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The Impact of Restaurant Letter Grades on Taxes and Sales: Micro Evidence from New York City

Michah W. Rothbart
Institute for Education and Social Policy
Wagner School PhD Student, New York University

Amy Ellen Schwartz
Institute for Education and Social Policy
Steinhardt and Wagner Schools, New York University

Thad Calabrese
Wagner School, New York University

Zachary Papper
New York City Department of Finance

Tod Mijanovich
Wagner School, New York University

Rachel Meltzer
Milano School, The New School

Diana Silver
Steinhardt School, New York University

And

Meryle Weinstein
Institute for Education and Social Policy
Steinhardt School, New York University

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I. Introduction

Do publicly posted restaurant letter grades influence restaurant sales? In a March 6, 2012 press release, New York City (NYC) Mayor Michael R. Bloomberg, announced that “total restaurant sales in New York City increased 9.3 percent – $800 million – in the first nine months since grading began compared to the year before” (City of New York, Office of the Press Secretary, 2012). This enthusiasm was not, however, universally shared by the restaurant industry, which charged that the grades were bad for business, due, perhaps, to their assessment of *what sales might have been*. Andrew Rigie, executive vice president of NYC’s chapter of the New York State Restaurant Association, explained “[i]f you define success as taxing small-business owners and making their lives miserable, then letter grades have been a complete success” (Saul, 2012). To some extent, the difference in assessment may reflect differences in perspective. That said, the impact of restaurant letter grades is likely to be heterogeneous, with "A" grades carrying different effects than “C” or “B” grades. In addition, changing economic conditions surrounding the implementation of the grading policy complicates the isolation of the causal effect of grades on restaurant sales and tax collections.

Public restaurant letter grades have a clear intuitive appeal: grades provide information that allows consumers to make decisions about where to eat; to “vote with their feet”, directing their business dollars to restaurants with high grades over those with low grades. Thus, a low grade (C) should reduce sales, ceteris paribus, while a high grade (A) may increase sales.

Restaurants, however, may anticipate such effects, making changes to forestall low grades so that there is, in the end, little variation in grades and little impact on sales – and little variation in grades as many act to become “A” restaurants.[1] Whether – or to what extent – this provision of information influences consumers to change their behavior and/or induces those subject to grading to improve their products is, in the end, an empirical question.

In this paper, we use richly detailed longitudinal administrative and inspection data for all NYC restaurants over a 5-year period to gain insight into one aspect of the effect -- the impact of the grades on the economic activity of restaurants. Using both difference-in-differences models and a regression discontinuity design we estimate the impact of public grades on restaurant revenues, sales taxes[2], restaurant closures and fines, controlling for a range of restaurant characteristics as well as restaurant fixed effects. More specifically, we use food safety inspection scores as the assignment variable to estimate the effect of receiving an "A" ("C") grade on revenues, sales taxes, closures, and fines, rather than a "B" grade.

Results suggest that, indeed, consumers "vote with their feet." Receiving an "A" grade – rather than "B" – decreases the probability that a restaurant closes, decreases fines assessed, and increases its sales and taxes. A “C” grade has the opposite effect – restaurants receiving a "C" are more likely to close and sales (and taxes) decrease compared to "B" restaurants.

The rest of the paper is organized as follows. In the second section, we provide a brief history of the policy in NYC. In section three, we review previous literature. Section four presents the data and measures. In the fifth section we discuss our empirical strategy. Results are

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[1] A similar logic motivates letter grading of public schools and hospitals, and the perceived success of these efforts fuels the enthusiasm to spread grading to other areas such as subway stations and transportation services, street vendors, among others.

Note that references to sales taxes in this paper always refer to sales tax liabilities owed to NYC.

in section six. In the seventh section we discuss future research items and in the final section we summarize the findings and discuss their implications.

II. Background on NYC's Restaurant Grading Policy

The NYC Department of Health and Mental Hygiene (DOHMH) has long inspected the City's restaurants to ensure proper food safety practices. In July 2010, DOHMH began requiring restaurants to post the summary results of their food safety inspections in the form of a letter grade ("A", "B", or "C") in a conspicuous location easily visible to the public near the restaurant's entrance. There was no change in the policy to close restaurants with violations that pose a large public health risk and that are not addressed during inspection. In addition, DOHMH posted the grades, specific code violations, and previous inspection results for each restaurant on their web site. The goal of the public grading law is to improve restaurant sanitary practices and decrease the incidence of restaurant-attributable food borne illness in NYC.

Under the new law, restaurant grades are assigned via formula based upon the inspection scores assigned in randomly timed site visits. According to DOHMH, the points for a particular violation depend on the health risk it poses to the public, and the overall inspection score is simply the sum of violation points assigned during inspections. The level of public health risk falls into three categories:

(1) public health hazards, which include violations such as failing to keep food at the proper temperature and leads to a minimum of 7 points per violation,

(2) critical violations, which include violations such as serving salad without properly washing it and leads to a minimum of 5 points per violation,

(3) and general violations, which include violations such as not properly sanitizing cooking utensils and leads to a minimum of 2 points per violation.[3]

Additional points are added to each violation to reflect the extent of the violation (on a scale of 1 to 5). The most extreme public health hazard violation leads to a maximum of 11 points. Points from violations are then summed to generate the inspection score. Restaurants with lower inspection scores are considered more hygienic than restaurants with higher inspection scores. Importantly, inspection scores were given in the period prior to the public grading program. At that time, inspection scores were assigned and publically available on the Internet, but summary results were not posted at the restaurant itself. The public grading program moved consumer information from an offsite database to the point of purchase and may have increased information salience. In addition, the public grading program created discrete salient grades: "A", "B", and "C" that were easily interpreted and had not been assigned in the pre-grading regime.

Restaurants with scores of 13 and below are "A" restaurants, those with scores of 14-27 are "B" restaurants, and those with 28 or higher are given "C" restaurants.[4] In addition to publically posting grades, restaurants receiving an "A" are visited less frequently for food safety inspections. Restaurants receiving an "A" grade during an initial inspection are inspected annually, those receiving a "B" are put on a 6 month inspection cycle, and those receiving a "C" are given an initial inspection every four months.

Complicating the process, the DOHMH gives restaurants multiple opportunities to earn "A" grades each inspection cycle. If an initial inspection leads to an inspection score in the "B" or "C" grade range those grades are not assigned immediately. Instead, the restaurant is reassessed within a one-month window during which the restaurant retains its previous grade.

[3] NYC Department of Health and Mental Hygiene. (2012).

[4] Restaurants can also be temporarily closed if they pose a large public safety risk, but we do not estimate impacts of health inspection closures in this paper.

Therefore, a grade is not assigned until a “re-inspection.” Further complicating the processes, inspection scores (and, therefore, grades) can be lowered (improved) through an adjudication process, which in turn can lower the level of fines assessed as well.[5] Restaurants are given the right to challenge violations assessed through an independent third-party tribunal. For a restaurant earning an "A" grade at either initial or re-inspection, this does not affect its posted grade. For a restaurant earning a "B" or "C" during its re-inspection, it is given the option of posting either its assigned grade ("B" or "C") or “Grade Pending” until a hearing date. The re-inspection and adjudication process provide restaurants multiple opportunities to earn "A" grades in every inspection cycle and provide them due process in the event that they feel a grade is undeserved. A simplified diagram of the inspection process can be found in Figure 1.

In addition to inspection scores and grades, the type and count of inspection violations also influences the level of fines assessed. Fines range from $200-$2,000 per violation and are assessed at a restaurant's adjudication hearing at the discretion of a hearing officer. If a restaurant does not send a representative to its adjudication hearing, they are mailed a fine bill. A restaurant has the option of arguing its case at the adjudication hearing and potentially lowering their fine bill. Restaurants are also given the option to waive their right to an adjudication hearing, accept the violations found during inspections, the assigned grade and inspection score, and to pay a lower fine. An important implication of this process is that, at the conclusion of each inspection, a restaurant is given an inspection score, grade, and adjudication date, but it is not told the level of fines to be assessed against them.[6] Importantly, after January 18, 2011, restaurants receiving an "A" grade at inspection were not fined for inspection violations As a result, restaurants earning an "A" at inspection do not incur any fines for much of the post-period.

[5]Silver, Rothbart, and Bae, in preparation, estimate the impact of public grades and public grading on the adjudication process for NYC food safety inspections.
[6] This policy changed in the summer of 2014, after our sample period.

III. Literature review

While the politics of restaurant grades has generated a lot of "heat," there has been relatively little empirical evidence to shed light on the impact of the policy. In a 2012 press release, the DOHMH and Mayor Bloomberg reported declines in reported cases of salmonella and hospitalizations due to food borne illness, improvements in compliance with food safety regulations, and increases in total restaurant sales following program implementation (City of New York, Office of the Press Secretary, 2012). However, it is unclear whether these declines were either wholly or partially due to the implementation of the restaurant grades policy.

As for academic work, Ho (2012) analyzes the publicly available restaurant grading data and concludes that the grading mechanisms were arbitrary. Ho observes that prior scores predict less than 2% of future grades and contends that "inconsistency" in application is the result of the complexity and imprecision of NYC's rules. Ho further concludes that such inconsistency makes restaurant grading an ineffective strategy for communicating the hygiene of inspected restaurants to customers and that the DOHMH, therefore, could not conclude that food safety compliance in the restaurant industry had improved.

Notice, however, that restaurant grading law was explicitly intended to encourage restaurants to take actions to improve (and thus change) their grades in future inspections. Therefore, the "inconsistency" observed by Ho may, instead, be interpreted as a sign of the success of the program. Indeed, the program is intended to incentivize restaurants to pay more attention to food safety practice than before, which should lead to changes in scores for subsequent inspections.

In a forthcoming article, DOHMH provides new evidence of improved compliance since the beginning of the public grading programs, showing marked increases in the probability of a restaurant scoring in the A-range during unannounced initial inspections and offers survey evidence of the program's high approval ratings among New Yorkers (Wong, et al, in press). These results (consistent with our findings in Schwartz, et al, in preparation) provide evidence of increased "congruence" (with the goal of improving hygiene in restaurants).

Two recent studies (Jin and Leslie, 2003; Simon et al., 2005) estimate the effects of the Los Angeles health inspection letter grade system, which required the posting of letter grades beginning in 1998. Jin and Leslie (2003) use OLS and difference-in-differences regression analyses in order to estimate the effect of the Los Angeles letter grades program on inspection scores, consumer demand, and foodborne illness hospitalizations. They find that grade cards improve restaurant inspection scores, that consumer demand responds to hygiene quality signals, and that foodborne-disease hospitalizations decrease in Los Angeles County following the implementation of the public letter grade program. They also suggest that the improvements in health outcomes cannot be explained by consumption choices alone, but are also likely a result of restaurant hygiene improvements.

Simon et al. (2005) use OLS regression analysis in order to estimate the effect of the grading program on foodborne disease related hospitalizations. They find a 13.1 percent decrease in foodborne-disease hospitalizations in Los Angeles County in the year following program implementation after controlling for temporal and geographic trends. They further find that the decrease in hospitalization is sustained over the next two years.

While Jin and Leslie (2003) and Simon et al. (2005) suggest the health benefits of such laws in Los Angeles, little work has examined the effects in other localities (generalizability) or to understand the effects of these laws on other stakeholders. In particular, we are not aware of any studies that have examined the impact of grades on economic activity or restaurant viability and that also control for restaurant food safety practice. In addition, current studies do not consider potential changes in public finances resulting from such programs. In a time of increasing competition for public resources, understanding the potential financial effects resulting from these public health initiatives for governments is critical and yet unexplored.

In order to study the effects of the letter grades law, we draw from a wider literature on public grading and the value of information. A key assumption of the restaurant letter grades law is that consumers will use this information, which is available at the point of sale, when making consumption decisions. This may lead to decreases in sales for restaurants in neighborhoods where there are other restaurant options that have earned better grades. Such assumptions have been studied in other contexts, including public education and food health. For example, many school districts grade public schools on their effectiveness (measured by improvements in test scores and other information), and they make these grades available to the public. There is some evidence that schools with low grades have short-term improvement in aggregate student achievement. Rockoff and Turner (2010), for example, find schools with lower grades have increased student achievement on English language arts and mathematics exams in the following year. Further, Winters and Cowen (2012) find evidence that schools with a failing grade have increased student achievement in English language arts in the following year. As another example, many cities require fast food restaurants to post the caloric content of menu items so that consumers may make more informed choices at point of purchase. The evidence regarding the public’s use of this information has been mixed and Elbel et al. (2009) find no impact of calorie labeling on the number of calories ordered at the point of purchase.

