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INSPECTION TECHNOLOGY, DETECTION AND COMPLIANCE: EVIDENCE FROM FLORIDA RESTAURANT INSPECTIONS

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ABSTRACT

Many regulations mandate government employees to inspect economic entities on a regular basis. In this paper we show that a small innovation in inspection technology can make substantial differences in inspection outcomes. For restaurant hygiene inspections, the state of Florida has introduced a hand-held electronic device, a portable digital assistant (PDA), which reminds inspectors of about 1,000 potential violations. Using administrative data on inspections from July 2003 to June 2009, we find that the adoption of PDAs led to 16% more detected violations. Subsequently, restaurants increased their compliance effort, but the response was neither immediate nor large enough to offset the initial PDA impact. Nevertheless, the heightened compliance induced by use of PDAs has contributed to reducing the risk of restaurant-related foodborne disease outbreaks.

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1. Introduction

Firms are inspected on a regular basis when their products or production processes involve potential environmental, public health, or safety hazards. However, little is known on the effectiveness of such inspections, mostly because inspection outcomes, often reported in terms of the number of violations, reflect both detection and compliance. Inspectors spend costly effort detecting violations, but detection is never perfect; the separation of detection from compliance poses a real empirical challenge. In this paper, we overcome this problem by exploiting a change in detection technology in restaurant hygiene inspections in Florida.

In particular, the Florida Division of Hotels and Restaurants (DHR hereafter) began introducing portable digital assistants (PDAs) in restaurant inspections in November 2003. Prior to the use of PDAs, inspectors made manual marks on a "bubble sheet" that listed 31 categories of critical violations and 24 categories of non-critical violations on two pages. A PDA is a hand-held computer that reminds inspectors of about 1,000 violations at the subcategory level with a detailed explanation of each violation accessible by a dropdown menu. With the help of a PDA, an inspector can also retrieve past reports easily and upload the current inspection report immediately onto a DHR server.

We present a simple theory to show that an unexpected adoption of PDAs can help separate the changes in detection efforts from changes in restaurant compliance. The idea is straightforward: in an inspection game between an inspector and a restaurant, the restaurant will comply in expectation of detection. To the extent that the first use of PDA is unexpected, restaurant compliance at the first PDA inspection reflects the restaurant's expectation of the old detection technology. Assuming equilibrium play under the old technology, the restaurant's compliance effort should be the same in the last paper inspection and the first PDA inspection. Therefore, the outcome difference between these two inspections reveals how much inspector detection effort has changed because of the PDA. After the first use, the restaurant expects a PDA use next time and adjusts its compliance accordingly. As detailed in our theory, a comparison between the first and subsequent PDA inspections will identify an upper bound of the change in restaurant compliance. It is an upper bound instead of a precise point estimate because the inspector has an incentive to reduce her detection effort if she anticipates greater restaurant compliance in response to PDA use.

We test these predictions using the universe of Florida restaurant inspection records from July 2003 to March 2010. Following a quick adoption of PDA in the first quarter of 2004, PDA adoption rate fluctuated between 2004 and 2006, mostly due to technical problems, before reaching nearly 100% by 2009. After showing evidence that these PDA changes are likely exogenous to individual restaurants, we find that the first use of a PDA increases the number of violations by 16.2%, which, according to our theory, reflects a significant increase in detection effort due to the PDA. Afterwards, each additional previous use of a PDA reduces the number of detected violations by 3%-5.1%. This effect identifies an upper bound of restaurant compliance in response to the increased detection effort because of the PDA.

Although the compliance response is neither immediate nor large enough to offset the initial PDA impact, we find that the heightened compliance has contributed to fewer restaurant foodborne disease outbreaks and therefore improves public health. In particular, we estimate that permanent adoption of PDAs decreases the likelihood of restaurant foodborne disease outbreaks by 1.4 percentage points, which is non-negligible compared to the average probability of restaurant foodborne disease outbreak per quarter per county in Florida (7.6 percent).

We believe our work contributes to several strands of literature. A rich theoretical literature focuses on the agency problem of inspectors and proposes solutions such as outcome-based contracts, targeted auditing, reduction of information rents (to inspectors), high penalties on corrupt inspectors, or intentional selection of biased employees.[2] These solutions are often difficult to implement in reality because bureaucratic agencies are subject to rigid compensation schemes and limited resources. Our paper shows that a simple change in inspection technology can go a long way toward improving detection and compliance, and it is not difficult to implement in a typical government-run program.

Game-theoretical interaction between inspectors and inspectees highlights the empirical difficulties in separating compliance from detection. To circumvent this problem, a number of taxation studies have used randomized detection to identify compliance (see Slemrod and Yitzhaki 2002 for a survey and Kleven et al. 2011 for a recent example). Similarly, we exploit PDA adoption as an exogenous source of detection change. However, we argue that a simple comparison of inspection outcomes with and without a PDA tells us little about the actual hygiene of the restaurant if we do not consider the game theory behind the change. We believe that the combination of game theory and empirical identification is useful for examining detection and compliance in other inspection programs, and our methodology complements the structural model of detection and compliance that Feinstein (1989) has developed for nuclear plant inspections. A few other papers have presented evidence of inspector heterogeneity (Feinstein 1989, 1991; Macher at al. 2010), an issue we downplay in this paper but fully address in a companion paper (Jin and Lee 2012). As shown below, the findings presented in this paper are robust to control of inspector heterogeneity.

Another related literature concerns the impact of technology on productivity. Some studies find that technology, often in the form of computers or electronic systems, has improved emergency health

[2] The agency problem of inspectors has been examined in Tirole (1986), Martimort (1999), Lafont and Tirole (1993), Mookherjee and Png (1989, 1995) and Prendergast 2007. Reviews of this literature are available in Prendergast (1999) and Dixit (2002).

care outcomes (Athey and Stern 2002), increased firm productivity (Brynjolfsson and Hitt 2003), increased capacity, revenue and resource allocations in the trucking industry (Hubbard 2003), and increased police departments' productivity when IT investments are supplemented with particular organizational and management practices (Garicano and Heaton 2010). Other studies find no positive effect of classroom computers on student learning (Angrist and Lavy 2002), or even find a harmful effect of computerized physician orders on the number of adverse drug events and higher medical costs (Berger and Kichak 2004). Compared with this literature, we link technology adoption to the mechanisms of productivity change. In our raw data, the average number of detected violations increases after introduction of a PDA if we simply compare inspections with or without a PDA. On the surface, this seems to suggest little improvement in compliance. However, when we separate detection from compliance, we are able to document a significant effect of PDA use on both. These findings help us understand the mechanisms underlying the technological impact on inspection and public health outcomes.

The rest of the paper is organized as follows. Section 2 describes PDA adoption in Florida. Section 3 presents a simple game theory between an inspector and a restaurant, and derives testable predictions pertaining to PDA use. Section 4 tests these predictions on the Florida restaurant inspection data. Section 5 links PDA use to the data on foodborne disease outbreaks in Florida. A brief conclusion is offered in Section 6.

2. Introduction of PDA to Restaurant Hygiene Inspection in Florida

In all states in the U.S., restaurants are required to be regularly inspected by licensed and trained inspectors. In Florida, all food establishments are required to be inspected twice per fiscal year by state laws and three times by administrative rules. Inspectors are public employees with a fixed salary scheme. They are assigned to inspection districts based on their residence, and they are responsible for restaurants within those districts. They have full discretion in deciding when and which restaurants to inspect. After inspections, they submit inspection reports to the Florida Division of Hotels and Restaurants (DHR hereafter) and, if necessary, the DHR determines disciplinary actions.

Inspectors are trained to inspect restaurants according to a predetermined inspection checklist, consisting of 55 categories in the case of Florida. The DHR classifies categories into two groups: critical and non-critical. Critical violations include 12 categories of foodborne illness risk factors plus another 19 categories "pertaining to life safety, business practices and food service good retail practices vital to support a good food safety system within an establishment." There are many subcategories within each category. For example, category 22 – "food contact surfaces clean and sanitized" – includes 8 subcategories such as “cooking equipment not rinsed of abrasives/detergents,” “presetting of unwrapped silverware” or “unused utensils not removed when consumer seated.” The number of subcategories differs by category, from 1 to 53 per category. Thus inspectors are supposed to check about 1,000 items at each inspection.

In November 2003, as part of an initiative to improve the efficiency of the inspection process, the DHR introduced a hand-held computer, called a portable digital assistant (PDA). Prior to the use of PDAs, inspectors wrote inspection reports with pencil and paper on a “bubble sheet” that listed violations only broadly, with 31 categories of critical violations and 24 categories of non-critical violations on two pages (Office of Program Policy Analysis & Government Accountability (OPPAGA), 2005). In comparison, the PDA reminds inspectors of about 1,000 violations at the subcategory level with a detailed explanation for each violation accessible by a dropdown menu. With the help of PDAs, inspectors can also retrieve past reports easily and upload inspection reports onto the agency server. Appendix Figure 1 displays the paper-form inspection report and Appendix Figure 2 shows screenshots of a PDA.

The introduction of PDAs was decided at the state level by the DHR. To confirm this understanding, Figure 1 shows the trends in PDA use in seven administrative districts as defined by the DHR. Across all districts, there was virtually no use of PDAs in 2003. The proportion of PDA inspections jumped in the first quarter of 2004 to over 80 percent in all districts but one (district 4, 74 percent). Across all seven districts, this proportion suddenly fell to below 50% in the last quarter of 2004, recovered in the first quarter of 2005, and dropped again in the second or third quarter of 2006. These sudden drops reflect some mechanical problems with the initial version of the PDA (OPPAGA, 2005). In the first quarter of 2007, PDA use quickly returned to the level prior to the 2006 drop. Afterwards, the proportion of PDA use went steadily upward and reached almost 100 percent by 2009. Similar trends across districts confirm that the new technology was adopted uniformly at the state level despite geographic heterogeneity across districts.

We know less about how the PDAs were distributed within a district. However, our raw data – which is the universe of restaurant inspection records from July 2003 to March 2010 in Florida – allow us to pin down the exact date when a PDA was first used by each individual inspector. For each of the seven adminstrative districts as defined by the DHR (Appendix Figure 3), we can single out a date when a number of inspectors acting in that district started to use PDAs. It turns out that PDAs were distributed on a specific date. For example, for district 1, a majority of active inspectors started to use PDAs on the same day, March 11, 2004. Other inspectors also started to use a PDA around the same day. Similarly, this “massive adoption” date was February 12, 2004 for district 2, March 4 for district 3, January 29 for district 4, January 8 for district 5, February 26 for district 6 and February 19 for district 7. This means that the timing of PDA introduction was determined at the district level rather than by individual inspectors.

To take a first look at the impact of PDA use on inspection outcomes, Figure 2A examines the trends in weekly average inspection outcomes for 10 weeks before and after the “massive adoption” day of PDA introduction. Consistent with the sudden and quick adoption of PDAs, the PDA usage rate jumped on the “massive adoption” day we identified and stayed high for ten weeks. Weekly average violations also increased discretely on the same day. Afterwards, the number of violations increased further, although the PDA usage rate did not change much after the “massive adoption” day. This may be because inspectors had to learn how to handle their new PDAs.

One issue fundamental to the exogeneity of PDA use is that PDAs were not selectively used for restaurants with bad records. We check this in two ways. First, we depict the average number of violations detected at the previous inspection for the restaurants inspected in each of the 10 weeks before and after the massive adoption date of PDAs. As shown in Figure 2B, there is no difference between before and after the adoption day. In a more systematic check, we focus on individual inspection records and examine whether the use of a PDA at a given restaurant depends upon the number of violations noted in its previous inspection. We estimate a linear probability model for each quarter of the year, allowing the effect of previous violations on PDA use to vary over time. In Figure 3, the dotted line represents the estimates without district fixed effects, while the real line represents those with district fixed effects. This graph shows that previous violations have little impact on whether or not to use a PDA at the current inspection. The marginal effect is small, even though it is defined as the effect of ten additional violations at the last inspection.

Above all, we conclude that PDA adoption was driven by state or district-level decisions, and there is no systematic evidence of any selective use of a PDA based on a restaurant’s inspection history.

3. Model and Identification

In this section we present a stylized static model in which restaurants choose their effort to clean up and inspectors decide their effort to detect violations. The model allows for heterogeneity in inspectors’ stringency as well as in taste regarding various hygiene factors. The model also allows for heterogeneity in restaurants’ inherent hygiene level. In the second part of this section we conduct comparative static analysis of the impact of PDAs and derive testable hypotheses for our empirical analysis in the next section.

