How Does Compliance Affect the Returns to Algorithms? Evidence from Boston's Restaurant Inspectors[i]

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Abstract

Algorithms have the potential to improve our ability to target services – but the returns are limited if employees make choices largely based on other considerations. Partnering with Boston's Inspectional Services Department, we compare the performance of three different methods of targeting restaurant hygiene inspections: (1) human judgment based on inspector discretion (the status quo); (2) a "data-poor" algorithm based on the average number of violations across historical inspections; and (3) a "data-rich" algorithm based on a random forest model trained on historical inspections and Yelp data. The "data-rich" algorithm slightly outperforms the "data-poor" algorithm, and both dramatically improve upon inspector discretion -- suggesting that the greatest gains come from using data to supplement inspectors' priors, rather than from sophisticated algorithm design. Yet, inspectors are only half as likely to comply with inspection directives based on either algorithm, relative to individual judgment. These findings suggest that the implementation gains from big data and machine learning are limited by employee compliance.

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1. Introduction

Since the 1970s, social scientists have emphasized that predictive algorithms can improve human judgment and decision-making (Dawes (1979), Dawes et al. (1989), Grove and Meehl (1996), Grove et al. 2000). Recent reductions in data and computing costs have further increased interest in putting predictive algorithms into practice (Chalfin et al. (2016), Kleinberg et al. (2017), Agarwal et al. (2018)), in contexts from hiring to medical diagnoses to bail determination (Dhami (2003), Kleinberg et al. (2017), Lakkaraju et al. (2017), Cowgill (2018)).

While abundant research documents the statistical gains from improved algorithms, the practical implementation of algorithms has been less widely studied (Jung et al. 2018).[vii] Yet, even the most sophisticated algorithms will do little if workers do not implement effectively and just follow their own priors. Recent empirical evidence shows the role of basic management practices – encompassing operations, monitoring, and appropriate incentives – in explaining productivity differences (Ichinowski et al (1997), Ichinowski and Shaw (2003), Bloom and Van Reenen (2007), Bloom et al (2013)). In particular, these studies have highlighted important complementarities between the returns to information technology investments and effective management (Bresnahan et al (2002), Bartel et al (2007), Bloom et al (2012), Aral et al (2012)). The gains from implementing algorithms may be especially likely to be impacted by effective management to clearly communicate and incentivize workers to ensure compliance.

In this paper, we explore the relative importance of algorithmic sophistication and worker compliance. We compare, in the field, the gains from enhanced predictive power with the gains from inducing workers to comply with predictions of a simple predictive model.

We partnered with the City of Boston's inspectional services department to implement and test algorithms aimed at identifying restaurants that are at risk of health code violations. Our setting is a natural place to test the power of predictive algorithms, since inspectors' scarce time must be allocated with a fundamentally predictive objective: identifying restaurants that have health code violations.[viii] Moreover, the inspectional services department's history of past violations and consumer reviews from platforms like Yelp together yield strong data inputs for a sophisticated prediction algorithm.

We compare three different approaches to allocate inspectors: (1) human judgment relying on inspector discretion ("business-as-usual"); (2) a "data-poor" algorithm based on the average number of historical violations of each restaurant; and (3) a "data-rich" algorithm based on a random forest model trained on historical violation data and Yelp reviews. Our "data-rich" algorithm theoretically yields an approximately 40 percent improvement in efficiency relative to the "business-as-usual" model (see Glaeser et al. (2016a,b)). We take the restaurants that have the largest predicted risk of hygiene violations according to each approach, and provide these to inspectors to guide their inspections over four periods of roughly eleven days each.

[vii] Recent empirical studies using regression discontinuity designs have shed light on the use of algorithmic tools in judicial decisions, but finds conflicting results across different contexts. For example, Stevenson (2017) finds only small, temporary impact of algorithms on pretrial release outcomes, while Berk (2017) finds large reductions in re-arrests.
[viii] While there are additional objectives in our setting, such as deterring restaurants from committing violations in the first place or ensuring fairness in the inspection allocation, our discussions with health departments highlighted the first-order importance of identifying and inspecting restaurants with the highest likelihood of health violations.

