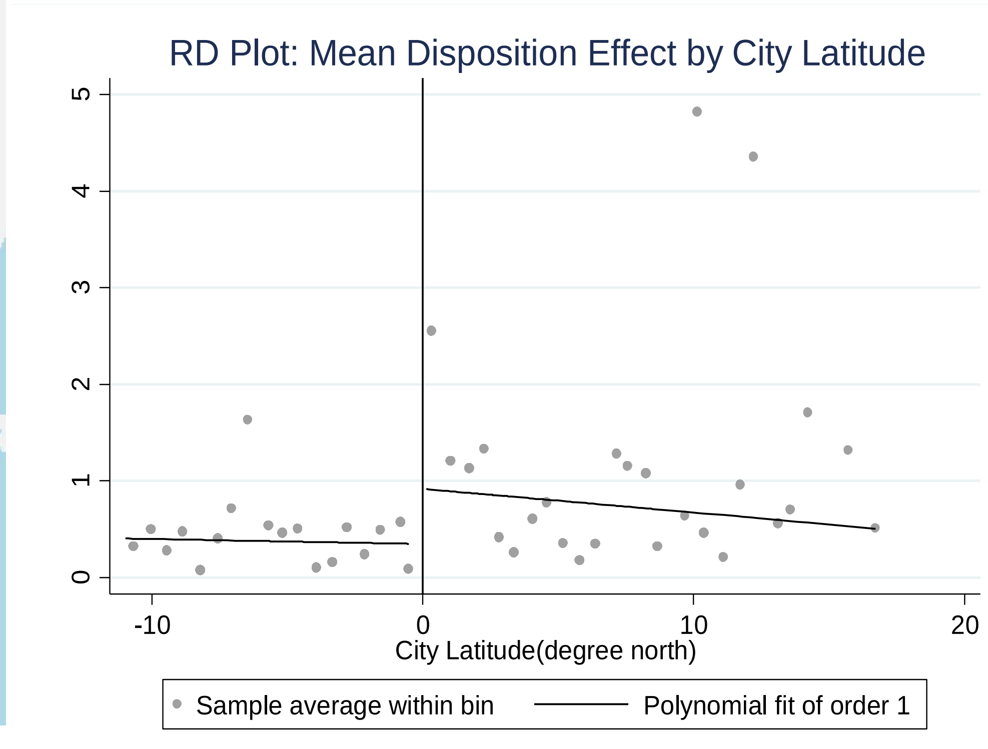
- Data and variable
- Baseline results

➢Two identification tests

- Robustness Checks

Identification (1): the Huai River Policy

- The quasi-experiment of "Huai-River policy" (free heating for north-Huai cities creates an unintended discontinuity in AQI; Almond et al., 2009) and the **regression discontinuity (RD)** test following Chen et al. (2013)



RD test (Step 1): discontinuity in bias in regression analysis

Panel B: Quadratic				
	(1)	(2)	(3)	(4)
	AQI		Disposition Effect	
D(North)	12.062***	11.689***	0.604***	0.649***
	(2.86)	(3.76)	(3.75)	(3.12)
Degree north	0.011	-0.086	-0.024***	-0.024**
	(0.02)	(-0.29)	(-3.10)	(-2.30)
Degree north squared	-0.179***	-0.156***	-0.000	-0.000
	(-4.71)	(-5.57)	(-0.37)	(-0.24)
Log_GDP		-1.843		-0.153
		(-0.61)		(-1.24)
Log_pop		12.377***		-0.118
		(2.84)		(-1.49)
Log_num_domestic_firm		-3.486		0.129
		(-1.77)		(1.44)
Log_gov_income		-0.090		0.046
		(-0.12)		(0.96)
Constant	72.716***	60.311**	0.088	1.682
	(62.37)	(2.07)	(1.03)	(1.55)
Time Fixed Effect	No	Yes	No	Yes
No. of Obs	678	678	678	678
R-Sqr	0.29	0.33	0.06	0.07

This dummy captures discontinuity

These two variables controls for any (quadratic) effect of latitude. Linear specification leads to similar results.

We observe that there are discontinuities both in AQI and in the Disposition effect.

RD test (Step 2): bias regressed on instrumented AQI

Step 2: in spirit of Chen et al. (2013), since cognitive bias is unlikely to jump across a river except through the AQI jump, we can use Huai-river-instrumented AQI to estimate its influence (two-stage regression).

