Does Monitoring Make Food Safer?

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- Municipal health departments conduct regular food inspections to ensure restaurants uphold hygiene standards
- Dearth of empirical studies that measure the efficacy of inspections on restaurant compliance
    - Inspection outcomes are endogenous - interaction between inspector and restaurant behaviors

Research Questions

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- Do citations from inspections incentivize restaurants to improve their sanitation practices?
  - Do restaurants shift attention and effort away from areas that they did well toward areas that got flagged?
  - How do the magnitudes of the results vary across different types of establishments (heterogenous effects)

Main Findings

- Marginal increase in the number of citations leads to improved conditions in subsequent inspections
  - Instead of focusing only on areas that they got cited, restaurants seem to improve in other areas as well
  - Limited heterogeneity based on Yelp characteristics
- More citations also reduces the probability that an establishment receives a complaint call

Road Map

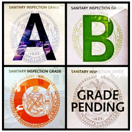
1. Literature Review

Audit and Compliance

- Restaurants: Jin and Lee (2014, 2016)
- Environmental Regulation: Duflo et al (2014)
- Workplace Safety: Levine, Toffel, and Johnson (2012)
- Tax: Feinstine (1991), Kleven et al (2011), Gemmell and Ratto (2012)

Certification and Customer Reviews

- LA Letter Grades: Leslie and Jin (2003, 2009)
- NYC Letter Grades: Ho (2012), Meltzer et al (2015), Wong et al (2015)



- Yelp: Kang et al (2013)

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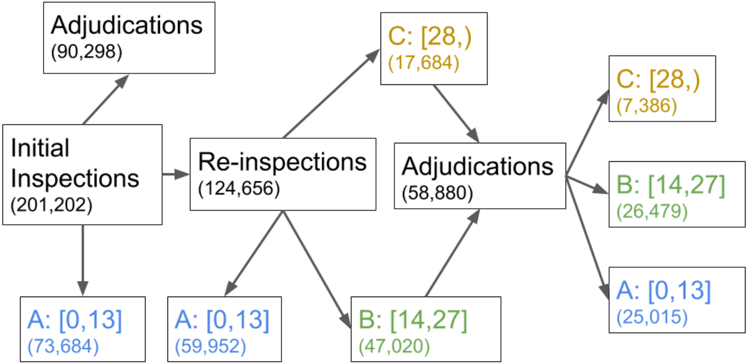
  - In the meantime, post previous grade
- The health department temporally closes a restaurant if it finds critical violations

Food Inspection Data

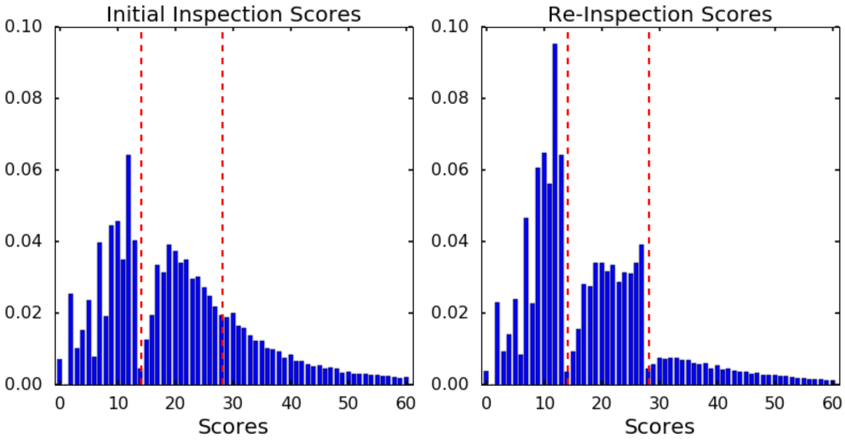
- Universe of all food inspections conducted in NYC (2007 - 2016)
- Inspection date and inspector ID
- Individual violation codes, total score, corresponding adjudication date, and modified score
- Restaurant level info: name, address, cuisine, service type, and venue type