3.1. Game-Theoretic Model of Detection and Compliance

Consider a regulatory regime of three parties: the principal (DHR), inspectors (government employees), and clients (restaurants). The principal defines inspection criteria, inspection technology, inspector assignment, and inspector compensation. Each inspector earns a fixed wage as a public employee. Assuming there are two categories of violations (e.g., critical and non-critical), the principal imposes a fine structure $F(y) = \tau_1 y_1 + \tau_2 y_2$ where y_1 and y_2 denote the number of violations and τ_1 and τ_2 denote penalty rate for the two categories, respectively. The assumption of constant penalty rates is a simplification. In practice, the penalty for a violation includes both monetary fines and the possibility of a callback visit (which incurs time and effort costs due to re-inspection).

The main task of an inspector is visiting a restaurant (at an unannounced time), detecting all the hygiene violations, and reporting them to the principal. Within the restaurant, the inspector has discretion as to how much effort to exert in detecting violations and how much information to report. In the eyes of the principal, hiding detected violations is equivalent to shirking on detection effort, so we do not distinguish the two in the model.[3] Rather, we consider every inspector to be honest and assume the cost of detection effort for inspector i is $C(e_i) = \theta_i e_i^2$, where θ_i is the parameter of detection cost, which is specific to the inspector.

Not only do inspectors differ in detection cost, but they may have their own interpretation of a regulation. Given the two categories of violations, we assume inspector i puts weight α_i on category 1 and $(1-\alpha_i)$ on category 2. Accordingly, inspector efforts in detecting violations are e_{i1} and e_{i2} for the two categories, respectively. Assumed between 0 and 1, e_{i1} and e_{i2} can be interpreted as the probability of detection for category 1 and 2. If true violations are $\tilde{y}_1$ and $\tilde{y}_2$, detected violations are $y_1 = \tilde{y}_1 e_{i1}$ and $y_2 = \tilde{y}_2 e_{i2}$. We do not allow inspectors to report non-existent violations (extortion) because in Florida an appeal procedure allows restaurants to contest any reported violations. Moreover, the expected fine is very low ($11 per inspection) and the fine amount is not determined by the inspector.

For tractability, we assume effort costs for categories 1 and 2 are independent and both depend on the same cost parameter θ_i. In this sense, θ_i also denotes the overall stringency of i. If θ_i differs by category, it is observationally equivalent to the inspector putting different weights on different categories. The goal of regulation is enforcing food safety, which implies minimization of actual violations. Since we focus on the interaction between inspector and restaurant, we do not model the principal-inspector relationship explicitly. Rather, we assume that the inspector, as an agent of the principal, derives negative utility from both detected and undetected violations. Because undetected violations may be ignored by the restaurant and pose a bigger public health risk, we assume that the inspector is more concerned about undetected violations. In other words, the DHR and its employees would like to see zero violations if all

[3] The incentive to hide perfectly-observable violations was the focus of many theories on inspector-firm collusion.

violations can be detected. However, given the existence of violations, identifying them is better than leaving them undetected. To capture this, we introduce $\lambda > 1$ as the disutility of an undetected violation relative to a detected violation. If $\lambda < 1$, the inspector will always prefer minimal effort and detect no violations. Note that λ reflects the inspector's preference, which may or may not coincide with that of the principal. In short, the inspector trades off her own preference for inspection outcomes for her effort cost. This captures the fact that government inspectors are paid a fixed salary and their efforts are likely more motivated by intrinsic preferences than by monetary returns (Prendergast, 2007).

We assume that consumers have no information on restaurant hygiene and therefore cleaning up does not change restaurant revenue.[4] For the restaurant, the only benefit from cleaning up is reducing fines for detected violations. To minimize fines, the restaurant can exert efforts e_{r1} on category 1 and e_{r2} on category 2. Normalizing maximum violation (per category) as 1, we have the actual violations $\tilde{y}_1 = 1 - e_{r1}$ and $\tilde{y}_2 = 1 - e_{r2}$. Consequently, the detected violations are $y_1 = \tilde{y}_1 e_{i1} = (1 - e_{r1})e_{i1}$ and $y_2 = \tilde{y}_2 e_{i2} = (1 - e_{r2})e_{i2}$.

Assuming the cost of restaurant effort is strictly convex ($C(e_r) = \theta_r e_r^2$) and applies to both categories independently, we can write the restaurant's problem as:

$$\min_{e_{r1}, e_{r2}} \quad W_r = \tau_1(1 - e_{r1})e_{i1} + \tau_2(1 - e_{r2})e_{i2} + \theta_r e_{r1}^2 + \theta_r e_{r2}^2.$$

The inspector's problem can be written as:

$$\begin{aligned} \min_{e_{i1}, e_{i2}} \quad W_i = {} & \alpha_i((1 - e_{r1})e_{i1} + \lambda(1 - e_{r1})(1 - e_{i1})) \\ & + (1 - \alpha_i)((1 - e_{r2})e_{i2} + \lambda(1 - e_{r2})(1 - e_{i2})) + \theta_i e_{i1}^2 + \theta_i e_{i2}^2. \end{aligned}$$

The timing of the game is as follows: at stage 0, the principal sets inspection criteria, inspector assignment, fine structure, and inspector compensation. At stage 1, the restaurant chooses e_{r1} and e_{r2}. At stage 2, the inspector walks in and chooses detection effort e_{i1} and e_{i2}. At the end of stage 2, detected violations (y_1 and y_2) are reported to the principal. Since no new information is generated between stages 1 and 2, the inspector-restaurant game is treated as a simultaneous game.

Figure 4 characterizes the equilibrium by two reaction curves: the restaurant's *compliance curve* (for category 1, $e_{r1} = \frac{\tau_1}{2\theta_r} e_{i1}$) shows that the restaurant is more willing to clean up if it knows that the

[4] Jin and Leslie (2003) show that restaurant revenue was insensitive to restaurant inspection outcomes before the introduction of restaurant hygiene report cards. As of 2011, Florida has no restaurant hygiene report card even though inspection outcomes have been posted online since 2009. This change will be controlled for by year-month fixed effects throughout Florida.

inspector exerts more effort, but the inspector's *detection curve* (for category 1, $e_{i1} = \frac{\alpha_i(\lambda-1)}{2\theta_i}(1-e_{r1})$) shows that the inspector will exert less effort if she knows that the restaurant has cleaned up.

In our simple model, by the timing of the game, the inspector can observe the restaurant's effort with no error. Note that the restaurant can also exactly figure out the inspector's detection curve after a single inspection. The restaurant should be notified by the inspector of the number of violations. The restaurant knows it is determined by $y_1 = (1-e_{r1})e_{i1}$ and $y_2 = (1-e_{r2})e_{i2}$. Since the restaurant knows its own compliance effort, it can figure out the inspector's detection effort e_{i1} and e_{i2}. Also, the restaurant knows the inspector's reaction function (for category 1, $e_{i1} = \frac{\alpha_i(\lambda-1)}{2\theta_i}(1-e_{r1})$). Knowing e_{i1} and e_{r1}, the restaurant can calculate $\frac{\alpha_i(\lambda-1)}{2\theta_i}$, which is enough for the restaurant to figure out the detection curve (the slope as well as the vertical intercept of the curve). This means that it takes one inspection for the inspection game to reach the equilibrium. Given preference and cost parameters, it is a steady-state equilibrium.

As the two curves intersect in Figure 4, we have a unique inner solution in equilibrium if $\theta_r > 0.5$, $0.5 < \frac{4\theta_i\theta_r}{(2\theta_r-\tau_1)(\lambda-1)} < 1$ and $0.5 < \frac{4\theta_i\theta_r}{(2\theta_r-\tau_2)(\lambda-1)} < 1$ [5]:

$$e_{i1} = \frac{2\theta_r\alpha_i(\lambda-1)}{4\theta_i\theta_r + \tau_1\alpha_i(\lambda-1)},\ e_{i2} = \frac{2\theta_r(1-\alpha_i)(\lambda-1)}{4\theta_i\theta_r + \tau_2(1-\alpha_i)(\lambda-1)}$$

$$e_{r1} = \frac{\tau_1\alpha_i(\lambda-1)}{4\theta_i\theta_r + \tau_1\alpha_i(\lambda-1)},\ e_{r2} = \frac{\tau_2(1-\alpha_i)(\lambda-1)}{4\theta_i\theta_r + \tau_2(1-\alpha_i)(\lambda-1)}.$$

Therefore, the equilibrium reported violations are as follows:

$$y_1 = (1-e_{r1})e_{i1} = \frac{8\theta_i\theta_r^2\alpha_i(\lambda-1)}{[4\theta_i\theta_r + \tau_1\alpha_i(\lambda-1)]^2},\ y_2 = (1-e_{r2})e_{i2} = \frac{8\theta_i\theta_r^2(1-\alpha_i)(\lambda-1)}{[4\theta_i\theta_r + \tau_2(1-\alpha_i)(\lambda-1)]^2}.$$

Our model highlights two fundamental identification problems if we want to use this framework to empirically identify detection from compliance: first, we observe only the intersection of the two reaction curves. Interestingly, this problem resembles the typical identification problem in the supply and demand model where the difficulty can be resolved by using exogenous demand (supply) shifters to trace

[5] These conditions imply that the cost of restaurant effort must be high enough so that it is meaningful to exert efforts to detect violations, but the inspector's effort cost and her view of undetected violations must be within a range such that she has the freedom to choose lower-than-maximum detection effort.

out the supply (demand) curve. However, identification is even harder in the inspection game because we observe only the product of non-compliance and detection ($\tilde{y}_j e_{ij}$), not the two separately. In other words, inspector heterogeneity (which shifts the detection curve) and restaurant heterogeneity (which shifts the compliance curve) cannot identify the two reaction curves. Similarly, exogenous policies that shift the inspector's detection curve or shift the restaurant's compliance curve cannot fully identify the two curves either.

Second, in the literature, researchers often regress detected violations on inspector fixed effects and interpret these fixed effects as inspector heterogeneity.[6] Under the assumption of perfect information, our theory suggests that inspector fixed effects reflect not only inspector heterogeneity in overall stringency and taste but also the differential compliance that restaurants adopt in response to the inspector heterogeneity.

3.2. Comparative Statics of Adoption of PDA

The PDA reminds inspectors of about 1,000 potential violations and therefore may reduce the cost of detection. This suggests that PDA use may substantially reduce inspector's detection effort cost (θ_i) in the model in the previous subsection. But the key prediction of the model is that restaurant response to the introduction of PDAs depends upon the restaurant's compliance effort as well as the inspector's detection effort.

Under the assumption that PDA adoption is unexpected and there is no change in inspector identity, we can derive some testable hypotheses from the model. In Figure 5, point A represents the equilibrium before the adoption of PDAs when the restaurant had correctly expected paper inspection. Suppose that PDA use reduces the inspector's detection cost from θ_i to θ_i', $\theta_i > \theta_i'$, which shifts up the inspector's detection curve. When the inspector walks in with a PDA for the first time, it is a surprise to the restaurant. Restaurant compliance remains at e_{r1}^A but inspector effort increases from e_i^A to e_i^B. Thus, at the first-PDA inspection, the number of detected violations should increase by the difference between A and B, and this difference is solely driven by the unexpected detection change:

$$\frac{y^B - y^A}{y^A} = \frac{(1 - e_r^A)e_i^B - (1 - e_r^A)e_i^A}{(1 - e_r^A)e_i^A} = \frac{e_i^B - e_i^A}{e_i^A} > 0. \tag{1}$$

Let us further assume that the restaurant expects continued use of the PDA and complies

[6] See Feinstein (1989) and Macher et al. (2010) for examples.

accordingly. In response to the increased compliance effort, the inspector should reduce her detection effort. As a consequence, we reach a new equilibrium at point C (note that B is enough for the restaurant to figure out the new detection curve). Compared to the first PDA inspection, the number of detected violations should decrease from B to C, and the decrease reflects both the restaurant's improved compliance ($e_r^C - e_r^B$) and the laxity of inspector detection ($e_i^C - e_i^B$). Thus, this reduction of detected violations is an *upper bound* of the restaurant's compliance response to the continued use of a PDA:

$$\frac{y^C - y^B}{y^B} = \frac{(1 - e_r^C)e_i^C - (1 - e_r^B)e_i^B}{(1 - e_r^B)e_i^B} < \frac{e_r^B - e_r^C}{1 - e_r^B} < 0. \tag{2}$$

It is ambiguous whether the equilibrium number of detected violations under a PDA inspection (point C) would increase or decrease relative to a paper inspection (point A). This is because point C corresponds to higher compliance and higher detection, and the two of them have opposite effects on the number of detected violation. Mathematically, the impact of PDAs on the equilibrium number of detected violations of category 1 can be written as:

$$\frac{\partial y_1}{\partial \theta_i} = \frac{8\theta_r^2 \alpha_i (\lambda - 1)(\tau_1 \alpha_i (\lambda - 1) - 4\theta_i \theta_r)}{(\tau_1 \alpha_i (\lambda - 1) + 4\theta_i \theta_r)^3} \tag{3}$$

The sign is ambiguous because the sign of $(\tau_1 \alpha_i (\lambda - 1) - 4\theta_i \theta_r)$ is ambiguous. Empirically this means that a simple comparison of violations before and after PDAs tells little about the actual hygiene of the restaurant. In theory, the actual hygiene must be improved by PDA usage if the PDA implies lower detection effort and the restaurant increases compliance accordingly.

