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Variation in Restaurant Sanitary Scores in New York City

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By

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Abstract

Recent efforts have been made to understand how regional differences affect sanitary incentives. A substantial body of literature exists that examines the effects of neighborhoods on several different and important outcomes. What has been overlooked is whether a neighborhood that a restaurant is located in affects the incentives the restaurant has to remain hygienic. The purpose of this study was to determine whether restaurants that are homogenous in nature would exhibit substantially different hygiene scores based on the underlying consumer learning behaviors present in the neighborhoods in which the restaurants are located. This study removed the supply side incentives involved with the provision of hygiene to isolate the differences as a product of neighborhood variations in consumer learning behaviors. Based on inspection results data from all restaurants in the five boroughs of New York City between February 2005 and August 2009, I employed OLS and logit regressions as well as hierarchical linear modeling (HLM) to test for regional variation of restaurant hygiene incentives of like-kind restaurants, without an attempt to show causality. The results of OLS, logit, and mixed effects regressions showed statistically significant results and indicated that the neighborhood a restaurant is located in affects its sanitary incentives.

Variation in Restaurant Sanitary Scores in New York City

It is widely accepted that the presence of poor sanitary conditions in eating establishments can contribute negatively to the health of patrons of those establishments. As such, the hygiene of restaurants in the United States is highly regulated. One might expect that hygiene in varying "class" of restaurant can be reasonably assumed, but even restaurants that are homogenous in nature do not necessarily exhibit uniform sanitary conditions. While variations in sanitary conditions between restaurants may exist for a variety of reasons, I posit that hygiene scores are influenced by the neighborhoods in which the restaurants are located.

This study is a response to, and built upon, a thesis by Ginger Zhe Jin and Phillip Leslie (Jin & Leslie, 2003; Jin & Leslie, 2009), who posited that consumer-learning capacity varies by region and, as such, affects the level of hygiene that is demanded and subsequently provided. Their position will be investigated further, later in this paper. The purpose of this study is to determine whether the sanitary conditions of like-kind restaurants are affected by the neighborhood in which they are located. In addition, the study focused on differences to the current discourse and to previous works. It emphasized examining like-kind restaurants and focused on specific and tangible geographic barriers as parameters for defining a region. It also employed Hierarchical Linear Modeling (HLM) as the cornerstone when interpreting variance.

I predict that the neighborhood a restaurant is located in plays a role in consumer learning as shown by varying demand for hygiene in common eating establishments. In order to pursue the hypothesis, I evaluated a cross section of quick service and fast food restaurant hygiene scores from 2005 to 2009. This data will serve to shed light on variations outside of presumed obvious supply side differentiation.

Theoretical Background and Hypothesis Development

Neighborhood Effects on Sanitary Conditions of Restaurants

I reviewed two bodies of literature for this study. The first body was written by Ginger Zhe Jin and Phillip Leslie and examines restaurants' behavior and the incentives they have to maintain certain levels of hygiene. It specifically explores the efficacy of prominently displayed grade cards on the hygiene of restaurants in Los Angeles County, and the regional variation in hygiene provided across restaurant. (Jin & Leslie, 2003; Jin & Leslie, 2009).

The second body of literature is more substantial and studies the effects of neighborhoods on several different and important outcomes. It argues that neighborhoods affect many forms of learning (Ellen, Mijanovich, & Dillman, 2001; Garner & Raudenbush, 1991; Pace, Barry, Clapp, & Rodriquez, 1998; Zenk et al., 2005). Whether addressing questions of learned dietary habit, learned behavioral norms, or outright traditional education learning standards, these authors have cited the neighborhood as a determining factor in many contexts.

Literature Review

Food establishments. As Jin and Leslie (2003) note, a useful frame of reference in understanding a restaurant's incentive, or lack thereof, to provide hygiene can be found in Akerlof's (1970) study on the market for "lemons". Similar to the difficulty consumers face when purchasing goods they do not entirely understand; it is equally, if not more, difficult to determine the cleanliness of a restaurant.

Beyond easily perceivable deficiencies, a restaurant's choice of hygiene that is based on profit maximization does not necessarily account for social costs and benefits. For example, a restaurant may decide to keep a lower level of hygiene in order to maximize profits via low costs. As a result, the restaurant's food may sicken its customers, who bear the costs of consuming contaminated food. Ensuring highly hygienic conditions may raise both hard and soft private costs for the restaurants substantially. Therefore, restaurants may neglect hygiene in order to maximize profits, as long as the changes are either not perceived or are deemed unimportant to the consumer.

Jin and Leslie's (2003) study was the first to discuss the incentives restaurants have to maintain hygienic standards. Their study analyzes inspection score data from Los Angeles County from July 1995 to December 1998. In an attempt to reduce supply side variance, the authors select a sample of restaurants that, while still representative of the data pool in its entirety, more accurately allows for the demonstration of changes in the variable of interest. The authors look at the effect of mandating restaurants in 1997 (made effective in 1998) to prominently display hygiene quality grade cards in their windows.

Using the law as an exogenous change, they structure a natural experiment using 1996 and 1997 as the period before the law. They use the change in restaurant inspection grade as their outcome of interest. They find that the resulting increase in information symmetry increased inspection scores, revenues, and public health. The increase in information available to consumers, via prominently displayed hygiene quality grade cards, proved that there are quantifiable incentives to providing cleanliness.

Restaurant reputation. In a subsequent paper, using the same data, Jin and Leslie (2009) discuss variations in incentives prior to the issuance of grade cards and the consequential increase in incentives across the sample. They contend that restaurants have varying incentives to provide hygiene based on consumer learning. To demonstrate their point, Jin and Leslie offer three related hypotheses. Firstly, they posit that franchised units using their chain affiliations tend to free-ride on the cleanliness of their company owned counterparts. To demonstrate this, the authors used all of the samples from the selected data from their 2003 study; data that was obtained before the grade cards were introduced. They then ran an ordinary least squares (OLS) regression using the hygiene scores to determine the effect of four major variables; whether the restaurant belongs to a chain, whether the restaurant is a franchised unit, the number of restaurants that belong to the same chain in Los Angeles, and the fraction of US chain units located in Los Angeles. They concluded that while chain affiliation significantly increases scores, franchisees have significantly lower hygiene scores. The implication is that franchisees rely on the positive perception of the brand allowing them to neglect their individual cleanliness responsibilities.

Secondly, they posit that restaurants with repeat business have a greater incentive to leave a good impression, and thus are more likely to remediate hygienic issues. Alternatively, restaurants with no expectation of, or necessity for, repeat business infer that no consumer learning takes place and therefore do not have the same incentive to maintain hygiene. While cognizant of the fact that neighborhoods are not easily definable in Los Angeles, the authors consider at least two proxies for geographic region or 'neighborhood'. One proxy is the distance that a restaurant is located from the freeway. Since the study was based in Los Angeles, the authors conclude that distance to freeway exit is not an adequate measure of repeat customers, largely because the freeway covers most of the city. A second proxy, as a substitute for defining variation based on geographic region, is the differentiation of 'tourist regions'. The authors utilize employment patterns in fields they believe indicate a lack of repeat business. They first test the effect of high incidence of hotel employment and then of high incidence of recreation employment. They follow by investigating proportional presence of chain restaurant locations. The authors run an OLS regression on a cross-section of the reporting Los Angeles restaurants, in which the dependent variable is pre-grade card hygiene score. The authors predict that each of the two employment markers implies low repeat business and therefore that the coefficient should be negative. They find, however, that the presence of hotel employees has a positive (and significant) effect. The presence of the recreational employees, however, has a negative (and significant) effect. The authors further predict that hygiene scores in areas in which at least 15 percent of restaurants present are chain restaurants should be negatively effected. In such cases, however, the coefficient is positive (and significant). The authors find more than mixed results; they find significance in the data contradicts their thesis. They therefore conclude that it is necessary to include the exogenous change of scorecard introduction in order to demonstrate conclusive variation.

Finally, while this facet of the study goes beyond the premise of relevant critique, the authors contend that if learning were the same from region to region, then each region's restaurants would have the same incentive to offer hygiene. The authors contend that once hygiene is fully observable, the dependent variable, hygiene scores, would have changed in a calculably consistent (affine) way across regions. Their results largely affirm their hypothesis that regional learning exists.