NYC Food Inspection Pipeline



[0] The numbers in the parenthesis are the number of inspections in those steps

Scores Clearly Bunch Around Grade Thresholds



311 Call Data

- 311 is a phone line for non-emergency municipal services - also carries complaint calls to Department of Health and Mental Hygiene concerning restaurants
  - Examples of complaints: 'Rodents/Insects/Garbage', 'Bare Hands in Contact w/ Food', 'Food Contains Foreign Object', 'Food Spoiled'
- From 2010 to present
- Each complaint has an incident address and date
- Use fuzzy string matching on street address to the inspection data

Yelp Data

- Restaurants' current star ratings and review counts
- Successfully matched over 20,000 establishments

Outcomes of Interests from Subsequent Inspections

- Overall inspection scores
- Whether a restaurants receives an A and does not need an re-inspection
- Whether a restaurant commits critical violations that results in temporarily closure

Empirical Strategy

$$Y_{i,t^{next}} = \beta Score_{i,t} + \delta_i + \tau_t + \tau_{t^{next}} + \varepsilon_{it}$$

- $Y_{i,t^{next}}$: outcome from next inspection: overall score, temporary closure, getting an A
- t^{next}: time period of next inspection
- $Score_{i,t^{next}}$: inspection score from the next inspection
- τ_t: time fixed effect
- δ_i: restaurant fixed effect
- ε_{it}: two-way clustered at zipcode and inspector levels[1]

[1](Cameron at el 2009)

Empirical Strategy

A challenge of OLS is that $SCORE_{it}$ is endogenous

- If β positive, places that do poorly in the past tend to do poorly in the future
  - Restaurant FE does not fix problem if we have persistence
- If β is negative, cannot rule out mechanical mean reversion.

Use Inspector Assignment as Instrument

Instrument for when inspector j assigned to restaurant i

$$Z_{ij} = \frac{1}{n_j - I_{ij}} \left(\sum_{kjt \neq ijt} Y_{kjt} \right)$$

- n_j total number of inspections done by inspector j
- I_{ij} is the number of times inspector j has inspected restaurant i
- Y_{kjt} is the outcome used to calculate inspector tendencies

Inspector Stringency is Highly Predictive of Inspection Score

$$score_{it} = \gamma Z_{it} + \delta_i + \tau_t + \varepsilon_{it}$$

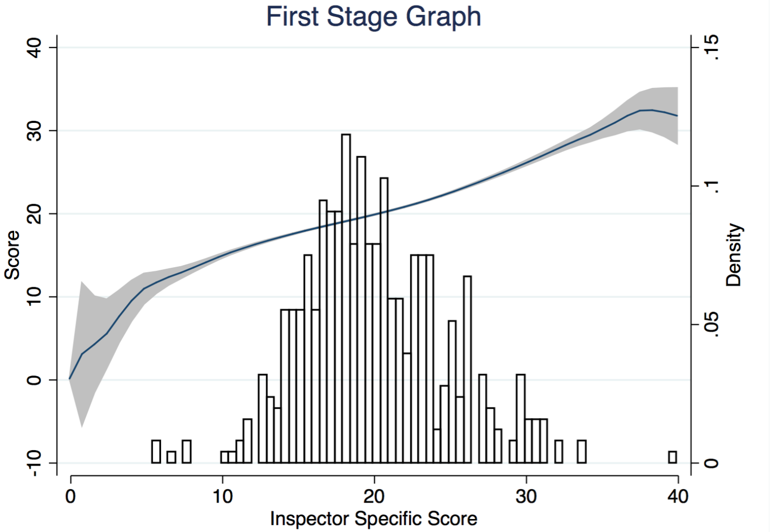
where Z_{it} is the leave-out propensity of inspector assigned to restaurant i in period t.