Above all, we have two clear predictions regarding PDA adoption: first, assuming PDA adoption is sudden and unexpected, the first PDA inspection should increase the number of detected violations, and this increase reflects the increased detection due to PDA usage. Second, assuming restaurants expect continuous use of a PDA, a subsequent use of a PDA should decrease the number of detected violations compared to the first PDA inspection, and this decrease reflects an upper bound of restaurant compliance response to the improved detection in the first use of a PDA. Because the above two predictions go against each other, a simple comparison of paper and PDA inspection outcomes (without accounting for the sequence of PDA use) yields no clear prediction of the number of detected violations, although the actual hygiene should have improved unambiguously because of PDA usage.

Note that the above discussion assumes no change of inspector identity. In a companion paper (Jin and Lee 2012), we expand the model to include inspector identity change and show that allowing inspector heterogeneity does not affect the above predictions about PDA use. Empirically, we will present our results with and without controls on inspector heterogeneity.

4. The Impact of PDA Use on Restaurant Inspection Outcomes

This section has four parts. We first describe the DHR restaurant inspection data, summarize the analysis sample, and then present the econometric specification. Regression results are discussed last.

4.1 Data and Sample Construction

We use three administrative data sets collected by the DHR: (1) restaurant/food service inspection files, (2) license files, and (3) restaurant disciplinary activity reports. The data include all restaurant inspections in Florida from July 2003 to March 2010. We start with July 2003 because July 2003 is the start of the 2003 fiscal year (referred to as FY 2003).

There are two types of inspections: the first type is regular inspections conducted at unannounced times, which Florida officials refer to as "initial" inspections. Depending on the results of a regular inspection, a callback may follow to ensure compliance. The time lag between a regular inspection and a callback has modes of one day, one week, two weeks, one month, or two months. In the raw data, about 81% are regular inspections and 19% are callbacks. The disciplinary activity reports specify whether a fine is imposed after each inspection and, if so, the amount of the fine. Any decisions related to fines are determined by a separate branch of the Department, not by individual inspectors. Complete disciplinary activity reports are only available from FY 2005 to FY 2009.

We clean our final analysis sample through several steps. Starting with 740,808 inspections in the raw data, we first exclude any inspections conducted prior to FY 2004 because Florida adopted a new classification system classifying violations into three groups – risk-factors, other critical and non-critical violations – in March 2004.[7] This reclassification requests inspectors to pay more attention to risk factors. If we do not exclude records before March 2004, one may argue that inspectors find more critical violations because of the DHR reclassification rather than PDA use. One alternative way to address this data issue is keeping records before FY 2004 but allowing different year-month fixed effects for risk-factors, other critical, and non-critical violations separately. We have done this alternative estimation and found very similar results regarding PDA use. By focusing on data after FY 2004, we do not need to separate risk factors from other critical violations in regression results. Constructing the sample since FY

[7] On the paper inspection form, risk factors are listed on the first page and other critical and non-critical categories are on the second page.

2004 also gives us more pre-sample data to define a restaurant's history of PDA use and inspector turnover, both of which turn out to have a significant effect on inspector outcomes.

We further drop inspections conducted during FY 2009 because we do not have complete inspection data for that fiscal year. By the above two sample selection criteria, we dropped 129,941 inspections. To ensure a valid count of history, our third step of data cleaning excludes the first six months of a restaurant since its first appearance in our data (90,251 dropped). In the fourth step, since callbacks are usually conducted on scheduled dates, we focus on initial inspections (90,811 dropped). Fifth, because we apply restaurant fixed effects in all estimations, we also exclude 11,929 restaurants that have only one inspection throughout the sample. Lastly, we delete observations with missing values, duplicates, non-restaurant inspections or inspections of restaurants outside Florida. The final sample includes 346,579 initial inspections from FY 2004 to FY 2008, covering 54,738 unique restaurants and 271 individual inspectors.[8] Each year there are more than 200 active inspectors.

4.2 Sample Summary

Table 1 shows summary statistics of our regression analysis sample. Following the DHR classification, we aggregate violations into two groups, critical (risk factors and other critical) and non-critical violations.[9] An average inspection finds about 8 violations, of which 5 are critical and 3 non-critical violations. Unfortunately, we do not have any demographic information about inspectors. However some characteristics of inspectors can be constructed from the inspection file. The probability of a "new" inspector (an inspector who has never inspected the restaurant during the data period) arriving is 28%. On average, an inspector has inspected the same restaurant 3.5 times before the observed inspection. As mentioned earlier, restaurants are required to be inspected at least twice per fiscal year according to state laws. However, due to labor shortage, the average number of regular inspections per restaurant per year is less than 2 except for FY 2008. About 30% of restaurants receive only one regular inspection per year.[10] The average number of days between the two inspections (including callbacks) is about 158. The burden of the job seems to be huge; each inspector has on average done about 1,757 inspections.

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[8] The original inspection files include 386 inspectors and 97,990 restaurants. We excluded those inspectors who conducted fewer than 200 inspections.

[9] For the DHR's classification, refer to http://www.myfloridalicense.com/dbpr/hr/inspections/FoodServiceCriticalViolations.html. For category 08, some subcategories are identified as risk factors while other subcategories are identified as other critical violations. We consider category 08 as risk factor. Also note that the three group distinction is made at the subcategory level. But our group distinction is made at the category level because we do not observe subcategories in our data.

[10] The average number of regular inspections is 1.66 in FY 2003; 1.93 in FY 2004; 1.67 in FY 2005; 1.72 in FY 2006; 1.85 in FY 2007; 2.14 in FY 2008. The proportion of restaurants that receive only one inspection is 50.6%; 22.4%; 39.9%; 26.2%; 15.2%, respectively.

Most inspections are "routine" ones, while 4% are initiated by consumer complaints and 0.1% are licensing inspections. The average restaurant age is 4 years, with a wide variation from restaurants that have just opened to those as old as 14 years. Restaurant age is calculated from the license issuing date. For about 24% of observations, this information is missing. Instead of dropping all these observations, we create a dummy for missing age and control for it. As mentioned earlier, inspectors have complete discretion over how many and which restaurants to inspect on a given day. On average, an inspector has completed 1.9 inspections before coming to the inspection under study and 25% of inspections are the first one conducted by that inspector on that day. The number of inspections prior to a specific inspection is important because it may represent the inspector's fatigue level, i.e., the inspector may become tired during the day and incur higher effort costs due to fatigue. For 11% of observations, the exact inspection time of the day is not recorded. As with restaurant age, we create a dummy for missing information and control for it. Lastly, 38% of the inspections occur during lunchtime (12:00-2:00pm). We control for whether inspections are done during lunchtime because most restaurants are busy at lunchtime and probably pay less attention to food safety.

In Table 2, we present summary statistics of variables associated with PDA use. Several patterns are worth highlighting. First, in our regression sample, 88% of inspections are done by PDA. This high percentage is mainly due to our sample restriction. By excluding data before FY 2004, many restaurants had their first PDA inspection before the start of the sample. However, as we have shown in Section 2, analysis of the complete data from 2003-2011 indicates that PDA adoption is a state-and-district decision and whether to use a PDA on a particular restaurant is independent of the restaurant's last inspection outcome. Since most restaurants are inspected no more than twice a year, some restaurants had completed all their inspections of a fiscal year before the massive adoption of PDA; hence, their first use of PDA did not happen until FY 2004 or after. This explains why, even though our analysis sample focuses on data since FY2004, about 20% of restaurants first had a paper inspection in our sample and then switched to PDA. About 36% of restaurants, after having adopted PDA inspections, experienced a switch back to paper-form inspection(s) due to technical problems in the first version of the PDA (OPPAGA 2005).

Another crucial variable is the number of previous PDA uses in a particular restaurant. For completeness, we construct this variable based on all the raw data, including initial and callback inspections. Conditional on a restaurant having had no PDA use before, the probability of using a PDA for the first time is 75%. Once the PDA was adopted, the probability of subsequent use increases. For example, conditional on having one inspection done by PDA, the probability is 82%. Once a PDA was used six times, the probability is over 90%. This means that the more inspections were done by PDA, the more likely restaurants expect a PDA to be used next time.

Table 3 shows the distribution of restaurants by frequency in the sample and the number of PDA inspections. There are 54,738 unique restaurants in the regression sample. Among them, 8,237 appear twice in the sample, and 6,438 appear three times. Most of them appear 10 times or fewer. As shown in Table 3, many restaurants experienced both paper and PDA inspections, either because they started with paper inspection and then moved to PDA, or because they were switched back from PDA to paper due to technical problems in the first version of the PDA. Both types of switches will help estimate the impact of PDA use within restaurants. As described below, these two types of switches have different implications for detection and compliance, as restaurants may have different expectation as to the likelihood of PDA use.

4.3 Econometric Model

This subsection presents an econometric specification that tests the model's predictions. We denote by y_{irt} the number of detected violations for restaurant r by inspector i at time t.[11] Since our dependent variable is a count of reported violations, we estimate a Poisson model with expected value given by:

$$E(y_{irt}) = exp(\beta_{det} D_{irt} + \beta_{comp} N_{ir}^{t-1} + \beta_{inter} D_{irt} N_{ir}^{t-1} + X'_{irt}\gamma + \mu_r + \mu_i + \mu_t) \qquad (4)$$

where D_{irt} indicates whether a PDA is used at t and N_{ir}^{t-1} represents the number of PDA inspections prior to t. Vector X_{irt} includes a constant term and other restaurant/inspector/inspection characteristics, such as whether the inspector is new to the restaurant, restaurant age, inspector tenure, whether the inspection occurs at lunchtime or not, and how many days it has been since the last inspection. Note that we control for a rich set of fixed effects: restaurant fixed effect (μ_r), inspector fixed effect (μ_i) and year-quarter fixed effect (μ_t). Restaurant-specific fixed effects should capture each restaurant's time-invariant difficulty or willingness to clean up. Inspector-specific fixed effects should capture each inspector's specific detection cost *and* the corresponding compliance effort by the restaurant under the assumption that the restaurant can perfectly predict that particular inspector. Any effort cost or taste change applicable to all inspectors and all restaurants during a given quarter of a year should be absorbed in year-quarter fixed effects.

The coefficients of our main interest are β_{det}, β_{comp} and β_{inter}. Our model predicts that the first use of a PDA detects more violations: $\frac{y^B - y^A}{y^A}$ as Equation (1) indicates. This corresponds to the movement from A to B in Figure 5, and we expect $\beta_{det} > 0$. Furthermore, theory predicts that the

[11] In fact, time indicates the order of the inspection in our sample. We control for the quarter of the year fixed effects to control for common time trends.

adoption of PDAs subsequently increases the restaurant's compliance effort, so we should observe the number of violations drop from the first PDA inspection to the next PDA inspection. In other words, the equilibrium changes from B to C in Figure 5 and this prediction corresponds to $\beta_{comp} + \beta_{inter} < 0$.

If the inspector does not bring back a PDA after the first use of PDA, she will find fewer violations for two reasons: first, the restaurant has increased compliance in expectation of PDA use; second, the inspector will engage in less detection effort due to both the higher detection cost of a paper inspection and an expectation of better compliance. This scenario of "paper inspection following the first use of PDA" corresponds to point D in Figure 5. Our model predicts fewer detected violations at D than at A, which implies $\beta_{comp} < 0$, and fewer detected violations at D than at C, which implies $\beta_{det} + \beta_{inter} > 0$.

Above all, we expect $\beta_{det} > 0$, $\beta_{comp} < 0$, $\beta_{det} + \beta_{inter} > 0$ and $\beta_{comp} + \beta_{inter} < 0$. β_{det} is interpreted as the effect of PDA use on inspector detection. Both β_{comp} and $\beta_{comp} + \beta_{inter}$ can be interpreted as an upper bound of restaurant compliance response to the increased detection due to PDA. If we take the theory literally, Figure 5 suggests $\beta_{inter} < 0$ because the reduction in inspection effort with a PDA (from B to C) is more than the reduction in inspection effort without a PDA (from A to D), given the same compliance change from e_{r1}^{A} to e_{r1}^{C}.