That said, while they seem to have presented a plausible scenario to affirm differences in regional incentives without exogenous change, their results do not show significant differences. One potential reason for this is that the choice of the city of interest did not enable them to find neighborhood effects. Los Angeles' disparate and expansive nature makes for a poor backdrop to define region and measure neighborhood differentiation. In Los Angeles, a zip code may either contain several neighborhoods or a neighborhood may be comprised of more than a single zip code. In addition, the authors made some broad generalizations when defining proxies for consumer learning. I contend that the measures they employed ultimately did not reflect consumer learning appropriately. I would argue that using a different city, specifically New York, might be more adequate in studying neighborhood effects. New York provides a more pedestrian-friendly element that largely removes travel barriers and as a result, it is more conceivable that a customer would more readily and regularly patronize a restaurant in a different zip code in New York than in Los Angeles. For this reason, New York City may provide a more precise picture of consumer learning.

Another potential inadequacy of the study is the authors' choice of model; OLS may have been insufficient for the task at hand. When analyzing data without the exogenous change, and subsequent creation of an unbiased control group, it is difficult to assign a specific subsample as the control. As such, a multi-level structure for interpreting the data may be best suited to this study. Similarly to how Garner and Raudenbush (1991) examined how students are grouped into classrooms and subsequently school districts, restaurants first exist in their immediate neighborhood, then in their borough, then in the metropolitan area at large.

In summation, Jin and Leslie (2009) assert that neighborhoods are a major factor in consumer learning behavior. They acknowledge and then demonstrate, however, the difficulty of defining those neighborhoods within the context of Los Angeles County. The introduction of the exogenous change is therefore necessary for them to demonstrate their point. It is my contention that New York City may serve as a superior location to further their point, without that exogenous change.

Effects of neighborhoods. There are several papers examining the effect of neighborhoods on various outcomes other than restaurant patronage. Much of the literature across outcomes indicates the neighborhood as a shaping variable. Similar to Jin and Leslie's (2009) employment of grade card implementation, Kling et al. (2005) provide evidence of neighborhood effects on crime using the 1992 Moving to Opportunity (MTO) program as an experimental design. Their results show that those housing voucher participants who took part in the program and relocated to a lower-poverty area reduced their probability of committing crimes. These results reinforce the idea that behavior and learning can differ by region. Voucher recipients who moved from high poverty to low poverty areas adapted their behavior and experienced social learning and were therefore less likely to commit felonies. The authors note that the effect of the program varied by gender; relocation reduced crime rates for female youth but produced mixed results for male youth. Even with the existence of varying results by gender, the study provides evidence that neighborhoods yield different effects on behavior and learning.

In the field of Urban Economics, Pace et al. (1998) provide another demonstration of the neighborhood as a contributing factor in the variation of an independent variable. They use 'geocoding', or spatiotemporal autoregressive models, to show neighborhood effects on housing prices. Geocoding allows researchers to accurately pinpoint the distance between a neighborhood of interest and a resource and, perhaps more pertinent to urban living, the exact number of locations to obtain that resource in a given neighborhood. The goal of their study is to estimate the effect of both spatial and temporal information on real estate prices while confronting the issue of having many indicator variables. Housing price data from Fairfax County, Virginia from 1969 to 1991 was studied with the results showing that the log of sales price of any house is strongly affected by the sales prices of previously sold houses in the neighborhood. In fact, the authors explain that in the specific context of Fairfax County, about 80% of the temporal difference in log sales prices comes from the nearest fifteen neighbors to a designated house. The fact that such a high percentage of the variation in price is attributed to the spatial or proximity (neighborhood) effects demonstrates the importance of this variable in comparison to other possible contributing factors. The price of the house depends greatly on the value of the neighboring houses.

Some critiques of group level analysis assert that outcome effects from grouping are instead the result of poorly defined individual-level modeling. Partly in response to this critique, a body of literature has developed in the field of sociology using Hierarchical Linear Modeling to examine the effects of the neighborhood. HLM is a method accounting for variations in individual level inputs and group level inputs simultaneously. Studies employing this approach, which will be described in greater detail shortly, are often used when discussing academic achievement (Garner & Raudenbush, 1991), and are able to determine the effects of school and district wide phenomena without discounting individual student or household factors that exist.

Garner and Raudenbush (1991) utilize data from several sources to look at the effect of neighborhoods on academic achievement. They employ HLM to fit several multilevel models. In doing so, they use two different types of equations that are estimated simultaneously; within-unit and between-unit. The within-unit equation, at the individual level, is an OLS regression that places educational outcome as the dependent variable and demographic information as independent variables. The between-unit equation focuses on the variances at the neighborhood level.

The authors explain that employing HLM allows for the explanation of a substantial proportion of the variation in educational outcomes. They contend that neighborhood effects can be illustrated in three different ways. Firstly, neighborhoods can affect the development of a child's personality, which affects his or her educational attainment. Secondly, a neighborhood can affect the quality and frequency of interactions between children, thus affecting their cognitive development. Thirdly, living in a poor neighborhood can result in adverse outcomes for the health of a child and may, for example, prevent him or her from attending school. As a result, the neighborhood has an important effect on education attainment. This effect is in addition to individual and family socioeconomic status. Based on the aforementioned theoretical insights, the following hypothesis was developed:

H1: Restaurants that are homogenous in nature will exhibit substantially different hygiene scores based on the underlying consumer learning behaviors present in the neighborhoods in which the restaurants are located.

Data and Methods

The main data used for this study comes from the New York City Department of Health and Mental Hygiene (DOHMH). It contains inspection results from all restaurants in the borough of Manhattan between February 2, 2005 and August 25, 2009. Restaurants receive anywhere from one to greater than five visits annually from the DOHMH. Each visit results in a unique score, which is the sum of point values associated with each individual violation of the health code. Each violation has a base point value that is then added to depending on the severity of the violation. The ideal score for a restaurant is zero. Each additional tally indicates a failure to comply with a health code standard. Standards cover many areas from hand washing, evidence of rodents and/or insects, and food temperature controls to legal documentation of fire safety and facility design, for example.

The severity of violations range from Condition Level I to Condition Level V, where Condition Level I is the least critical. An example would be violation 11D; a signage violation. For this category, only a minor violation exists (Condition Level I). Alternatively, violations related to contamination of food pose a public health hazard and are treated as the most severe violations. For example, violation 4E – Toxic chemical improperly labeled, stored or used so that food contamination may occur – is a violation that may result in a 7 (Condition Level I) to 28 (Condition Level V) point score added to a restaurant's tally. For a single incident in any given inspection, the restaurant would receive a 7 point score. For two incidences a restaurant would receive 8 points. For five incidences in any given inspection a restaurant would receive 28 points. In the event that a restaurant accumulates more than 28 total points in a single visit, the restaurant fails the inspection and will receive a subsequent visit within 30 days. If the restaurant does not pass the inspection on this subsequent visit, the inspector has the authority to immediately close the establishment.

In addition to the inspection scores, data was gathered from the United States Decennial Census. This study chose to explore nine metrics all at the a zip code level; population, median age, median income, percentage of the population that is white, number of families, number of housing units, average household size, median rent, and the percent of housing units that are owner occupied.

The main contribution of this study comes from a more precise definition of 'region', and the exploration of HLM as a tool to further understand variation at the regional level, or group effects. As noted earlier, Jin and Leslie (2009) present a compelling argument that regional differences can explain why restaurants may have different hygiene standards. The use of New York minimizes the effect of urban sprawl on results and allows use of actual geographic region in place of proxies, as were used in Gin and Leslie (2009). The extensive literature on neighborhoods (previously reviewed) reinforces the plausibility of neighborhood effects.

In this study, I analyze neighborhoods as zip code, and, as such, use the two terms interchangeably throughout. In order to isolate the effect of the neighborhood, data is limited to restaurants geared towards quick service or short order food; the purpose of which, ideally, is to eliminate some of the variation stemming from the size or cache of restaurants that may be less prevalent in some neighborhoods. Therefore, the difference between two pizza restaurants in two different neighborhoods can ideally only be attributed to the intrinsic neighborhood quality in which they are located, rather than the echelon and price points of food being offered. For the purposes of this study, incomplete or mislabeled results were dropped and only observations from zip codes with at least 10 restaurants were kept.