Taken together, the previous literature provides some evidence to suggest that overall hygiene might improve as a result of posting letter grades in restaurants. There is also some evidence that consumers or graded entities may change behavior in response to salient public information, as is suggested in Jin and Leslie (2003) and found in the school grade literature. The current literature, however, does not yet address the heterogeneity in grading impacts or the broader public finance implications. We aim to fill both of these gaps in the current analysis.

IV. Data and Measures

This study utilizes richly detailed, longitudinal, inspection and restaurant-level data from the NYC Department of Health and Mental Hygiene (DOHMH) matched on Employer Identification Numbers (EINs) with highly detailed, longitudinal sales tax data from the NYC Department of Finance (DOF). The DOHMH data include restaurant characteristics and zip codes, inspection date and score information, adjudication dates[7], grades assigned, and fines assessed. Restaurant characteristics include number of seats, number of employees, an indicator for chain restaurant (at least 15 locations nationwide), and a series of indicator variables for cuisine offered, service type, and venue type. "Cuisine offered" measures type of food served. DOHMH defines over 80 cuisine types. The most common cuisines are American, Chinese, and Pizza (Table 1). Service type measures service offered in a restaurant including wait service only, wait service and counter service, takeout only, etc (see Table 1). There are 13 service types in our sample. Venue is a measure of a restaurant's setting. There are 26 venue codes including diner, arena-stadium concession stand, bar/pub/brewery (food served), night club, restaurant

[7] After 2 inspections (an initial and a re-inspection), restaurants have the right to due process and may challenge inspection violations at a third party tribunal.

(with bar), and restaurant (no bar).[8] Restaurant characteristics are measured at the most recent restaurant inspection and therefore are time-invariant variables.

Our data includes the universe of inspection scores for every DOHMH inspection from December 1, 2007 through February 28, 2013, including inspections during a two and a half year period prior to public grading and two and a half years following public grading implementation (here forth referred to as "pre-period" and "post-period", respectively). We observe inspection scores both before and after adjudication. We use pre-adjudicated final inspection scores for all analyses in this paper, but test the sensitivity of the findings to alternative measures of inspection scores including initial scores (available upon request). We also observe assigned grades before and after adjudication. We use pre-adjudicated grades and post-adjudicated grades depending on the analysis. Pre-adjudicated grades are “intention-to-treat,” because these are grades earned at inspection. These grades can be either "A", "B", or "C" depending on the inspection score of the restaurant. Importantly, during the pre-adjudicated period, restaurants have the option of posting "Grade Pending" instead of a "B" or "C" to indicate that they have not yet had due process. The post-adjudicated (here forth, “posted grades”) are the treatment, because this is the information a restaurant publicly posts and that consumers see at the point of sale. The frequency of intention-to-treat grades and treatment grades by quarter are shown in Figures 2 and 3, respectively

We use restaurant closure as an indicator of economic activity. If a restaurant is not operating for three straight inspection attempts (on different days and at different times of day), then it is identified has having stopped operation (or out-of-business). The out-of-business date is then assigned as the first failed inspection attempt (that is, the first day for which the restaurant is observed to be no longer operating). Assuming a restaurant never reopens, we measure closure as a restaurant going out-of-business within 365 days of an inspection. Closure is measured with

[8] A full list of cuisine, service, and venue types is available upon request.

error, because a restaurant could have been closed prior to the first inspection attempt. Therefore, our measure is likely a conservative measure of restaurant closure date.[9]

Fines assessed may affect the NYC budget, but are also an expense for restaurants. Fines are assigned following an adjudication hearing, and we observe final (post-adjudication) fines assessed for each inspection, the adjudication date, and whether or not inspection scores change through the adjudication process. All fines are adjusted using urban CPI to real 2013 dollars.

During the five-year sample period, over 40,000 restaurants operate and over 200,000 inspections are made by the City. We include all hygiene inspections that are not later replaced by further re-inspection within the same inspection cycle. Our regression sample is restricted to the post-period for all analyses in this paper in order to estimate the effects of "A", "B", and "C" grades during the post-period on closure and fines. The sample includes 82,977 inspections of 29,742 restaurants in all.

The DOF data include measures of quarterly sales and sales tax liabilities (here forth, sales taxes). For our empirical analysis, we aggregate monthly data into quarters.[10] NYC restaurants are required to levy sales tax on food and beverage sales at a rate of 8.875% of gross sales (4.875% is owed to New York State and 4.0% is remitted by the State to NYC). Through remittance process, New York State shares entity-level data on business activity that can only be used for limited purposes by the DOF. DOF matches these data to DOHMH food safety inspection data on restaurant EIN.

The DOF is unable to provide restaurant-level sales and tax data to outside researchers in order to preserve business privacy. Moreover, DOF is unable to provide information on for any

[9] Future work will estimate impact of grades on restaurant closure using DOF data, measuring closure as zero sales during a quarter. These results are not yet available.
[10] Restaurants with $300,000 or less of sales in the previous quarter may remit sales taxes to New York State quarterly, while restaurants with more than $300,000 of sales in the previous quarter remit monthly to the State.

group of less than 10 entities. For our data set, the NYC DOF Office of Tax Policy aggregate restaurant-level data by randomly assigning restaurants to the minimum group size of 10 entities. They first stratify restaurants by quarters of operation (both number and timing of operation) and then aggregate restaurant-level data into a group level data set in which each observation carries the summary statistics for the group of 10 restaurants. For example, DOF starts with all restaurants operating from the beginning to the end of our panel (December 1, 2007 to February 28, 2013) and randomly assigns these restaurants to groups of 10. DOF then takes all restaurants operating all but the last quarter of our panel and randomly assigns these restaurants to groups of 10. They then continue this process, sequentially, until all restaurants are assigned to groups. The data set includes quarterly means and standard deviations for all DOHMH variables outlined above as well as quarterly means and standard deviations of sales, log(sales), sales taxes, and log(sales taxes). By construction, every restaurant in each group will have positive sales in each observed period; all restaurants in a given group begin and cease operation in the same quarter as measured by nonzero sales and no group ever includes fewer than 10 establishments.

Further complicating the analysis, some DOHMH graded establishments are not primarily restaurants (and therefore a large share of revenues can come from other goods/services). When estimating the impact of grades, estimates are unbiased if fluctuations in other revenue streams are uncorrelated with food inspection grades. Given our empirical strategy, the likelihood of bias is quite low. Still, including entities that primarily earn revenue through alternative streams, such as hotels, increases statistical noise. Therefore, we use a subsample of primarily food and beverage providers as identified by their North American Industry Classification System (NAICS) code for the analyses in this paper.[11] As a robustness

[11] We use all NAICS codes beginning with 722, as well as 445299, 445291, and 445120 to flag primary food and beverage establishments. We use the same set of code identifiers used and recommended by the NYC DOF.

check, we use the full set of matched establishments, randomly assign all establishments to a new set of groups, and find consistent results.[12]

The set of matched entities includes 9,647 observations of 1,684 groups, which is comprised of 17,514 establishments in all. Our regression sample, focusing on food and beverage establishments, includes 9,182 observations across 1,538 groups (including 15,899 restaurants or bars observed during the 9 quarters post-policy-implementation).[13]

V. Empirical Strategy

A. Fines and Closures

We use a regression discontinuity design to estimate the impact of "A" and "C" grades on fines and closures as compared to a "B" grade. For our regression discontinuity (RD) analyses, we will also limit the sample to restaurants with inspection scores within an interval immediately above and below the “A” grade threshold, and the regression will take on the following form:

$$(1)\quad y_{it} = \beta_0 + \beta_1 A_{it} + \beta_2 Score_{it} + \beta 3Xit + \gamma i + \delta t + \varepsilon$$

Where y is a restaurant-specific outcome (closure and fines); A is a variable indicating if the restaurant received an “A;” Score is the inspection score for restaurant *i* at time *t*; X is a vector of restaurant characteristics including cuisine, service, and venue type; γ and δ are zip code and quarter fixed effects, respectively; and ε is an error term with the usual properties. This basic specification assumes a constant (and linear) relationship between the outcome(s) and the score within the identified interval around the “A” grade cutoff. We estimate model (1) using local linear estimates, as well. The remaining variables are identical to those defined above. We will also estimate a similar set of models for restaurants with inspection scores within an interval

[12] These estimates are available upon request of the authors.
[13] The policy is implemented in the middle of the 2nd sales tax quarter in 2011. We define the “post-period” as data observed from the 3rd quarter of 2011 on.

immediately above and below the “C” grade threshold.

B. Sales and Sales Taxes

As outlined previously, all restaurants are inspected, given a grade, and given an adjudication hearing date to argue their case. While posted grades are assigned based on post-adjudicated scores, there is reason to believe that post-adjudicated inspection scores are endogenous (for example, if well-resourced restaurants can hire a higher quality representative). For the time being we will consider pre-adjudicated inspection scores only, and estimate the effect of grades using a fuzzy regression discontinuity design. In an RD framework, an initial inspection score is the assignment variable for grade earned if a restaurant earns an "A" on its initial inspection, and this is a sharp discontinuity. A re-inspection score is the assignment variable for all restaurants that do not earn an "A" on initial inspection, and this is a fuzzy discontinuity due to the adjudication process.

Ideally, we would observe daily inspection scores, grades, and sales by restaurant. We derive our estimator for the impact of grades on sales beginning with a model for the effect of daily grades on daily sales.

$$(2)\ y_{it} = \tau_1 A_{it} + \tau_2 C_{it} + \tau_3 GP_{it}^B + \tau_4 GP_{it}^C + \tau_5 score_{it} + \tau_6 X_{it} + \delta_t + \varepsilon_{it}$$

Where y_{it} are sales for restaurant i on day t; A and C indicate if restaurant i's extant grade is an "A" or "C" on day t; GP^B and GP^C indicate if restaurant i has earned a "B" or "C" at inspection, but has the option of posting “Grade Pending”; score is the assignment variable and is a restaurant's most recent inspection score; X is a vector of restaurant characteristics; δ_t are day fixed effects. In this case, it does not matter that restaurants are inspected on different cycles or that inspections are not evenly dispersed over time within restaurant; this provides a day-level estimate of the effect of the extant score and grade on sales.

We do not, however, observe daily sales. Restaurant sales are only observed on a quarterly basis and restaurants are inspected at different times throughout a quarter. We do observe on which day a restaurant is inspected and graded. In order to estimate the effect, we must aggregate daily sales, grades, and scores, to the least common time period, quarters.

We take the mean of each of the terms in equation (2) over all days, t, in quarter, q:

$$(3)\ \overline{y_{\iota q}} = \tau_1\overline{A_{\iota q}} + \tau_2\overline{C_{\iota q}} + \tau_3\overline{GP^B_{\iota q}} + \tau_4\overline{GP^C_{\iota q}} + \tau_5\overline{score_{\iota q}} + \tau_6\overline{X_{\iota q}} + \overline{\delta_q} + \overline{\varepsilon_{\iota q}}$$

$\overline{y_{\iota q}}$ are the restaurant's average daily sales in quarter q; $\overline{A_{\iota q}}$ and $\overline{C_{\iota q}}$ are now defined as the percent of days in quarter q a restaurant holds an "A" or "C" grade; $\overline{GP^B_{\iota q}}$ and $\overline{GP^C_{\iota q}}$ are now defined as the percent of days in quarter q a restaurant holds a "B" or "C" but can post "Grade Pending"; and $\overline{score_{\iota q}}$ is a restaurant's average daily score over the course of the quarter. τ_1 and τ_2 are interpreted as the effect of a 100% increase in share of quarter q that restaurant i has an "A" or "C" on average daily sales. This provides an unbiased and consistent estimate of the grade effect if daily error terms are uncorrelated.

