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AAWE WORKING PAPER
No. 171
Economics

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

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Oct 2014

www.wine-economics.org

Inspection Technology, Detection, and Compliance: Evidence from Florida Restaurant Inspections

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February 2014

In this article, 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 handheld electronic device, the portable digital assistant (PDA), which reminds inspectors of 1,000 potential violations that may be checked for. Using inspection records from July 2003 to June 2009, we find that the adoption of PDA led to 11% more detected violations and subsequently restaurants may have gradually increased their compliance efforts. We also find that PDA use is significantly correlated with a reduction in restaurant-related foodborne disease outbreaks.

Keywords: Inspection technology, PDA, Regulation, Detection, Compliance, Restaurant hygiene.
JEL classification codes: D81, D82, H75, I18, K32, L51.

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Acknowledgement: We thank Michael Grubb, John Ham, Daifeng He, and the seminar participants at the College of William and Mary, MIT, the Federal Board of Governors, and Brown University for their constructive comments. Yiyan Liu has provided excellent research assistance throughout the project. We are especially grateful to various people at the Florida Division of Hotels and Restaurants for providing us with the data and patiently answering our questions. Jin acknowledges financial support from the Sloan Foundation. Lee's work was supported by a Sogang Research Frontier (SRF) grant. All errors are our own.

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 of the effectiveness of such inspections, mainly because inspection outcomes, which are often reported in terms of the number of violations, reflect both detection and compliance. While efforts to detect violations are costly, this detection is never perfect, and separating detection from compliance poses a real empirical challenge. In this article, we overcome this problem by exploiting a change in detection technology for restaurant hygiene inspections in Florida.

In particular, the Florida Division of Hotels and Restaurants (DHR hereafter) introduced portable digital assistants (PDAs) to restaurant inspections in November 2003. Prior to the use of PDAs, inspectors manually marked up to 31 categories of critical violations and 24 categories of noncritical violations on a two-page "bubble sheet." These PDAs are handheld computers that remind inspectors of about 1,000 violations at the subcategory level, with a detailed explanation of each violation accessible by a dropdown menu. With a PDA, an inspector can also easily retrieve past reports and upload the current inspection report immediately onto the DHR's server.

We present a simple theory to show that the unexpected adoption of PDAs can help separate 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 a 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-based inspection and the first PDA inspection. Therefore, the outcome differences between these two inspections reveal how much inspector detection effort has changed because of PDA use. After the first use, the restaurant expects a PDA to be used in the next detection and adjusts its compliance accordingly. As detailed in our theory, a comparison of the first and subsequent PDA inspections will identify an upper bound of the change in restaurant compliance (note that as the compliance effect is negative—that is, compliance decreases violations—the comparison identifies the upper bound in absolute terms). It is an upper bound instead of a precise point estimate because the inspector has an incentive to reduce his/her detection effort if he/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 June 2009. Following the quick adoption of the PDA in the first quarter of 2004, the PDA adoption rate fluctuated between 2004 and 2006, mostly because of 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 11.3%, which, according to our theory, reflects a significant increase in detection effort because of the PDA. Subsequently, each additional use of a PDA reduces the number of detected violations by 5.4%. This effect identifies an upper bound of restaurant compliance in response to increased detection effort because of the PDA.

Although the compliance response is gradual and not large enough to offset the initial PDA impact immediately, we find that heightened compliance has contributed to fewer restaurant foodborne disease outbreaks, and it has therefore improved public health. In particular, we estimate that the permanent adoption of PDAs would decrease the likelihood of observing any restaurant foodborne disease outbreaks per county per 15 days by 1.2%, which is non-negligible compared to the Florida average (4.5%).

We believe our work contributes to the field in several ways. The rich theoretical literature focuses on the agency problem of inspectors and proposes solutions such as outcome-based contracts, targeted auditing, reduction in information rents (to inspectors), high penalties for corrupt inspectors, and the intentional selection of biased employees.[1] These solutions are often difficult to implement in reality because bureaucratic agencies are subject to rigid compensation schemes and limited resources. Our article shows that a simple change in inspection technology can go a long way toward improving detection and compliance and is not difficult to implement in a typical government-run program.

Game-theoretic analysis of the 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 a 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) developed for nuclear plant inspections. Several other articles have presented evidence of inspector heterogeneity (Feinstein 1991; Macher et al. 2010), an issue we downplay in this article but have fully addressed in a companion article (Jin and Lee 2012). As shown later, the findings presented in this article are robust to the control of inspector heterogeneity.

Another related strand of literature concerns the impact of technology on productivity. Some studies have found that technology, often in the form of computers or electronic systems, has improved emergency health care outcomes (Athey and Stern 2002), increased firm productivity (Brynjolfsson and Hitt 2003), increased capacity, revenue, and resource allocation 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 found no positive effect of classroom computers on student learning (Angrist and Lavy 2002), or even found a harmful effect of computerized physician orders on the number of adverse drug events and higher medical costs (Berger and Kichak 2004). We adopt a similar thought process by linking technology adoption to the mechanisms of productivity change. In our raw data, the average number of detected violations increases after the 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 elements. These findings help us understand the mechanisms underlying the technological impact on inspection and public health outcomes.

The rest of the article 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 data on foodborne disease outbreaks in Florida. A brief conclusion is offered in Section 6.

2. Introduction of the PDA in Restaurant Hygiene Inspections in Florida

In the United States, restaurants are required to be regularly inspected by licensed and trained inspectors under local governments. In Florida, all food establishments are required to be inspected twice per fiscal year by state laws and thrice by administrative rules. Inspectors are public employees with a fixed salary scheme. They are assigned to inspection districts based on their residence and are responsible for restaurants within those districts. They have full discretion in deciding which restaurants to inspect and when. After inspections, they submit inspection reports to the DHR; if necessary, the DHR determines disciplinary actions.

Inspectors are trained to inspect restaurants according to a predetermined inspection checklist; Florida's checklist consists of 55 categories. The DHR classifies categories into two groups: critical and noncritical. 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,” and “unused utensils not removed when consumer seated.” The number of subcategories differs by category, from 1 to 53 per category. Thus, inspectors are responsible for checking 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 handheld computer, the PDA. Prior to the use of PDAs, inspectors used a two-page paper “bubble sheet” that listed only broad violations; they used pencils to report up to 31 categories of critical violations and 24 categories of noncritical violations (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 of each violation accessible via a dropdown menu. With the help of PDAs, inspectors can also easily retrieve past reports and upload inspection reports onto the agency server. Figure A.1 in the Appendix displays the paper inspection report, and Figure A.2 shows the screenshots of a PDA.