4.4 Regression Results

Tables 4-6 present the results from fixed-effect Poisson regressions. Table 4 shows the results for all violations, Table 5 for critical violations, and Table 6 for non-critical violations. In each table, we try different specifications for robustness; in Column (1), we include only PDA-related variables of our main interest, and in Column (2) we include control variables. In all of the three specifications, we control for restaurant-specific fixed effects and quarter-of-year dummies. In Column (3), we additionally control for inspector-specific fixed effects.

First, it is notable that inspectors detect more violations when using a PDA. The impact is sizable. The estimated β_{det} in Table 4 Column (1) indicates that the first use of a PDA increases the expected number of violations increases by 17.6%. When we add more controls, the estimate changes only slightly to 16.8% in Column (2) and 16.2% in Column (3). As explained in Section 2.2, the impact reflects an increase in the detection effort due to a PDA.

Secondly, we find that, as a PDA is repeatedly used, the number of detected violations decreases. As explained above, both β_{comp} and $\beta_{comp} + \beta_{inter}$ are expected to be negative. These predictions are well confirmed in the data: β_{comp} varies from -0.051 in Column (1) to -0.026 in Column (2) and -0.03 in

Column (3). Since β_{inter} is estimated to be negative as well, $\beta_{comp} + \beta_{inter}$ is slightly more negative than β_{comp}, ranging from -0.067 in Column (1) to -0.044 in Column (2) and -0.048 in Column (3). Recall that both β_{comp} and $\beta_{comp} + \beta_{inter}$ tend to overestimate the restaurant's compliance response to the increased detection effort by PDA. Taking Column (3) as our preferred specification, these estimates imply that the restaurant's compliance response is no greater than a 2.96% decrease in the number of detected violations per additional previous use of PDA.

The compliance response strikes us as small. Assuming a PDA is continuously used, our estimates suggest that it takes at least five inspections to offset the initial increase in the number of violations detected by a PDA. However, one needs to be careful with this interpretation. Note that once the inspector increases her detection effort, the restaurant subsequently increases its compliance effort. As long as the compliance effort is increased, the restaurant's actual hygiene should improve no matter how many more violations are detected.

Many other coefficients reported in Table 4 are also statistically significant. For example, new inspectors are more likely to find more violations, repeat inspectors report fewer violations when they have a longer relationship with the restaurant, and a new inspector following the last inspector's longer history of the restaurant reports even more violations. We explain these results in light of game theory in a companion paper (Jin and Lee 2012). Other coefficients of Table 4 suggest that more violations are reported if the inspection is the first one conducted by the inspector on that particular day or if the inspection takes place during lunchtime. The latter likely reflects a higher food safety risk at lunchtime, and the former can be explained by lower attention cost of the inspector on her first visit of the day. Consistently, the fatigue coefficient of Table 4 shows that the more inspections an inspector has done during the day, the lower the number of reported violations.

Tables 5 and 6 repeat the above exercise but treat critical and non-critical violations separately. Coefficients from both tables show similar signs and statistical significance as we have seen for total violations in Table 4. This consistency adds robustness to our theoretical interpretation of the PDA effects. Interestingly, the magnitudes of key coefficients are greater for critical than for non-critical violations. This suggests that, when detection cost is reduced, inspectors pay more attention to the categories that are emphasized by their principal.

One remaining question is why PDA use decreases detection cost. One possibility is that it reminds inspectors of potential violations.[12] If this is the case, inspectors using a PDA should find more violations in the items that are easy to ignore. Arguably, such attention bias is more severe in categories that have many subcategories. We test this prediction and find indeed that the detection effect of a PDA is

[12] This effect is suggested by our contact in the DHR.

greater in the categories that contain 20 or more subcategories. The results in Table 7 confirm the argument that inspectors have limited attention to detail and a PDA is more effective than the paper form at restoring their attention to easy-to-ignore items.

Our last analysis of restaurant inspection records focuses on a discrepancy between the model and reality. In particular, our model assumes that the restaurant will learn about the PDA effect in detection cost after only one PDA inspection and then fully expect continued use of a PDA next time. In reality, given the technical problem encountered in the first version of the PDA, restaurants may learn more slowly and their expectation of subsequent PDA use may not jump to 100% immediately. This introduces an interesting empirical question: how do the detection and compliance effects of a PDA change over time as a PDA is repeatedly used?

As a first pass, we run an OLS regression of detected violations on the dummy of PDA use for each year-quarter separately. The estimated coefficient on the PDA dummy, as plotted in Figure 6, was large initially but diminished to zero after 2006. This figure alone does not necessarily suggest that the detection effect of PDA use diminished over time, because each above-mentioned regression literally compared PDA and paper inspections in a specific quarter. As more and more restaurants clean up in expectation of PDA use in the near future, the extra violations that can only be found by using a PDA should decline over time.

To better separate the detection and compliance effects of PDA use over time, we rerun the same Poisson regression by allowing β_{comp} and β_{inter} to vary by the number of previous PDA inspections. In particular, we define 10 dummies for previous PDA usage equal to 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10+. As shown in Table 8, β_{comp} is insignificant when the number of previous PDA usage is below 3, and then becomes significant and progressively negative as previous PDA usage approaches 10+. In comparison, β_{inter} is always negative and significant, and becomes more negative as we increase the number of previous PDA uses. These patterns suggest that restaurant compliance in response to PDA use is gradual, which is consistent with the cruder data analysis shown in Figure 6.

5. PDA and Public Health

One central finding from the restaurant inspection records is that PDA use increases detection and this change generates greater compliance from restaurants. It follows that, even if more violations are reported after the first and subsequent uses of a PDA than without a PDA, PDA use should improve the actual restaurant hygiene because of compliance. This implication motivates us to link PDA use to public health outcomes directly. Below we first describe the Florida foodborne disease outbreak data and then present regression results that associate PDA use with restaurant-related outbreaks.

5.1 Florida Foodborne Disease Outbreak Data

We collect information on foodborne disease outbreaks from the surveillance database of the Florida Department of Health.[13] The Center of Disease Control (CDC) defines a foodborne outbreak as any cluster of two or more similar infections that are shown by investigation to result from ingestion of the same food. Most foodborne outbreaks are investigated by the state or local health department and if an outbreak involves at least two individuals, the department is required to report the event to the CDC. The Florida outbreak database includes both the cases reported to the CDC as well as the cases that Florida investigated but did not report to the CDC. We choose to use the Florida outbreak data instead of the CDC-collected outbreak data because the former reports the counties of outbreaks but the latter reports only states.

In addition to county information, the Florida outbreak database provides details about each outbreak, such as the date of the outbreak, the number of individuals involved, and whether the outbreak is related to a restaurant or a non-restaurant entity (such as grocery store, home, or school). The data are available from 1997 to 2009. We focus on the period starting July 2003. From the raw outbreak data, we construct a panel of 5,226 observations by county-month (67 counties×78 months) for restaurant- and non-restaurant outbreaks separately. Restaurant-related outbreaks account for two-thirds of total outbreaks. We choose county-month as the unit of observation since foodborne outbreaks are typically short-lived and localized. Only 7.6% of county-month observations are associated with a restaurant-related foodborne outbreak, as a foodborne outbreak is a rare event. Conditional on having any outbreaks, the average number of reported cases is about 12 per county-month. There are some outliers. In two observations, the number of reported cases is greater than 500 (see Appendix Figure 4 for the monthly trends.)

5.2 Regression Analysis

To better understand the association between restaurant hygiene violations and restaurant related foodborne outbreaks, we estimate the following equation:

$$R_{ct} = \gamma_1 y_{ct} + \gamma_2 NR_{ct} + \mu_c + q_t + m_t + v_{ct}$$

[13] Source: http://doh.state.fl.us/environment/medicine/foodsurveillance/Online_FWBD_Outbreak_Database.html

where R_{ct} is an indicator of whether there were any incidence of restaurant-related foodborne disease outbreaks in county c in month t. We use a binary indicator rather than the count of foodborne disease outbreaks because a foodborne disease outbreak is a rare event (about 7.6 percent per county-month). Also, given the nature of a foodborne disease outbreak, once it occurs, there could be an explosion of similar incidences. y_{ct} is the average number of detected violations per inspection, so γ_1 is the coefficient of our interest, showing to what extent increased detection induces compliance and therefore improves actual restaurant hygiene level. To control for unobservable trends of general conditions regarding food safety, we include NR_{ct}, which is the number of non-restaurant foodborne disease outbreaks. We include county-specific fixed effects (μ_c) to control for time-invariant unobservable county characteristics. And we include year-quarter fixed effects (q_t) to control for statewide time trends and month fixed effects (m_t) to account for seasonality.

The OLS estimate for γ_1 is likely biased. For example, counties with more hard-to-clean restaurants should have a higher likelihood of foodborne disease outbreaks and more violations, but this positive cross-sectional correlation does not necessarily reflect the effect of non-compliance. To estimate the causal effect, we employ an instrumental variable (IV) method. We use the proportion of PDA inspections in a given county-month as the instrument for y_{ct}, because the previous section has shown that PDA use generates greater detection, greater compliance, and in aggregate more reported violations.

The estimation results are presented in Table 9. Column (1) of the top panel presents the first-stage estimation results. Consistent with the previous finding, we find that PDA use increases violations significantly. If a county adopts PDA use suddenly and uses PDA for all inspections, the number of violations increases on average by about 3.4. Columns (2) and (3) present the OLS estimate of the main regression, one without county fixed effects and one with county fixed effects. Column (4) presents the IV estimates with county fixed effects. Column (5) presents the reduced-form estimate, i.e., the direct effect of PDA adoption rate on the likelihood of foodborne disease outbreaks. Column (6) adds PDA adoption rate of the previous month to Column (5) for robustness check. In the bottom panel, we examine non-restaurant foodborne disease outbreaks. This is a placebo test since restaurant inspection outcomes should not directly affect non-restaurant food safety.

The OLS results show that the incidence of foodborne disease outbreak is positively correlated with the average number of reported violations per inspection in Column (2), but this correlation becomes negative when we control for county fixed effects in Column (3). These results are reasonable because across counties under similar detection technology more violations imply dirtier restaurants and thus a greater likelihood of outbreak. However, over time, changes in reported violations within a county could be driven by enhanced detection, which in turn motivates better compliance.

After controlling for county fixed effects, the IV estimate in Column (4) shows that detecting one additional violation decreases the likelihood of restaurant foodborne disease outbreaks by 0.4 percentage points, and the estimate is significant at the 90% confidence level. The OLS estimate is upwardly biased, which makes sense given that more violations are detected in counties with dirtier restaurants and restaurant food safety is lower there. Column (5) presents the reduced-form estimate, which suggests that full adoption of PDA use decrease the likelihood of foodborne disease outbreaks by 1.4 percentage points. This effect is non-negligible compared to the average probability of restaurant foodborne disease outbreak per quarter per county in Florida (7.6 percent). At the inspection level, we have found that compliance response is gradual, which motivates us to test whether the effect of PDA adoption on foodborne disease outbreak is gradual as well. Unfortunately, because PDA adoption is progressive in our data and we have to measure PDA adoption rate by county-month in the outbreak regression, PDA adoption rate is highly correlated with its one-month lag within a county. When we add lagged PDA adoption rate in the reduce-form regression (Column 6), its coefficient is negative, of slightly smaller magnitude than the coefficient of concurrent PDA adoption rate, but not statistically significant.

The results in the bottom panel show that neither detected violations nor PDA inspections affect non-restaurant foodborne disease outbreaks. The estimates are not only statistically insignificant but also nearly zero. This confirms that the results in the top panel are likely a consequence of restaurants increasing compliance effort in response to PDA use.

6. Conclusions

Food safety is of considerable concern in public health. In the U.S., food consumed away from home amounts to a quarter of the total expenditure on eating (Hamermesh, 2007); thus a substantial amount of tax money is spent on monitoring restaurant food safety. Hygiene inspections are a major component of such policy; accordingly, a key question is how to use inspection tools to effectively induce restaurant compliance. This question is difficult to answer because inspection outcomes are by definition a mixture of detection and compliance.