An alternative option uses measures of restaurant grades and scores at the beginning or the end of the quarter. Using beginning or ending quarter grades guarantees restaurant grades are measured with error, but estimated impacts are consistent if restaurant inspection timing is random within quarter (as is the case for DOHMH food safety inspections). Thus, we estimate the impact of grades and inspection scores with more statistical noise, but without bias. We can estimate the impact of beginning a quarter with each grade on quarterly sales using the model

$$(4)\ \text{A. } y_{iq} = \tau_1 BegA_{iq} + \tau_2 BegC_{iq} + \tau_3 BegGP^B_{iq} + \tau_4 BegGP^C_{iq} + \tau_5 Begscore_{iq} + \tau_6 X_{iq} + \delta_t + \varepsilon_{iq}$$

Where y_{iq} are the restaurant's sales in quarter q and BegA, BegC, $BegGP^B$, $BegGP^C$, and Begscore denote restaurant inspection grades and score at the beginning of quarter q. We can also estimate the impact of ending a quarter with each grade on quarterly sales using the model:

$$(4)\ \text{B. } y_{iq} = \tau_1 EndA_{iq} + \tau_2 EndC_{iq} + \tau_3 EndGP^B_{iq} + \tau_4 EndGP^C_{iq} + \tau_5 Begscore_{iq} + \tau_6 X_{iq} + \delta_t + \varepsilon_{iq}$$

Where all variables are defined the same as previously indicated and EndA, EndC, $EndGP^B$, $EndGP^C$, and Endscore denote restaurant inspection grades and score at the end of quarter q.

All three models (3, 4A, and 4B) provide unbiased estimates of the posted grade effect on sales and sales taxes if changes in manager ability to improve grades at adjudication over time is exogenous with sales and inspection timing is random within quarter. We use 4A and 4B as a robustness check to our analysis and the results are largely consistent.[14] We note, however, that estimated effects of Grade Pending will not converge, because they are actually different parameters in each model. Due to the chronology of each inspection cycle, Grade Pending at the end of the quarter indicates that a restaurant must post "Grade Pending" or its grade in the final days of a quarter, but will by construction never have to post the grade during the quarter of observation (Figure 1 illustrates a simplified version of each inspection cycle). Conversely, Grade Pending at the beginning of the quarter indicates that the restaurant's adjudication date will be assigned for the quarter of observation and very well may have to post their inspection grade during the quarter of observation (Silver, Rothbart, and Bae, in preparation, estimates the likelihood of grade improvement through adjudication). The coefficient on "Grade Pending" for "B" and "C" restaurants measured at the beginning of the quarter is more likely to have an impact

[14] Results of these models are shown in the appendix and available upon request of the authors.

on sales than the measure at the end of the quarter.[15] Moreover, estimates for the effect of "A" and "C" grades as compared to "B" grades will converge in limit.

We do not observe data by individual restaurants, even on a quarterly basis. Instead, to protect privacy, we group restaurants randomly by quarter of operation. To derive our group-level estimator, we first use model (3) and continue with model (5) below. Similar derivations are trivial using models (4)A. and (4)B., as well. We control for time-invariant restaurant characteristics using restaurant fixed effects, shown in equation (5) below.

$$(5)\ \overline{y_{\iota q}} = \tau_1 \overline{A_{\iota q}} + \tau_2 \overline{C_{\iota q}} + \tau_3 \overline{GP^B_{\iota q}} + \tau_4 \overline{GP^C_{\iota q}} + \tau_5 \overline{score_{\iota q}} + \tau_6 \overline{X_{\iota q}} + \gamma_i + \overline{\delta_q} + \overline{\varepsilon_{\iota q}}$$

Equation (5) provides an unbiased estimate of the effect of an "A" or "C" grade for the entire quarter if we have measured all relevant time-varying restaurant characteristics in vector $\overline{X_{\iota q}}$.

Further complicating our analysis, we do not observe individual restaurant sales. Instead we observe summary statistics for randomly assigned groups of restaurants. Due to the fact that restaurants i are randomly assigned to group g, we can re-write the above equation as:

$$(6)\ \overline{y_{gq}} = \tau_1 \overline{A_{gq}} + \tau_2 \overline{C_{gq}} + \tau_3 \overline{GP^B_{gq}} + \tau_4 \overline{GP^C_{gq}} + \tau_5 \overline{score_{gq}} + \tau_6 \overline{X_{gq}} + \gamma_g + \overline{\delta_q} + \overline{\varepsilon_{gq}}$$

Where $\overline{y_{gq}}$ are the group's average daily restaurant sales in quarter q; $\overline{A_{gq}}$ and $\overline{C_{gq}}$ are now defined as the average percent of days in quarter q the restaurants in group g hold an "A" or "C" grade; $\overline{GP^B_{gq}}$ and $\overline{GP^C_{gq}}$ are the average percent of days in quarter 1 the restaurants in group g have a "B" or "C" grade, but are allowed to post "Grade Pending"; and $\overline{score_{gq}}$ is a group's average inspection score over the course of the quarter weighted by restaurant-days. τ_1 and τ_2 are interpreted as the effect of a 100% increase in share of quarter q that group g has an "A" or "C" on average daily sales. These coefficients can be interpreted as daily restaurant-level effects if restaurant i's average grade in group g in quarter q only affects restaurant i's sales and not the

[15] This is consistent with our results.

sales of other restaurants in group g.[16] These models provides an unbiased and consistent estimate of the grade effect if the error terms of the individual restaurant equations are uncorrelated within group g. We find this assumption believable due to restaurant random assignment to groups and the inclusion of the quarter fixed effect, $\overline{\delta_q}$. We fit a model with sales taxes as the outcome variable as well in order to estimate the impact of grades on sales taxes and identify differences in tax incidence across restaurants. All estimates are of restaurant-level impacts, but the standard errors are larger than if estimates were from individual-level models.

Posted grades are publically visible at the point of consumption, but are endogenous if managers with greater ability (to earn revenue, for example) are more capable of winning in adjudication and improving grades at the discontinuity margin. In this case, model 6 provides an unbiased estimate of the difference in sales for a restaurant receiving an "A" as opposed to a "B", but grades may reflect something like management ability in addition to marginal differences in food safety environments. To address this threat, we estimate a model that imputes grades based exclusively on the inspection process. These are the grades that would be given based solely on inspection performance rather than adjudication performance as well. For these models, there is no such thing as "Grade Pending," improvement of grades through adjudication are ignored, and grades solely reflect a restaurant's most recent inspection score. We estimate this effect using:

$$(7)\ \overline{y_{gq}} = \tau_1 \overline{ITTA_{gq}} + \tau_2 \overline{ITTC_{gq}} + \tau_3 \overline{score_{gq}} + \tau_4 \overline{X_{gq}} + \gamma_g + \overline{\delta_q} + \overline{\varepsilon_{gq}}$$

Where $\overline{ITTA_{\iota q}}$ and $\overline{ITTC_{\iota q}}$ are the average intention-to-treat grades for group g in quarter q. τ_1 and τ_2 are interpreted as the effect of a 100% increase in share of quarter q that group g is inspected as an "A" or "C" on average daily sales. We call estimates from model (7) "intention-

[16] As a robustness check, we estimate the impact of grades on percent changes in average daily sales using average of log(sales) as the outcome variable. Log model estimates are qualitatively similar to the results shown in this paper and are available upon request of the authors.

to-treat" (ITT) estimates. We expect coefficients in the ITT model to be of smaller magnitude than the posted grades because inspection grades are less easily consumed by the public and only available at the point of sale if they match the posted grade (customers could look up inspection scores online, but may see either "Grade Pending" or a "B" or "C" grade in the window). For our ITT estimates we use beginning of the quarter inspection grades because these best reflect which grades will be posted in the rest of the quarter due to the restaurant food safety inspection cycle.[17] For example, a restaurant can post "Grade Pending" after a "C"-graded inspection and the "C" is often not posted until late in the quarter (if at all). For end of quarter measures, therefore, ITT grades are a worse measure of the impact of grades earned through inspection. We would expect, however, beginning of quarter ITT grades to be predictive of posted grades later in the quarter and to impact future consumption decisions and sales within a given quarter.[18]

VI. Results

A. Are "A" restaurants less likely to close? Are "Cs" more likely?

The results in Table 3 show the impact of "A" and "C" inspections on restaurant closure within a year. As shown in column 1, inspections yielding an "A" grade are 4.2 percentage points less likely to lead to restaurant closure than "B" inspections, controlling for quarter-year fixed effects. Column 2 of Table 3 shows linear regression discontinuity estimates of the impact of grades on closure. "A" inspections are 2.6 percentage points less likely to lead to closure than "B" inspections, still a significant and meaningful dip. Column 3 includes controls for observable restaurant characteristics and zip code fixed effects and are not statistically or substantively different than the uncontrolled model. Column 4 shows estimated effects for a model including a

[17] We present results from the other two model specifications measuring inspection grades by daily average and at the end of the quarter in Appendix E.
[18] We report beginning of the quarter ITT grade estimates in this paper, but all three are available in the appendix.

restaurant fixed effects. The impact of an inspection yielding an "A" is no different than the estimates in column 2. An "A" inspection is 2.6 percentage points less likely to lead to closure than a "B" inspection. All else equal, controlling for observed and unobserved differences in restaurants, "A" inspections are less likely to lead to restaurant closure than "B" restaurants.

Similarly, as shown in column 1 of Table 3, inspections yielding "C" grades are 4.9 percentage points more likely to lead to restaurant closure than "B" inspections, controlling for quarter-year fixed effects. Column 4 shows results from our preferred model, controlling for inspection score and restaurant fixed effects and suggest a "C" inspection is 2.1 percentage points more likely to lead to a closure than an otherwise equivalent "B" inspection, still a significant rise in the likelihood of closure within a year.

Table 4 shows RDD estimates grade impacts restricting the sample to inspections near grade cut points. Estimates from our preferred model can be found in columns 1 and 4. These models restrict the sample to inspections 1 point above and one point below the cut point. The estimate in column 1 shows that restaurants earning "A" grades at inspection are 4.9 percentage points less likely to close within a year than those with "B" inspections. The estimate in column 4 shows that "C" inspections are 4.2 percentage points more likely to result in closure than "B" inspections. The point estimates are not sensitive to increasing the bandwidth to 2 points or to inclusion of restaurant characteristics and zip code fixed effects. We also estimate these effects using local linear regression and find that estimates are not sensitive to model specification.[19] Local linear regression estimates in graphical form can be found in Appendix B.

[19] Local linear estimates use an optimal bandwidth, which minimizes MSE, as in Imbens and Kalyanaraman (2009). The optimal bandwidth for determining the effect of an "A" inspection is 1.293. The optimal bandwidth for determining the effect of a "C" inspection is 1.939. These are not meaningful in the context of inspection scores, so we use 1 and 2 points in the linear regressions.

In addition to the analysis of the impact of inspection grades on restaurant closure in the post-grading period, we perform a falsification test estimating the impact of imputed grades in the pre-grading period. That is, what if grades were assigned using the same grading formula in the period before public grades and this information were private? The results of the falsification test are shown both in table and graphical form in the Appendix C and D, respectively. We find that the impact of imputed grades is smaller in the pre-period and is insignificant at the 95% level for all but 1 model, suggesting that estimated impact of grades in the post-period are a result of the grades themselves rather than landing in a specific part of the score distribution.

B. Do differences in public grades affect incidence of fines?

Figure 4 shows total citywide fines levied by quarter during the full sample period. Total fines levied are higher in the post-grading period than in the pre-grading period in terms of real fine dollars, though total fines levied have decreased since the peak three quarters following the implementation of public grading. Figure 5 plots fines over time per restaurant in real dollars. While fines per restaurant increase in the year immediately following program implementation, this actually follows a pre-existing trend (that temporarily discontinues during program implementation). Moreover, the increasing trend is reversed and average quarterly level of fines paid reaches pre-program levels by the end of tax year 2013. The fine levels shown in Figures 4 and 5 demonstrate a similar trend: restaurant fines initially increase during the first few quarters of the grading program and then fall to pre-program levels. This was initially driven by an increased number of inspections as well as a slight uptick in fines per inspection, but fines per inspection have fallen dramatically over time since then. In fact, in other analysis not shown here, we find fines per inspection in the final 3 quarters of our sample are lower than in any pre-period quarter in our sample. These figures show trends in fines overall, but mask possible heterogeneity across restaurants. For example, it is probable that fines for relatively hygienic restaurants, which have better inspection scores and grades, have fallen due to the fact that restaurants are no longer fined if they receive an "A" at inspection.