The introduction of PDAs was decided by the DHR at the state level. 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 second quarter of 2004 to over 80% in all districts but one (District 4, 74%). Across all seven districts, this proportion suddenly fell 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 various mechanical and software 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. Thereafter, the proportion of PDA use rose steadily, reaching almost 100% by 2009.[2] 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 (the universe of inspection records of restaurants in Florida from July 2003 to June 2009) allow us to identify the exact date when a PDA was first used by each individual inspector. For each of the DHR’s seven administrative districts (Figure A.3), we can identify a specific date when a number of inspectors acting in that district first used PDAs. Our investigations show that the PDAs were distributed on a specific date. For example, for District 1, the majority of active inspectors started to use PDAs on the same day, March 11, 2004. Other inspectors also started to use PDAs 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.

As a preliminary view of the impact of PDA use on inspection outcomes, Figure 2 examines the trends in the weekly average inspection outcomes for 10 weeks before and 11 weeks after the massive adoption day (including one week of the massive adoption day). 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 10 weeks. Weekly average violations also increased discretely on the same day. Thereafter, the number of violations increased, although the PDA usage rate did not change substantially after the massive adoption day. This may be because inspectors had to learn how to use their new PDAs efficiently.

One issue fundamental to the exogeneity of PDA use is that the 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 the PDAs. As shown in Figure 2B, there is no systematic difference between the periods before and after the adoption day.[3] In a more systematic check, we focus on individual inspection records and examine whether the use of a PDA at a given restaurant depends on 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 solid line represents those with district fixed effects. This graph shows that previous violations have little impact on PDA usage at a current inspection. The marginal effect is small, even though it is defined as the effect of 10 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 PDA use based on a restaurant's inspection history.

3. Model and Identification

In this section, we first present a stylized static model in which a restaurant chooses the extent of its clean-up effort and inspectors decide the extent of their effort to detect violations. Second, we conduct a comparative static analysis of the impact of PDAs. In the next section, we derive testable hypotheses for our empirical analysis.

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 sets the inspection criteria, inspection technology, inspector assignment, and inspector compensation. Each inspector earns a fixed wage as a public employee. Assume that the principal imposes a fine structure $F(y) = \tau y$, where y denotes the number of detected violations and τ denotes the penalty rate for each violation. The assumption of a constant penalty rate is a simplification. In practice, penalties for violations include monetary fines as well as the possibility of a callback visit (which incurs time and effort costs because of reinspection). In an earlier version of this model, we allowed violations to occur in multiple categories and inspectors to be heterogeneous in taste across categories. As that model produces the same theoretical predictions about PDA usage, for simplicity, we ignore these multiple categories in the model presented here.

The main task of an inspector is to visit a restaurant (unannounced), detect all hygiene violations, and report them to the principal. Within the restaurant, the inspector uses his/her discretion to determine the effort to expend in detecting violations and the extent of the information to report. In the eyes of the principal, hiding detected violations is equivalent to shirking on detection effort; therefore, we do not distinguish between the two in the model.[4] Rather, we consider every inspector to be honest and assume the cost of the detection effort for inspector i to be $C(e_i) = \theta_i e_i^2$, where θ_i is the cost parameter specific to the inspector, which denotes the inspector's leniency.

Assumed to lie between 0 and 1, e_i can be interpreted as the probability of detection. If the true violations are $\tilde{y}$, the detected violations are $y = e_i \cdot \tilde{y}$. We do not allow inspectors to report nonexistent violations (to resort to 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.

The goal of regulation is enforcing food safety, which implies the minimization of actual violations. Since we focus on the interaction between the inspector and the 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 detected as well as 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 the 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 his/her own preference for inspection outcomes for his/her effort cost. This captures the fact that government inspectors are paid a fixed salary and that their efforts are likely more motivated by intrinsic preferences than by monetary returns (Prendergast 2007). The inspector's problem can be written as follows:

$$\min_{e_i} \quad W_i = (1 - e_r)e_i + \lambda(1 - e_r)(1 - e_i) + \theta_i e_i^2.$$

For the restaurant, the benefits from cleaning up include reduced fines for detected violations and the reduced risk of bad publicity owing to foodborne illness outbreaks.[5] To minimize both, the restaurant can exert efforts e_r in cleaning up. Normalizing the maximum violation as 1, we have the actual violations, $\tilde{y} = 1 - e_r$. Consequently, the detected violations are $y = e_i \cdot \tilde{y} = e_i(1 - e_r)$, and the fine is $\tau \cdot y$. For simplicity, we assume that the risk of bad publicity is a linear function of actual violations ($R \cdot \tilde{y}$), where R can be interpreted as the marginal expected penalty or reputational cost that consumers impose on restaurants with actual violations.

Assuming the cost of the restaurant's effort to be strictly convex ($C(e_r) = \theta_r e_r^2$), we can write the restaurant's problem as follows:

$$\min_{e_r} \; W_r = \tau \cdot e_i \cdot (1 - e_r) + \theta_r e_r^2 + R \cdot (1 - e_r).$$

The timing of the game is as follows: At stage 0, the principal sets the inspection criteria, inspector assignment, fine structure, and inspector compensation. At stage 1, the restaurant chooses e_r. At stage 2, the inspector walks in and chooses detection effort e_i. At the end of stage 2, detected violations y 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* ($e_r = \frac{\tau \cdot e_i + R}{2\theta_r}$) shows that the restaurant is more willing to clean up if it knows that the inspector will exert more effort, but the inspector's *detection curve* ($e_i = \frac{(\lambda - 1)(1 - e_r)}{2\theta_i}$) shows that the inspector will exert less effort if he/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 determine the inspector's detection curve exactly after a single inspection. The restaurant is notified by the inspector of the number of violations. The restaurant knows that this number is determined by $y = e_i \cdot (1 - e_r)$. Since the restaurant knows its own compliance effort, it can calculate the inspector's detection effort e_i. In addition, the restaurant knows the inspector's reaction function ($e_i = \frac{(\lambda - 1)(1 - e_r)}{2\theta_i}$). Knowing e_i and e_r, the restaurant can calculate $\frac{\lambda - 1}{2\theta_i}$, which is sufficient for it to determine the detection curve (the slope as well as its vertical intercept). This means that it takes one inspection for the inspection game to reach equilibrium. Given the 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 $\theta_r > \frac{R}{2}$ and $\theta_i > (\lambda - 1)(\frac{1}{2} - \frac{\tau+R}{4\theta_r})$ [6]:

$$e_i = \frac{(2\theta_r - R)(\lambda - 1)}{4\theta_i\theta_r + \tau(\lambda - 1)},\ e_r = \frac{2\theta_i R + \tau(\lambda - 1)}{4\theta_i\theta_r + \tau(\lambda - 1)}.$$