VARIABLES	(1) Score	(2) Score	(3) Score
Z	0.961***	0.997***	1.135***
	(0.00948)	(0.00983)	(0.0162)
Observations	330,469	330,466	325,681
R-squared	0.149	0.201	0.414
Restaurant Controls	NO	YES	NO
Restaurant FE	NO	NO	YES
F Statistics	10271	10270	4908

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[1] First column consists of all inspections after 10/1/2010. The sample for the second column is reduced to inspections with non-empty zipcode, chain indicator, cuisine type, venue type, and service type. Standard errors are two-way clustered at the inspector and zipcode level.

Graphical Representation of First Stage



Assignment Process of Inspectors to Restaurants

- DOHMH claims that each inspector is randomly assigned to each inspection
- Implies:

$$Z_{ijt} = \beta X_i + \delta L_{i,t-1} + \varepsilon,$$

with X_i as restaurant characteristics (cuisine, service type, venue type, chain, etc) and $L_{i,t-1}$ as restaurant specific lag terms (previous scores and previous grades), $\beta = \delta = 0$.

Coefficients Close to 0 and Insignificant

VARIABLES	Score		Inspector Stringency		Inspector Stringency	
VARIABLES	(> 50 Inspections)	se	(> 50 Inspections)	se	(> 650 Inspections)	se
last score	0.218***	(0.00746)	-0.000440	(0.00199)	-0.00193	(0.00205)
last grade = B	1.430***	(0.131)	0.0178	(0.0628)	0.0837	(0.0683)
last grade = C	1.495***	(0.206)	-0.0494	(0.0764)	0.0240	(0.0807)
last inspector propensity	-0.298***	(0.0104)	-0.00363	(0.00491)	-0.00529	(0.00551)
chain	-3.644***	(0.179)	-0.0274	(0.0644)	-0.0300	(0.0734)
Sea Food	0.301	(0.412)	-0.0687	(0.129)	-0.0648	(0.136)
Chinese	1.588***	(0.307)	-0.0952*	(0.0510)	-0.0511	(0.0546)
Pizza/Italian	0.305**	(0.118)	-0.0893***	(0.0342)	-0.0614	(0.0384)
Coffee/Tea	-2.219***	(0.162)	-0.0421	(0.0889)	-0.0514	(0.0966)
Latin	1.534***	(0.303)	-0.0714	(0.0556)	-0.0390	(0.0583)
Spanish	1.560***	(0.261)	0.0125	(0.0615)	-0.0435	(0.0691)
Caribbean	1.542***	(0.288)	-0.0637	(0.0608)	-0.0619	(0.0544)
Sandwich	0.661**	(0.297)	-0.00916	(0.0472)	0.0180	(0.0488)
Concession Stands	-4.379***	(0.722)	0.295	(0.197)	0.209	(0.211)
Fast Food Restaurant-Food Court	0.570***	(0.187)	0.0394	(0.0881)	-0.0211	(0.0868)
Restaurant	1.453***	(0.158)	0.0449	(0.0662)	0.00343	(0.0641)
Buffet Service	2.564***	(0.365)	-0.182*	(0.107)	-0.196	(0.118)
Cater Service	-1.897***	(0.609)	-0.200	(0.190)	-0.193	(0.219)
Counter Service	-0.635***	(0.185)	0.0273	(0.0613)	0.0123	(0.0684)
Take-out Service	-1.410***	(0.185)	-0.153	(0.110)	-0.173	(0.123)
Wait Service	1.205***	(0.166)	0.0418	(0.0481)	0.0404	(0.0525)
Cafeteria Service	-3.541***	(0.500)	-0.280*	(0.156)	-0.200	(0.168)
Observations	299,174		299,174		244,099	
F Statistics	101.6		2.423		2.249	

Robust standard errors in parentheses
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[1] Standard errors are two-way clustered at the inspector and restaurant level.