The results in Table 5 show the impact of "A" and "C" inspections on fines. We only show our preferred model, restricting the sample to inspections within 1 or 2 points of the grade cut point. As shown in Column (1), "A" inspections 1 point from the grade cut point yield fines $518.46 lower than similar "B" inspections, controlling for quarter-year fixed effects. The results are not particularly sensitive to a 1 point wider bandwidth. As shown in Column (3), "C" inspections near the grade cut point do not yield fines appreciably different than similar "B" inspections. While the results change in terms of statistical significance in Column (4), this may reflect changes in inspection scores rather than effects from inspection grades. We also estimate these effects using local linear regression and find that estimates are not particular sensitive to model specification.[20] Local linear regression estimates can be found in Appendix B. Receiving an "A" grade reduces fines as compared to an otherwise similar "B" grade, but this effect does not exist for "C" grades. Of note, this due to changes in program rules 6 months after program implementation that eliminate fines for "A" graded inspections.

C. How does an "A" impact restaurant sales and taxes? What are the effects of a "C"?

As shown in Figure 6, mean sales remain largely unchanged in the post-grading period as compared to the pre-grading period in real dollars. Figure 6 shows mean restaurant sales, which masks growth in the number of restaurants since public grading (a growth that may result from

[20] Local linear estimates use an optimal bandwidth, which minimizes MSE, as in Imbens and Kalyanaraman (2009). The optimal bandwidth for determining the effect of an "A" inspection is 3.774. The optimal bandwidth for determining the effect of an "C" inspection is 10.35.

public grading increasing restaurant-going or may reflect a changing economic environment during the observed period). Mean sales figures are quite high (nearly $200,000) and mask a fairly high level of heterogeneity across restaurants.

Figure 7 shows that mean sales taxes remain largely unchanged since restaurant grading began. Sales taxes are closely tied to sales revenue, so this result is unsurprising. There is a small decline in sales taxes during the period 2 years to 1 year before program implementation. This trend reverses before public grading and mean taxes remain largely unchanged after public grading. Both Figures 6 and 7 mask a great deal of heterogeneity between restaurants. For example, while mean restaurant sales remain largely unchanged (with a slight uptick) following public grading, restaurants receiving "A" grades might have an increase in sales, while those receiving "C" grades might have a decrease. This may result in differential impacts on sales tax burden as well. In particular, while a greater fine burden might be born on restaurants with worse hygiene practices, a greater sales tax burden might fall on restaurants with "A" grades.

Table 6 shows difference-in-differences model estimates of the impact of grades on sales revenue (in 2013 dollars). The estimates in the Posted Grades model are in the expected direction for all three measures of inspection grades (beginning, end, and daily average of the quarter), though only the estimates of the impact of daily average grades are shown here.[21] We find that "A" grades increase sales and that "C" grades decrease sales (the impact of "C" grades is imprecisely estimated in this model, but is statistically significant in the log model).[22] Due to restaurant random assignment to groups, we assume that restaurant grades effect only own restaurant sales. With this assumption, we find that a posted "A" grade is associated with a $145 increase in mean daily sales as compared to a "B". If a restaurant posts a "C" grade, average

[21] Results from models that estimate the impact of posted grades at the beginning or the end of the quarter can be found in Appendix E.
[22] Log model estimates are available upon author request.

daily sales are estimated to decrease by $104, but this result is not statistically significant in this model specification. The estimated effect of days in which a restaurant is allowed to post "Grade Pending" is insignificant as compared to the period in which a restaurant must post a "B" grade. Further, the estimated impact of a "B"-inspected restaurant during the period in which "Grade Pending" may be posted is statistically insignificantly different than the estimated impact of a "C"-inspected restaurant during the period in which "Grade Pending" can be posted. Due to power issues we cannot say for certain that there is no difference in sales impact between a "B" and "C" grade during the grade pending period, but this does suggest that the effect of a "C" grade as compared to a "B" grade (which is insignificant to begin with) is muted.

The intention-to-treat estimates in Table 6 have greater power due to increased size of the reference group (GP^B restaurants are simply treated as having earned a B). These results are interpreted as the impact of a restaurant's most recent "A", "B", or "C" inspection grade, regardless of grade post timing (for example, we do not observe if a "B" restaurant posts "Grade Pending" or “B” before their adjudication date). We find that "A" grade inspection periods increase restaurant sales by about $78 a day and that "C" grade inspection periods decrease restaurant sales by about $122 per day. These estimates are not statistically different than the Posted Grades estimates, but are more precisely estimated due to increased power. While marginal restaurants may be able to improve grades through the adjudication process, inspection grades have an impact on quarterly sales on average.

Our difference-in-differences estimates are endogenous if there are aspects of a restaurant’s food safety environment that are correlated with grades and affect sales, but are not a result of the grades themselves. For example, customers may observe the relative cleanliness of restaurants and choose where to eat based on those observations or may actually use the scores posted on the online portal. These choices are based on observation of behavior or scores correlated with restaurant hygiene rather than based on grades posted. One way to control for this form of endogeneity is with a regression discontinuity model. We control for the assignment variable, underlying inspection scores, and estimate the independent effect of grades in Table 7.

The results in Table 7 show that inspection scores are uncorrelated with restaurant sales, once controlling for posted grades. In other words, increased sales from improved food safety practice is driven by improved grades. The independent effect of posted grades on sales is quite large. In comparing restaurants with very similar food safety scores, we estimate that those with "A" grades have an increase of $123 in sales a day as compared to "B" grades. Conversely, those with "C" grades earn about $113 less than restaurants with "B" grades, but this is imprecisely estimated. Our estimates from the regression discontinuity model are similar to those from the difference-in-differences model, which suggests that consumers mostly use the posted grade information when making consumption decision. Again, the impact of "Grade Pending" on sales are insignificant as compared to the period in which a restaurant must post a "B" grade. This impact is estimate is insignificant for both restaurants receiving a "B" and a "C" at inspection. Due to power issues we cannot say for certain that there is no difference in sales impact between a "B" and "C" grade during the grade pending period, but this does suggest that the effect of a "C" grade as compared to a "B" grade (which is insignificant to begin with) is muted.

The intention-to-treat results in Table 7 again have greater power due to increased reference group size. These are estimated impacts of "A", "B", or "C" inspections, regardless of the enforced posting timing. We again used beginning of the quarter measures of inspection score for ITT estimates.[23] We find that "A" grade inspection periods increase restaurant sales by

[23] We present results from the other two model specifications measuring inspection grades by daily average and at the end of the quarter in Appendix F.

about $83 a day and that "C" grade inspection periods increase restaurant sales by about $144 per day. These estimates are not statistically different from the Posted Grades estimates, but are more precisely estimated due to increased power. They are also very similar to the difference-in-differences estimates, suggesting that restaurant grades are the primary source of food safety information for consumers, rather than underlying inspection scores.

Table 8 shows the sales tax implications of restaurant grades. Restaurants with posted "A" grades pay about $6 a day more in taxes than those with "B" grades. Similarly, restaurants with posted "C" grades pay about $5 less a day in taxes than those with "B" grades, though this point estimate is imprecise. These are small effects each day, but they imply that the City should expect approximately $2,000 more in taxes annually for restaurants with "A" grades than otherwise similar restaurants with "B" grades. There is no statistical difference in the sales taxes between "B" and "C" graded restaurants during the grade pending period.

The ITT estimates in Table 8 are of similar magnitude and direction to the Posted Grades estimates. Beginning a quarter with an "A"-range inspection score leads to on average about $4 more in sales taxes owed each day in the following quarter than beginning the quarter in the B-range. Conversely, beginning a quarter with a "C"-grade inspection leads to owing about $6 less in sales taxes each day in the following quarter than a "B"-grade inspection, on average.[24] Interestingly, the average impact of grades on sales taxes is much larger than the impact on fines, despite greater public scrutiny over the relationship between public grades and fines.

VII. Other Impact Analysis

This paper provides the first evidence on the impact of public restaurant grades on economic activity since Jin and Leslie (2003). The paper is one of multiple steps in a larger

[24] The alternative set of RDD estimates of impact on sales taxes are shown in Appendix G.

research agenda to identify the costs and benefits of public grading on NYC, its citizens, and its restaurants. This paper provides insight into the impact of grades on restaurants, but other work identifies the impact of the public grading program itself on inspection scores, fines, and sales (Schwartz et al., in preparation). Moreover, we will examine heterogeneous impacts based on restaurant characteristics and location. This paper controls for restaurant location, cuisine, venue, and service type. Future analysis will examine, for example, how grades impact take-out Chinese restaurants differently than sit-down French restaurants and how grading impacts restaurants in neighborhoods with high tourist density differently than those in residential neighborhoods.

In other work, we examine direct program costs to the city. One direct cost is the program's implementation cost. We use detailed budget information to analyze changes to full-time equivalent (FTE) employees, spending by specific line items, and revenues by source for the division during grading program startup. We also allocate an appropriate portion of fringe benefits (employee health insurance, pension costs, etc.) from the budget to the division in charge of inspections. In doing so, we capture total program costs. A second direct cost is increased costs due to changes in the law and ongoing program maintenance. In particular, there might be higher inspection costs and higher costs resulting from violation challenges. Inspection costs are likely to increase because of additional personnel costs from increased inspector hires as a result of the change in law. Further, these inspectors need training in the new program. We estimate the costs of increased numbers of inspectors in our program impact analysis as well.

Another critical aspect of the program's implementation is the cost of adjudication, both to the city and to restaurants. Restaurant owners have the right to challenge inspection violations through adjudication. Violation challenges by restaurant owners are likely to increase because the cost of a lower grade has increased due to the change in law. In another paper, we test the impact of restaurant grades and the public grading program on the adjudication process and also examine the adjudication process using qualitative methods (Silver, Rothbart, and Bae, in preparation). Owners of restaurants just below a grade threshold now have a greater incentive to challenge inspection results than before and we find impacts of grades on adjudication outcomes after grading that do not exist before.

Other future research will center around the effect of the law on citizen health. Like previous research on restaurant grades, we will estimate the effect on acute cases of food-borne illnesses using data on hospitalizations and emergency department (ED) encounters related to foodborne illness. Further, we will exploit location specific information on hospitalizations (and ED encounters) and restaurants in order to estimate differential impact based on the relative hygiene of restaurants in the area.

VIII. Conclusions

This paper offers preliminary economic impact estimates of public grades. We present evidence on four main impacts of grades earned:

(1) The impact of getting an "A" rather than a "B" is a 3-5 percentage point decrease in probability of restaurant closure within a year. Conversely, the impact of getting a "C" rather than a "B" is a 2-5 percentage point increase in probability of restaurant closure.

(2) The impact of getting an "A" rather than a "B" is a large decrease in fines assessed on a restaurant, but there is little evidence of such an effect of a "C".

(3) Sales at "A" restaurants rise by $80-120 a day as compared to getting a "B" grade. In contrast, "C" graded restaurant sales decline by about $110-140 a day as compared to a "B".

(4) Sales taxes for restaurants with "A" grades increase and "C" grades decrease as compared to restaurants with "B" grades with a magnitude commiserate with the changes in sales.

These results provide evidence of large and significant economic impacts of public grades, motivating our other research on the impact of the public grading program. Moreover, the results suggest that public grades change the composition of NYC's revenue sources. That is, restaurants earning "A" grades are more likely to stay open, pay fewer fines, and accrue higher sales taxes than restaurants earning "B" grades, perhaps making the City more reliant on these restaurants long-term for revenues and less reliant on restaurants with worse food safety practices.

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TABLES

Table 1. Restaurant Descriptive Statistics

	Pre-Public Grading	**Post-Public Grading**
Number		
Inspections	3.3	6.2
Final Inspections	3.3	3.2
Workers	6.5	5.9
Seats	29.6	29.5
Cuisine		
American	0.22	0.24
Chinese	0.09	0.11
Pizza	0.04	0.06
Latin	0.04	0.04
Café/Coffee/Tea	0.03	0.04
Other*	0.38	0.51
Missing	0.20	0.00
	1.00	1.00
Service		
Takeout-Limited Eat in	0.35	0.39
Wait Service	0.15	0.18
Wait and Counter Service	0.11	0.17
Takeout Only	0.08	0.08
Counter Service	0.07	0.12
Other*	0.06	0.07
Missing	0.20	0.00
	1.00	1.00
Chain	0.10	0.11
Annual Closure Rate	0.16	0.12
N	31,245	29,864

Notes: 29,644 restaurants operate continuously for the entire sample period. Inspections include initial and re-inspections. Final inspections include all inspections in the pre-period, initial “A” inspections in the post-period, and re-inspections for those initially receiving “B” or “C” in the post-period. Workers, seats, cuisine, service, and chain are time invariant restaurant characteristics. Annual closure rate is the fraction of open restaurants closing each year. *Other includes 76 additional cuisine types and 8 additional service types we can identify.