Therefore, the equilibrium reported violations are as follows:

$$y = e_i \cdot (1 - e_r) = \frac{2\theta_i(\lambda - 1)(2\theta_r - R)^2}{[4\theta_i\theta_r + \tau(\lambda - 1)]^2}.$$

Our model highlights two fundamental identification problems if we want to use this framework to empirically distinguish 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 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 ($\tilde{y} \cdot e_i$), and 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 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.[7] Under the assumption of perfect information, our theory suggests that inspector fixed effects reflect not only inspector heterogeneity in overall stringency, but also the differential compliance that restaurants adopt in response to inspector heterogeneity.

Comparative Statics of PDA Adoption

The PDA reminds inspectors of about 1,000 potential violations, and therefore, it may reduce the cost of detection. This suggests that PDA use may substantially reduce an inspector's detection effort cost (θ_i) in the model in subsection 3.1. However, the key prediction of the model is that a restaurant's response to the introduction of PDAs depends upon its compliance effort as well as the inspector's detection effort.

Under the assumptions that PDA adoption is unexpected and that 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 correctly expected a paper inspection. Suppose that PDA use reduces the inspector's detection cost from θ_i to $\theta_i^{'}$, $\theta_i > \theta_i^{'}$, which shifts the inspector's detection curve upwards. When the inspector walks in with a PDA for the first time, it is a surprise to the restaurant. Restaurant compliance remains at e_r^A, but the inspector's 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 the continued use of the PDA and complies accordingly. In response to the increased compliance effort, the inspector should reduce his/her detection effort. As a consequence, we reach a new equilibrium at point C (note that B is sufficient for the restaurant to determine the new detection curve). Compared to the first PDA inspection, the number of detected violations should decrease from B to C, and this decrease reflects both the restaurant's improved compliance $(e_r^C - e_r^B)$ and the laxity of the inspector's 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, which have opposite effects on the number of detected violations. Mathematically, the impact of PDAs on the equilibrium number of detected violations can be written as follows:

$$\frac{\partial y}{\partial \theta_i} = \frac{2(2\theta_r - R)^2(\lambda - 1)(\tau(\lambda - 1) - 4\theta_i\theta_r)}{(4\theta_i\theta_r + \tau(\lambda - 1))^3}. \tag{3}$$

The sign is ambiguous because the sign of $(\tau(\lambda - 1) - 4\theta_i\theta_r)$ 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 owing to PDA usage. Second, assuming that restaurants expect the continuous use of PDAs, 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 the restaurant's compliance response to the improved detection during the first use of a PDA. Because these two predictions contradict 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.

Several points are worth noting. First, this discussion assumes no change in inspector identity. In a companion article (Jin and Lee 2012), we expanded the model to include inspector identity change and showed that allowing inspector heterogeneity does not affect the two predictions about PDA use. Empirically, we control for inspector heterogeneity by inspector–restaurant fixed effects. Second, the assumption of sudden PDA adoption may be violated in reality if a restaurant owner hears from other restaurants about PDA adoption and its effect on enhanced detection. In that case, however, the extra violations reported in the first PDA inspection should underestimate the actual change of detection, which suggests that our empirical estimate is likely more conservative than the true effect. Third, the model assumes that restaurant compliance will move to the new equilibrium immediately after the first PDA inspection. In reality, the process may be gradual if the expected probability of PDA use the next time is less than one or if the restaurant is aided by an inspector who educates it on how to correct the detected violations. To the extent that the inspector's education effort focuses on detected violations, it is part of the compliance response.

4. The Impact of PDA Use on Restaurant Inspection Outcomes

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

Data and Sample Construction

We merge the 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 it is the start of the 2003 fiscal year (FY 2003).

There are two types of inspections. The first type comprises 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 and not by individual inspectors. Complete disciplinary activity reports are only available from FY 2005 to FY 2009. As detailed in Jin and Lee (2012), the expected fine is very low (on average, $11 per inspection).[8]

We clean our final analysis sample through several steps. Starting with 740,808 inspections in the raw data, we first drop inspections conducted during FY 2009 because we do not have complete inspection data for that fiscal year. Second, we exclude any inspections conducted prior to FY 2004 because Florida adopted a new system that classified violations into three groups—risk factors, other critical, and noncritical violations—in March 2004.[9] This reclassification asks inspectors to pay more attention to risk factors. If records before March 2004 are not excluded, it may be argued that inspectors find more critical violations because of the DHR reclassification than because of PDA use. One alternative way to address this data issue is to keep the records from before FY 2004 but to allow different year-month fixed effects for risk factors, other critical violations, and noncritical violations separately. We have done this alternative estimation and found very similar results for PDA use. Since we focus on the data since FY 2004, we do not need to separate risk factors from other critical violations in the regression results. Constructing the sample since FY 2004 also gives us more pre-sample data by which 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. For the same reason, we exclude those inspections done in the first six months following each restaurant’s first appearance in the data. For these earlier inspections, we do not have enough information about previous inspections. In the third step, because callbacks are usually conducted on scheduled dates, we focus on initial inspections. In the fourth step, because we use restaurant–inspector fixed effects in all specifications, we exclude observations that either have only one inspection per restaurant throughout the sample or have no variation in reported violations across multiple observations within the same restaurant–inspector group. Last, we delete observations with missing values, duplicates, non-restaurant inspections, and inspections of restaurants outside Florida. The final sample includes 290,179 initial inspections from July 2004 to June 2009, covering 51,192 unique restaurants and 271 individual inspectors.[10] There are more than 200 active inspectors for each year.