TSLS Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Score (OLS)	Score (IV)	Closure (OLS)	Closure (IV)	Grade A (OLS)	Grade A (IV)
Score	-0.139***	-0.242***	-0.000565***	-0.00101***	-8.49e-05	0.00222***
	(0.00492)	(0.0162)	(7.05e-05)	(0.000185)	(0.000127)	(0.000556)
Observations	149,831	149,831	134,365	138,674	149,831	149,831
Inspection Date FE	YES	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES	YES
dependent mean	21.08	21.08	0.0154	0.0162	0.372	0.372

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[1] Standard errors are two-way clustered at zipcode and inspector levels. Closure samples exclude inspections resulting in scores over 28 points.

Heterogenous Effects Based on Yelp Characteristics

- Might restaurants with more "exposure" or higher rating on yelp respond differently to inspections?
    - Define "exposure" as number of reviews divided by length of time in business
- $$Y_{it^{next}} = \tau_t + \delta_i + \beta_1 Score_{it} + \beta_2 plus\_4_i \times Score_{it} + \beta_3 high\_exp_i \times Score_{it} + \beta_4 high\_exp_i \times plus\_4_i Score_{it} + \varepsilon_{it},$$
    - $plus\_4_i$ is an indicator for whether restaurant i's current rating is at least 4
    - $high\_exposure_i$ is whether "exposure" in top half

Heterogenous Effect Based on Yelp Characteristics: Result

VARIABLES	(1) Score	(2) Closure	(3) Grade A
Score	-0.244***	-0.00114***	0.00238***
	(0.0213)	(0.000230)	(0.000699)
Score X Plus_4	0.0251	0.000118	-0.00127
	(0.0217)	(0.000243)	(0.000847)
Score X High Exposure	-0.00544	-2.90e-05	0.000529*
	(0.00868)	(9.44e-05)	(0.000294)
Score X Plus_4 X High Exposure	-0.0125	-0.000247	-5.70e-06
	(0.0140)	(0.000154)	(0.000495)
Observations	86,273	86,273	86,273
Inspection Date FE	YES	YES	YES
Restaurant FE	YES	YES	YES
dependent mean	20.77	0.0161	0.379

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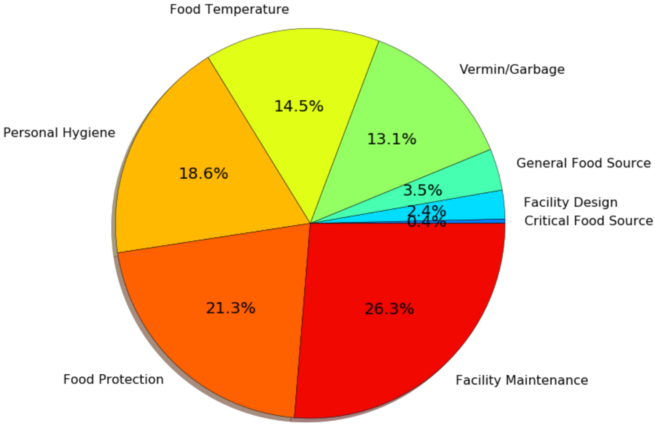
Multi-Dimensionality of Food Inspections

- Individual Violation Codes Groped into Eight Groups:



Multi-dimensional 1st Stage

Instrument Construction:

$$Z_{ijg} = \frac{1}{n_j - I_{ij}} \left(\sum_{kjgt \neq ijgt} \#Cited_{ijgt} \right)$$

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1st Stage:

$$\# Cited_{ijgt} = \sum_{g' \in \mathcal{G}} \theta_{gg'} Z_{ijg'} + \varepsilon_{ijgt}$$

- $\# Cited_{ijgt}$ is the number of group g violation that inspector j finds in restaurant i at time t and $\mathcal{G}$ is the set of violation groups
- $\theta_{gg'}$: measures how inspector's propensity to find violation in group g' relates to one's probability of finding violation in group g