First stage: $AQI_{j,t} = \beta_0 + \beta_1 \times D(North)_j + f(R_j) + \beta_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t}$

Second stage: $Disp_{j,t} = \gamma_0 + \gamma_1 \times \widehat{AQI_{j,t}} + f(R_j) + \gamma_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t}$

Panel A: Disposition Effect Regressed on Instrumented AQI (Full Sample Analysis)

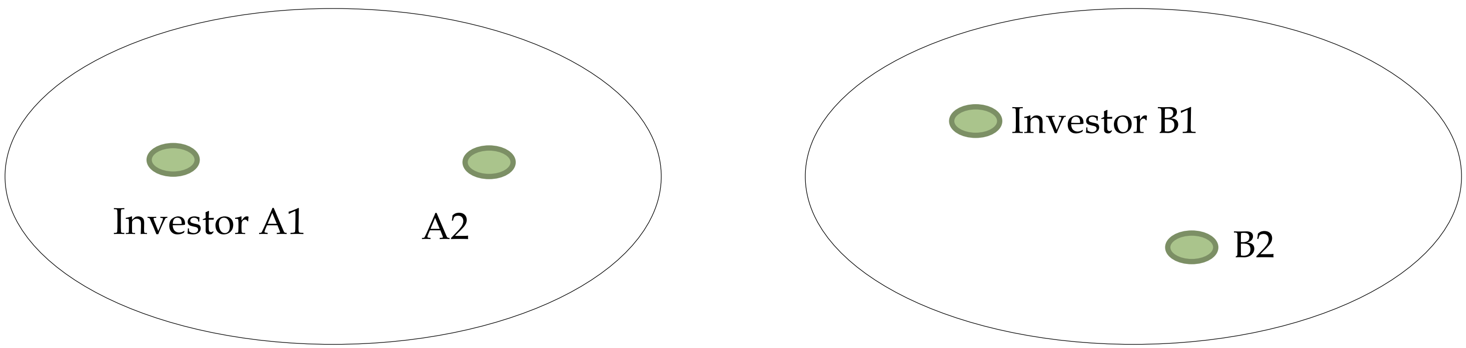
	(1)	(2)	(3)	(4)
	Linear Specification		Quadratic Specification	
AQI_hat	0.024**	0.022**	0.020***	0.019**
	(2.54)	(2.08)	(2.70)	(2.17)
Degree North	-0.013	-0.007	-0.005	-0.001
	(-0.72)	(-0.94)	(-0.52)	(-0.18)
Degree North Squared			0.003**	0.003**
			(2.04)	(2.22)
Controls	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
No. of Obs	709	709	709	709

1. We see that in two stage regression, instrumented AQI explains the disposition effect (about 13%-standard-deviation of the bias).
2. This relationship is highly **significant in heating seasons** and becomes **insignificant in non-heating seasons**. This effect cannot be driven by city-fixed effect.
3. **A placebo test**: if we create artificial "**fake-Huai-river**" at 5% north or south to the real river, the same regression does not yield any results.
4. Robustness checks on other technical parameters provide consistent results.

Identification (2): Diff-in-Diff on AQI drops

City A
(The Treatment Group)

City B
(The Control Group)



Before (Mon-Tues): City A has an AQI of 200

Before (Mon-Tues): City B has a similar AQI of 200

Treatment event: Big AQI drops especially due to Big Wind in City A in mid week (NOT in city B)

After (Wed~Friday): AQI in City A drops sharply and stays there.

After (Wed~Friday): AQI in City B remains unchanged (high pollution)

$$Disp_{j,t} = \rho_1 \times Treated_{j,t} + \boxed{\rho_2 \times Treated_{j,t} \times After_{j,t}} + \rho_3 \times After + \rho_4 \times X_{j,t} \dots$$

1. Version 1: Treatment effect = drastic AQI drops in general (for more than 2-stdev)
2. Version 2: Treatment effect = Strong winds (for more than 5 meters/second)

DID version 1 (event = sharp AQI drops)

A1: Univariate Analysis (Treatment Event = Drastic Drops in AQI)

AQI	Before Event	After Event	After-Before
Treated	165.92	84.99	-80.93***
Control	156.8	153.03	-3.77
Treated-Control	9.12	-68.04***	-77.16***
			(-24.71)
Disposition			
Treated	0.348	0.084	-0.264**
Control	0.301	0.278	-0.023
Treated-Control	0.047	-0.194**	-0.241**
			(-2.49)

In Univariate analysis, **AQI** values in treated cities are drastically reduced after the event.