This sample (referred to as the "restricted" sample) is used in our main empirical analysis. As a robustness check, we also use an "unrestricted" sample that includes those inspections during FY 2003 and during the first six months of each restaurant. The unrestricted sample has 332,010 initial inspections and 61,861 unique restaurants. One important tradeoff between the two samples is that while the restricted sample does not confound PDA effects with the increased emphasis on risk factors and is more precise on the variables that describe a restaurant's PDA history, it excludes the initial period of PDA introduction. Some restaurants did not receive their PDA inspection(s) until FY 2004 even if inspectors used PDAs in other restaurants, and we can thus still identify a detection effect from the restricted sample thanks to the low frequency of regular inspections as well as the technical difficulties of using PDAs initially. If these restaurants anticipated PDA usage before their first PDA experience, we tend to underestimate the detection effect from the restricted sample. Results from the unrestricted sample will hint at the magnitude of such a bias. In the restricted as well as unrestricted samples, the number of previous PDA uses is constructed from a restaurant's history in the raw data before any sample restriction. Thus, it includes the number of PDA uses at callbacks.

Sample Summary

Table 1 shows the summary statistics of our restricted sample. Following the DHR classification, we aggregate violations into two groups: critical (risk factors and other critical violations) and noncritical violations.[11] An average inspection finds about 7.89 violations, of which 4.85 are critical and 3.04 are noncritical. Excluding the first six months of each restaurant in our data, the probability of a "new" inspector (an inspector who has never inspected the restaurant during the data period) arriving is 17%; on average, an inspector has inspected the same restaurant 3.62 times before the observed inspection. As mentioned earlier, restaurants are required to undergo inspection at least twice per fiscal year according to state laws. However, because of the labor shortage, barring FY 2008, the average number of regular inspections per restaurant per year was less than two. About 30% of restaurants received only one regular inspection per year.[12] The average number of days between the two inspections was about 181, with 4% of inspections having taken place more than one year after the last inspection. The workload is quite heavy: each inspector has, on average, done about 1,830 inspections.

Most regular inspections are "routine," while 4% are initiated by consumer complaints and 0.1% are licensing inspections. The average restaurant age is 4.11 years, with a wide variation from restaurants that have just opened to those as old as 14 years. Restaurant age is calculated from the date the license is issued. 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 1.85 inspections before coming to the inspection under study, and 25% of inspections are the first 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—the inspector may become tired during the day and incur higher effort costs because of fatigue. In the regression, we include the linear and quadratic terms of this variable to control for (the potentially nonlinear effect of) 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 (12:00–2:00 pm). Most restaurants are busy at lunchtime and probably pay less attention to food safety. To capture this and other hourly effects, we control for a full set of inspection hour-of-day fixed effects.

In Table 2, we present the summary statistics of the variables associated with PDA use. Several patterns are worth highlighting. First, in our regression sample, 89% of inspections are done using PDAs. This high percentage is mainly because most PDAs were first introduced in the beginning of 2004, and our restricted sample starts with July 2004. As we have shown in Section 2, the analysis indicates that PDA adoption is a state and district decision, and the decision to use a PDA at 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 for a fiscal year before the massive adoption of PDAs; hence, their first inspection with a PDA may not have occurred until FY 2004 or after. Overall, about 16% of restaurants in our sample first had a paper inspection and were then subjected to an inspection with a PDA. After having been subjected to PDA inspections, about 30% of restaurants experienced a switch back to paper inspections because of technical problems in the first version of the PDA (OPPAGA 2005).

Another crucial variable is the number of previous PDA inspections in a particular restaurant. Conditional on a restaurant having had no PDA inspections previously, the probability of being inspected with a PDA for the first time was 75%. Once the PDA was adopted, the probability of subsequent inspections with the PDA increased. For example, conditional on having one inspection with a PDA, the probability was 82%. When the PDA was used six times, the probability was over 90%. This means that the more inspections were done using the PDA, the more likely restaurants expected it to be used the next time.

Table 3 shows the distribution of restaurants by frequency in the sample and the number of PDA inspections. There are 51,192 unique restaurants in the regression sample. Among them, 10,359 appear twice in the sample and 5,885 appear thrice. Most of them appear 10 times or fewer. As shown in Table 3, many restaurants experienced paper as well as PDA inspections, either because they started with paper inspections and then moved to PDA inspections or because they were switched back from PDA to paper inspections because of technical problems with 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 expectations as to the likelihood of PDA use.

Econometric Model

This subsection presents an econometric specification that tests the model's predictions. y_{irt} is the number of detected violations for restaurant r by inspector i at time t.[13] Since our dependent variable is a count of reported violations, we estimate a Poisson model with expected value given as follows:

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

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, inspection hour of the day, and the number of days since the last inspection. Note that we control for a rich set of fixed effects: inspector–restaurant fixed effects (μ_{ir}) and year-quarter fixed effects (μ_t). Inspector–restaurant fixed effects should capture each restaurant's time-invariant difficulty or willingness to clean up, each inspector's time-invariant detection cost, *and* the corresponding compliance effort under the assumption that the restaurant can perfectly predict that particular inspector. The unobserved detection or compliance cost can even be specific to inspector–restaurant pairs as long as they do not change over time. Any effort cost change that is 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 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, the theory predicts that the adoption of PDAs subsequently increases restaurants' compliance efforts, so we should observe a drop in the number of violations between the first and second PDA inspections. In other words, the equilibrium changes from B to C in Figure 5, and this prediction corresponds to $(\beta_{comp} + \beta_{inter}) \cdot N_{ir}^{t-1} < 0$. Because N_{ir}^{t-1} is positive (the sample mean is 4.55), when β_{comp} or β_{inter} have an impact on detected violations, this predicts $\beta_{comp} + \beta_{inter} < 0$.

If the inspector does not return with a PDA after its first use, he/she will find fewer violations for two reasons: first, the restaurant will have increased compliance in expectation of PDA use, and second, the inspector will expend less detection effort owing to both the higher detection cost of a paper inspection and the expectation of better compliance. This scenario of "a paper inspection following the first use of a PDA" corresponds to point D in Figure 5. Our model predicts fewer detected violations at D than at A, which implies $\beta_{comp} \cdot N_{ir}^{t-1} < 0$, and fewer detected violations at D than at C, which implies $\beta_{det} + \beta_{inter} \cdot N_{ir}^{t-1} > 0$.