Multi-task First Stage Equations

VARIABLES	(1) Facility Maintenance	(2) Food Protection	(3) Personal Hygiene	(4) Food Temperature	(5) Vermin/Garbage	(6) Gen. Food Source	(7) Facility Design	(8) Crit. Food Source
Facility Maintenance	1.051***	-0.0550**	0.0115	-0.0256*	-0.0104	0.00857	0.00276	0.000821
	(0.0177)	(0.0227)	(0.0147)	(0.0132)	(0.0139)	(0.00553)	(0.00395)	(0.00139)
Food Protection	-0.00719	0.726***	-0.00429	0.0709*	-0.0911***	0.00237	-0.0105	0.00328
	(0.0372)	(0.0419)	(0.0287)	(0.0388)	(0.0284)	(0.0126)	(0.00883)	(0.00391)
Personal Hygiene	0.00395	-0.127***	0.952***	-0.00446	-0.0686***	0.00179	-0.00719*	-0.00161
	(0.0197)	(0.0199)	(0.0192)	(0.0193)	(0.0128)	(0.00524)	(0.00415)	(0.00185)
Food Temperature	0.000328	-0.0810***	-0.0890***	0.808***	-0.0638***	0.00215	-0.0150**	-0.00488***
	(0.0236)	(0.0297)	(0.0179)	(0.0226)	(0.0182)	(0.00836)	(0.00609)	(0.00181)
Vermin/Garbage	0.0116	0.121**	-0.118***	-0.186***	1.011***	-0.0250	-0.0274**	-0.00804*
	(0.0486)	(0.0562)	(0.0419)	(0.0601)	(0.0383)	(0.0178)	(0.0136)	(0.00466)
Gen. Food Source	-0.00784	-0.0505	-0.0105	-0.0591	-0.0410	0.959***	-0.0233*	0.00318
	(0.0456)	(0.0451)	(0.0393)	(0.0407)	(0.0281)	(0.0220)	(0.0129)	(0.00365)
Facility Design	-0.0288	-0.112	-0.0860	0.0153	-0.116*	-0.0878**	0.845***	-0.0102
	(0.0915)	(0.130)	(0.0950)	(0.0930)	(0.0680)	(0.0347)	(0.0256)	(0.0105)
Crit. Food Source	-0.0660	0.0496	-0.487*	-0.115	0.145	-0.0241	-0.0630	0.921***
	(0.333)	(0.440)	(0.260)	(0.329)	(0.244)	(0.0868)	(0.0686)	(0.0454)
Observations	149,831	149,831	149,831	149,831	149,831	149,831	149,831	149,831
dependent mean	1.013	0.840	0.863	0.671	0.518	0.135	0.0827	0.0149

Robust standard errors in parentheses
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Multi-dimensional 2nd Stage

$$\#Cited_{igt^{next}} = \sum_{g' \in \mathcal{G}} \beta_{gg'} \#Cited_{igt} + \delta_i + \tau_t + \varepsilon_{igt},$$

where

- $\#Cited_{igt}$: number of group g violations that restaurant i receives on date t
- τ_t: date fixed effect
- δ_i: restaurant fixed effect