We can see that **the disposition effects** in treated cities are drastically reduced after the event as well.

A2: DID Test (y = Disposition Effect)

	(1)	(2)	(3)
Treated*After	-0.239**	-0.234**	-0.234**
	(-2.36)	(-2.29)	(-2.29)
Treated	0.124	0.137*	0.136
	(1.56)	(1.69)	(1.65)
After	0.132	0.121	0.121
	(1.56)	(1.44)	(1.44)
Control Variables	No	Some	Full
Time and City FE	Yes	Yes	Yes

Consistently, in regression analysis **Treated*After** is **significantly negative**.

By contrast, both “Treated” and “After” are not significant on its own. Hence, the two groups have similar disposition in the beginning, and city B does not have significant change in disposition before and after the event.

DID version 2 (event = big wind)

Panel B: DID Test based on Strong Wind as the Treatment Event			
Treated*After	-0.368**	-0.384**	-0.391***
	(-2.41)	(-2.41)	(-2.85)
Treated	0.281*	0.245	0.232
	(1.88)	(1.53)	(1.58)
After	0.115	0.11	0.113
	(1.02)	(0.93)	(1.38)
Panel C: Placebo Test on Strong wind without Air Pollution			
Treated*After	0.016	0.011	0.013
	(0.21)	(0.15)	(0.17)
Treated	-0.016	-0.006	-0.003
	(-0.23)	(-0.09)	(-0.05)
After	-0.066	-0.061	-0.061
	(-1.24)	(-1.10)	(-1.10)
Control Variables	No	Some	Full
Time and City FE	Yes	Yes	Yes

Using **big wind** as the treatment event, Treated*After remains significantly negative.

The significance disappears in our **Placebo test**: **big wind** in cities having **no pollution** to begin with. Wind does not affect bias.

Robustness Tests and Extensions (1)

- RD tests:
  - The test is **significant** only in **heating season** (not in non-heating one)
  - **A placebo test** based on "**fake-Huai-river**" at 5% north/south to the real river does **not** yield any results.
  - Subsample tests based on **migrant investors** born in southern China (i.e., having low pollution) exhibit similar effects. This result eliminates concerns regarding the cultural background of cities.
  - The main test is robust using different bandwidth choices.
- DID tests
  - Big **AQI jumps** are associated with **increases in bias**.
  - The results are robust when we include the event weekday or use different thresholds of AQI drops/wind speed.

Robustness Tests and Extensions (1)

- PSL (as opposed to PSW) is more vulnerable to air pollution.
- Bias regressed on AQI interacted with investor characteristics:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log_AQI	0.064***	0.061***	0.025**	0.024**	0.039**	0.038**	0.081***	0.080***	0.060***	0.059***
	(3.82)	(3.64)	(2.56)	(2.48)	(2.48)	(2.51)	(4.33)	(4.29)	(4.30)	(4.19)
Log_AQI*Old_High	-0.041**	-0.038*								
	(-2.09)	(-1.90)								
Log_AQI* Female_High			0.067**	0.068**						
			(2.42)	(2.44)						
Log_AQI*Migrant_High					-0.006	-0.007				
					(-0.15)	(-0.17)				
Log_AQI* Education_High							-0.061***	-0.060***		
							(-2.83)	(-2.81)		
Log_AQI*Experience_High									-0.051***	-0.049***
									(-2.94)	(-2.82)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238
R-Sqr	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

We can see that the influence of AQI is magnified for:

- Younger investors
- Female investors
- Less educated investors
- Less experienced investors

Conclusion

- Air pollution (AQI) significantly increases the disposition effect in general.
- Two identification tests support a causal interpretation:
  - Regression Discontinuity (RD) of the "**Huai-River policy**" (Almond et al., 2009; Chen et al., 2013)
  - Difference-in-difference (DID) tests based on **sharp drops in AQI** (especially those driven by **strong winds**)
- Between the two legs of the disposition effect, selling-loser is more influence by AQI. Moreover, the influence of AQI seems to be **stronger** for **younger** investors, **female** investors, **less educated** and **less experienced** investors.

➢Air pollution may incur indirect social effect/cost via cognitive bias.