Table 2. Inspection Statistics, by treatment period

		All Restaurants	Continuously Operating
Pre		24.64 (75,519)	23.31 (29,644)
Quarters Post			
1-5	Initial	24.85 (42,280)	24.01 (17,667)
	Final Inspection Score	18.15 (40,412)	17.40 (17,305)
6-10	Initial	22.24 (42,963)	21.50 (17,103)
	Final Inspection Score	15.64 (41,308)	15.08 (16,718)

LOWER SCORES INDICATE MORE HYGIENIC RESTAURANT CONDITION
Includes pre-adjudicated inspection scores. Mean score shown on top; number of inspections shown parenthetically. Final inspection score includes all "A"-graded inspections and re-inspections of restaurants that do not get an "A" grade on initial inspection. An inspection score of 13 or lower leads to an "A" grade. A final inspection score of 14-27 leads to a "B" grade and restaurants can post “Grade Pending” until adjudication. A final inspection score of more than 27 leads to a "C" grade and restaurants can post “Grade Pending” until adjudication. Continuously Operating Restaurants are open for every quarter of the sample period.

Table 3. Regression results, restaurant closure, RD Estimate

	Out of Business Within A Year			
	(1)	(2)	(3)	(4)
A	-0.042*** (0.002)	-0.026*** (0.004)	-0.027*** (0.003)	-0.026*** (0.004)
C	0.049*** (0.004)	0.021*** (0.006)	0.016*** (0.006)	0.021*** (0.006)
Inspection Score		0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Constant	0.104*** (0.008)	0.076*** (0.009)	0.115* (0.065)	0.076*** (0.009)
Quarter-Year FE	Y	Y	Y	Y
Rest. Char.	N	N	Y	N
Zip FE	N	N	Y	N
Restaurant FE	N	N	N	Y
# of Inspections	82,977	82,977	82,977	82,977
Restaurants	29,742	29,742	29,742	29,742

LOWER SCORES INDICATE MORE HYGIENIC RESTAURANT CONDITION
Robust standard errors, adjusted for within-restaurant clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Closure=1 if a restaurant is permanently closed within the next four fiscal periods. Columns (2), (3), and (4) include a control for the inspection's score. Column (3) includes restaurant controls for chain restaurants, number of workers, number of seats, and a set of indicator variables for restaurant cuisine, service type, and venue type as well as zip code fixed effects. Restaurant controls are time invariant and are measured in the most recent restaurant inspection. Column (4) includes a restaurant fixed effect and excludes time invariant restaurant and location controls. The reference group is inspections given a "B" grade.

Table 4. Regression results, restaurant closure, Wald RD Estimate

	A - B			C - B		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
A	-0.049*** (0.017)	-0.040*** (0.017)	-0.047*** (0.010)	--	--	--
C	--	--	--	0.042* (0.023)	0.039* (0.024)	0.043*** (0.015)
Constant	0.116*** (0.017)	0.281* (0.165)	0.115* (0.010)	0.114*** (0.006)	-0.223 (0.209)	0.112*** (0.005)
Q-Y FE	Y	Y	Y	Y	Y	Y
Rest. Char.	N	Y	N	N	Y	N
Zip FE	N	Y	N	N	Y	N
# Inspections	7,387	7,387	17,113	2,921	2,921	5,398
Restaurants	6,812	6,812	13,609	2,710	2,710	4,744
Bandwidth	1 points	1 points	2 points	1 points	1 points	2 points

Robust standard errors, adjusted for within-restaurant clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Columns (1), (2), (4), and (5) restrict the sample to inspections 1 point above and 1 point below the grade cutoff. Columns (3) and (6) restrict the sample to inspections 2 points above and 2 points below the grade cutoff. The optimal bandwidth for a local linear RD estimate of an "A" inspection effect, which minimizes MSE as in Imbens and Kalyanaraman (2009), is 1.293 points. The optimal bandwidth for a local linear RD estimate of a "C" inspection effect is 1.939 points. The estimated effects in local linear models are exactly equal to columns (1) and (4), respectively. Columns (2) and (5) include a include restaurant controls for chain restaurants, number of workers, number of seats, and a set of indicator variables for restaurant cuisine, service type, and venue type as well as zip code fixed effects. Restaurant controls are time invariant and are measured in the most recent restaurant inspection. The reference group is inspections given a "B" grade.

Table 5. Regression results, Regression Discontinuity Model, Inspection-Level Fines

	A - B		C - B	
	(1)	**(2)**	**(3)**	**(4)**
A	-518.46*** (34.53)	-553.00*** (18.19)	—	—
C	—	—	-17.40 (53.29)	100.37** (39.01)
Constant	1129.91*** (46.00)	1157.09*** (29.75)	1016.17*** (124.21)	1127.49*** (93.89)
Q-Y FE	Y	Y	Y	Y
Rest. Char.	N	N	N	N
Zip FE	N	N	N	N
# Inspections	7,387	17,113	2,921	5,398
Restaurants	6,812	13,609	2,710	4,744
Bandwidth	1 points	2 points	1 points	2 points

Robust standard errors, adjusted for within-restaurant clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Columns (1) and (3) restrict the sample to inspections 1 point above and 1 point below the grade cutoff. Columns (2) and (4) restrict the sample to inspections 2 points above and 2 points below the grade cutoff. The optimal bandwidth for a local linear RD estimate, which minimizes MSE as in Imbens and Kalyanaraman (2009), is 3.77 for columns (1) and (2) and 10.35 for columns (3) and (4). The estimated effects in local linear models are qualitatively similar (-609.21 and significant for "A"; 22.32 and insignificant for "C"). The reference group is inspections given a "B" grade.

Table 6. Regression results, Difference-in-Differences Model, Level of Sales Post-Grading

VARIABLES	Posted	ITT
A	144.71***	77.61**
	(51.58)	(31.91)
C	-103.77	-122.26***
	(124.06)	(43.83)
Grade Pending:		
B	1.54	--
	(67.38)	
C	-20.00	--
	(84.37)	
Ungraded	45.26	58.65
	(63.43)	(44.87)
Building Class FE	Y	Y
Quarter FE	Y	Y
Group FE	Y	Y
Constant	2,347.31***	2,393.44***
	(449.56)	(448.36)
Observations	9,182	9,182
Groups	1,538	1,538
R-squared	0.98	0.98

Robust standard errors, adjusted for within-group clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Table shows estimated impact of restaurant grades on daily sales. “Posted” shows estimates of the impact of daily average grade for the quarter on sales. “ITT” shows estimates of the impact of grade earned at inspection by the beginning of the quarter on sales. “A” and “C” are share of a group with an "A" or "C" grade, respectively, and, due to the fact that estimates are reported on the means of all variables, are estimates of impacts on a single restaurant. “Grade Pending” are share of group with the option to post either grade pending or the grade indicated in their window. All models control for inspection score, building class, group fixed effects (which controls for time invariant group characteristics such as share serving each cuisine type), and quarter-year fixed effects. The reference group is restaurants posting "B" grades.

Table 7. Regression results, Regression Discontinuity Model, Level of Sales Post-Grading

VARIABLES	Posted	ITT
A	123.33**	82.86**
	(55.06)	(35.77)
C	-113.04	-143.65***
	(126.41)	(53.67)
Grade Pending:		
B	6.40	--
	(67.59)	
C	13.12	--
	(88.38)	
Inspection Score	-0.68	0.80
	(1.47)	(1.44)
Ungraded	61.40	73.34
	(63.60)	(45.31)
Building Class FE	Y	Y
Quarter FE	Y	Y
Group FE	Y	Y
Constant	2,396.65***	2,380.98***
	(449.78)	(449.27)
Observations	9,182	9,182
Groups	1,538	1,538
R-squared	0.98	0.98

Robust standard errors, adjusted for within-group clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Table shows estimated impact of restaurant grades on daily sales. “Posted” shows estimates of the impact of daily average grade for the quarter on sales. “ITT” shows estimates of the impact of grade earned at inspection by the beginning of the quarter on sales. “A” and “C” are share of a group with an "A" or "C" grade, respectively, and, due to the fact that estimates are reported on the means of all variables, are estimates of impacts on a single restaurant. “Grade Pending” are share of group with the option to post either grade pending or the grade indicated in their window. All models control for inspection score, building class, group fixed effects (which controls for time invariant group characteristics such as share serving each cuisine type), and quarter-year fixed effects. The reference group is restaurants posting "B" grades.

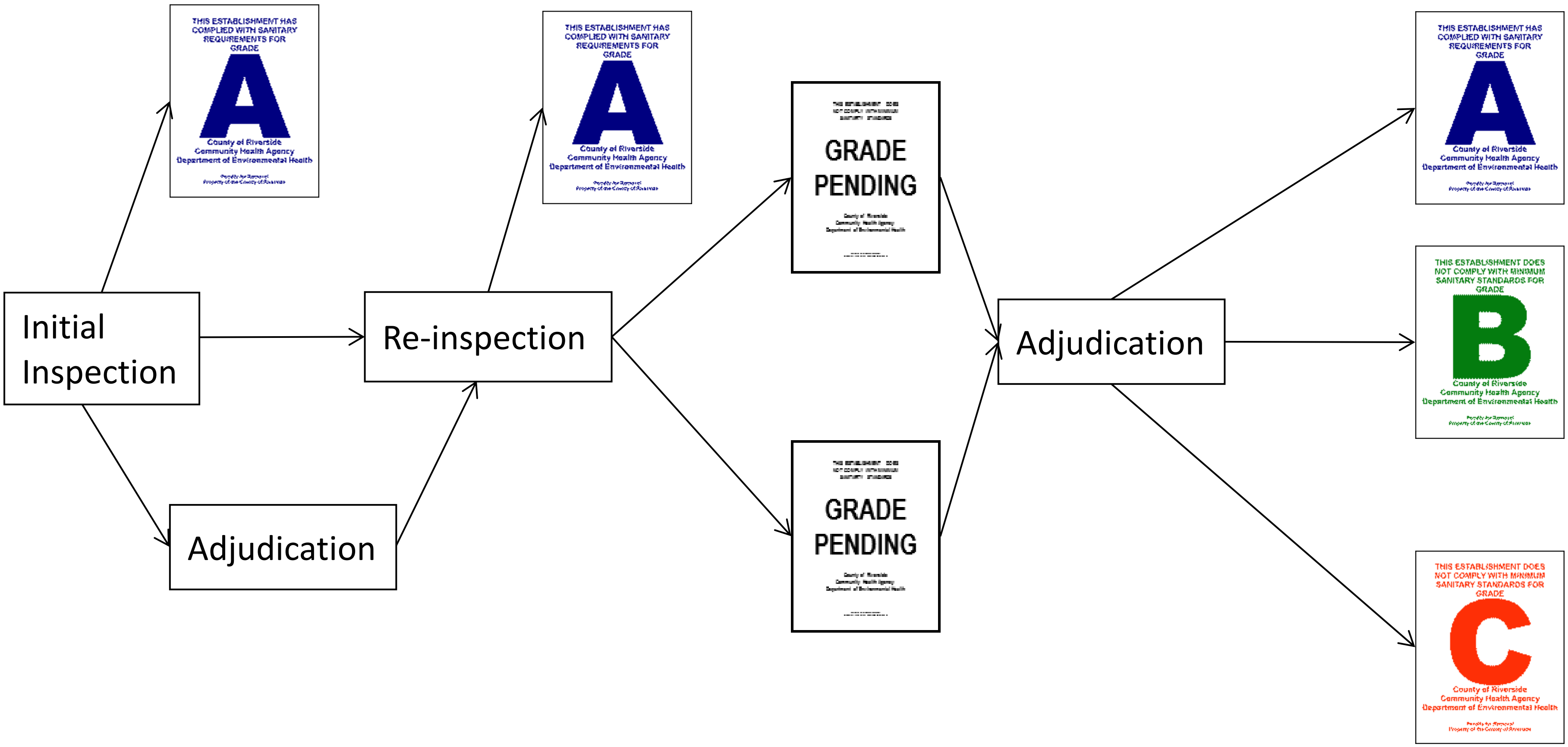
Table 8. Regression results, Regression Discontinuity Model, Sales Taxes Post-Grading

VARIABLES	Posted	ITT
A	5.93**	4.08***
	(2.44)	(1.58)
C	-5.07	-5.97**
	(5.59)	(2.37)
Grade Pending:		
B	0.83	--
	(2.99)	
C	0.41	--
	(3.91)	
Inspection Score	-0.01	0.05
	(0.07)	(0.06)
Ungraded	2.13	2.61
	(2.81)	(2.00)
Building Class FE	Y	Y
Quarter FE	Y	Y
Group FE	Y	Y
Constant	107.84***	107.30***
	(19.89)	(19.88)
Observations	9,182	9,182
Groups	1,538	1,538
R-squared	0.98	0.98

Robust standard errors, adjusted for within-group clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Table shows estimated impact of restaurant grades on daily sales taxes. “Posted” shows estimates of the impact of daily average grade for the quarter on sales taxes. “ITT” shows estimates of the impact of grade earned at inspection by the beginning of the quarter on sales taxes. “A” and “C” are share of a group with an "A" or "C" grade, respectively, and, due to the fact that estimates are reported on the means of all variables, are estimates of impacts on a single restaurant. “Grade Pending” are share of group with the option to post either grade pending or the grade indicated in their window. All models control for inspection score, building class, group fixed effects (which controls for time invariant group characteristics such as share serving each cuisine type), and quarter-year fixed effects. The reference group is restaurants posting "B" grades.