Above all, we expect $\beta_{det} > 0$, $\beta_{comp} < 0$, $\beta_{det} + \beta_{inter} \cdot N_{ir}^{t-1} > 0$, and $\beta_{comp} + \beta_{inter} < 0$. β_{det} is interpreted as the effect of PDA use on inspector detection. Both $\beta_{comp} \cdot N_{ir}^{t-1}$ and $(\beta_{comp} + \beta_{inter}) \cdot N_{ir}^{t-1}$ can be interpreted as an upper bound of restaurant compliance response to increased detection owing to PDA use. If we take the theory literally, Figure 5 suggests $\beta_{inter} \cdot N_{ir}^{t-1} < 0$ because the reduction in inspection effort with a PDA (from B to C) is more than the reduction in inspection effort without it (from A to D) given the same compliance change from e_{r1}^{A} to e_{r1}^{C}.

Regression Results

Table 4 shows the main results we obtained on using a fixed effects Poisson model. Column (1) includes only the PDA-related variables of our main interest with restaurant fixed effects and year-quarter fixed effects. Column (2) adds control variables as well as more detailed inspector–restaurant fixed effects and inspection hour-of-day fixed effects. Both Columns (1) and (2) use the restricted sample, while Column (3) uses the unrestricted sample for comparison.

As we expect, inspectors detect more violations when using a PDA, and this impact is sizable. The estimated β_{det} in Column (1) of Table 4 indicates that the first use of a PDA increases the expected number of violations by 11.5%. When we add more controls, the estimate changes only slightly, to 11.3% in Column (2). As explained in Section 2.2, the impact reflects an increase in detection effort because of PDA use. The detection effect estimated from the unrestricted sample (in Column 3) is slightly larger. This is not surprising given that PDA adoption should be more unexpected by restaurants in the initial period of PDA introduction.[14]

As the PDA is used repeatedly, 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 -0.082 in Column (1) to -0.054 in Column (2). Since β_{inter} is estimated to be negative as well, $\beta_{comp} + \beta_{inter}$ is slightly more negative than β_{comp}, ranging from -0.092 in

Column (1) to -0.067 in Column (2). Recall that both β_{comp} and $\beta_{comp} + \beta_{inter}$ tend to overestimate a restaurant's compliance response to the increased detection effort through PDA use. Similar results are found in the unrestricted sample in Column 3, suggesting that the effects of PDA use do not change greatly over time, although PDA technology may have been improved after Florida solved the mechanical and software problems with the PDAs. Taking Column (2) as our preferred specification, these estimates imply that a restaurant's compliance response is no greater than a 5.3% decrease in the number of detected violations per additional previous use of a PDA.

Assuming a PDA is continuously used, our estimates suggest that it takes at least two inspections to offset the initial increase in the number of violations detected. However, care is needed in the interpretation of this suggestion. Note that once the inspector increases his/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 irrespective of the additional number of detected violations.

Because the number of previous PDA uses is counted in the raw data, which include regular as well as callback inspections, dirtier restaurants may be more likely to get callbacks and therefore be subject to a greater number of previous PDA inspections. Note that the inherent cleanliness of a restaurant, if unchanged over time, is absorbed into the restaurant–inspector fixed effects. To address the remaining concern that the number of previous PDA uses may affect the likelihood of callbacks, we recount the number of previous PDA inspections from regular inspections only and redo the estimation. The results are similar to those reported in Column 2 of Table 4.[15]

Many other coefficients reported in Table 4 are also statistically significant. First, new inspectors are more likely to find more violations, a repeat inspector reports fewer violations when he/she has a longer relationship with the restaurant, and a new inspector, following the last inspector's (longer) history with the restaurant, reports even more violations. We have explained these results in light of game theory in a companion article (Jin and Lee 2012). Second, we find that more violations are reported if the inspector is less experienced. The results in Column (2) show that those inspectors whose past inspections are less than the median detect 2.7% more violations. Novice inspectors, who have done only 30 or fewer inspections, find significantly more violations (about 20%). Third, we find that inspectors find fewer violations in inspections they conduct later in the day. This might be because inspectors schedule inspections for more problematic restaurants earlier in the day. Alternatively, it may be because inspectors are more focused or less fatigued earlier in the day.[16] Fourth, the longer the time since the last inspection, the more the violations, although fewer violations are found when more than one year has elapsed since the last inspection. Fifth, more violations are found for older restaurants. Lastly, inspections initiated by a citizen's complaint or conducted for license renewal find fewer violations.

Table 5 separates the regression results into three periods: the adoption period of the unrestricted sample up to the fourth quarter of 2004, the earlier half of the restricted sample up to the third quarter of 2006, and the latter half of the restricted sample after the third quarter of 2006. Because of space constraints, we only report the coefficients of the PDA-related variables. These coefficients suggest that the detection effect is identified from the earlier half of the sample and is of a greater magnitude in the adoption period (0.200 of Column 1 versus 0.148 of Column 2). In comparison, the compliance effect is not significant in the adoption period and tends to increase over time. This is not surprising, as the detection effect depends on the unexpected adoption of and switch from the PDA, which occurred mostly before 2006, while the compliance effect depends on changes in the number of previous PDA inspections, whose variations originate from periods after PDA adoption.

One remaining question is why PDA use may reduce the cost of detection. One possibility is that it reminds inspectors of potential violations.[17] To test this, Table 6 reports the key coefficients by two groupings of violations. The first two columns compare critical and noncritical violations, while the last three columns compare categories with <10, 10–19, and 20+ subcategories.

Because inspectors are trained to believe that critical violations are more important in terms of health risk (which corresponds to a higher λ in our model), they should pay more attention to critical violations even without a PDA. If this implies less room for improvement, one may expect a smaller detection effect of the PDA on critical violations. Conversely, the PDA effect on detection can be magnified for critical violations, as a PDA reminder may be more salient for items that register greater importance in an inspector's mind. As shown in Table 6, the estimated detection effects are remarkably similar: 0.112 for critical and 0.117 for noncritical violations. This suggests that a PDA can improve detection for critical as well as noncritical violations and that the compliance response to these improvements may translate into a lower health risk, a topic examined in Section 5.