We overcome this difficulty by exploiting the introduction of a new inspection technology that exogenously reduces the effort cost of inspectors. With the help of game theory, we identify the effect of the technology on detection as well as an upper bound of compliance response to the detection change. Our findings have several policy implications. First, a small technology can go a long way toward improving the efficiency of detection. Human inspectors are not perfect and have limited attention spans. With the help of a small electronic device, which simply shows a checklist in detail, inspectors find significantly more violations, even some critical ones. Second, restaurants do increase compliance in response to higher detection effort by inspectors. However, their response is neither immediate nor significant unless the reform in the inspection program is expected to be permanent. In the case of Florida, after becoming aware of the adoption of PDAs, restaurants improved their hygiene level but quite slowly. This may be because the new technology is not fully used afterwards and often is withdrawn due to technical problems and thus fails to change restaurants' expectations about future detection. Lastly, despite the slow response, the increased detection rate and subsequent compliance does correlate to a lower risk of restaurant-related foodborne disease outbreak. We do not have the exact dollar estimates for the cost of PDAs, the cost of restaurant compliance, or the benefits from fewer outbreaks. Nevertheless, our quantitative findings should help policy makers make such a benefit-cost analysis.

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Figure 1. Trends of PDA Inspection by District

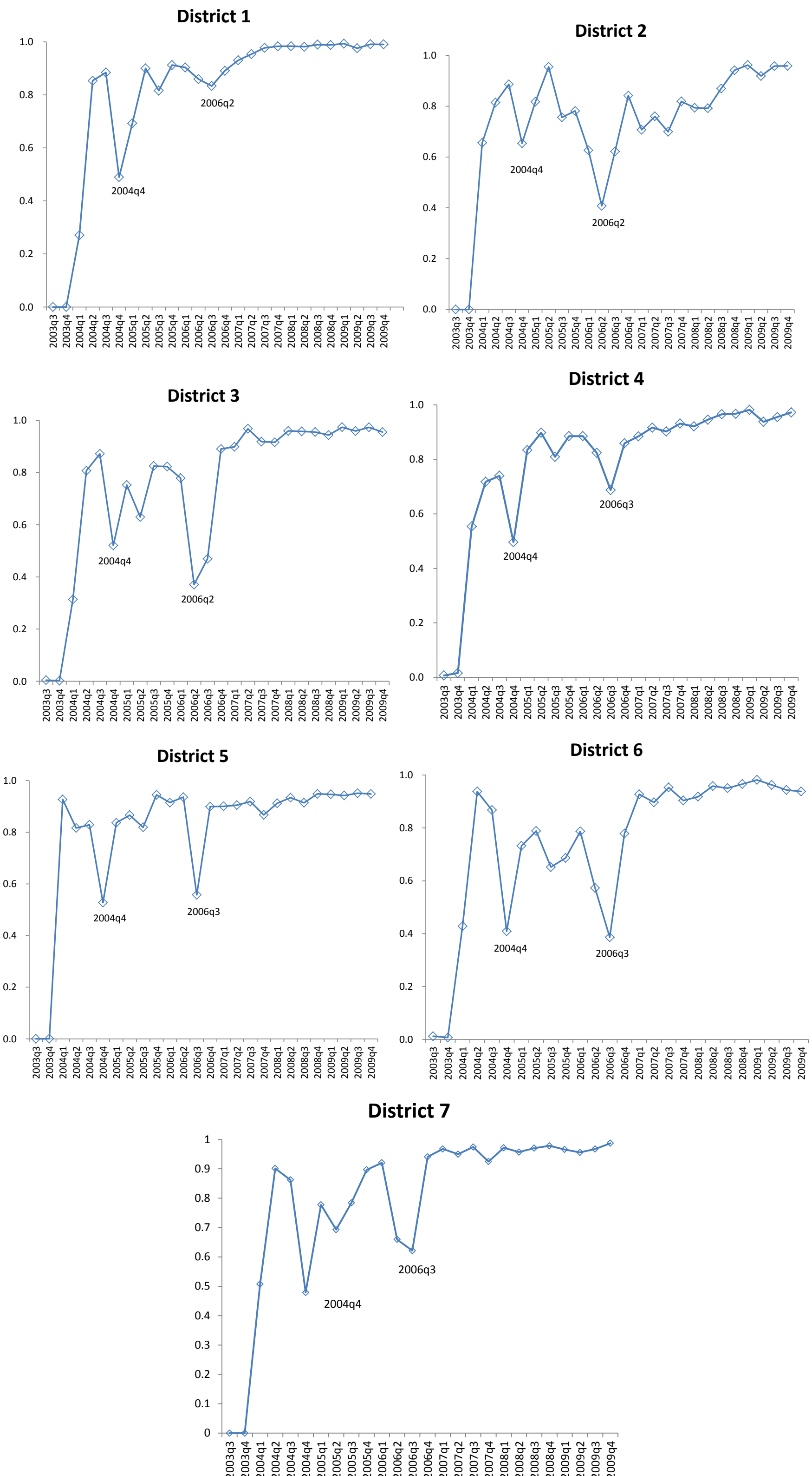
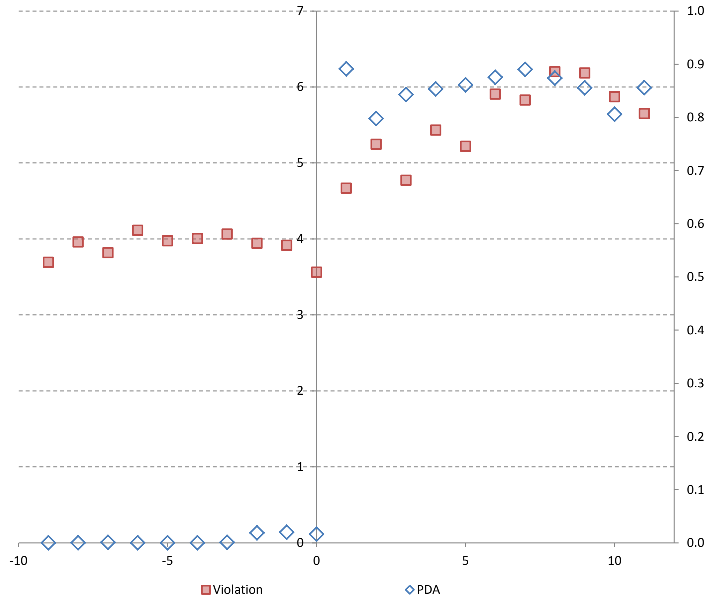


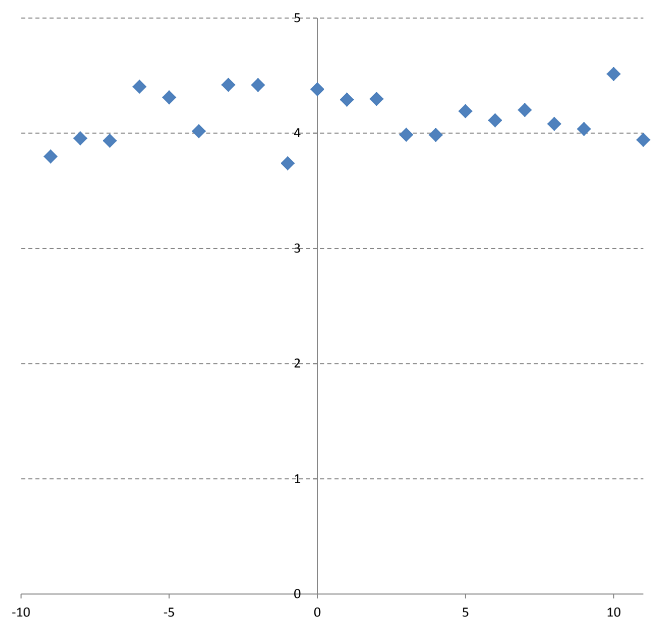
Figure 2. First Adoption of PDA
(10 Weeks Before and After the District's Massive Adoption Date)

A. PDA Adoption and Effects on Violations



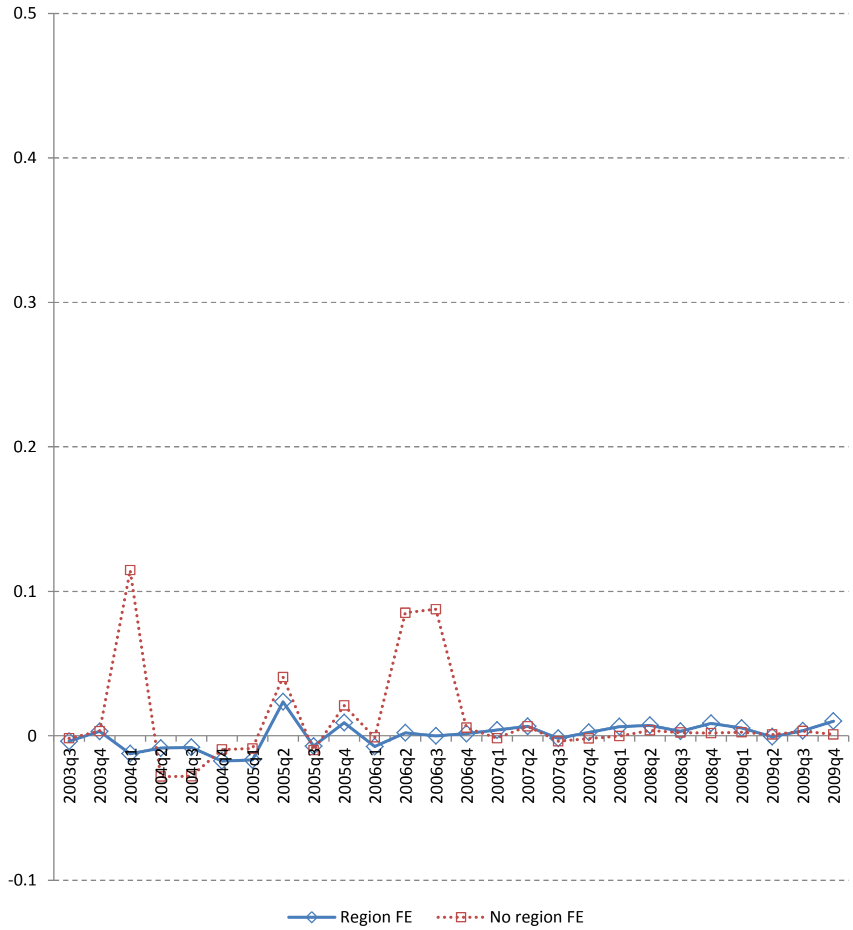
Notes: Horizontal axis represents weeks around the date when most inspectors adopted PDAs in each district. Diamonds represent the proportion of inspections done by PDA in each week. Squares represent the average number of detected violations per inspection in each week.

B. Effects of Past Violations on PDA Use



Notes: Horizontal axis represents weeks around the date when most inspectors adopted PDAs in each district. Dots represent the average number of violations detected at the last inspection for restaurants inspected in each week.

Figure 3. Effects of Previous Violations on the Probability of PDA Use



Notes: Horizontal axis represents quarter of year from July 2003 to December 2009. For each quarter, we ran regression of PDA use on previous violations. Squares represent the OLS estimates and diamonds represents the estimates after controlling for district fixed effects.