By examining both "data-poor" and "data-rich" algorithms, we can assess how differences in algorithmic quality impact inspection efficiency in the field. Our design overcome a selective labels problem by observing outcomes across each method. We also observe counterfactual inspector decisions and (non-)compliance behavior. By asking inspectors which restaurants they would prioritize prior to providing algorithmic recommendations, we can explore whether choices change with access to algorithmic predictions.

We find that our predictive algorithms outperform business-as-usual by identifying restaurants with 50 percent more weighted violations. Most of the gains stem from integrating historical violations data – the data-poor algorithm results in improvements as large as those from the data-rich algorithm.

Yet despite our algorithms' superior performance, inspectors are only half as likely to inspect restaurants based on the algorithm, relative to those based on their own judgment. Thus, in the context we study, worker compliance appears to be far more important than algorithm sophistication.

Our work shows the potential for algorithms to increase the number of hygiene violations found. At the same time, our findings do not imply that hygiene inspectors are making poor decisions, as they may have objectives (e.g., fairness) other than maximizing the number of violations found. While we also cannot claim that our work generalizes to other settings, the case of Boston hygiene inspectors suggests that effective management of worker compliance – through incentives as well as clear communication and prioritization of objectives – can be more important than even significant refinements of predictive algorithms.

2. Empirical Context

The Boston Inspectional Services Department conducts inspections to "serve the public by protecting the health, safety, and environmental stability of Boston's business and residential communities" (Boston). The Division of Health Inspections within the department oversees food safety codes, which are regulated by the state-level Massachusetts State Sanitary Code. The department employs 20-30 inspectors at any given time, who are assigned to at least one of 22 "wards" that divide up Boston into neighborhoods. A few wards have multiple inspectors assigned to cover different areas, and inspectors' ward assignments are changed every two years.

Inspectors are responsible for inspecting all licensed establishments, with the objective of targeting the highest-risk establishments more frequently. Facilities like hospitals, nursing homes, day care centers, schools, and caterers require three inspections per year. These are followed by restaurant establishments that prepare, cook, and serve most products immediately. The department aims to conduct at least two inspections per restaurant per year, but in practice inspectors' time budget constraint binds, so that inspectors are sometimes not able to visit a restaurant more than once in an inspection cycle. Inspectors are encouraged to conduct inspections that are in close proximity to each other, but their main objective is to prioritize inspections of establishments with the highest risk to public health.[ix]

Inspections vary in the number of violations found: between 2007 and 2015, restaurant inspectors found anywhere from 0 to 60 weighted violations per inspection (Figure 1). Weights are assigned based on the severity of the violation: Level I corresponds to non-critical violations such as

[ix] Furthermore, other priority situations such as re-inspections are prioritized above geographic proximity.

building defects or standing water. Level II violations are "Critical Violations," such as the presence of fruit flies, which are more likely than Level I violations to create food contamination, illness or environmental hazard. Level III violations are considered "Food-borne Illness Risk Factor[s]"; examples include insufficient refrigeration or a lack of allergen advisories on menus. A Level I violation has a weight of 1, Level II a weight of 2, and Level III a weight of 5. When critical violations are found in a restaurant, the City reinspects that restaurant within 30 days.[x]

3. Empirical Design

Between February 1 and March 25, 2016, we partnered with the City of Boston to compare three methods of allocating inspectors. At the beginning of each of the four inspection periods in our study window (February 1-12, February 15-26, February 29-March 11, and March 14-25), Boston's Head Inspector asked all inspectors to rank the restaurants in their ward by the order in which they felt those restaurants should be inspected.[xi]

For each inspection period, inspectors received a docket of restaurants to inspect. This docket was presented as a "new way of doing inspections" to guide inspector decisions.[xii] The docket consisted of the top fifteen ranked restaurants from each of three approaches to targeting inspections, sorted in random order.