A more straightforward test of the reminder mechanism is to examine whether PDA use has greater effects on easy-to-ignore items. Arguably, the inspector's attention bias is more severe in categories that have many subcategories. As shown in the last three columns of Table 6, we find that the detection effect of a PDA is only significant in categories with 10+ subcategories and is greatest in categories that contain 20 or more subcategories. In comparison, the (upper bound of the) compliance effect is roughly similar across the three groups. This suggests that inspectors have limited attention to detail and that a PDA inspection is more effective than a paper inspection at drawing 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 on the detection cost after only one PDA inspection, and subsequently, it will fully expect the continued use of a PDA. In reality, given the technical problems encountered in the first version of the PDA, restaurants may learn more slowly, and their expectations 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 it is repeatedly used?

As a first pass, we run an ordinary least squares (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 later. This figure is consistent with the period-by-period results reported in Table 5. 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: 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10+. As shown in Table 7, β_{comp} is insignificant when the number of previous PDA uses is 1, and becomes significant and progressively negative as previous PDA usage approaches 10+. In comparison, β_{inter} is always negative and significant, and it tends to be more negative as we increase the number of previous PDA uses.[18] 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 and Table 5.

More interestingly, although the overall effects are similar for critical and noncritical violations (see Table 6), they differ in the timing of the effects. As shown in the last two columns of Table 7, when we distinguish between previous PDA usage from 1 to 10+ for critical and noncritical violations, β_{comp} is always negative and significant for critical violations, but it is not significant for noncritical violations until the previous PDA usage is 6 or more. The absolute magnitude of β_{comp} is also much larger for critical than for noncritical violations. In comparison, the significance of β_{inter} is similar between the two columns, and the absolute magnitude of β_{inter} is usually larger for noncritical than for critical violations. One explanation is that restaurants are more keenly and more quickly correcting critical violations than before because of either higher fines on critical violations or more inspector education efforts on methods to correct critical violations.

Discussion

Our empirical findings are largely consistent with our theoretical predictions: PDA usage tends to increase detection and compliance. It is important to identify four limitations of our analysis. First, our model assumes that the first use of a PDA is unexpected for any restaurant. If this is not true (for example, a restaurant owner may have heard about increased detection by a PDA in other restaurants), the owner should have increased his compliance effort before the first PDA use. In this case, the coefficient of PDA use in our regression should be interpreted as a conservative estimate of the true detection effect.

Second, our estimate on compliance is only an upper bound of the actual compliance. Because real improvement in health risk depends on actual compliance rather than on reported violations, we will address this caveat in Section 5 by associating PDA usage with foodborne illness outbreaks.

Third, the estimated effects may capture not only the inspectors' productivity improvements in detecting violations, but also their increased productivity in educating restaurants about food safety. We cannot distinguish between the two if both are linked to PDA usage. For example, if education focuses on how to correct detected violations rather than on how to prevent hypothetical violations, the education effort will naturally increase with detection.

Fourth, all the regression analyses shown above are conducted at the inspection level. If each PDA inspection takes longer than a paper inspection, whether because of heightened inspector attention or the technical difficulty of using a PDA, its usage may reduce inspection frequency, and such a reduction can counteract the benefits of PDA usage. To address this concern, we plot the PDA use rate and inspection rate by quarter, where the PDA use rate is defined by the proportion of inspections that used a PDA in a quarter, and the inspection rate is defined as the number of inspected restaurants during a certain quarter divided by the total number of licensed restaurants in the year of that quarter. If inspectors have reduced inspection frequency because of PDA use, then the two trends should be negatively correlated.

As shown in Figure A.4, during the initial adoption period, when the PDAs were first introduced and withdrawn because of technical problems (from the third quarter of 2003 to the fourth quarter of 2004), inspection and PDA use rates are indeed negatively correlated. This suggests that although PDAs made it possible for inspectors to check the more detailed list of items, it slowed them down. However, from 2005 onward, supposedly after the initial technical problems were fixed, PDA use and inspection rates have been positively correlated.[19] Combined with our regression results, this suggests that the slow-down effect of PDA use is limited to the initial adoption period; after 2005, the overall PDA effects for the state of Florida may be even higher than our result at the inspection level because PDA use is accompanied by a higher inspection rate.

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 them, PDA use should improve restaurant hygiene because of compliance. This implication motivates us to link PDA use to public health outcomes directly. We now first describe the data on foodborne disease outbreaks in Florida and then present regression results that associate PDA use with restaurant-related outbreaks.

Florida Foodborne Disease Outbreak Data

We collect information on foodborne disease outbreaks from the surveillance database of the Florida Department of Health.[20] The Center for Disease Control and Prevention (CDC) defines a foodborne disease outbreak as any cluster of two or more similar infections that are shown by investigation to result from the ingestion of the same food. Most foodborne disease 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 cases reported to the CDC as well as cases investigated by the state but not reported to the CDC. We choose to use the state's outbreak data instead of the CDC's outbreak data because the former reports the outbreaks by county, whereas the latter categorizes them by state.

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 non-restaurant entity (such as a 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 10,385 observations by county and 15-day intervals (67 counties $\times$ 155 intervals) for restaurant and non-restaurant outbreaks separately. Restaurant-related outbreaks account for two-thirds of the total outbreaks. We choose to define the unit of observation as county by a 15-day interval since foodborne outbreaks are typically short-lived and localized. Only 4.5% of county-interval 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 per interval. There are some outliers. In two observations, the number of reported cases is greater than 500 (see Figure A.5 for the monthly trends).

Regression Analysis

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

$$R_{ct} = \gamma_1 PDA_{ct-1} + \gamma_2 NR_{ct} + \mu_c + m_t + v_{ct}$$

where R_{ct} is an indicator of whether there were any incidences of restaurant-related foodborne disease outbreaks in county c in the 15-day interval t. We use a binary indicator rather than the number of foodborne disease outbreaks because such outbreaks are rare events (about 4.5% per county-interval). Also, given the nature of foodborne disease outbreaks, once one occurs, there could be an explosion of similar incidences. As PDA_{ct-1} is the proportion of PDA inspections in a given county-interval (lagged by one interval), γ_1 is the coefficient of interest: it shows to what extent the PDA usage of $(t-1)$ induces compliance and therefore improves the actual restaurant hygiene level at t. 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.[21] We also include 15-day time interval fixed effects (m_t) to account for seasonality as well as statewide trends.