How Current Citations Affect Subsequent Citations

VARIABLES	(1) Facility Maintenance	(2) Food Protection	(3) Personal Hygiene	(4) Food Temperature	(5) Vermin/Garbage	(6) Gen. Food Source	(7) Facility Design	(8) Crit. Food Source
Facility Maintenance	-0.236***	0.00733	0.000184	-0.00506	-0.000922	-0.00159	0.000981	-0.000509
	(0.00961)	(0.0119)	(0.0107)	(0.00944)	(0.00766)	(0.00380)	(0.00295)	(0.00140)
Food Protection	-0.0776**	-0.177***	-0.00731	-0.0142	-0.0397*	-0.0100	0.00372	0.00780*
	(0.0378)	(0.0306)	(0.0410)	(0.0253)	(0.0227)	(0.0113)	(0.0108)	(0.00400)
Personal Hygiene	0.0222	-0.00484	-0.189***	-0.00771	-0.000551	0.00458	0.00129	0.00217
	(0.0156)	(0.0103)	(0.0148)	(0.00957)	(0.00892)	(0.00489)	(0.00320)	(0.00173)
Food Temperature	0.0148	-0.0261	0.0133	-0.214***	-0.00923	0.00613	-0.00622	-0.00153
	(0.0216)	(0.0163)	(0.0162)	(0.0134)	(0.0128)	(0.00722)	(0.00573)	(0.00243)
Vermin/Garbage	0.132***	-0.0784*	0.00134	0.0446	-0.174***	0.0128	-0.0105	-0.00126
	(0.0439)	(0.0404)	(0.0544)	(0.0318)	(0.0283)	(0.0159)	(0.0138)	(0.00404)
Gen. Food Source	-0.0114	-0.00139	-0.0456	-0.0103	-0.0395*	-0.191***	-0.0147	-0.000895
	(0.0291)	(0.0348)	(0.0374)	(0.0334)	(0.0202)	(0.0199)	(0.00933)	(0.00395)
Facility Design	0.0265	-0.195**	-0.00742	0.0168	-0.0235	0.00421	-0.199***	0.0169*
	(0.0787)	(0.0925)	(0.0776)	(0.0551)	(0.0612)	(0.0296)	(0.0239)	(0.00977)
Crit. Food Source	0.274	-0.284	0.279	0.125	-0.0346	-0.0233	-0.0643	-0.185***
	(0.248)	(0.207)	(0.244)	(0.195)	(0.142)	(0.0848)	(0.0682)	(0.0298)
Observations	149,831	149,829	149,831	149,829	149,829	149,831	149,829	149,831
Dependent mean	0.989	0.802	0.842	0.645	0.503	0.125	0.0694	0.0126

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[1] Standard errors are two-way clustered at zipcode and inspector levels

Impact of Inspection Results on Complaint Calls

Sample Construction

- Convert from inspection level data to a restaurant-month level panel data
- When an inspection occurs in the middle of a month:
  - Consider only calls that were made in between the latest event and the end of the month
  - Calculate a weight variable as the fraction of days since the event to the end of the month

Impact of Restaurant Score on Complaint Call Specification

- 2nd Stage

$$Pr(Called_{it}) = \delta_i + \tau_t + \beta_0 Score_{it} + \beta_1 Month\_Since\_Inspection_{it}$$
$$+\beta_2 Month\_Since\_Inspection_{it} \times Score_i t + \varepsilon_{it}$$

  - β_3 tests whether the effect of the inspection score changes across time
- Instrument $Score_{it}$ with inspector stringency

Results

VARIABLES	(1) Prob Call (OLS)	(2) Prob Call (OLS)	(3) Prob Call (OLS)	(4) Prob Call (IV)	(5) Prob Call (IV)	(6) Prob Call (IV)
SCORE	-4.67e-05***	-6.95e-06	-9.01e-05***	-8.98e-05*	-9.18e-05*	-6.21e-05
	(1.53e-05)	(1.57e-05)	(1.78e-05)	(4.77e-05)	(4.99e-05)	(6.17e-05)
Months Since Inspection		0.000540***	-1.81e-05		0.000498***	0.000735*
		(3.72e-05)	(6.61e-05)		(4.33e-05)	(0.000435)
Months Since Inspection $\times$ SCORE			5.02e-05***			-2.16e-05
			(5.80e-06)			(3.98e-05)
Observations	1,223,207	1,223,207	1,223,207	1,223,207	1,223,207	1,223,207
Year-Month FE	YES	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES	YES
dependent mean	0.0145	0.0145	0.0145	0.0145	0.0145	0.0145

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*** p<0.01, ** p<0.05, * p<0.1

Concerns of Empirical Strategy

Exclusion Restriction

- Inspectors adjust their grading, given the identities of the previous inspectors
  - Unlikely, given geographically dispersed and random assignment, inspectors need to mentally track the tendencies of hundreds of inspectors
- Inspectors affect restaurant outcomes through channels other than the inspections
- The causal channel of inspection results is through its influence on the subsequent inspectors' behaviors