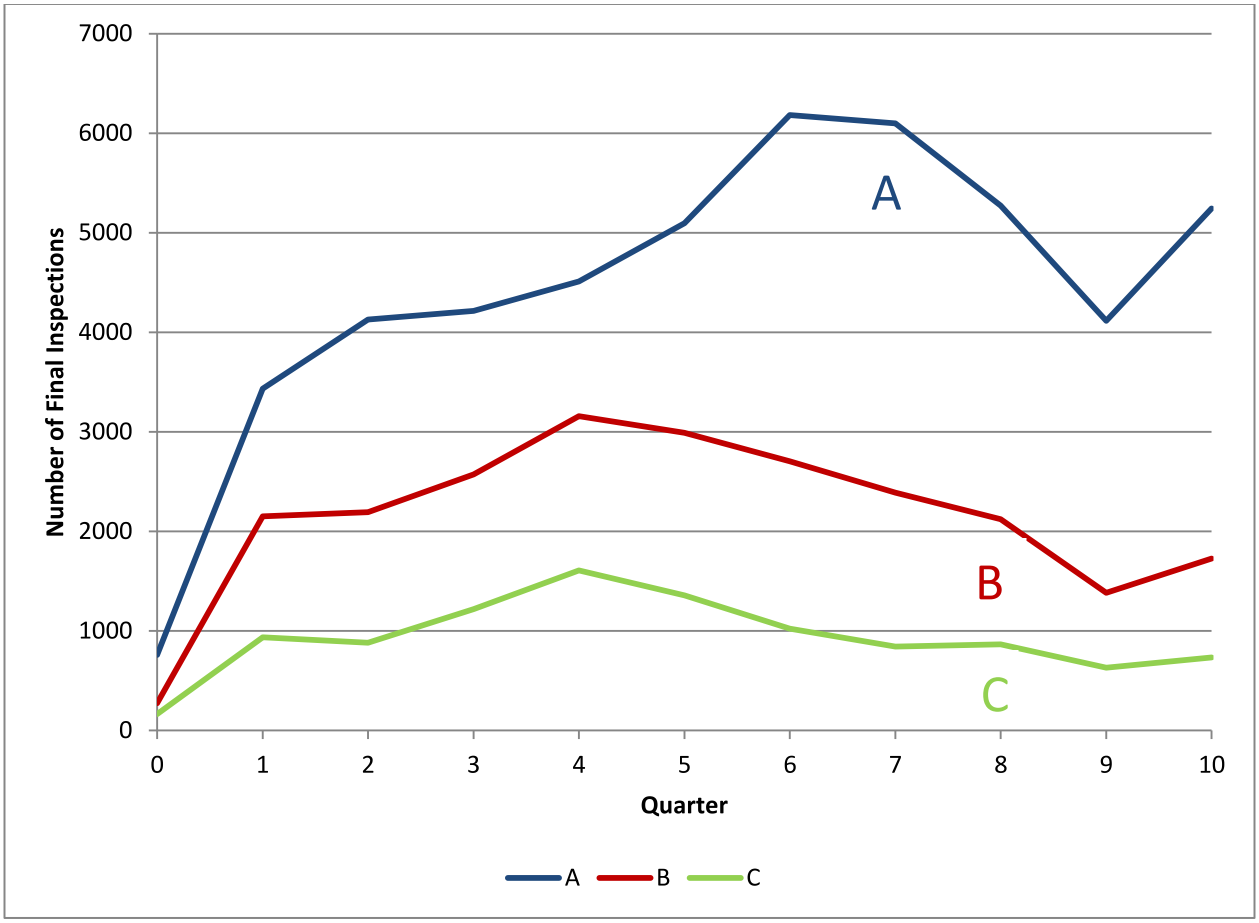
FIGURES

Figure 1. A Simplified Model Of The Inspection Cycle Post-Grading



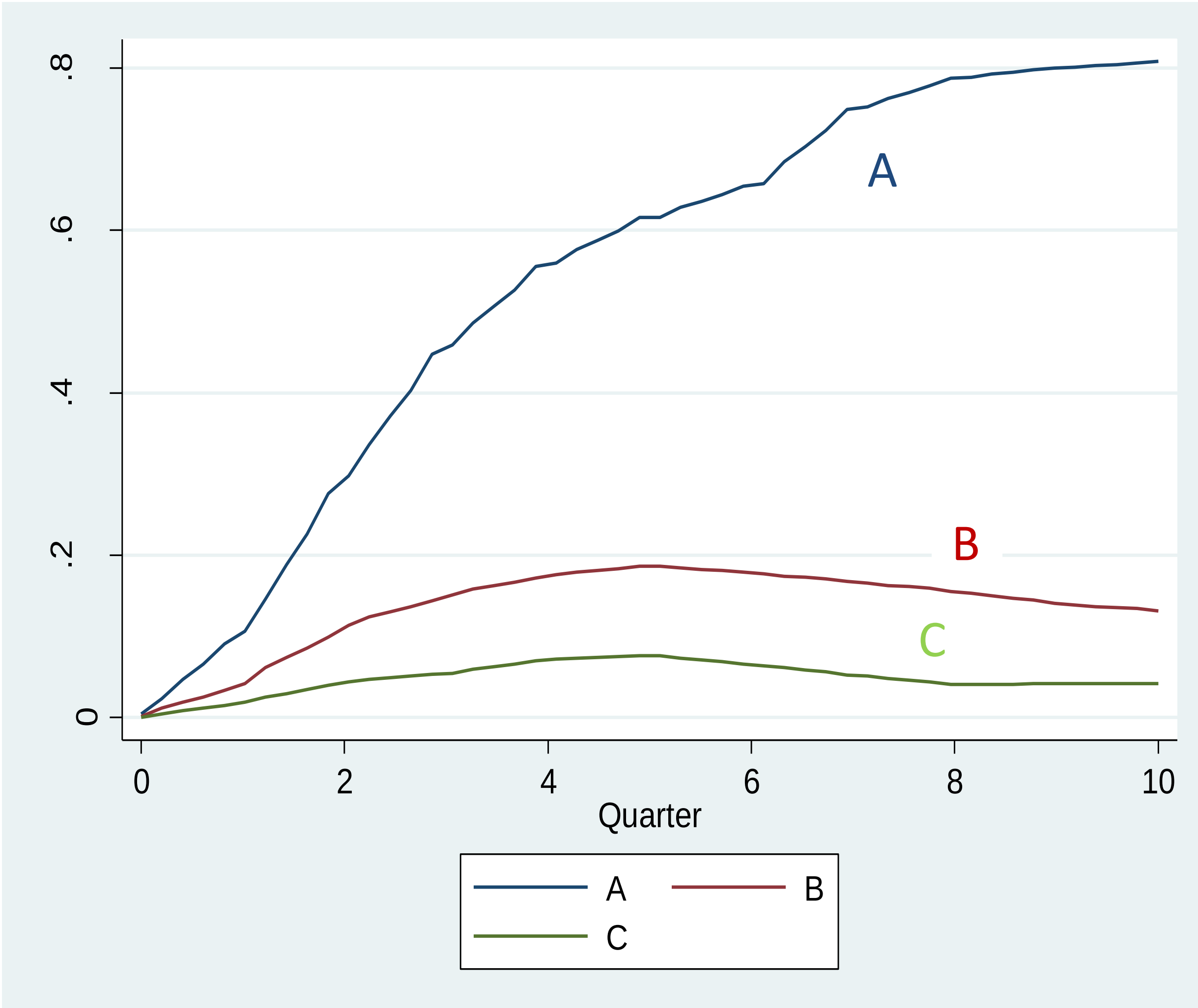
Fines assessed for violations at each inspection that does not lead to an "A" (assessed for "A" inspections for first 6 months of grading)

Figure 2. Inspection Grades Awarded by Quarters Post Public Grading, Intention-to-Treat



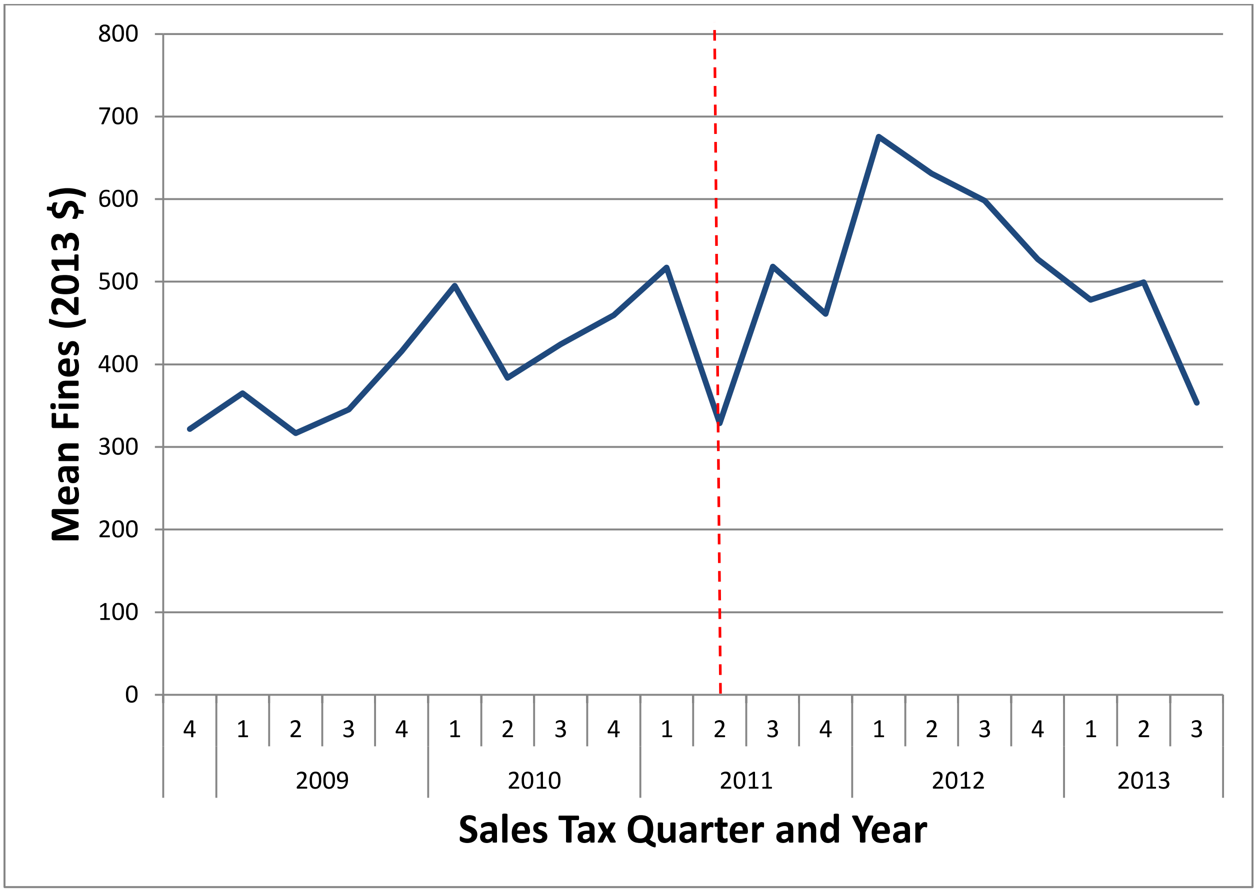
The number of "A" grade inspections increases over the first 10 quarters of the program, with a small dip in the quarter of and following Hurricane Sandy. The number of "B" and "C" grade inspections increases for the first 4 quarters and then begins to decline.