Figure 4. Equilibrium with Perfect information (Category 1)

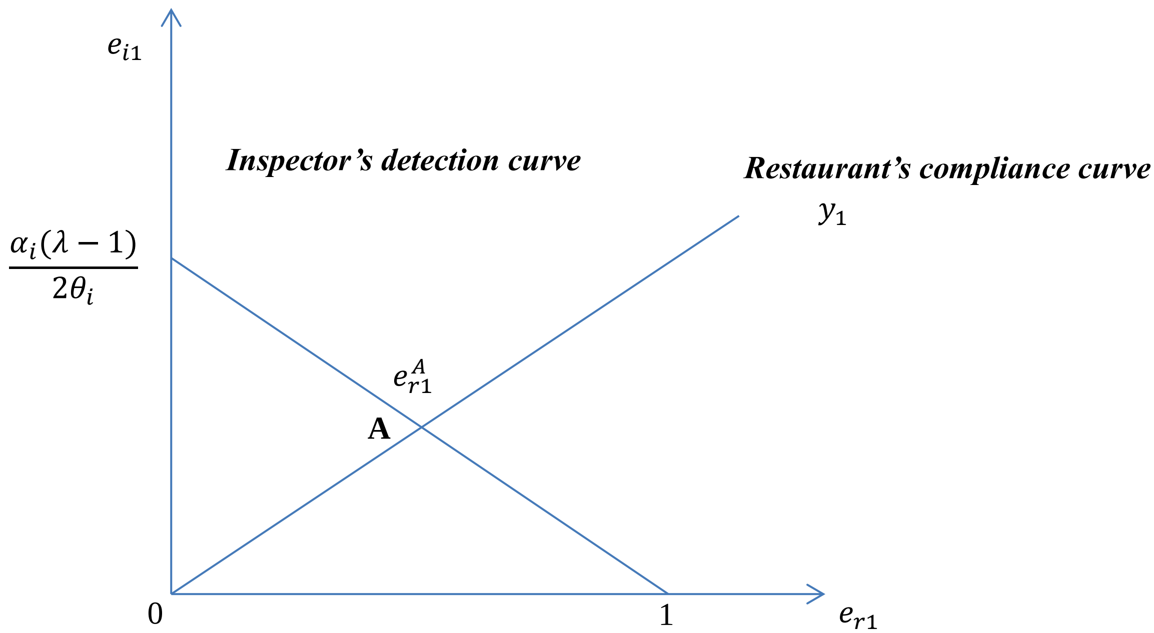


Figure 5. Comparative Statics by PDA adoption ($\theta_i \rightarrow \theta_i', \theta_i > \theta_i'$, Category 1)

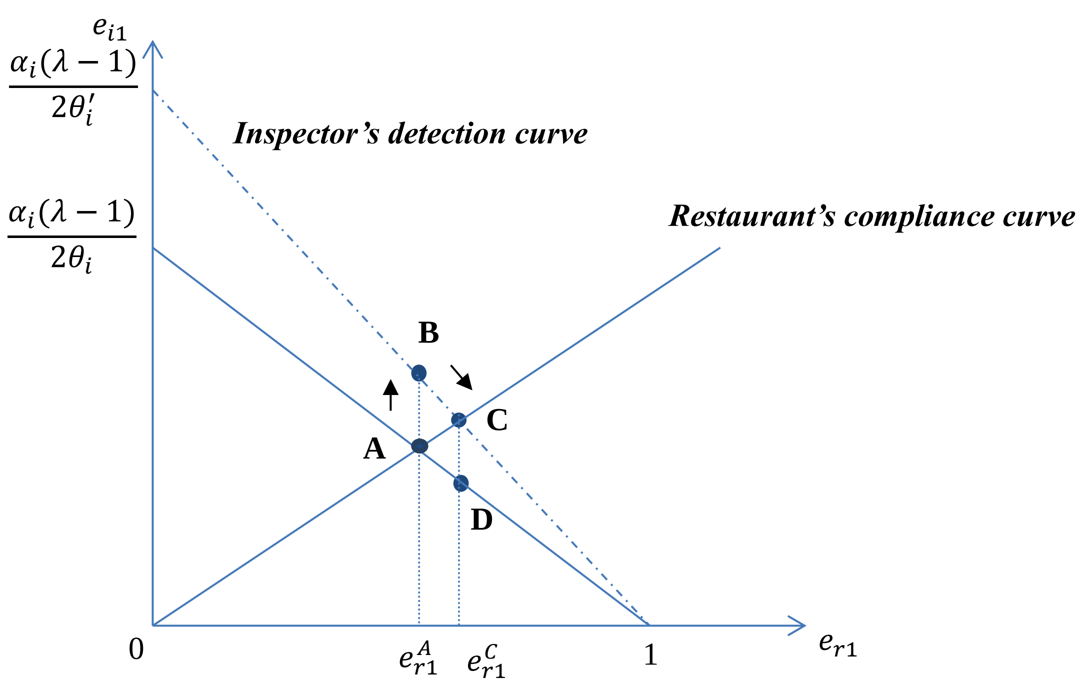


Figure 6. Detection Effects over Time

Notes: Horizontal axis represents quarter of year from July 2003 to December 2009. For each quarter, we ran regression of detected violations on PDA use. Squares represent the OLS estimates and diamonds represents the estimates after controlling for district fixed effects.

Table 1. Summary Statistics of Variables Used in Regression Analysis

	Mean	SD	Min	Max
Detected violations				
Total violations	8.06	7.22	0	111
Critical violations	4.97	4.68	0	66
Non-critical violations	3.08	3.31	0	52
Inspector characteristics				
New inspector (new to the current restaurant)	0.28	0.45	0	1
Number of inspections by previous inspector	3.46	2.83	1	37
Days since previous inspection	178	95	1	1754
More than one year since the last inspection	0.04	0.20	0	1
Inspector's past inspections	1757	1230	0	6480
Inspection and restaurant characteristics				
Inspection performed in response to a citizen's complaint	0.04	0.19	0	1
Inspection performed upon initial license or change of ownership	0.001	0.034	0	1
Restaurant age in years	4.02	2.63	0	14.19
Number inspections done before the current inspection per day	1.85	1.70	0	36
First inspection today	0.25	0.43	0	1
Inspection during lunch time (noon-2:00PM)	0.38	0.49	0	1

Notes: N = 346,579. Observations with non-missing restaurant age = 261,702. Observations with non-missing inspection time = 307,575.

Table 2. Summary Statistics of PDA Variables

	Mean	SD
PDA	0.88	0.33
Previous PDA inspections	4.55	3.38
Restaurants with paper inspection initially in the sample*	0.20	0.40
Restaurants which experienced switching back to paper**	0.36	0.48
No previous PDA inspection	0.08	0.27
One previous PDA inspection	0.12	0.32
Two previous PDA inspections	0.13	0.34
Three previous PDA inspections	0.12	0.33
Four previous PDA inspections	0.11	0.31
Five previous PDA inspections	0.09	0.29
Six previous PDA inspections	0.08	0.27
Seven previous PDA inspections	0.07	0.25
Eight previous PDA inspections	0.06	0.23
Nine previous PDA inspections	0.04	0.21
10 or more previous PDA inspections	0.09	0.29
PDA conditional on no previous PDA inspection	0.75	0.43
PDA conditional on one previous PDA inspection	0.82	0.39
PDA conditional on two previous PDA inspections	0.85	0.36
PDA conditional on three previous PDA inspections	0.87	0.34
PDA conditional on four previous PDA inspections	0.88	0.33
PDA conditional on five previous PDA inspections	0.89	0.31
PDA conditional on six previous PDA inspections	0.91	0.28
PDA conditional on seven previous PDA inspections	0.93	0.25
PDA conditional on eight previous PDA inspections	0.95	0.23
PDA conditional on nine previous PDA inspections	0.96	0.20
PDA conditional on 10 or more previous PDA inspections	0.97	0.17
Probability of switching back to paper***	0.10	0.30

Notes: * represents the proportion of restaurants with paper inspection at the first inspection in the sample, out of 54,738 restaurants included in the regression analysis. ** represents the proportion of restaurants that experienced switching back to paper inspection, out of those once adopted PDA (44,028). *** represents the proportion of paper inspections for those restaurants that once adopted PDA. The other statistics are calculated from the inspection-level regression sample.

Table 3. Distribution of Restaurants by Total Number of Observations in the Sample and Total Number of PDA Inspections

	Number of PDA Inspections																				
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Total
2	244	1,537	6,456																		8,237
3	38	371	1,540	4,489																	6,438
4	10	107	470	1,456	3,509																5,552
5	2	48	143	507	1,373	2,546															4,619
6	1	6	36	169	493	1,314	2,029														4,048
7	0	28	44	50	176	621	1,401	1,815													4,135
8	1	4	14	22	85	271	836	1,589	1,833												4,655
9	0	0	1	11	25	114	370	1,019	1,842	1,969											5,351
10	0	0	0	1	6	40	158	452	1,101	2,116	1,862										5,736
11	0	0	0	0	1	8	25	111	360	821	1,263	954									3,543
12	0	0	0	0	0	1	8	20	72	167	380	488	392								1,528
13	0	0	0	0	0	0	0	5	6	29	79	143	200	103							565
14	0	0	0	0	0	0	0	1	3	1	18	26	57	64	39						209
15	0	0	0	0	0	0	1	0	1	2	4	8	15	10	22	11					74
16	0	0	0	0	0	0	0	0	0	1	0	1	4	5	6	8	4				29
17	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	1	3	0			10
18	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	1	2		6
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	2
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Total	296	2,101	8,704	6,705	5,668	4,915	4,828	5,012	5,218	5,107	3,606	1,620	668	187	68	21	9	2	2	1	54,738

Notes: The number in each cell represents the number of restaurants. There are 54,738 restaurants in total in the sample. For each restaurant we count its frequency in the sample and total number of PDA inspections. For example, the first cell shows that there are 244 restaurants that appear twice in the sample and they received no PDA inspection (i.e., the two inspections were both done by paper).

Table 4. Fixed-Effect Poisson Model: Total Number of Violations

	(1)	(2)	(3)
PDA	0.162***	0.156***	0.150***
	(0.008)	(0.010)	(0.010)
Previous PDA inspections	-0.051***	-0.027***	-0.030***
	(0.002)	(0.002)	(0.002)
Previous PDA inspections * PDA	-0.016***	-0.018***	-0.018***
	(0.002)	(0.002)	(0.002)
New inspector (new to the current restaurant)		0.120***	0.100***
		(0.005)	(0.004)
Inspections by the previous inspector * New inspector		0.004***	0.005***
		(0.001)	(0.001)
Inspections by the previous inspector		-0.009***	-0.007***
		(0.001)	(0.001)
Inspector's past inspections less than median		0.024***	0.030***
		(0.004)	(0.005)
Inspector's past inspections 30 or less		0.202***	0.204***
		(0.013)	(0.013)
Number inspections done before the current inspection per day		-0.028***	-0.032***
		(0.001)	(0.001)
First inspection today		0.014***	0.012***
		(0.004)	(0.004)
Missing inspection time		-0.097***	-0.091***
		(0.008)	(0.008)
Days since the last inspection		0.000***	0.000***
		(0.000)	(0.000)
More than one year since the last inspection		-0.076***	-0.082***
		(0.008)	(0.007)
Lunch time (noon-2PM)		0.011***	0.016***
		(0.003)	(0.003)
Restaurant age in years		0.006**	0.006**
		(0.003)	(0.002)
Missing restaurant age		0.199	0.128
		(0.226)	(0.187)
Inspection performed in response to a citizen's complaint		-0.136***	-0.135***
		(0.007)	(0.007)
Inspection performed upon initial license or change of ownership		-0.339***	-0.352***
		(0.052)	(0.049)
Restaurant FE	Yes	Yes	Yes
Quarter-by-year FE	Yes	Yes	Yes
Inspector FE	No	No	Yes
Number of restaurants	54,738	54,738	54,738
Observations	346,579	346,579	346,579

Table 5. Fixed-Effect Poisson Model: Critical Violations

	(1)	(2)	(3)
PDA	0.173***	0.173***	0.160***
	(0.008)	(0.011)	(0.010)
Previous PDA inspections	-0.063***	-0.035***	-0.038***
	(0.003)	(0.003)	(0.002)
Previous PDA inspections * PDA	-0.012***	-0.016***	-0.015***
	(0.002)	(0.002)	(0.002)
New inspector (new to the current restaurant)		0.131***	0.105***
		(0.005)	(0.005)
Inspections by the previous inspector * New inspector		0.006***	0.008***
		(0.001)	(0.001)
Inspections by the previous inspector		-0.013***	-0.011***
		(0.001)	(0.001)
Inspector's past inspections less than median		0.013***	0.025***
		(0.004)	(0.005)
Inspector's past inspections 30 or less		0.179***	0.178***
		(0.014)	(0.014)
Number inspections done before the current inspection per day		-0.027***	-0.032***
		(0.001)	(0.001)
First inspection today		0.015***	0.013***
		(0.004)	(0.004)
Missing inspection time		-0.095***	-0.098***
		(0.009)	(0.008)
Days since the last inspection		0.000***	0.001***
		(0.000)	(0.000)
More than one year since the last inspection		-0.075***	-0.081***
		(0.009)	(0.008)
Lunch time (noon-2PM)		0.008**	0.015***
		(0.003)	(0.003)
Restaurant age in years		-0.000	-0.001
		(0.003)	(0.002)
Missing restaurant age		0.209	0.150
		(0.235)	(0.197)
Inspection performed in response to a citizen's complaint		-0.148***	-0.146***
		(0.008)	(0.008)
Inspection performed upon initial license or change of ownership		-0.313***	-0.319***
		(0.055)	(0.051)
Restaurant FE	Yes	Yes	Yes
Quarter-by-year FE	Yes	Yes	Yes
Inspector FE	No	No	Yes
Number of restaurants	54,380	54,380	54,380
Observations	345,342	345,342	345,342

Notes: Fixed effects Poission models. Robust standard errors clustered by restaurants. Included are Restaurant FE, Inspector FE, and Quarter-by-Year FE. Asterisks *** denote significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 6. Fixed-Effect Poisson Model: Non-Critical Violations