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Monotonicity condition

- The inspection score is strictly increasing in inspector stringency

Monotonicity Tests

- Because inspections are multi-dimensional, monotonicity might not hold
  - Ex. A frozen yogurt establishment may get a better score from a more stringent inspector if that inspector cares only about hot food being kept above a certain temperature
- Two empirical implications:
  - Test 1: Stringent inspectors should be strict for different types of restaurants
    - Run first stage for various sub-samples (baseline sample)
  - Test 2: Inspectors who are strict for one type of restaurants should be strict for other types
    - Recalculate inspector stringency for each sub-sample with inspection results outside of that sub-sample (inverse-sample)

Monotonicity Test Results

Baseline-Sample

VARIABLES	(1) 1st Quartile	(2) 2nd Quartile	(3) 3nd Quartile	(4) 4th Quartile
Estimate	0.407***	0.681***	0.852***	1.231***
	(0.0270)	(0.0240)	(0.0213)	(0.0256)
Observations	80,172	81,817	81,901	86,433

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Inverse-Sample

VARIABLES	(1) 1st Quartile	(2) 2nd Quartile	(3) 3nd Quartile	(4) 4th Quartile
Estimate	0.369***	0.612***	0.779***	1.609***
	(0.0340)	(0.0247)	(0.0254)	(0.0674)
Observations	75,188	81,328	81,481	85,851

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Baseline-Sample

VARIABLES	(1) Manhattan	(2) Bronx	(3) Brooklyn	(4) Queens	(5) Staten-Isl
Estimate	1.005***	1.082***	0.985***	0.969***	0.944***
	(0.0156)	(0.0275)	(0.0198)	(0.0206)	(0.0286)
Observations	131,900	31,010	79,664	77,186	10,507

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Inverse-Sample

VARIABLES	(1) Manhattan	(2) Bronx	(3) Brooklyn	(4) Queens	(5) Staten-Is.
Estimate	0.990***	1.082***	0.954***	0.934***	0.938***
	(0.0269)	(0.0344)	(0.0238)	(0.0248)	(0.0308)
Observations	128,977	30,334	76,973	74,933	10,468

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Baseline-Sample

VARIABLES	(1) American	(2) Pizza/Italian	(3) Chinese	(4) Coffee	(5) Japanese
Estimate	0.957***	0.994***	1.086***	0.796***	1.096***
	(0.0241)	(0.0180)	(0.0402)	(0.0354)	(0.0262)
Observations	75,330	38,432	38,785	13,303	10,915

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Inverse-Sample

VARIABLES	(1) American	(2) Pizza/Italian	(3) Chinese	(4) Coffee	(5) Japanese
Estimate	0.929***	0.990***	1.070***	0.782***	1.098***
	(0.0298)	(0.0199)	(0.0449)	(0.0363)	(0.0273)
Observations	74,954	38,312	38,424	13,292	10,910

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Baseline-Sample

VARIABLES	(1) Counter Service	(2) Takeout Service	(3) Wait Service
Estimate	1.055***	0.894***	1.127***
	(0.0177)	(0.0140)	(0.0178)
Observations	127,981	127,365	73,381

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Inverse-Sample

VARIABLES	(1) Counter Service	(2) Takeout Service	(3) Wait Service
Estimate	1.064***	0.810***	1.160***
	(0.0269)	(0.0181)	(0.0236)
Observations	126,011	124,867	72,645

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[1] To reduce noise, only inspections conducted by inspectors who have done at least 50 inspections remain in the regressions.

Conclusion and Discussion

- Marginally more citations leads to improved subsequent inspection results
  - Restaurants improve the most in the areas in which they received citations
  - Some complementarity in cleanliness (ex. better refrigerator leads to few food temperature and food protection violations).
- Customers also perceive the improvement in sanitation by reducing complaint calls
  - One standard deviation increase in inspection score decreases the probability of complaint call by 10%