The estimation results are presented in Panel A of Table 8. The first two columns use the dummy of any restaurant-related outbreak as the dependent variable, the next two columns use the dummy of having more than four restaurant-related outbreaks in order to capture the degree of outbreaks, and the last two columns use the dummy of any non-restaurant-related outbreaks as a placebo test.[22] Table 8, Panel A shows that overall, the incidence of restaurant foodborne disease outbreaks is negatively correlated with PDA usage in the previous time interval, but not for the intervals two periods ago. Specifically, moving from no PDA usage to 100% PDA usage decreases the likelihood of any restaurant foodborne disease outbreaks by 1.2% and the likelihood of having more than four restaurant-related outbreaks by 0.6%. Both estimates are significant at the 90% confidence level. Table 8, Panel B reruns the same regressions, excluding data before July 2004, to be consistent with the period of our restricted sample in the inspection outcome analysis shown in Section 4. The results are consistent with that of Panel A, but with a slightly smaller magnitude: the effect of moving from no PDA usage to 100% PDA usage on the likelihood of any restaurant foodborne disease outbreaks is reduced from 1.2% to 0.9%, and its statistical significance is at the 90% level instead of 95%. The effect on the likelihood of having more than four restaurant-related outbreaks changes from 0.6% to 0.5% but remains significant at the 90% confidence level. These effects are non-negligible compared to the average probability of any restaurant foodborne disease outbreak per county-interval (4.5%) or that of more than four restaurant-related outbreaks (1.8%) in Florida. Because PDA usage does not directly affect non-restaurant foodborne disease outbreaks, we believe that the reduction in restaurant-related outbreaks is likely a consequence of restaurants increasing their compliance efforts in response to PDA use.

6. Conclusions

Food safety is of considerable concern in public health. In the United States, 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 overcame this difficulty by exploiting the introduction of a new inspection technology that exogenously reduces the effort cost of inspectors. Using game theory, we identified the effect of this technology on detection as well as the upper bound of the compliance response to the detection change. Our findings have several policy implications. First, a simple technology can substantially improve the efficiency of detection. Human inspectors are not perfect and have limited attention spans. With the help of a small electronic device that simply shows a checklist in detail, inspectors find significantly more violations, some of which are critical. Second, restaurants do increase compliance in response to higher detection effort by inspectors. However, their response is gradual and increases by the expected permanency of the reform. Lastly, despite the gradual 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 costs of restaurant compliance, or the benefits from fewer outbreaks. Nevertheless, our quantitative findings should help policy makers attempt such a benefit–cost analysis.

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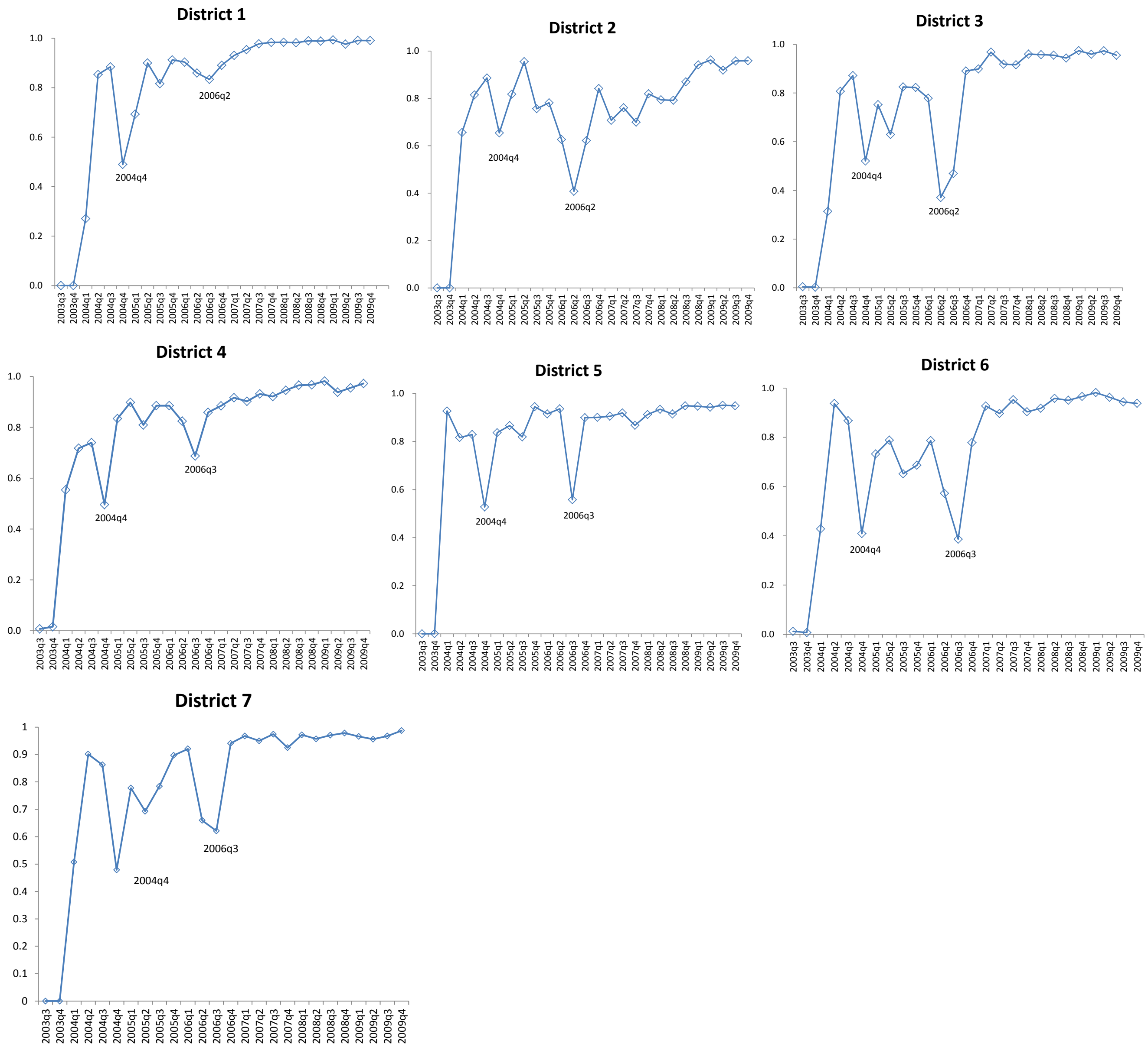
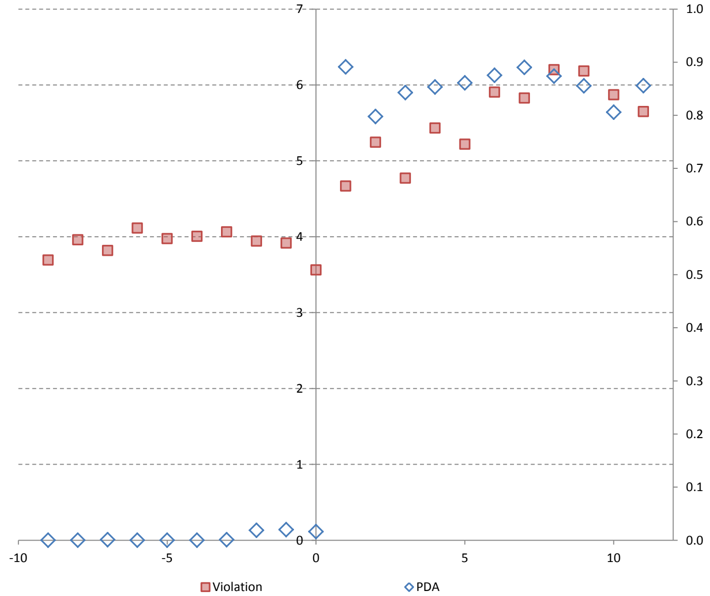
Figure 1. Proportion of Inspections with PDAs over Time by District