The first method for determining the dockets – "business-as-usual" – relied on inspectors' own rankings. The second method, which we call a "data-poor" algorithm, used the average number of violations per historical inspection to rank restaurants in each ward from most to least likely to have violations. The third method ranked restaurants according to a "data-rich" algorithm, which used a random forest model trained on both historical violations and Yelp data including the number of Yelp reviews, Yelp rating, price range, hours, services available (e.g., wifi, alcohol, take-out, appointments), business ambience (e.g., noise level, children-friendly, ages allowed), and business neighborhood.[xiii]

In subsequent periods, restaurants from the previous period's docket that were not inspected were added to the docket first, followed by a new crop of restaurants, chosen through the same mechanism as before. The docketing system exogenously influenced which restaurants were inspected when, allowing us to separate confounding effects of when inspectors decided to visit certain restaurants and tease out whether algorithmically-ranked restaurants indeed had a higher number of violations. Our approach also provided us with a way to observe which restaurants – of those listed on their dockets – inspectors chose to prioritize.

Not all restaurants were ranked, as some inspectors listed fewer restaurants than others. Inspectors were also not able to inspect all restaurants that had been ranked during the study period. Across all

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[x] If violations are deemed to pose an imminent public health risk, the City may temporarily suspend the restaurant's food permit.

[xi] In order to isolate confounds, we excluded from rankings any high-risk establishments (e.g., hospitals and nursing homes), as well as restaurants that had a mandated priority to re-inspect, such as prior inspections that yielded major violations requiring a re-inspection in 30 days.

[xii] The Health Commissioner chose this wording in order to avoid calling attention to the new docket practice.

[xiii] This method was the second-place winner in a tournament that the City of Boston ran to source algorithms for predicting hygiene violations (described in detail in Glaeser et al. (2016a,b)). This option provided theoretical efficiency gains of around 40% relative to using inspector discretion; it was chosen above the first-place winner because the City of Boston felt it would be it substantially easier to implement in-house.

three targeting methods, we observed a total of 1,042 restaurants that were ranked, and 361 restaurants that were inspected. To ensure consistent availability of rankings across the three docket formats, we limit our analysis to the top 20 restaurants ranked by each condition for each ward, which comprise of 245 restaurants out of the full set of 361 that were inspected, and result in 372 restaurant-method level observations.[xiv]

We use linear regression to test for the difference in weighted violations across the three methods, with the following model for the number of weighted violations Y_{im} associated with restaurant i ranked by method m:

$$Y_{im} = \alpha + \beta T_{data-rich,im} + \gamma T_{data-poor,im} + \varepsilon_{im}.$$

Here, α represents the mean number of weighted violations for restaurants ranked by human judgment; β and γ represent the mean expected increase in weighted violations for a restaurant drawn from the ranking by the data-rich and data-poor algorithms relative to a restaurant drawn from ranking by human judgment, respectively. For each restaurant inspected, these coefficients inform how many more weighted violations the City may expect to find if they use the data-rich or data-poor algorithm relative to business-as-usual.

4. Results

4.1. Assessing the gains from algorithmic methods

We begin by comparing the performance of the three methods over the study period. Our outcome of interest is the weighted sum of violations found during an inspection.

Table 1 presents our estimates of $\alpha, \beta,$ and γ under two specifications. Column 1 shows a data-poor comparison of mean weighted violations according to the ranking method. The mean number of weighted violations for restaurants ranked by human judgment is 8.19. This is equivalent to having one each of a Level I, II, and III violation. Our estimates of β and γ are 4.51 and 4.02 respectively. They are not statistically distinguishable, though we lack the statistical power to reject meaningful differences. The difference between the algorithm and human judgment equates to targeting a restaurant with on average one more Level III violation and one more Level I violation.

In Column 2 of Table 1, we explore whether the improvements in performance differ depending on the ranking position in the list. We find that the impact of rank is not statistically significant, and coefficients are both small and relatively precise around 0, suggesting that improvements are spread across the ranking distribution.

We draw three conclusions from Table 1. First, the data-poor and data-rich algorithms outperform human judgment for predicting weighted violations. These performance improvements are on the order of 50% and statistically significant. Second, the performance of the data-poor and data-rich algorithms are statistically indistinguishable, suggesting that the marginal benefit of additional data may be limited in this case. Third, the improvements are spread across the ranking distribution.

[xiv] Our results are robust to other definitions of this threshold, including focusing on restaurants in the top 5, 10, and 15 of each method's ranking.