The data contains 89,360 unique inspection results from 2005 to 2009 from 19,180 restaurants across the five boroughs. As seen in *Figure* 1 and Table 1, the data show scores that range from 0 to 252. The scores are significantly skewed right with a skewness over 1.9 and are severely peaked with a kurtosis of over 9.8. The mean is approximately 18.4. As would be expected with such a skew and range, the sd of score is approximately 16. The median and mode are smaller both at 15. Further, 18.4% percent of inspections resulted in failure.

The study was restricted to quick service restaurants in an endeavor to remove obvious price and reputational variation across star rating of restaurants in various publications (Zagat, Michelin, Yelp, etc.) for the purpose of treating restaurants homogenously regardless of their location. Plainly, the study is designed to view a pizza restaurant in neighborhood A as largely the same as a pizza restaurant in neighborhood B with the exception of inherent neighborhood learning.

Accounting for that restriction, *Figure* 2 and Table 2 show that 31,758 scores from 5,245 restaurants in 168 zip codes are left with a mean score of approximately 17.5 and standard deviation of approximately 15.5. The data is again highly skewed right and peaked with a skewness of 1.9 and kurtosis of 10. The median and mode remain smaller than the mean but have both fallen to 14. The percent of inspections that resulted in failure fell notably to 16.6%. Considering that the type of restaurant is restricted to quick service, which are generally perceived as 'less than', the lower rate of failure is somewhat counter intuitive, but in line with Jin and Leslie's (2009) findings.

In addition, the study found that more than half of all of these the inspections resulted in a score of less than 14, as seen in *Figure* 3. Though I did not explore causality directly, I believe the low average is due to a restaurants necessity to maintain a standard higher than that of easily perceivable cleanliness in order to carry on normal business.

As discussed earlier in the literature review, there is some concern that group effects could simply be misinterpreted individual effects. This study endeavours to review some of those underlying factors using HLM, and, as such, summary information regarding those demographic variables is shown on Table 3 for reference.

Results and Discussion

As a preliminary investigation, the study employed a basic comparative interpretation using OLS and logit to compare neighborhood scores and failure rates with a control neighborhood. Simply seeing significant variation from one neighborhood against the control could demonstrate the plausibility of neighborhood variation, and subsequently neighborhood learning. *Table* 1 shows the results of OLS and logit regressions. The study used zip code 10009 in Manhattan as the reference group on both the neighborhood and borough level. The 10009 zip code delimits the area in Lower Manhattan between E Houston St and E 20th St, east of 1st Avenue. Though subjective, this zip code represents a suitable reference group; it is a firmly established, longstanding neighborhood with a diverse population and unremarkable variation in land use that includes a considerable mix of commercial, residential, educational and student population.

The OLS regression used the inspection score as the dependent variable and first borough dummy variable and used zip code indicators as independent variables. Two of the five boroughs showed statistically significant lower (cleaner) scores. The Bronx results were 4.9 points lower at the 99% level and the Staten Island results were 3.3 points lower at the 95% level. Also, 34 of the 168 neighborhoods (approximately 20%) showed statistically significant variation. 10 neighborhoods were significant at 90%, 17 at 95%, and 7 at 99%.

Of the 34 significant coefficients, 30 were negative, and only 4 were positive, meaning that 10009 scored higher (or dirtier) than most of the neighborhoods that differed with significance. The F score for this regression (where at least one of the zip codes variances is of a magnitude greater than 0) is 1.687, which is convincing considering the degrees of freedom.

In the case of the logit regression, the dependent variable is the probability that a restaurant will fail its inspection (scoring higher than 28). The results are consistent with the OLS model. It stands to reason that restaurants in neighborhoods with significantly higher or lower average scores are, in turn, significantly more or less likely to fail their inspection.

Only one of the five boroughs showed a statistically significant lower probability of failure. The Bronx was 57.9 % less likely to fail the 90% level. Also, 32 of the 168 neighborhoods (approximately 19%) showed statistically significant variation. 18 neighborhoods were significant at 90%, 12 at 95%, and 2 at 99%. Of the 32 significant variances, 30 were negative and only 2 were positive, meaning that 10009 skewed higher in probability of failure than most of the neighborhoods that differed with significance. The chi-squared score of this regression (that at least one of the zip codes variance is of a greater magnitude than 0) is 183.3, which is less convincing than the score regression, but still significant given the degrees of freedom.

One potential issue with these results is that using neighborhood dummy variables accounts for all neighborhood differences; both demand and supply side. In order to determine if demand side characteristics affect restaurant inspection scores, the study includes neighborhood demographic characteristics and aims to discover who or what the demand is comprised of and what it looks like.

In an attempt to rule out this variation, refer to the mean and standard deviation of the demographic statistics from Table 3. Table 4(a) shows the mean of each demographic statistic in a handful of zip codes that exhibited significant variation both in score and propensity to fail. The information includes population estimate, number of families, household units, median age, average household size, median income, percentage of residents that are white, and the percentage of housing units that are owner occupied. As Table 4(b) shows, individual demographic statistics do not vary in magnitude consistently across neighborhoods nor do individual neighborhoods vary consistently in magnitude across an individual demographic statistics.

One plausible concern with the study involves the variance coming not from an intrinsic holistically regional characteristic, but rather from one or two specific underlying characteristics. For example, looking only at individual neighborhoods that vary significantly in score, if specific demographic statistics consistently showed notable variation when compared to the average across all neighborhoods, then it is possible the variance is not coming from the region, but instead from that isolated demographic.

Taking this further, the study explored whether an OLS and logit regression can capture the effect of these demographic statistics. Table 5 presents OLS and logit regression results using the same demographic variables across all zip codes. As can be seen, five of the nine demographic statistics effect the score of an inspection significantly. Population (+), number of families (-), percent owner occupancy (-), median age (+), and average household size (+) all have the directional effect that one would expect. Only two statistics effect the probability of failure significantly: Population (+), and number of families (-). Both move the probability in the expected direction.

It is reasonable to assume, however, that many of these statistics are highly correlated, which likely underrepresents their effects, both when calculated independently and with the neighborhood dummies. This is explored in Table 6. The variables demonstrate relatively high co-variations. For example, the correlation coefficient between median income and percentage of white population is 0.68. This identifies a strong positive correlation between the two variables. The correlation may demonstrate collinearity, which would potentially underestimated individual demographic statistics in the regression results.

To further explore this, Table 7 and present bivariate OLS and logit regression results for each demographic statistic run against the dependent variables score and fail, respectively. The aim is not to isolate one of these demographic variables as more or less influential than any of the others, but is rather to demonstrate that they are statistically significant in their own right. In fact, every demographic variable was statistically significant at the 95% level, and all but one at the 99% level for both score and fail. For example, for each percentage point increase in the population of Caucasian residents, the expected score decreased by .937 points. For each additional member in a household, the expected score increased by .46 points. For each percentage point increase in owner occupancy, the expected probability of failure decreased by 34.1%.

As previously alluded to, scholars tend to employ one of several methods outside of OLS to discuss regional variation. The method this study chose to employ was HLM. Within a hierarchical structure, while all scores center on a grand mean, subsets of the data can be fixed into groups. The data points in these groups, in turn, center on their own group mean without losing the grand mean when all individual data points are considered. Sub-dividing the subsets again, each subsequent subgroup centers on its own mean as well. This does not minimize the importance of the variation evident in first subdivision, however.

The borough and neighborhood effects were tested first on the grand mean of score and the grand mean of failure rate. Table 9(a) shows that the effects are significantly non-zero at both the borough and zip levels for both score and fail. For all tables forward, while stars still represent significance at the tope level of the regressions, variation at the group levels are evaluated by confidence intervals. The significance is determined by an interval that does not include zero. This is presented as such due to statistical tests of significance that the standard deviation is equal to zero are not defined.

For the HLM regressions, I additionally explore the borough effects not only in magnitude, but in direction as well, to see if there is material impact to significance. As such, a follow-up regression was conducted on score and probability of failure whereby a dummy variable for each borough was an independent variable that affected the score and fail at the highest level of the regression. The neighborhood effects were then explored. As can be seen from Table 9(b), Brooklyn restaurants demonstrate significantly higher (dirtier) scores at the 99% level, and Staten Island restaurants demonstrate significantly lower (cleaner) scores at the 99% level. Brooklyn restaurants also demonstrate a 12.9% higher probability of failure at the 99% level. Changes at the neighborhood level in both cases are significantly non-zero for both score and fail. To illustrate variation further at the zip level, or 'zipeffects', please reference Figure 5 and Figure 6, which demonstrate the wide array of magnitude and direction by which, each individual zip mean varies from the grand mean of the data for both score and fail.