	(1)	(2)	(3)
PDA	0.146***	0.129***	0.136***
	(0.009)	(0.012)	(0.012)
Previous PDA inspections	-0.031***	-0.013***	-0.019***
	(0.003)	(0.003)	(0.003)
Previous PDA inspections * PDA	-0.022***	-0.023***	-0.021***
	(0.002)	(0.002)	(0.002)
New inspector (new to the current restaurant)		0.103***	0.093***
		(0.006)	(0.005)
Inspections by the previous inspector * New inspector		0.000	-0.001
		(0.001)	(0.001)
Inspections by the previous inspector		-0.004***	-0.000
		(0.001)	(0.001)
Inspector's past inspections less than median		0.041***	0.037***
		(0.005)	(0.006)
Inspector's past inspections 30 or less		0.241***	0.253***
		(0.016)	(0.016)
Number inspections done before the current inspection per day		-0.030***	-0.033***
		(0.001)	(0.001)
First inspection today		0.013**	0.012**
		(0.005)	(0.005)
Missing inspection time		-0.102***	-0.080***
		(0.010)	(0.010)
Days since the last inspection		0.000***	0.000***
		(0.000)	(0.000)
More than one year since the last inspection		-0.077***	-0.083***
		(0.010)	(0.009)
Lunch time (noon-2PM)		0.016***	0.018***
		(0.004)	(0.004)
Restaurant age in years		0.013***	0.014***
		(0.003)	(0.003)
Missing restaurant age		0.184	0.109
		(0.236)	(0.207)
Inspection performed in response to a citizen's complaint		-0.120***	-0.122***
		(0.009)	(0.008)
Inspection performed upon initial license or change of ownership		-0.388***	-0.411***
		(0.061)	(0.059)
Restaurant FE	Yes	Yes	Yes
Quarter-by-year FE	Yes	Yes	Yes
Inspector FE	No	No	Yes
Number of restaurants	52,626	52,626	52,626
Observations	338,773	338,773	338,773

Notes: Fixed effects Poission models. Robust standard errors clustered by restaurants. Included are Restaurant FE, Inspector FE, and Quarter-by-Year FE. Asterisks *** denote significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7. Impacts of PDA by Number of Subcategories

	(1) Large 20 or more	(2) Medium 10~19	(3) Small Less than 10
PDA	0.210***	0.129***	0.064***
	(0.011)	(0.012)	(0.014)
Previous PDA inspections	-0.026***	-0.037***	-0.027***
	(0.002)	(0.003)	(0.003)
Previous PDA inspections * PDA	-0.022***	-0.015***	-0.012***
	(0.002)	(0.002)	(0.002)
New inspector (new to the current restaurant)	0.094***	0.118***	0.078***
	(0.005)	(0.005)	(0.006)
Inspections by the previous inspector * New inspector	0.005***	0.007***	0.001
	(0.001)	(0.001)	(0.002)
Inspections by the previous inspector	-0.004***	-0.010***	-0.004***
	(0.001)	(0.001)	(0.001)
Inspector's past inspections less than median	0.034***	0.035***	0.012*
	(0.006)	(0.006)	(0.007)
Inspector's past inspections 30 or less	0.169***	0.229***	0.238***
	(0.015)	(0.015)	(0.019)
Number inspections done before the current inspection per day	-0.035***	-0.034***	-0.025***
	(0.001)	(0.001)	(0.002)
First inspection today	0.011**	0.011**	0.016***
	(0.005)	(0.005)	(0.006)
Missing inspection time	-0.101***	-0.083***	-0.082***
	(0.009)	(0.009)	(0.011)
Days since the last inspection	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
More than one year since the last inspection	-0.086***	-0.079***	-0.081***
	(0.009)	(0.009)	(0.011)
Lunch time (noon-2PM)	0.005	0.017***	0.039***
	(0.003)	(0.003)	(0.004)
Restaurant age in years	0.011***	-0.000	0.004
	(0.003)	(0.003)	(0.003)
Missing restaurant age	0.005	0.364	-0.039
	(0.191)	(0.236)	(0.159)
Inspection performed in response to a citizen's complaint	-0.142***	-0.126***	-0.138***
	(0.008)	(0.008)	(0.010)
Inspection performed upon initial license or change of ownership	-0.355***	-0.323***	-0.406***
	(0.055)	(0.058)	(0.068)
Restaurant FE	Yes	Yes	Yes
Quarter-by-year FE	Yes	Yes	Yes
Inspector FE	Yes	Yes	Yes
Number of restaurants	53,393	53,027	51,797
Observations	341,535	339,965	336,056

Notes: Fixed effects Poission models. Robust standard errors clustered by restaurants. Included are Restaurant FE, Inspector FE, and Quarter-by-Year FE. Asterisks *** denote significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 8. Detection and Compliance Effects over Repeated Uses of PDA

	(1) All	(2) Critical	(3) Non-Critical
PDA	0.210***	0.205***	0.215***
	(0.014)	(0.015)	(0.017)
Previous PDA inspections = 1	0.022	-0.003	0.060***
	(0.015)	(0.017)	(0.019)
Previous PDA inspections = 2	-0.019	-0.067***	0.054***
	(0.016)	(0.018)	(0.020)
Previous PDA inspections = 3	-0.023	-0.092***	0.080***
	(0.018)	(0.019)	(0.022)
Previous PDA inspections = 4	-0.059***	-0.140***	0.066***
	(0.019)	(0.021)	(0.024)
Previous PDA inspections = 5	-0.050**	-0.142***	0.091***
	(0.020)	(0.022)	(0.026)
Previous PDA inspections = 6	-0.101***	-0.198***	0.045
	(0.023)	(0.024)	(0.029)
Previous PDA inspections = 7	-0.110***	-0.208***	0.045
	(0.026)	(0.028)	(0.032)
Previous PDA inspections = 8	-0.173***	-0.266***	-0.027
	(0.029)	(0.031)	(0.037)
Previous PDA inspections = 9	-0.256***	-0.355***	-0.100**
	(0.032)	(0.035)	(0.042)
Previous PDA inspections = 10 or more	-0.255***	-0.370***	-0.074**
	(0.031)	(0.033)	(0.038)
PDA * (Previous PDA inspections = 1)	-0.070***	-0.062***	-0.081***
	(0.016)	(0.017)	(0.020)
PDA * (Previous PDA inspections = 2)	-0.081***	-0.063***	-0.107***
	(0.016)	(0.017)	(0.020)
PDA * (Previous PDA inspections = 3)	-0.127***	-0.096***	-0.169***
	(0.017)	(0.018)	(0.021)
PDA * (Previous PDA inspections = 4)	-0.130***	-0.094***	-0.181***
	(0.017)	(0.019)	(0.021)
PDA * (Previous PDA inspections = 5)	-0.180***	-0.142***	-0.236***
	(0.018)	(0.019)	(0.022)
PDA * (Previous PDA inspections = 6)	-0.175***	-0.139***	-0.224***
	(0.020)	(0.021)	(0.025)
PDA * (Previous PDA inspections = 7)	-0.208***	-0.174***	-0.260***
	(0.022)	(0.024)	(0.027)
PDA * (Previous PDA inspections = 8)	-0.180***	-0.165***	-0.202***
	(0.026)	(0.027)	(0.033)
PDA * (Previous PDA inspections = 9)	-0.144***	-0.123***	-0.173***
	(0.029)	(0.031)	(0.038)
PDA * (Previous PDA inspections = 10 or more)	-0.235***	-0.211***	-0.270***
	(0.025)	(0.027)	(0.031)
Control variables	Yes	Yes	Yes
Restaurant FE	Yes	Yes	Yes
Quarter-by-year FE	Yes	Yes	Yes
Inspector FE	Yes	Yes	Yes
Number of restaurants	54,738	54,380	52,626
Observations	346,579	345,342	338,773

Table 9. Impacts of PDA on Foodborne Disease Outbreak

	(1)	(2)	(3)	(4)	(5)	(6)
	First stage	OLS	OLS	IV	Reduced	Reduced
County fixed effect	Yes	No	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-of-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Dependent variable (sample average)	Violations (5.6)	Restaurant foodborne disease outbreaks (0.076)				
PDA	3.368***				-0.014*	-0.012*
	(0.309)				(0.009)	(0.007)
PDA in the previous month						-0.009
						(0.010)
Number of detected violations		0.004*	-0.002*	-0.004*		
		(0.001)	(0.001)	(0.003)		
Non-restaurant foodborne disease outbreaks	-0.001	0.003***	0.001*	0.001*	0.001*	0.001*
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared (within group)	0.292	0.023	0.017	0.016	0.017	0.017
F statistic	116.1					
Dependent variable =		Non-restaurant foodborne disease outbreaks (0.042)				
PDA					-0.002	-0.002
					(0.008)	(0.008)
PDA in the previous month						-0.002
						(0.006)
Number of detected violations		0.003*	0.000	-0.000		
		(0.002)	(0.001)	(0.002)		
R-squared (within group)		0.011	0.010	0.010	0.010	0.010

Notes: N = 5226 = 67 counties * 78 months. The dependent variable in Column (1) is the average number of violations per inspection. PDA is the proportion of PDA inspections. In the remaining columns the dependent variable is the indicator for restaurant-related food-borne disease outbreaks in top panel and for non-restaurant foodborne disease outbreaks in bottom panel. R-squared is within-group one whenever the county fixed effect is included. PDA is the lagged proportion of PDA inspections. The linear probability model is estimated with county-specific, month-specific and quarter-of-year fixed effects. Robust standard errors, clustered by county, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Figure 1. Inspection Report (Page 1)

Florida Department of Business & Professional Regulation

Division of Hotels and Restaurants

LEGAL NOTICE
Food Service Inspection Report

☐ **MET INSPECTION STANDARDS** during this visit

☐ **FOLLOW-UP INSPECTION REQUIRED** Violations require further review, but are not an immediate threat to the public.

☐ **FACILITY TEMPORARILY CLOSED** Operations ordered stopped until violations are corrected.

Page 1 of ____

LICENSE TYPE

☐ 2010 Permanent Food Service
☐ 2012 Theme Park Food Cart
☐ 2013 Catering
☐ 2014 Mobile Food Dispensing Vehicle
☐ 2015 Vending Machine
☐ 2051 Unlicensed Food

LICENSE NUMBER

REMINDER: Your license expires ____/____/____

☐ Original Visit ☐ Callback

FOR CALLBACKS, ORIGINAL VISIT DATE WAS: ____/____/____

INSPECTION TYPE

☐ Unscheduled (ROUT)
☐ Licensing (LIC)
☐ Complaint Full (COMP)
☐ Complaint Partial (CPAR)
☐ Disaster Response (DSTR)
☐ Service Request (SERV)
☐ Quality Assurance (QA)
☐ Training (TRNG)

Owner Name:

Business (DBA) Name:

Location Address: Seats/Units:

City, State, Zip:

Inspector Area	Visit Date			Visit Time	
	Month	Day	Year	Start	End

FOODBORNE ILLNESS RISK FACTORS AND PUBLIC HEALTH INTERVENTIONS (Items marked "OUT" of compliance require immediate corrective action)

The circled letters to the left of each item indicate that item's status at the time of inspection
IN = in compliance **OUT** = not in compliance **N/O** = not observed **N/A** = not applicable

Mark "X" in appropriate box for COS and/or R
COS = corrected on-site during inspection **R** = repeat violation

	COMPLIANCE STATUS						COS	R
Approved Source	IN	OUT			01a	Food obtained from approved source		
	IN	OUT	N/O		01b	Wholesome, sound condition		
	IN	OUT	N/O	N/A	02	Original container; properly labeled, date marking, shell stock tags		
Consumer Advisory	IN	OUT		N/A	02-11	Consumer advisory on raw/undercooked oysters		
	IN	OUT		N/A	02-13	Consumer advisory on raw/undercooked animal products		
Potentially Hazardous Food Time/Temperature	IN	OUT		N/A	03a	Cold food at proper temperatures during storage, display, service, transport, and cold holding		
	IN	OUT	N/O	N/A	03b	Hot food at proper temperature		
	IN	OUT	N/O	N/A	03c	Foods properly cooked/reheated		
	IN	OUT	N/O	N/A	03d	Foods properly cooled		
Protection from Contamination	IN	OUT			07	Unwrapped or potentially hazardous food not re-served		
	IN	OUT			08a	Food protection during storage, preparation, display, service, transportation		
	IN	OUT			08b	Cross-contamination, equipment, personnel, storage		
	IN	OUT			22	Food contact surfaces clean and sanitized		
Personnel	IN	OUT	N/O		09	Foods handled with minimum contact		
	IN	OUT			11	Personnel with infections restricted		
	IN	OUT	N/O		12a	Hands washed and clean, good hygienic practices (observed), alternative operating plan		
	IN	OUT	N/O		12b	Proper hygienic practices, eating/drinking/smoking (evidence)		
	IN	OUT			32	Restrooms with self-closing doors, fixtures operate properly, facility clean, supplied with hand soap, disposable towels or hand drying devices, tissue, covered waste receptacles		
Chemical	IN	OUT			41a	Toxic substances properly stored		
	IN	OUT			41b	Toxic substances properly labeled, used		
Demonstration of Knowledge	IN	OUT			53a	Food management certification valid		
	IN	OUT			53b	Employee Training verification PROGRAM:		

TEMPERATURE OBSERVATIONS				CERTIFIED FOOD MANAGERS	
Item/Location	Temp	Item/Location	Temp	Name	Date

INSPECTION DISPOSITION

☐ Inspection Completed – No Further Action (ISAT)	☐ Callback – Complied (CBCM)	☐ Administrative Complaint Recommended (ACRQ)	☐ Emergency Order Recommended (EOCL)
☐ Warning Given (WARN)	☐ Callback – Extension Given (CBEX)	☐ Administrative Complaint Callback – Complied (ACCM)	☐ Emergency Order Callback – Complied (EOCM)
☐ Seasonal (SEAS)	☐ Callback – Administrative Complaint Recommended (CBNO)	☐ Administrative Complaint Callback – Time Extension (ACEX)	☐ Emergency Order Callback – Time Extension (EOEX)
☐ Closed – Out of Business (COFB)	☐ Administrative Determination Recommended (ADDT)	☐ Administrative Complaint Callback – Not Complied (ACNO)	☐ Emergency Order Callback – Not Complied (EONO)

FAILURE TO COMPLY WITH THIS NOTICE MAY INITIATE AN ADMINISTRATIVE COMPLAINT THAT MAY RESULT IN SUSPENSION OR REVOCATION OF YOUR LICENSE AND FINES UP TO $1,000 PER VIOLATION.