While these results suggest that prior violations play an important role in predicting current violations, one can imagine important reasons why a city might not want to use this to guide inspection decision. For example, if heterogeneity is driven by variation in inspector stringency as opposed to true variation in violations, as found in Jin and Lee (2018), we may be concerned in relying heavily on past data. Furthermore, as with any simple algorithm, using historical violations to guide decisions may facilitate gaming, eventually reducing the efficacy of this approach.

4.2. Do improvements in performance differ across the ranking distribution?

We next explore differences between inspector discretion and algorithmic methods to better understand what might be driving the observed differences in performance. To explore which restaurants each method prioritizes, Table 2 reports summary statistics for restaurants ranked in the top 20 for each method, with Columns 1-3 presenting the mean of each variable for each method and Columns 4 and 5 respectively, showing the *p*-value for a *t*-test for the equality of means between (4) the data-rich algorithm and data-poor algorithm and (5) the data-rich algorithm and human-judgment ranked restaurants. We examine characteristics that may be of interest to policymakers and consumers: chain status, Yelp ratings, Yelp review count, type of cuisine, delivery, price range, availability of takeout, and years of operation. Notably, the data-rich and data-poor algorithms are less likely to prioritize inspecting chain restaurants and more likely to prioritize inspecting restaurants with ethnic cuisine and restaurants that deliver. The targeting of ethnic cuisine suggests that implementations of algorithms optimized for efficiency also requires managers to explicitly identify and engineer the fairness constraints that we have in place (based on interviews we conducted, some inspection departments are sensitive to this type of targeting).

4.3. The problem of worker compliance

Despite the large gains from using algorithmic methods, we found that inspectors were roughly twice as likely to inspect restaurants from dockets based on their own priors, relative to dockets suggested by our algorithms. This non-compliance issue highlights an important implementation concern: in practice, effective management of worker compliance may be key to helping organizations realize the gains from using algorithms. At the same time, it presents a potential problem of attrition: we are able to observe violation results for only a subset of the restaurants on each docket – and the results described in the prior two sections depend upon having a representative sample from each method's rankings.

Table 3 shows the extent of the non-compliance we observe. There are two sources of missing data related to non-compliance. Some inspectors did not provide full rankings across all restaurants in their wards. Due to challenges in implementation, we observe 94%, 93% and 72% of the rankings for the data-rich algorithm, data-poor algorithm, and inspectors, respectively (Column 1 of Table 3). In addition, inspectors did not inspect all restaurants assigned to them from each method (Column 2 of Table 3). Among restaurants for which we observe a ranking in the top 20, 31%, 32% and 61% were inspected from the data-rich algorithm, data-poor algorithm, and inspector list, respectively.

While this non-compliance result is interesting to observe, it also poses two potential threats to our results. The first concern arises in comparing performance across the algorithms. It may be, for instance, that inspectors were more likely to inspect restaurants ranked highly by the data-rich and data-poor algorithms. The differences we observe across methods could then be driven primarily by not observing the outcomes for restaurants ranked lower by the data-rich and data-poor algorithms;

we test this concern in Column 1 of Table 4 by looking for differences in average ranking by targeting method for restaurants that were inspected.

The point estimates suggest that there is a slight bias in favor of restaurants ranked highly by the data-rich and data-poor algorithms, but the differences are small. Only the data-poor algorithm shows a statistically significant difference in average ranking, coming in 1.5 positions higher on average than under business-as-usual. There is no statistically significant difference in comparing average rankings among inspected restaurants targeted by the data-rich and business-as-usual methods.

We also find little differences in average ranking by method for all ranked restaurants, lessening our concern that we may be observing different parts of the ranking distribution for each method and misattributing these differences to differences in characteristics. Column 2 of Table 4 shows a similar pattern to Column 1 of Table 4, albeit with even smaller magnitudes. Given the high magnitude of differences in restaurant characteristics observed in Tables 2 and 3, we do not see Column 2 of Table 4 as a major threat to validity.

These results, in context of our broader findings, suggest that the performance differences we observe between the algorithmic approaches and inspector discretion are unlikely to be primarily driven by differences in the ranking positions of restaurants inspected under each method. First, while there may be selection in the restaurants that inspectors choose to inspect, inspectors do not appear to choose substantially dirtier restaurants from the algorithmic approaches compared to their own list. This suggests that inspectors may not be making sophisticated tradeoffs, and it is difficult to construct a clear alternative story driven by selection. Second, the magnitude of the differences we observe between algorithmic approaches and inspector discretion is quite large, and does not differ significantly across rankings. Given this, it seems unlikely that selection would change these results directionally.