I separated the zipeffects figures by color-coding them by borough in an attempt to see if any easily identifiable patterns emerged visually. It can be seen that Queens appears to house the extrema in "Score" and Manhattan seems to house them in "Fail", but, unfortunately, outside of this not much else is discernable.

One of the benefits of understanding modeling within a hierarchy or a 'mixed effects' model is that, as with the borough dummy variables used above, many independent variables can be tested at any level of the regression in addition to attempting to capture the variation evident in the region or sub-region means. In fact, though I do not explore it in this paper, the same independent variables can be measured at multiple levels of the regression, making for some very interesting comparison of their effect on different regional or sub regional means versus the grand mean. The exploration of these effects at the group level are called variable effect versus my exploration of top-level variation, or fixed effects.

In my next regression I test the fixed effects of the demographic statistics on the score and probability of failure, while still considering if neighborhood and borough have an effect. In Table 10(a) one can see that median age increases the score by .11 points and this effect is significant at the 95% level. Also, the gross number of families decreases the propensity of restaurant failure by almost 27% at the 90% confidence level. Borough and neighborhood changes remain significantly non-zero. Similar to the exploration in Table 9(b), when allowing for variance in direction of each borough independently, the median age still has a significant effect, but now only at the 90% level, and with a slightly lower magnitude of .097. Average household size increases the propensity to fail by 17.6% at the 90% level. As seen in Table 10(b), in this model restaurants in The Bronx are likely to score 1 point lower and are 15% less likely to fail, both significant at a 95% level. Restaurants in the Queens are 19% less likely to fail at the 99% level. Changes at the neighborhood level, however, remain significantly non-zero.

As discussed earlier, however, the correlation and interaction of the demographic statistics may misrepresent the effect of each variable and subsequently overestimate the effect of the region or sub region. To correct for this, I ran bivariate regressions at the highest level of the HLM for each individual demographic statistics against the score and failure probability. As can be seen in Table 11(a) and Table 12(a), with the exception of median age on score, all demographic statistics independently have an effect on the score and the probability of failure; most at the 99% level. Taking this into account, however, borough and neighborhood still have a significantly non-zero effect for every regression.

As with the previous regressions, in tables 11(b) and 12(b) boroughs were allowed to vary directionally and independent of one and other, and the only change was that the effect of the number of household units in a neighborhood on the probability of failure lost its significance. Otherwise, most demographic statistics still affect their respective dependent variables significantly, and borough and neighborhood still have significantly non-zero effect for every regression.

Conclusions and Future Research Direction

This study examined whether the neighborhood a restaurant is located in affects the incentives that the restaurant has to remain hygienic. The methodology used was improved from Jin and Leslie (2009), who were the first to suspect that regional differences affect sanitary incentives. Rather than using proxy variables to define region, as had been done in previous studies, this study used neighborhoods, more precisely zip codes and boroughs to analyze restaurants in New York City. This was done first through an OLS and then through an hierarchical lens. The results clearly demonstrate that for homogeneous restaurants, the neighborhood in which a restaurant is located effects its hygienic standards.

The focus of this study was to establish variation by region in health inspection scores in New York City. While the results point to the existence of variation in sanitary incentives by region, their determinants, or the underlying causality, remain mostly unknown. While we have discussed consumer-learning behavior a number of times in this presentation, it should be noted that consumer learning could be the product of a myriad of variables. One could explore neighborhood variation in commercial vs residential use, repeat patronage, educational achievement, supply side variation, retail rents, among others. Future research could explore any or all of these individual factors that comprise the region's overall characteristics, and subsequently effect the incentives a restaurant has to remain hygienic and whether these individual factors or causes vary region to region.

Additionally, more individual restaurant unit information is needed for comparison purposes to improve the literature on this topic (e.g. number of seats, number of restrooms, square footage, average check, average unit volume, etc.) When that information becomes available, both additional HLM and geocoding could help shed light on this topic.

This course of study may also benefit from reviewing the data in a strictly residential urban environment. While New York offers many advantages to the earlier work done in California, the mixed land use and high concentration of a non-residential population in New York City may ultimately be problematic; it presents many variables that could cloud census demographics as a representation of the underlying intrinsic neighborhood quality, and restaurant patronage and propensity to learn. A city with more defined commercial centers and less mixed-use real estate, such as Chicago or Detroit perhaps, may be better suited for further investigation. While many questions remain, this study presents a solid framework with which to investigate the inequalities in restaurant hygiene that face some communities.

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Appendix

TABLE 1 – Five Borough Distribution

VARIABLES	mean	sd	skew	k	p50	mode	min	p25	p75	max
Score	18.41	16.05	1.92	9.83	15	15	0	7	24	252
Fail	0.184	0.387	1.64	3.67						
No. of Inspections	89,360									
No. of Restaurants	19,180									
No. of Zips Codes	178									
No. of Boroughs	5									

TABLE 2 – Restricted Type Distribution

VARIABLES	mean	sd	skew	k	p50	mode	min	p25	p75	max
Score	17.47	15.47	1.932	9.996	14	14	0	7	23	248
Fail	0.166	0.372	1.796	4.227	0	0	0	0	0	1
No. of Inspections	31,758									
No. of Restaurants	5,245									
No. of Zips Codes	168									
No. of Boroughs	5									

TABLE 3 – Demographic Statistic Distribution

VARIABLES	mean	sd	skewness	kurtosis	p50	mode	min	p25	p75	max
Population	46,912	25,723	0.32	2.27	41,936	41,936	229	27,427	65,154	106,154
No. of Families	10,859	6,170	0.38	2.28	9,943	9,943	10	6,000	15,736	25,450
No. of Housing Units	17,734	10,002	0.69	4.10	16,074	16,074	13	9,866	25,389	61,774
Median Age	34.7	4.3	-0.02	3.22	34.5	34.5	20.3	32.2	37.7	46.5
Avg Household Size	2.61	0.50	-0.55	2.64	2.69	2.69	1.47	2.32	2.97	3.66
Median Rent	790	278	2.37	10.59	753	753	299	644	827	2,001
Median Income	43,291	18,162	0.98	4.49	40,928	40,928	14,271	29,488	54,688	112,947
Percent White	0.48	0.28	-0.10	1.73	0.52	0.52	0.02	0.25	0.73	0.95
Percent Owner Occ.	0.34	0.22	0.54	2.28	0.29	0.29	0.01	0.17	0.50	0.90

TABLE 4(a) – Mean Of Demographic Statistics Of Significantly Variable Zip Codes

VARIABLES	10004	10040	10455	10456	11369	11430	10303	11004	11361
Population	1,225	46,599	37,465	76,656	36,110	229	23,530	14,682	29,206
No. of Families	209	10,643	8,562	17,749	8,284	10	5,683	3,822	7,427
No. of Housing Units	622	16,180	11,966	25,169	11,072	13	7,388	5,708	11,084
Median Age	34.4	32.9	28.1	27.6	33.3	20.3	29.9	40.5	38.3
Avg Household Size	1.79	2.82	3.01	2.98	3.21	2.92	3.15	2.53	2.59
Median Rent	2,001	647	460	489	809	1,125	636	758	919
Median Income	101,868	27,905	19,389	16,664	39,936	85,197	42,463	55,156	55,250
Percent White	0.74	0.31	0.23	0.14	0.29	0.22	0.42	0.61	0.66
Percent Owner Occ.	0.21	0.07	0.07	0.07	0.53	0.46	0.54	0.67	0.55