I acknowledge receipt of these inspection forms and comments. **Violations must be corrected by:** ____/____/____ ____:____ ☐ AM ☐ PM

ADDITIONAL VIOLATIONS & COMMENTS ON PAGE 2

Person In Charge Name (Please Print)	Title	Inspector's Name (Please Print)	
Person In Charge Signature	Telephone	Inspector's Signature	Inspector's Telephone

DBPR Form HR 5022-015 61C-1.002, FAC www.MyFloridaLicense.com/dbpr/hr/ 2009 October 1

Inspection Report (Page 2)

Florida Department of Business & Professional Regulation

Division of Hotels and Restaurants

LEGAL NOTICE

Food Service Inspection Report

Page 2 of ____

LICENSE NUMBER

GOOD RETAIL PRACTICES ☒ *Not In Compliance Mark "X" in appropriate box for COS and/or R* **COS** = corrected on-site during inspection **R** = repeat violation

ITEMS MARKED WITH AN ASTERISK (*) ARE OF CRITICAL CONCERN AND MUST BE CORRECTED IMMEDIATELY

COMPLIANCE STATUS	COS	R	COMPLIANCE STATUS	COS	R
☐ *04 Facilities to maintain product temperature			☐ 34 Outside storage area clean, enclosure properly constructed		
☐ *05 Thermometers provided and conspicuously placed			☐ *35a Presence on Insects/rodents. Animals prohibited		
☐ *06 Potentially hazardous foods properly thawed			☐ *35b Outer openings protected from insects, rodent proof		
☐ *08c Potential for cross-contamination, storage practices; damaged food segregated			☐ 36 Physical facilities-floors properly constructed, clean, drained, coved		
☐ 10 In use food dispensing utensils properly stored			☐ 37 Physical facilities-walls, ceilings and attached equipment, constructed, clean		
☐ 13 Clean clothes, hair restraints					
☐ 14 Food contact surfaces designed, constructed, maintained, installed, located			☐ 38 Lighting provided as required. Fixtures shielded		
			☐ 39 Rooms and equipment – vented as required		
☐ 15 Non-food contact surfaces designed, constructed, maintained, installed, located			☐ 40 Employee lockers provided and used, clean		
			☐ 42 Premises maintained, no unnecessary articles. Cleaning & maintenance equipment properly stored. Kitchen restricted.		
☐ *16 Dishwashing facilities designed, constructed, operated 1. Wash 2. Rinse 3. Sanitize			☐ 43 Complete separation from living/sleeping area, laundry		
☐ *17 Thermometers, gauges, test kits provided			☐ 44 Clean and soiled linen segregated and properly stored		
☐ 18 Pre-flushed, scraped, soaked			☐ *45 Fire extinguishers – proper and sufficient		
☐ 19 Wash, rinse water clean, proper temperature			(FOR REPORTING PURPOSES ONLY)		
☐ *20a Sanitizing concentration ppm			FIRE EXTINGUISHERS: Date(s)	SUPPRESSION SYSTEMS: Date(s)	
☐ *20b Sanitizing temperature ° Fahrenheit					
☐ 21 Wiping cloths clean, used properly, stored					
☐ 23 Non-food contact surfaces clean			☐ *46 Exiting system – adequate, good repair (FOR REPORTING PURPOSES ONLY)		
☐ 24 Storage/handling of clean equipment, utensils			☐ *47 Electrical wiring – adequate, good repair (FOR REPORTING PURPOSES ONLY)		
☐ 25 Single service items properly stored, handled, dispensed			☐ *48 Gas appliances – properly installed, maintained (FOR REPORTING PURPOSES ONLY)		
☐ 26 Single service articles not re-used					
☐ *27 Water source safe, hot and cold under pressure			☐ *49 Flammable/combustible materials – properly stored (FOR REPORTING PURPOSES ONLY)		
☐ *28 Sewage and waste water disposed properly					
☐ 29 Plumbing installed and maintained			☐ *50 Current license, properly displayed		
☐ *30 Cross-connection, back siphonage, backflow			☐ 51 Other conditions sanitary and safe operation		
☐ *31 Toilet and hand washing facilities, number, convenient, designed, installed			☐ *52 False/misleading statements published or advertised relating to food/beverage		
☐ 33 Garbage containers covered, adequate number, insect and rodent proof, emptied at proper intervals, clean			☐ 54 Florida Clean Indoor Air Act Compliance		
			☐ 55 Automatic Gratuity Notice		

OBSERVATIONS AND CORRECTIVE ACTIONS

Item No.	Violations cited in this report must be corrected within the time frames below, or as stated on page 1.

☐ **Additional Comments on Attached Sheet**

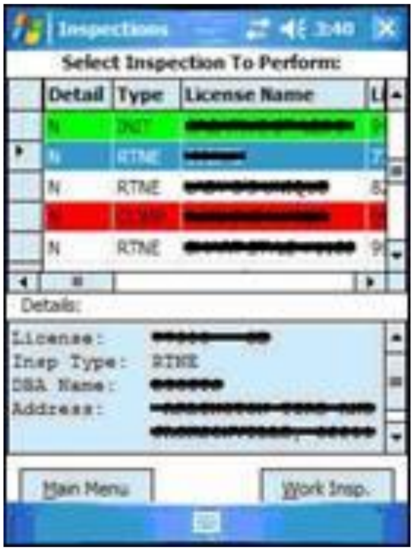
FAILURE TO COMPLY WITH THIS NOTICE MAY INITIATE AN ADMINISTRATIVE COMPLAINT THAT MAY RESULT IN SUSPENSION OR REVOCATION OF YOUR LICENSE AND FINES UP TO $1,000 PER VIOLATION.

Person in Charge (Signature) ______________________ **Date** ________

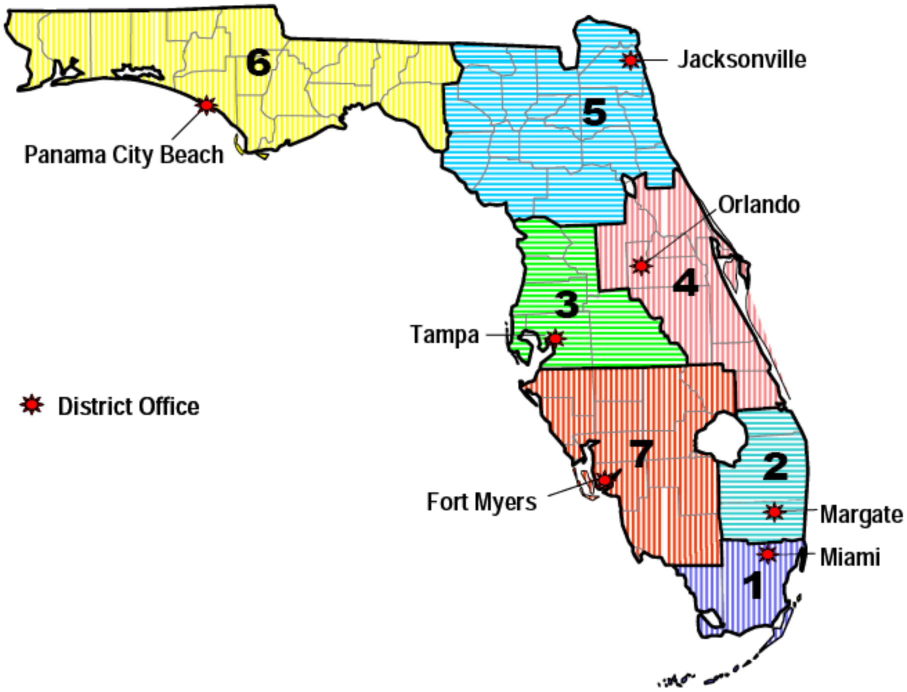
Inspector (Signature) ______________________ **Date** ________

DBPR Form HR 5022-015 61C-1.002, FAC www.MyFloridaLicense.com/dbpr/hr/ 2009 October 1

Appendix Figure 2. Screenshots of PDA

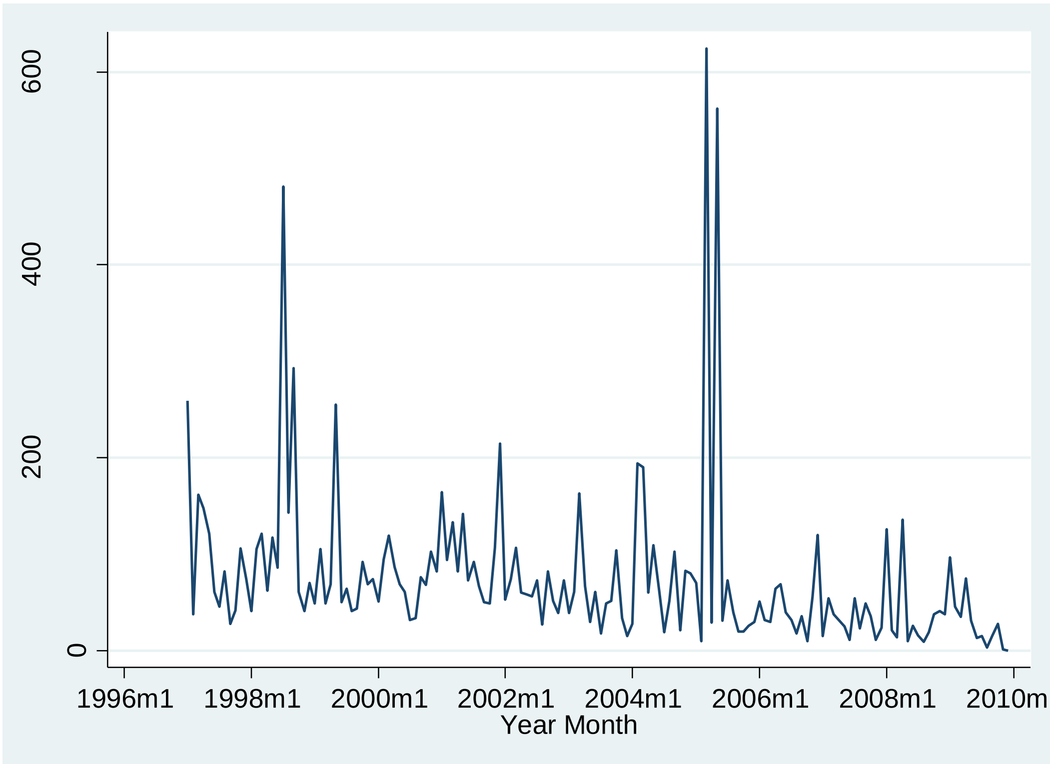


Appendix Figure 3. Seven Districts of Florida Restaurant Inspection



Source: Division of Hotels and Restaurants.

Appendix Figure 4. Trends of Restaurant Foodborne Disease Outbreaks (1997~2009, Number of Reported Cases)



Data source: Florida Department of Health, Online Database
http://doh.state.fl.us/environment/medicine/foodsurveillance/Online_FWBD_Outbreak_Database.html