Figure 3. Grades in the Window By Quarters Post Public Grading, Rollout of Treatment



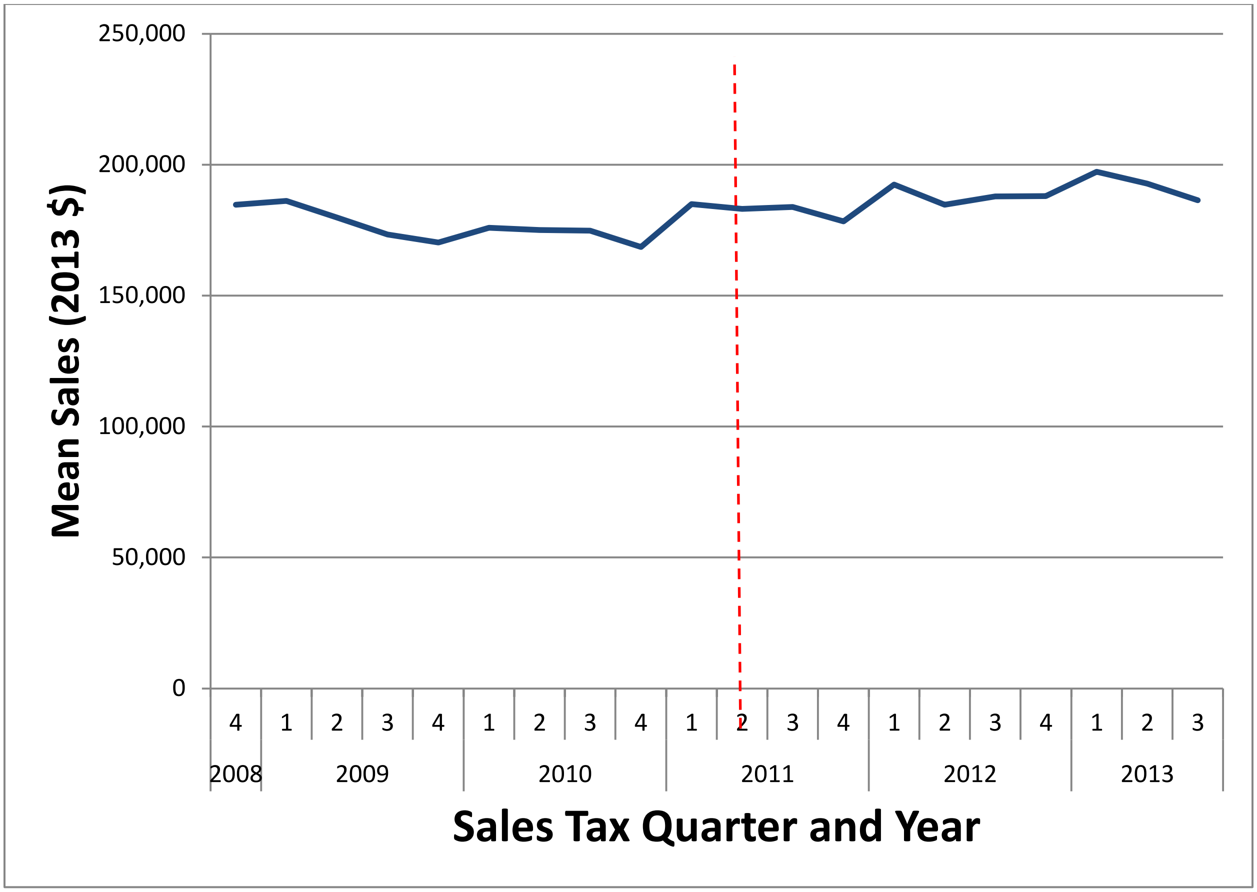
The share of restaurants with "A" grades posted in the window increases over the first 10 quarters of the program and reaches 80% by the end of the sample period. The share of restaurants with "B" and "C" grades posted in the window increases for the first 5 quarters and then begins to decline.

Figure 5. Average Fine by Quarter for Operating Restaurants



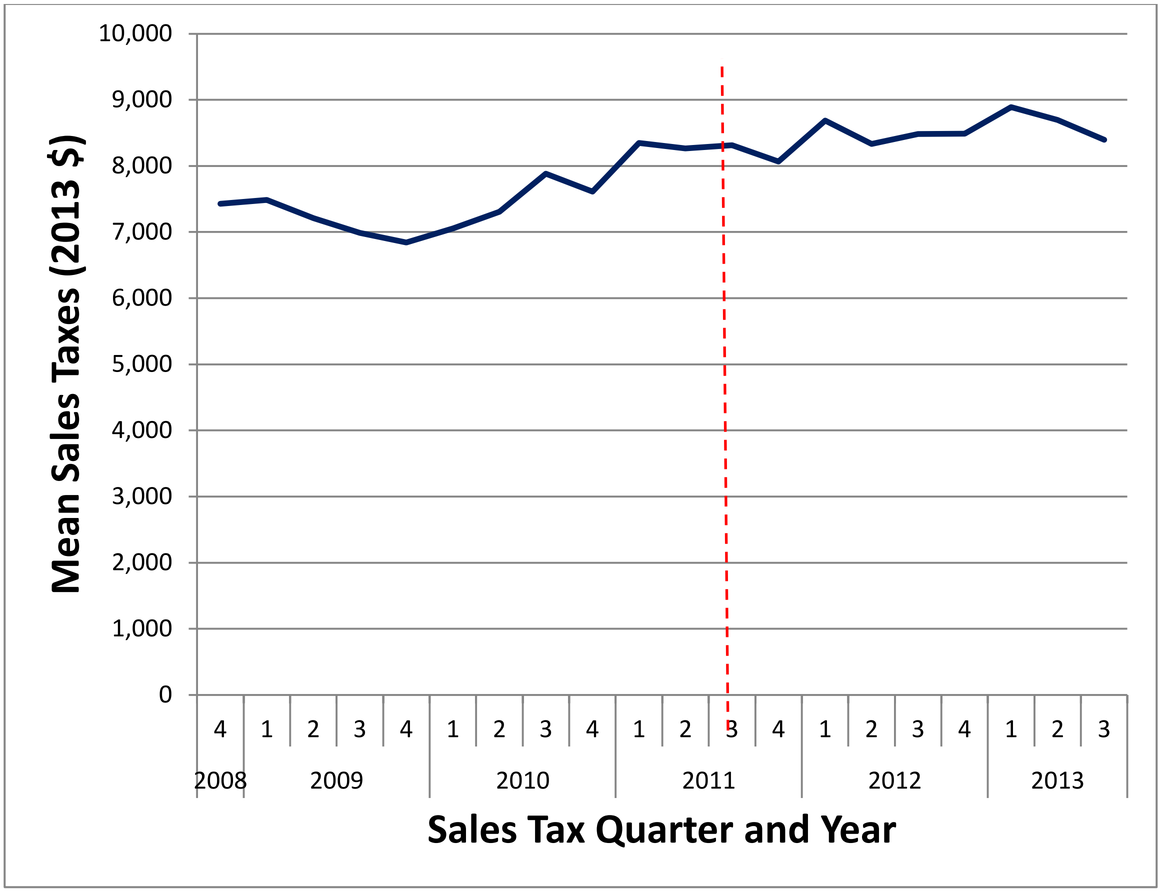
Mean fines by quarter. Average quarterly fines range from about $300 to about $700 over the studied period. Average fines increase substantially in the first year after the restaurant grades law and then steadily decline from there. Average fines levied citywide are at pre-program levels on a quarterly basis starting in the middle of the 2013 sales tax year.

Figure 6. Average Sales, Operating Food And Beverage Entities



Average restaurant sales increase following the implimentation of the public grades program in the second quarter of FY 2011 (July, 2010). Mean sales during this period ranges from about $175,000 a quarter to close to $200,000 a quarter. There is a slight rise in sales after grading that is statistically significant in a regression framework (controlling for restaurant FE and seasnal trends), suggesting that food and beverage entities have gotten a bump in sales following the grading program implementation, but this could be caused by other macro-level trends as well. There are heterogenous impacts across grades that this paper explores.

Figure 7. Average Sales Taxes, Operating Food And Beverage Entities



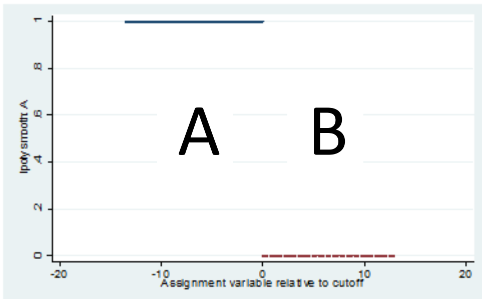
The mean sales tax trend closely mirrors the overall sales trend. Average restaurant sales taxes increase following the implimentation of the public grades program in the second quarter of FY 2011 (July, 2010). Mean sales taxes during this period ranges from about $7,000 a quarter to close to $9,000 a quarter. There is a slight rise in sales taxes after grading that is statistically significant in a regression framework (controlling for restaurant FE and seasnal trends), but this could be caused by other macro-level trends as well. There are heterogenous impacts across grades that this paper explores.

APPENDIX A: Number of Inspections by Quarter

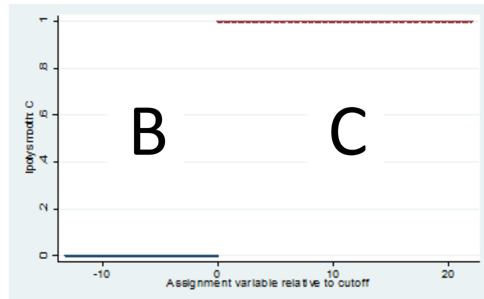
Includes initial and re-inspections. Public grading was introduced at Quarter=0.

APPENDIX B: Local Linear RD Estimates

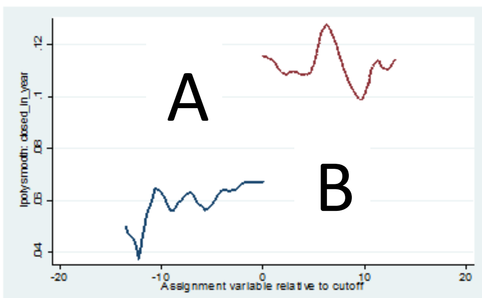
Grade A Discontinuity



Grade C Discontinuity

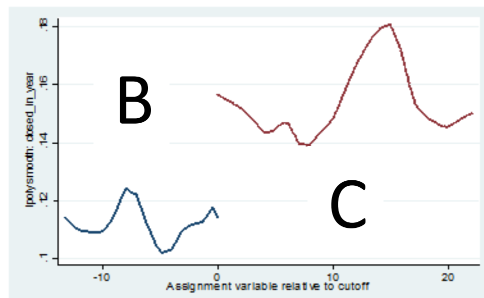


Estimated Effect of A on Closure, RD Optimum Bandwidth



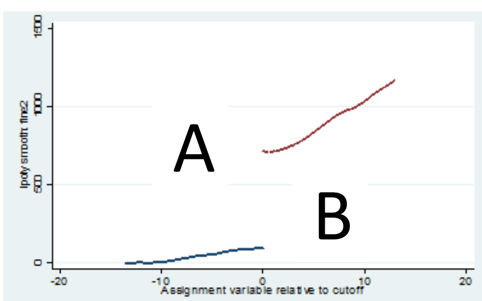
Bandwidth: 1.293, Wald Estimate: -0.0485