TABLE 4(b) – Mean Of Demographic Statistics Of Significantly Variable Zip Cod

VARIABLES	10004	10040	10455	10456	11369	11430	10303	11004	11361
Population	1.776	0.012	0.367	1.156	0.420	1.815	0.909	1.253	0.688
No. of Families	1.726	0.035	0.372	1.117	0.417	1.758	0.839	1.141	0.556
No. of Housing Units	1.711	0.155	0.577	0.743	0.666	1.772	1.034	1.202	0.665
Median Age	0.058	0.403	1.509	1.625	0.311	3.307	1.095	1.348	0.841
Avg Household Size	1.648	0.423	0.805	0.744	1.207	0.624	1.086	0.160	0.040
Median Rent	4.348	0.515	1.187	1.083	0.067	1.202	0.555	0.116	0.462
Median Income	3.225	0.847	1.316	1.466	0.185	2.307	0.046	0.653	0.658
Percent White	0.924	0.604	0.910	1.228	0.701	0.951	0.218	0.451	0.631
Percent Owner Occ.	0.578	1.217	1.247	1.260	0.864	0.559	0.929	1.525	0.956

TABLE 5 – Regression Of All Demographic Statistics On Score And Fail

VARIABLES	Score	Fail
Population	0.696**	0.0850*
	(0.280)	(0.0481)
No. of Families	-2.019**	-0.262*
	(0.812)	(0.141)
No. of Housing Units	-0.231	-0.0232
	(0.365)	(0.0637)
Median Age	0.118***	0.00946
	(0.0409)	(0.00713)
Avg. Household Size	0.834*	0.0483
	(0.487)	(0.0848)
Median Rent	0.0958	-0.00111
	(0.112)	(0.0200)
Median Income	-0.190	-0.0345
	(0.219)	(0.0391)
Percent White	0.108	0.0358
	(0.542)	(0.0942)
Percent Owner Occ.	-2.189*	-0.196
	(1.210)	(0.213)
Constant	11.12***	-1.961***
	(2.194)	(0.382)
Observations	31,758	
R-squared	0.002	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 6 – Demographic Statistic Correlation Table

VARIABLES	Percent White	Population	No. of Families	No. House Units	Percent Owner Occ.	Median Age	Avg House Size	Median Rent	Median Income
Percent White	1								
Population	-0.22	1							
No. of Families	-0.27	0.97	1						
No. of Housing Units	0.12	0.86	0.76	1					
Percent Owner Occ.	0.3	-0.12	-0.02	-0.11	1				
Median Age	0.64	-0.21	-0.19	0.09	0.47	1			
Avg Household Size	-0.65	0.41	0.52	-0.05	0.13	-0.57	1		
Median Rent	0.61	-0.31	-0.38	0.01	0.19	0.42	-0.65	1	
Median Income	0.68	-0.33	-0.38	0.02	0.44	0.55	-0.64	0.92	1

TABLE 7 – Bivariate Regressions Of Each Demographic Statistics On Score

VARIABLES	Population	No. of Families	No. House Units	Median Age	Avg House Size	Median Rent	Median Income	Percent White	Percent Owner Occ.
Demographic Stat	0.193***	0.709***	0.365***	-0.0458**	0.460***	-0.104***	-0.216***	-0.937***	-2.024***
	(0.0324)	(0.131)	(0.0807)	(0.0214)	(0.151)	(0.0323)	(0.0486)	(0.336)	(0.514)
Constant	16.45***	16.64***	16.69***	19.06***	16.35***	18.33***	18.42***	17.97***	18.05***
	(0.193)	(0.178)	(0.193)	(0.748)	(0.378)	(0.278)	(0.230)	(0.197)	(0.169)
Observations	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758
R-squared	0.001	0.001	0.001	0.000	0.000	0.000	0.001	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 8 – Bivariate Regressions Of Each Demographic Statistics On Fail

VARIABLES	Population	No. of Families	No. House Units	Median Age	Avg House Size	Median Rent	Median Income	Percent White	Percent Owner Occ.
Demographic Stat	0.0236***	0.0863***	0.0395***	-0.00979***	0.0707***	-0.0245***	-0.170***	-0.0428***	-0.341***
	(0.00563)	(0.0227)	(0.0139)	(0.00372)	(0.0263)	(0.00583)	(0.0582)	(0.00864)	(0.0911)
Constant	-1.742***	-1.718***	-1.700***	-1.276***	-1.788***	-1.416***	-1.526***	-1.429***	-1.520***
	(0.0341)	(0.0313)	(0.0337)	(0.130)	(0.0664)	(0.0494)	(0.0337)	(0.0400)	(0.0293)
Observations	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 9(a) – HLM Regression On Score And Fail Grand Mean

	Score	Fail
Mean	17.23***	-1.632***
	[16.57,17.90]	[-1.708,-1.557]
sd(Boro)	0.692	0.0735
	[0.317,1.509]	[0.0323,0.167]
sd(Zip)	0.938	0.0877
	[0.711,1.238]	[0.0479,0.161]
Observations	31,758	31,758
No. of Boroughs	5	5

95% confidence intervals in brackets

* p<0.10, ** p<0.05, *** p<0.01

TABLE 9(b) – HLM Regression On Score And Fail Allowing Borough Variation Showing Remaining Constant

	Score	Fail
Bronx	-0.588	-0.0285
	[-1.331,0.155]	[-0.137,0.0799]
Brooklyn	1.077***	0.129***
	[0.443,1.712]	[0.0406,0.217]
Queens	-0.12	-0.0871*
	[-0.737,0.496]	[-0.177,0.00327]
Staten Island	-1.381***	-0.119
	[-2.431,-0.332]	[-0.282,0.0449]
Constant	17.37***	-1.620***
	[16.94,17.79]	[-1.678,-1.562]
sd(Zip)	0.903	0.0839
	[0.680,1.199]	[0.0444,0.159]
Observations	31,758	31,758
No. of Zips	168	168

95% confidence intervals in brackets
* p<0.10, ** p<0.05, *** p<0.01

TABLE 10(a) – HLM Regression With All Demographic Statistics On Score And Fail Included At the Top Level

VARIABLES	Score	Fail
Population	0.524	0.069
	[-0.230,1.277]	[-0.0324,0.170]
No. of Families	-1.67	-0.267*
	[-3.917,0.576]	[-0.574,0.0408]
No. of Housing Units	-0.0764	0.0045
	[-1.051,0.898]	[-0.125,0.134]
Median Age	0.110**	0.0126
	[0.00181,0.219]	[-0.00292,0.0281]
Avg Household Size	0.888	0.142
	[-0.411,2.186]	[-0.0424,0.326]
Median Rent	0.0662	0.00538
	[-0.211,0.343]	[-0.0355,0.0463]
Median Income	-0.166	-0.0418
	[-0.702,0.370]	[-0.121,0.0372]
Percent White	-0.0252	0.0225
	[-1.336,1.285]	[-0.170,0.215]
Percent Owner Occ.	-2.199	-0.158
	[-5.264,0.866]	[-0.599,0.283]
sd(Boro)	0.471	0.0674
	[0.200,1.106]	[0.0287,0.158]
sd(Zip)	0.738	0.0269
	[0.509,1.068]	[0.000258,2.808]
Observations	31,758	31,758
No. of Boroughs	5	5

95% confidence intervals in brackets
* p<0.10, ** p<0.05, *** p<0.01

TABLE 10(b) – HLM Regression With All Demographic Statistics On Score And Fail Included At the Top Level Allowing Borough Variation

VARIABLES	Score	Fail
Population	0.428	0.0584
	[-0.325,1.182]	[-0.0434,0.160]
No. of Families	-1.386	-0.243
	[-3.686,0.914]	[-0.560,0.0749]
No. of Housing Units	-0.0253	0.0134
	[-0.985,0.934]	[-0.114,0.141]
Median Age	0.097*	0.0122
	[-0.0157,0.210]	[-0.00404,0.0284]
Avg Household Size	0.964	0.176*
	[-0.334,2.261]	[-0.00363,0.355]
Median Rent	0.0407	0.00632
	[-0.239,0.320]	[-0.0351,0.0477]
Median Income	-0.14	-0.0443
	[-0.673,0.394]	[-0.123,0.0346]
Percent White	0.0974	0.0344
	[-1.267,1.461]	[-0.166,0.235]
Percent Owner Occ.	-2.036	-0.108
	[-5.176,1.104]	[-0.561,0.346]
Bronx	-1.038**	-0.153**
	[-2.002,-0.0745]	[-0.292,-0.0142]
Brooklyn	0.569	0.00691
	[-0.324,1.461]	[-0.118,0.132]
Queens	-0.303	-0.190***
	[-1.232,0.627]	[-0.323,-0.0562]
Staten Island	-0.843	-0.127
	[-2.429,0.743]	[-0.368,0.113]
sd(Zip)	0.701	0.0107
	[0.476,1.032]	[1.15e-14,9.90260e+09]
Observations	31,758	31,758
No. of Zips	168	168