However, one key limitation to our analysis is that we do not know how clean the restaurants inspectors do not visit may be. Although inspectors are not systematically prioritizing restaurants that are predicted to have the most violations, it remains possible that the uninspected restaurants are much cleaner than the inspected ones, which would affect the magnitude of gains to algorithms in a higher compliance world.

5. Discussion

Our study shows that at least for the case of restaurant hygiene inspections, using predictive algorithms can significantly improve efficiency. Even a simple algorithm based on internal historical data improved predictions relative to inspector discretion. Moreover, a simple algorithm provided gains nearly as large as those from a more data-rich algorithm. But we also found worker compliance to be a first-order issue: inspectors frequently chose to prioritize restaurants based on their own judgment, rather than those based on algorithms.

What might account for this non-compliance? In many settings, algorithm aversion (Dietvorst et al. 2015) may play an important role, though it appears unlikely in our setting as inspectors were not informed of the source that generated the dockets. Rather, the reasons that may account for the non-compliance we observe all broadly point to the importance of effective management practices. It is possible that the directive to inspect the full docket of restaurants was not clear to inspectors, leading them to systematically prioritize a subset of restaurants based on their own judgment. Furthermore, among the multiple objectives that the inspection department targets, their prioritization may not have been clearly determined, communicated, or incentivized throughout the organization. Confusing targets, unclear communication, and weak incentives may have led to conflicting objectives being pursued across inspectors, who may potentially over-value other objectives than reducing the number of violations, such as speed, convenience, or fairness concerns not factored into algorithmic recommendations.

Chicago and NYC have run pilots using new targeting technologies, and our findings speak to the promise and challenge involved in implementing this at scale. Our results show a clear role for algorithms, but also highlight that improving organizational efficiency is rarely just a matter of better prediction. Academics are often interested in intellectually challenging problems, such as improving predictive accuracy or policy nuance, but in many practical settings, basic management capacity – such as managing workers to follow directions – is far more important. Workers with discretion will not comply with algorithms that ignore workers' priors and preferences, which means that algorithms must either cater to those preferences or managers must tether worker discretion with targeted incentives.

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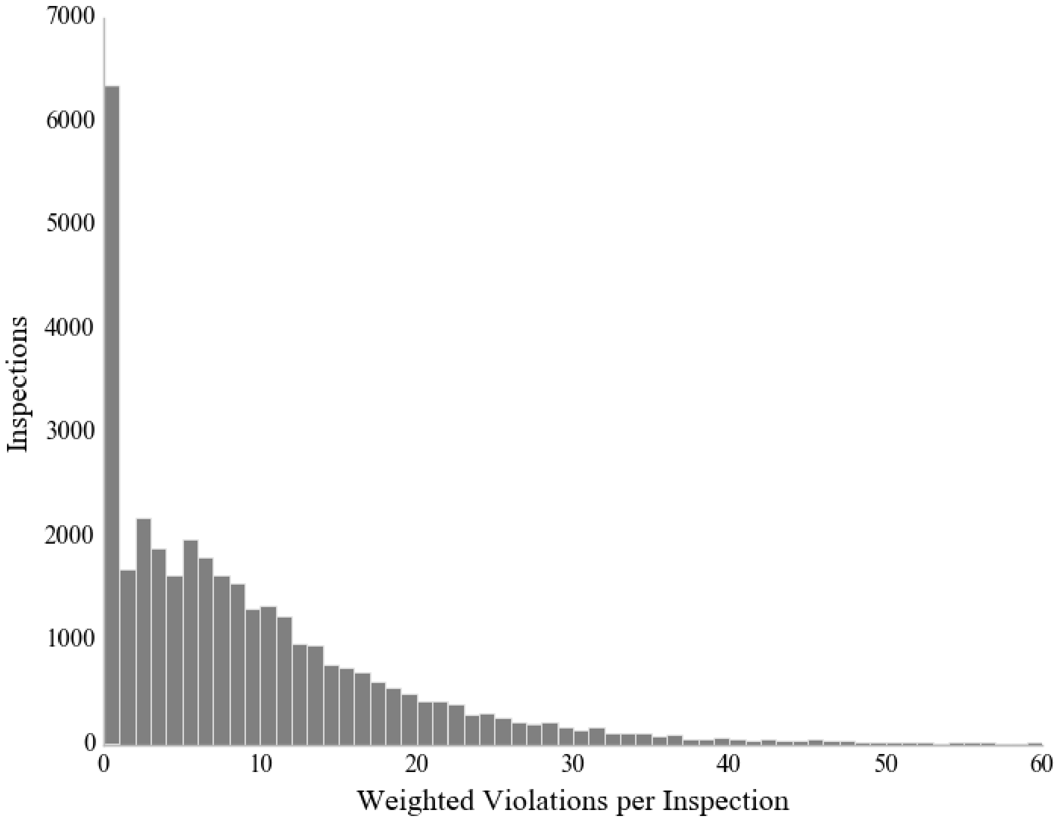
Figures