Estimated Effect of C on Closures, RD Optimal Bandwidth



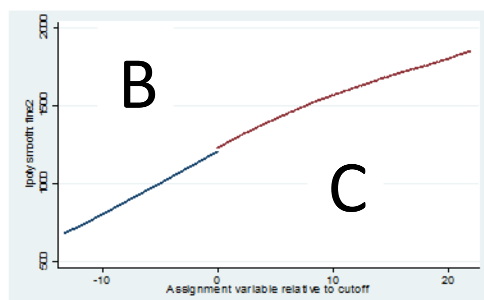
Bandwidth: 1.939, Wald Estimate: 0.0422

Estimated Effect of A on Fines, RD Optimal Bandwidth



Bandwidth: 3.774, Wald Estimate: -609.21

Estimated Effect of C on Fines, RD Optimal Bandwidth



Bandwidth: 10.35, Wald Estimate: 22.32

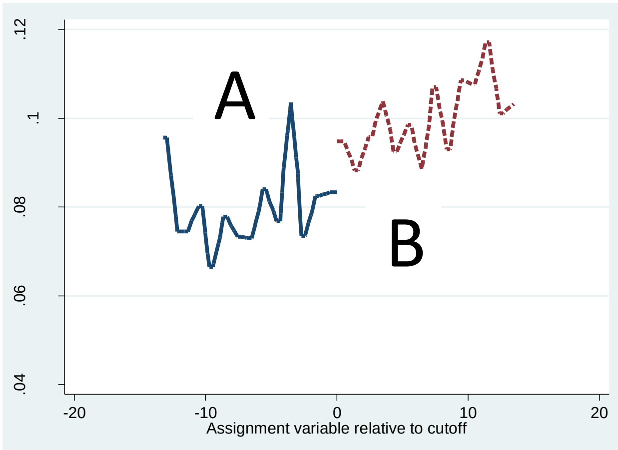
APPENDIX C: Falsification Test, Restaurant Closure, Pre-Period

	A - B			C - B		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
A	-0.012 (0.009)	-0.014* (0.008)	-0.009 (0.006)	--	--	--
C	--	--	--	0.031** (0.015)	0.001 (0.013)	0.030 (0.020)
Constant	0.064*** (0.014)	-0.293*** (0.041)	0.059*** (0.009)	0.066*** (0.0173)	0.753*** (0.029)	0.057*** (0.011)
Q-Y FE	Y	Y	Y	Y	Y	Y
Rest. Char.	N	Y	N	N	Y	N
Zip FE	N	Y	N	N	Y	N
# Inspections	4,436	4,436	9,431	2,745	2,745	5,960
Restaurants	4,156	4,156	8,268	2,626	2,626	5,400
Bandwidth	1 points	1 points	2 points	1 points	1 points	2 points

Robust standard errors, adjusted for within-restaurant clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Columns (1), (2), (4), and (5) restrict the sample to inspections 1 point above and 1 point below the grade cutoff. Columns (3) and (6) restrict the sample to inspections 2 points above and 2 points below the grade cutoff. The optimal bandwidth for a local linear RD estimate of an "A" inspection effect, which minimizes MSE as in Imbens and Kalyanaraman (2009), is 1.510 points. The optimal bandwidth for a local linear RD estimate of a "C" inspection effect is 1.688 points. Columns (2) and (5) include a include restaurant controls for chain restaurants, number of workers, number of seats, and a set of indicator variables for restaurant cuisine, service type, and venue type as well as zip code fixed effects. Restaurant controls are time invariant and are measured in the most recent restaurant inspection. The reference group is inspections given a "B" grade.

APPENDIX D: Falsification Test, Restaurant Closure, Local-Linear RD Pre-Period Graphs

Estimated Effect of Imputed A In Pre-Period on Closure, RD Optimum Bandwidth

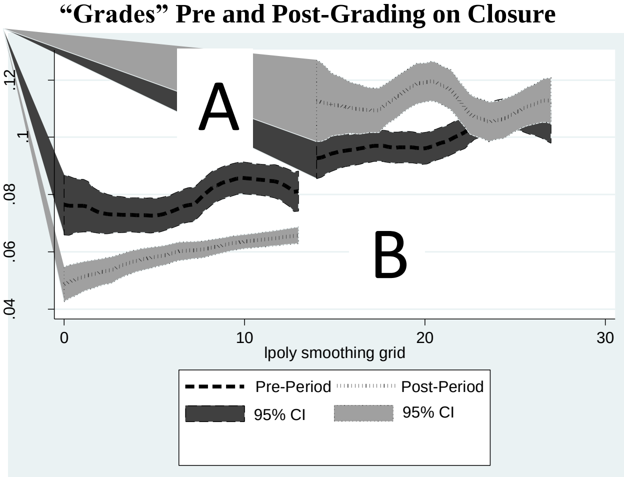


Bandwidth: 1.510; Wald Estimate: -0.0144

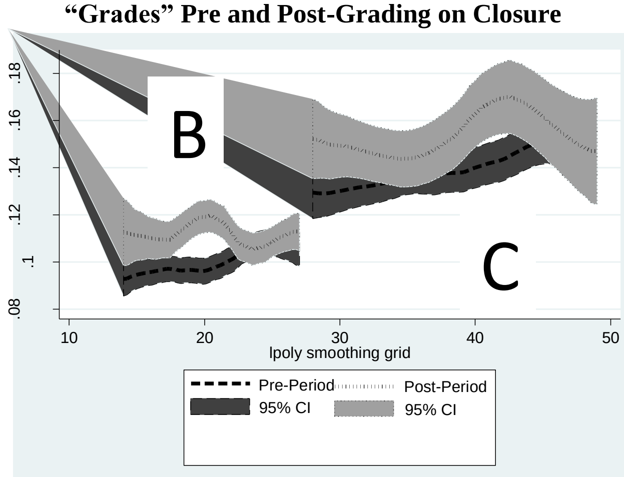
Estimated Effect of Imputed C In Pre-Period on Closure, RD Optimum Bandwidth

Bandwidth: 1.688; Wald Estimate: 0.0332

Local Polynomial Estimates of the Effect Of "A" "Grades" Pre and Post-Grading on Closure



Local Polynomial Estimates of the Effect of "C" "Grades" Pre and Post-Grading on Closure



APPENDIX E. Regression results, Difference-in-Differences Model, Level of Sales Post-Grading

	Posted			ITT		
Measurement Time:	Beginning	End	Daily Average	Beginning	End	Daily Average
A	115.56**	111.12**	144.71***	77.61**	24.50	48.18
	(49.42)	(47.16)	(51.58)	(31.91)	(31.63)	(35.48)
C	-147.05	-105.88	-103.77	-122.26***	-47.08	-117.77**
	(118.27)	(112.59)	(124.06)	(43.83)	(42.95)	(53.06)
Grade Pending:						
B	-70.57	79.08	1.54	--	--	--
	(56.97)	(54.95)	(67.38)			
C	-76.42	44.20	-20.00	--	--	--
	(70.20)	(68.38)	(84.37)			
Ungraded	52.49	0.62	45.26	58.65	-74.96	18.55
	(56.91)	(57.58)	(63.43)	(44.87)	(51.23)	(51.38)
Building Class FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Group FE	Y	Y	Y	Y	Y	Y
Constant	2,373.86***	2,383.63***	2,347.31***	2,393.44***	2,452.30***	2,422.82***
	(449.30)	(449.23)	(449.56)	(448.36)	(448.40)	(448.91)
Observations	9,182	9,182	9,182	9,182	9,182	9,182
Groups	1,538	1,538	1,538	1,538	1,538	1,538
R-squared	0.98	0.98	0.98	0.98	0.98	0.98

Robust standard errors, adjusted for within-group clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Table shows estimated impact of restaurant grades on sales. “Posted” shows estimates of the impact of grade on sales where grade is measured at the beginning, end, or averaged over the quarter where indicated. “ITT” shows estimates of the impact of grade earned at inspection on sales, where grade is measured at the beginning, end, or averaged over the quarter where indicated. “A” and “C” are share of a group with an "A" or "C" grade, respectively, and, due to the fact that estimates are reported on the means of all variables, are estimates of impacts on a single restaurant. “Grade Pending” are share of group with the option to post either grade pending or the grade indicated in their window. All models control for building class, group fixed effects (which controls for time invariant group characteristics such as share serving each cuisine type), and quarter-year fixed effects. The reference group is restaurants posting "B" grades.

APPENDIX F. Regression results, Regression Discontinuity Model, Level of Sales Post-Grading

	Posted			**ITT**		
Measurement Time:	Beginning	End	Daily Average	Beginning	End	Daily Average
A	106.01**	80.16	123.33**	82.86**	7.61	33.21
	(51.88)	(49.73)	(55.06)	(35.77)	(35.97)	(39.61)
C	-137.16	-83.74	-113.04	-143.65***	-21.09	-104.68
	(119.86)	(113.55)	(126.41)	(53.67)	(54.22)	(64.33)
Grade Pending:						
B	-69.52	73.96	6.40	--	--	--
	(57.30)	(54.89)	(67.59)			
C	-64.05	62.07	13.12	--	--	--
	(72.14)	(70.13)	(88.38)			
Inspection Score	-0.70	-0.75	-0.68	0.80	-1.06	-0.66
	(1.17)	(1.25)	(1.47)	(1.44)	(1.59)	(1.69)
Ungraded	70.01	26.49	61.40	73.34	-57.36	24.76
	(57.29)	(57.26)	(63.60)	(45.31)	(50.79)	(51.20)
Building Class FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Group FE	Y	Y	Y	Y	Y	Y
Constant	2,397.90***	2,469.73***	2,396.65***	2,380.98***	2,540.30***	2,471.45***
	(450.09)	(447.04)	(449.78)	(449.27)	(446.62)	(449.11)
Observations	9,182	9,182	9,182	9,182	9,182	9,182
Groups	1,538	1,538	1,538	1,538	1,538	1,538
R-squared	0.98	0.98	0.98	0.98	0.98	0.98

Robust standard errors, adjusted for within-group clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Table shows estimated impact of restaurant grades on sales. “Posted” shows estimates of the impact of grade on sales where grade is measured at the beginning, end, or averaged over the quarter where indicated. “ITT” shows estimates of the impact of grade earned at inspection on sales, where grade is measured at the beginning, end, or averaged over the quarter where indicated. “A” and “C” are share of a group with an "A" or "C" grade, respectively, and, due to the fact that estimates are reported on the means of all variables, are estimates of impacts on a single restaurant. “Grade Pending” are share of group with the option to post either grade pending or the grade indicated in their window. All models control for inspection score, building class, group fixed effects (which controls for time invariant group characteristics such as share serving each cuisine type), and quarter-year fixed effects. The reference group is restaurants posting "B" grades.

APPENDIX G. Regression results, Regression Discontinuity Model, Sales Taxes Post-Grading

	Posted			ITT		
Measurement Time:	Beginning	End	Daily Average	Beginning	End	Daily Average
A	4.47*	4.00*	5.93**	4.08***	0.48	1.97
	(2.30)	(2.20)	(2.44)	(1.58)	(1.59)	(1.75)
C	-5.13	-3.39	-5.07	-5.97**	-0.83	-4.23
	(5.30)	(5.02)	(5.59)	(2.37)	(2.40)	(2.85)
Grade Pending:						
B	-3.37	3.42	0.83	--	--	--
	(2.54)	(2.43)	(2.99)			
C	-2.99	3.04	0.41	--	--	--
	(3.19)	(3.10)	(3.91)			
Inspection Score	-0.02	-0.02	-0.01	0.05	-0.04	-0.01
	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)
Ungraded	1.86	1.13	2.13	2.61	-3.08	0.52
	(2.53)	(2.53)	(2.81)	(2.00)	(2.25)	(2.26)
Building Class FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Group FE	Y	Y	Y	Y	Y	Y
Constant	108.45***	111.14***	107.84***	107.30***	114.66***	111.27***
	(19.91)	(19.77)	(19.89)	(19.88)	(19.76)	(19.86)
Observations	9,182	9,182	9,182	9,182	9,182	9,182
Groups	1,538	1,538	1,538	1,538	1,538	1,538
R-squared	0.98	0.98	0.98	0.98	0.98	0.98

Robust standard errors, adjusted for within-group clusters, in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Table shows estimated impact of restaurant grades on sales taxes. “Posted” shows estimates of the impact of grade on sales taxes where grade is measured at the beginning, end, or averaged over the quarter where indicated. “ITT” shows estimates of the impact of grade earned at inspection on sales taxes, where grade is measured at the beginning, end, or averaged over the quarter where indicated. “A” and “C” are share of a group with an "A" or "C" grade, respectively, and, due to the fact that estimates are reported on the means of all variables, are estimates of impacts on a single restaurant. “Grade Pending” are share of group with the option to post either grade pending or the grade indicated in their window. All models control for inspection score, building class, group fixed effects (which controls for time invariant group characteristics such as share serving each cuisine type), and quarter-year fixed effects. The reference group is restaurants posting "B" grades.