95% confidence intervals in brackets

* p<0.10, ** p<0.05, *** p<0.01

TABLE 11(a) – HLM Bivariate Regression Of Each Demographic Statistics On Score Included At the Top Level

VARIABLES	Population	No. of Families	No. House Units	Median Age	Avg House Size	Median Rent	Median Income	Percent White	Percent Owner Occ.
Demographic Stat	0.177***	0.702***	0.325***	-0.0362	0.742**	-0.136***	-0.256***	-0.891*	-2.313***
	[0.0840,0.270]	[0.304,1.101]	[0.0924,0.558]	[-0.0963,0.0239]	[0.156,1.328]	[-0.234,-0.0374]	[-0.401,-0.112]	[-1.837,0.0539]	[-3.812,-0.814]
sd(Boro)	0.56	0.605	0.584	0.687	0.786	0.724	0.651	0.654	0.587
	[0.238,1.316]	[0.264,1.382]	[0.252,1.354]	[0.315,1.495]	[0.369,1.675]	[0.336,1.560]	[0.301,1.410]	[0.300,1.423]	[0.273,1.266]
sd(Zip)	0.854	0.866	0.902	0.924	0.873	0.893	0.866	0.915	0.872
	[0.628,1.163]	[0.639,1.172]	[0.675,1.204]	[0.696,1.227]	[0.643,1.184]	[0.670,1.190]	[0.645,1.164]	[0.688,1.218]	[0.645,1.178]
Observations	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758
No. of Boroughs	5	5	5	5	5	5	5	5	5

95% confidence intervals in brackets

* p<0.10, ** p<0.05, *** p<0.01

TABLE 11(b) – HLM Bivariate Regression Of Each Demographic Statistics On Score Included At the Top Level Allowing Borough Variation

VARIABLES	Population	No. of Families	No. House Units	Median Age	Avg House Size	Median Rent	Median Income	Percent White	Percent Owner Occ.
Demographic Stat	0.167***	0.679***	0.293**	-0.0358	0.836***	-0.141***	-0.255***	-0.831*	-2.253***
	[0.0740,0.260]	[0.280,1.078]	[0.0624,0.524]	[-0.0957,0.0242]	[0.238,1.434]	[-0.239,-0.0424]	[-0.401,-0.109]	[-1.785,0.122]	[-3.863,-0.643]
Bronx	-0.866**	-0.994**	-0.575	-0.749*	-1.285***	-1.114***	-1.225**	-0.829**	-0.612*
	[-1.597,-0.135]	[-1.750,-0.237]	[-1.304,0.155]	[-1.535,0.0376]	[-2.162,-0.408]	[-1.930,-0.297]	[-2.033,-0.417]	[-1.615,-0.0428]	[-1.333,0.109]
Brooklyn	0.617*	0.506	0.961***	0.983***	0.42	0.651*	0.586	0.940***	1.222***
	[-0.0408,1.275]	[-0.190,1.202]	[0.332,1.589]	[0.334,1.632]	[-0.351,1.191]	[-0.0361,1.339]	[-0.0872,1.259]	[0.293,1.586]	[0.600,1.844]
Queens	-0.206	-0.337	0.0128	-0.138	-0.847**	-0.382	-0.356	-0.236	0.377
	[-0.801,0.388]	[-0.947,0.273]	[-0.600,0.626]	[-0.752,0.475]	[-1.645,-0.0493]	[-1.015,0.251]	[-0.969,0.257]	[-0.861,0.389]	[-0.314,1.067]
Staten Island	-1.378***	-1.571***	-1.197**	-1.396***	-2.100***	-1.722***	-1.383**	-1.260**	-0.421
	[-2.393,-0.362]	[-2.598,-0.545]	[-2.241,-0.154]	[-2.440,-0.352]	[-3.247,-0.954]	[-2.782,-0.662]	[-2.405,-0.361]	[-2.309,-0.210]	[-1.651,0.810]
sd(Zip)	0.815	0.827	0.863	0.888	0.833	0.859	0.832	0.88	0.837
	[0.592,1.122]	[0.604,1.131]	[0.641,1.163]	[0.664,1.188]	[0.608,1.143]	[0.640,1.152]	[0.614,1.126]	[0.656,1.179]	[0.614,1.141]
Observations	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758
No. of Zips	168	168	168	168	168	168	168	168	168

95% confidence intervals in brackets

* p<0.10, ** p<0.05, *** p<0.01

TABLE 12(a) – HLM Bivariate Logit Regression Of Each Demographic Statistics On Fail Included At the Top Level

VARIABLES	Population	No. of Families	No. House Units	Median Age	Avg House Size	Median Rent	Median Income	Percent White	Percent Owner Occ.
Demographic Stat	0.0216***	0.0849***	0.031*	-0.00883**	0.156***	-0.0295***	-0.0489***	-0.186***	-0.339***
	[0.00811,0.03]	[0.0283,0.141]	[-0.0027,0.0646]	[-0.0175,-0.000172]	[0.0726,0.239]	[-0.0438,-0.0153]	[-0.0695,-0.0283]	[-0.320,-0.0508]	[-0.556,-0.121]
sd(Boro)	0.0572	0.0619	0.0630	0.0694	0.101	0.0767	0.0696	0.0714	0.0602
	[0.0226,0.145]	[0.0254,0.151]	[0.0257,0.154]	[0.0301,0.160]	[0.0475,0.216]	[0.0341,0.173]	[0.0310,0.156]	[0.0322,0.159]	[0.0257,0.141]
sd(Zip)	0.0767	0.0780	0.0863	0.0804	0.0572	0.0701	0.0630	0.0753	0.0742
	[0.0361,0.163]	[0.0376,0.162]	[0.0462,0.161]	[0.0403,0.160]	[0.0173,0.189]	[0.0316,0.155]	[0.0248,0.160]	[0.0352,0.161]	[0.0340,0.162]
Observations	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758
No. of Boroughs	5	5	5	5	5	5	5	5	5

95% confidence intervals in brackets

* p<0.10, ** p<0.05, *** p<0.01

TABLE 12(b) – HLM Bivariate Logit Regression Of Each Demographic Statistics On Fail Included At the Top Level Allowing Borough Variation

VARIABLES	Population	No. of Families	No. House Units	Median Age	Avg House Size	Median Rent	Median Income	Percent White	Percent Owner Occ.
Demographic Stat	0.0197***	0.0807***	0.0251	-0.00853*	0.176***	-0.0307***	-0.0501***	-0.187***	-0.340***
	[0.00625,0.0331]	[0.0231,0.138]	[-0.00768,0.0579]	[-0.0173,0.000252]	[0.0936,0.258]	[-0.0452,-0.0162]	[-0.0713,-0.0289]	[-0.325,-0.0484]	[-0.584,-0.0962]
Bronx	-0.0632	-0.0795	-0.0271	-0.07	-0.184***	-0.142**	-0.155***	-0.087	-0.0365
	[-0.171,0.0450]	[-0.192,0.0325]	[-0.135,0.0808]	[-0.185,0.0450]	[-0.309,-0.0589]	[-0.259,-0.0252]	[-0.271,-0.0395]	[-0.201,0.0270]	[-0.142,0.0686]
Brooklyn	0.0742	0.0597	0.120***	0.104**	-0.0168	0.0379	0.034	0.0952**	0.149***
	[-0.0186,0.167]	[-0.0388,0.158]	[0.0314,0.208]	[0.0142,0.194]	[-0.123,0.0889]	[-0.0557,0.132]	[-0.0573,0.125]	[0.00666,0.184]	[0.0632,0.235]
Queens	-0.103**	-0.119**	-0.077*	-0.0945**	-0.248***	-0.144***	-0.137***	-0.116**	-0.021
	[-0.191,-0.0141]	[-0.210,-0.0276]	[-0.168,0.0137]	[-0.183,-0.00542]	[-0.362,-0.134]	[-0.235,-0.0528]	[-0.225,-0.0489]	[-0.206,-0.0256]	[-0.119,0.0771]
Staten Island	-0.12	-0.144*	-0.103	-0.122	-0.274***	-0.189**	-0.116	-0.0932	0.0262
	[-0.280,0.0408]	[-0.307,0.0176]	[-0.267,0.0614]	[-0.284,0.0394]	[-0.447,-0.101]	[-0.352,-0.0267]	[-0.274,0.0414]	[-0.254,0.0680]	[-0.164,0.216]
sd(Zip)	0.0715	0.0729	0.0815	0.0763	0.0499	0.0662	0.0584	0.0708	0.0685
	[0.0313,0.164]	[0.0328,0.162]	[0.0417,0.159]	[0.0365,0.160]	[0.0113,0.220]	[0.0282,0.156]	[0.0207,0.164]	[0.0310,0.162]	[0.0286,0.164]
Observations	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758	31,758
No. of Zips	168	168	168	168	168	168	168	168	168