Figure 1: Distribution of Violations



The figure shows the distribution of weighted violations across inspections from January 2007 through June 2015. (Level I has a weight of 1; Level II, a weight of 2; and Level III, a weight of 5.)

Tables

Table 1: Performance of Rankings

Outcome:	(1) Total Violations b/se	(2) Total Violations b/se
Ranked by Data-rich Algorithm	4.508***	3.365**
	(0.792)	(1.354)
Ranked by Data-poor Algorithm	4.023***	3.741
	(0.928)	(2.698)
Data-rich Algorithm x Rank		0.107
		(0.120)
Data-poor Algorithm x Rank		0.024
		(0.229)
Rank		-0.029
		(0.113)
Constant	8.190***	8.519***
	(0.942)	(0.982)
Observations	372	372
Including Ranking Up To:	20	20

The sample consists of 372 restaurant-condition observations. Only restaurants ranked within the top 20 by any condition are included. Total violations are a weighted sum of one, two, and three star violations.
* p< 0.1, ** p<0.05, *** p<0.01.

Table 2: Mean Characteristics of Restaurants Ranked by Each Approach

	(1) Data-rich Algorithm	(2) Data-poor Algorithm	(3) Inspector Discretion	(4) p: 1=2	(5) p: 1=3
Chain	0.321	0.365	0.494	0.301	0.011**
Review Average	3.438	3.352	3.494	0.092*	0.409
% Trusted Reviews	0.786	0.798	0.795	0.014**	0.285
Review Count	141.041	175.232	172	0.026**	0.208
Ethnic Cuisine	0.538	0.542	0.319	0.133	0.000***
Restaurant Delivers	0.612	0.529	0.41	0.002***	0.009***
Price Range	1.632	1.596	1.573	0.5	0.462
Take Out Offered	0.967	0.974	0.945	0.835	0.413
Restaurant Age	18.938	20.527	28.645	0.433	0.157

Columns (1)-(3) show the mean value of each characteristic across restaurants ranked by each approach. Column (4) shows p-values testing whether the mean in column (1) is significantly different from that in column (2); column (5) shows p-values testing whether the mean in column (1) is significantly different from column (3).

Table 3: Inspector Compliance

	% of Top 20 Rankings Observed	% of Observed Rankings Inspected
Data-rich Algorithm	94.44	31.18
Data-poor Algorithm	92.78	32.33
Business-as-Usual	71.94	61.01

Column 1 shows the percent of restaurants that were ranked by each method. Column 2 shows the percent of restaurants inspected among those that were ranked by each method.

Table 4: Differences in Ranking

Outcome:	(1) Ranking b/se	(2) Ranking b/se
Data-rich Algorithm	-0.750	-0.285
	(0.630)	(0.185)
Data-poor Algorithm	-1.501**	-0.584**
	(0.600)	(0.243)
Constant	11.278***	10.629***
	(0.429)	(0.150)
Observations	372	933

The sample consists of restaurant-condition observations ranked within the top 20 by any condition. Column 1 further restricts the sample to restaurants that were inspected.

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