95% confidence intervals in brackets

* p<0.10, ** p<0.05, *** p<0.01

FIGURE 1 –

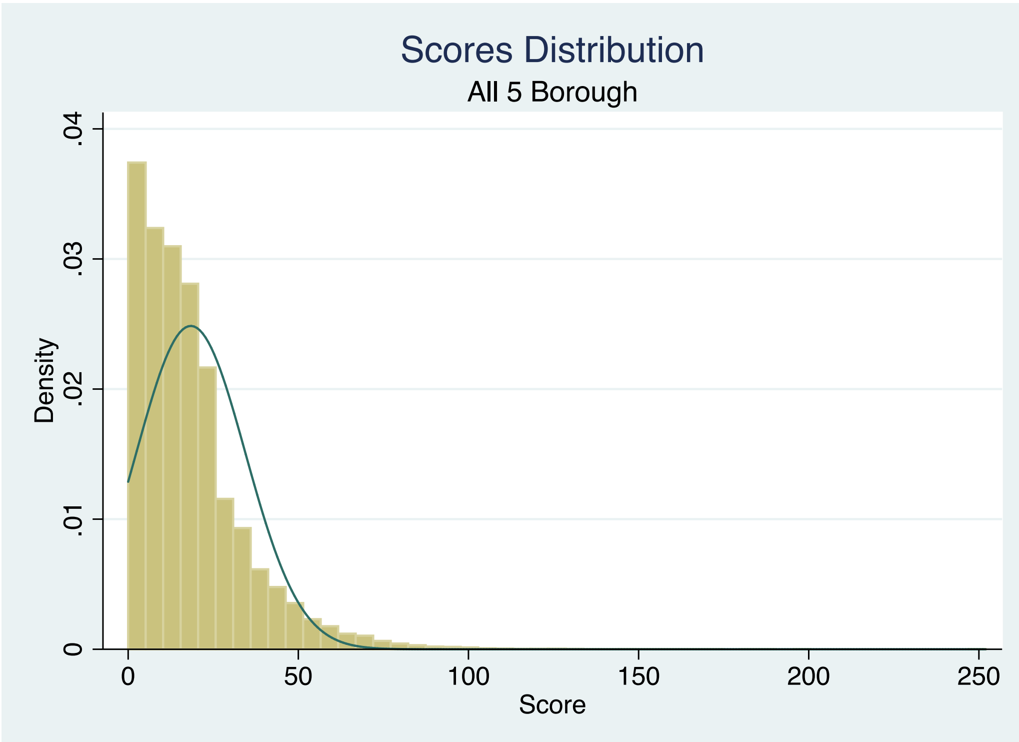

Scores Distribution
All 5 Borough
Density
0
.01
.02
.03
.04
0
50
100
150
200
250
Score

FIGURE 2 –

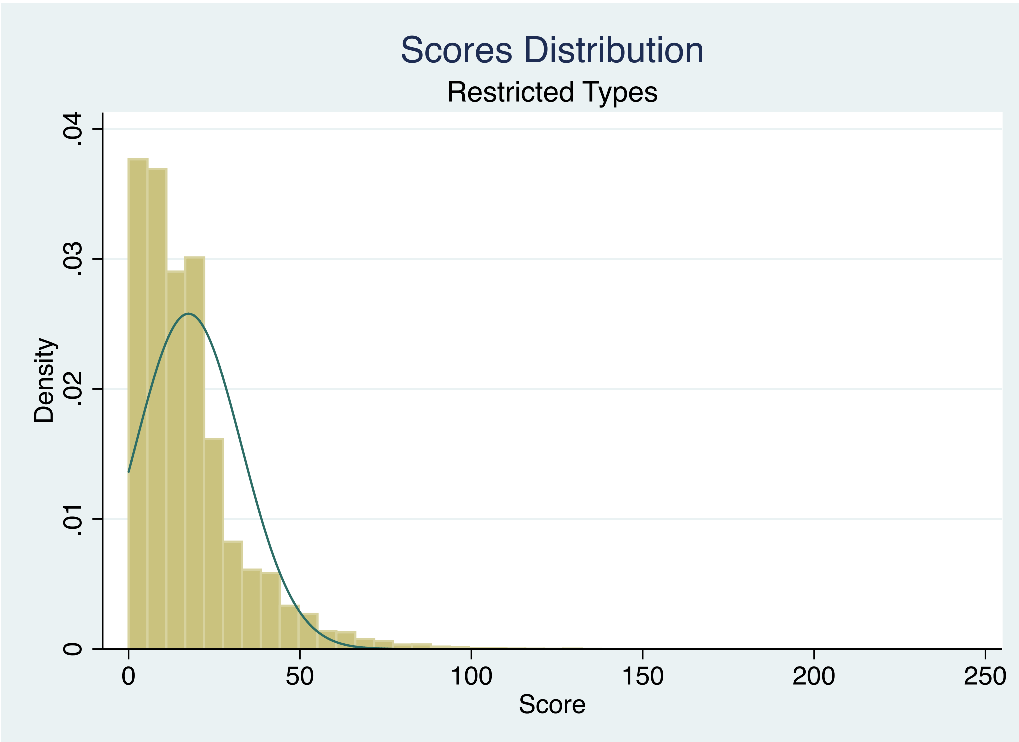

Scores Distribution
Restricted Types
Density
0
.01
.02
.03
.04
0
50
100
150
200
250
Score

FIGURE 3 –

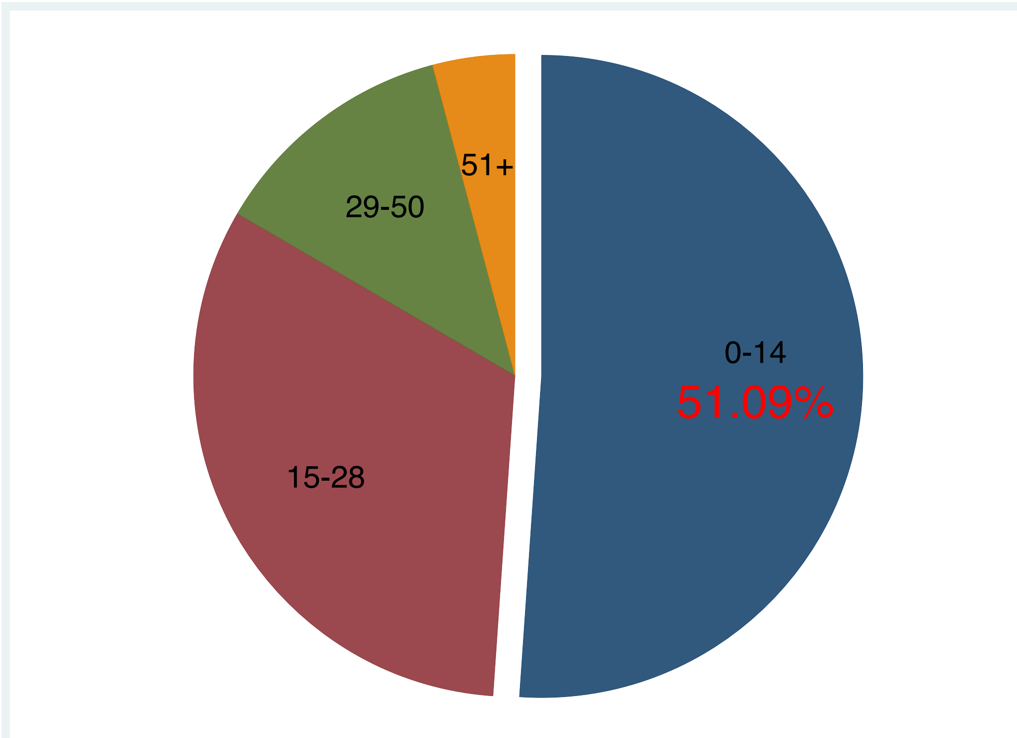


FIGURE 5 –

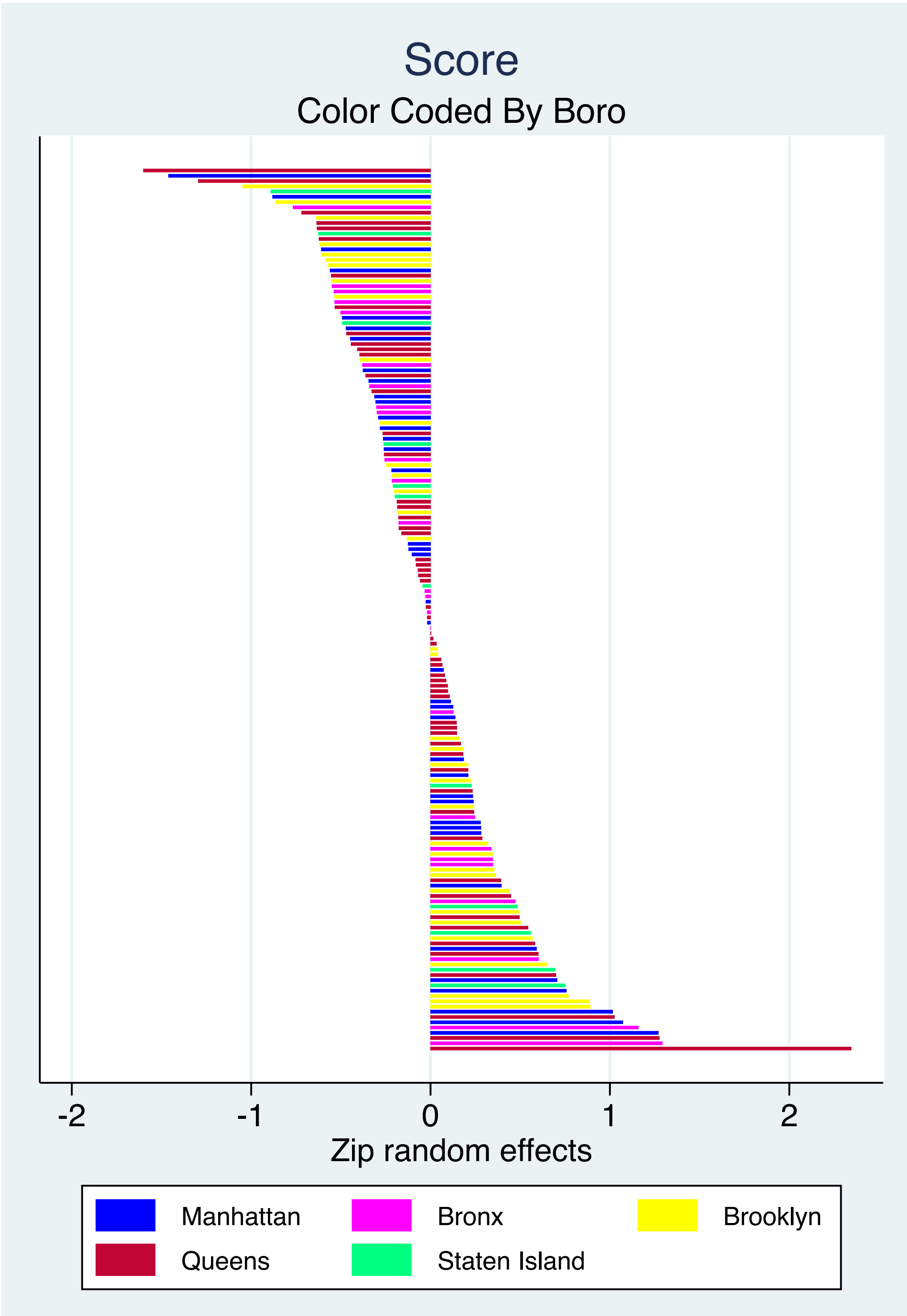
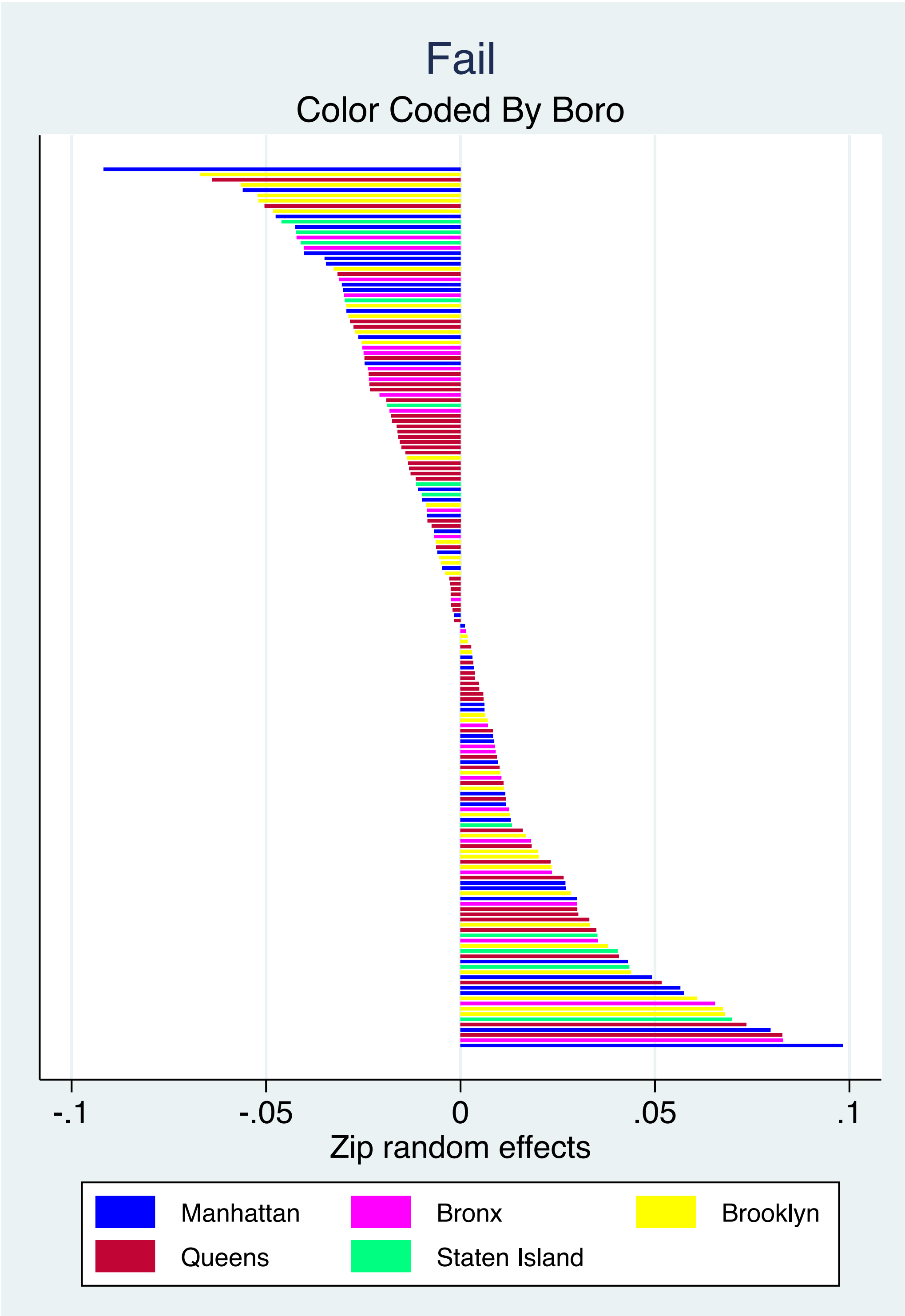

Score
Color Coded By Boro
-2
-1
0
1
2
Zip random effects
Manhattan
Bronx
Brooklyn
Queens
Staten Island

FIGURE 6 –


Fail
Color Coded By Boro
-.1
-.05
0
.05
.1
Zip random effects
Manhattan
Bronx
Brooklyn
Queens
Staten Island