Notes: The graphs show the time trends of the proportion of inspections with PDAs by Florida inspection district. There are seven districts in Florida. The time unit is a quarter. The sample period spans from the third quarter of 2003 to the last quarter of 2009.

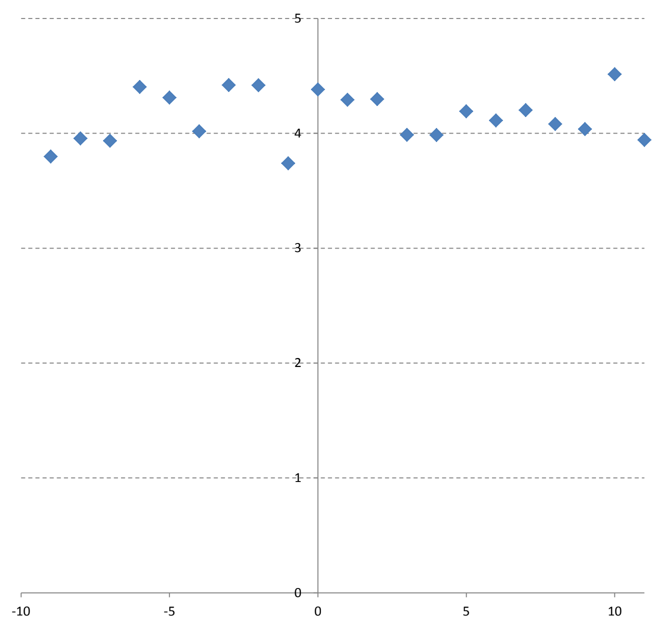
Figure 2. Impact of the First Adoption of PDAs on Violations and Exogeneity of PDA Adoption (10 Weeks before and after the District's Massive Adoption Date)

A. PDA Adoption and Effects on Violations



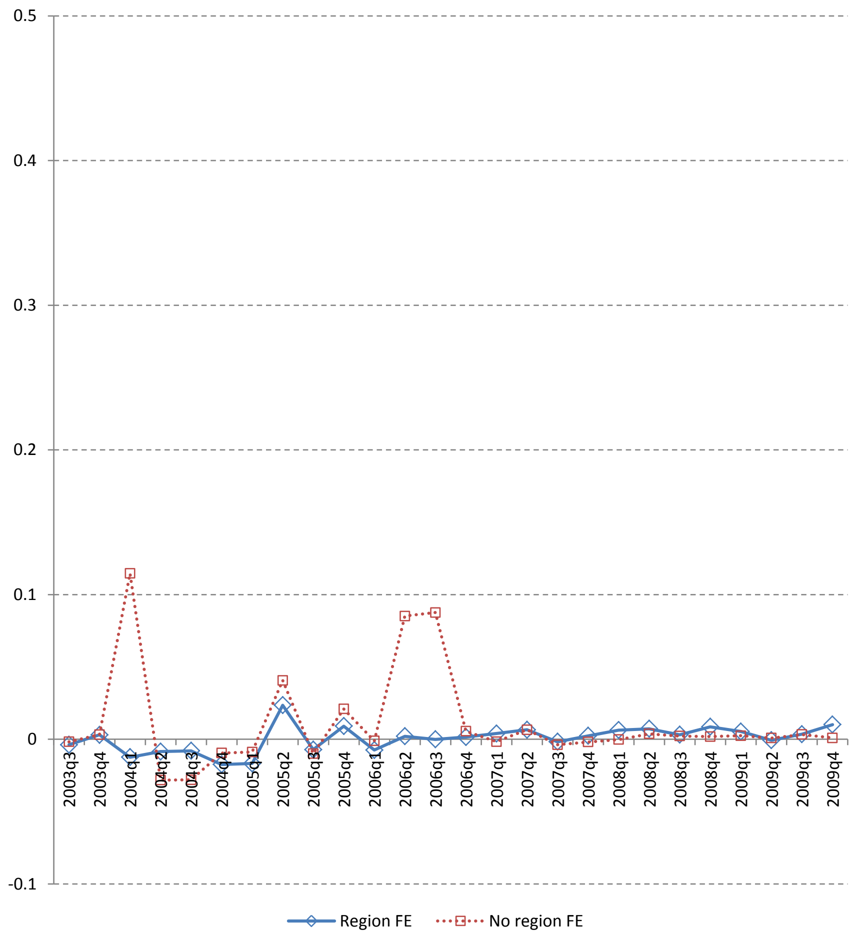
Notes: The horizontal axis represents the weeks around the date when most inspectors adopted PDAs in each district. The diamonds represent the proportion of inspections done using a PDA in each week. The squares represent the average number of detected violations per inspection in each week.

B. Effects of Past Violations on PDA Use



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

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



Notes: The horizontal axis represents the period from July 2003 to December 2009 by quarter. For each quarter, we run a regression of PDA use on previous violations. The squares represent the OLS estimates and the diamonds represent the estimates after controlling for district fixed effects.

Figure 4. Equilibrium with Perfect Information

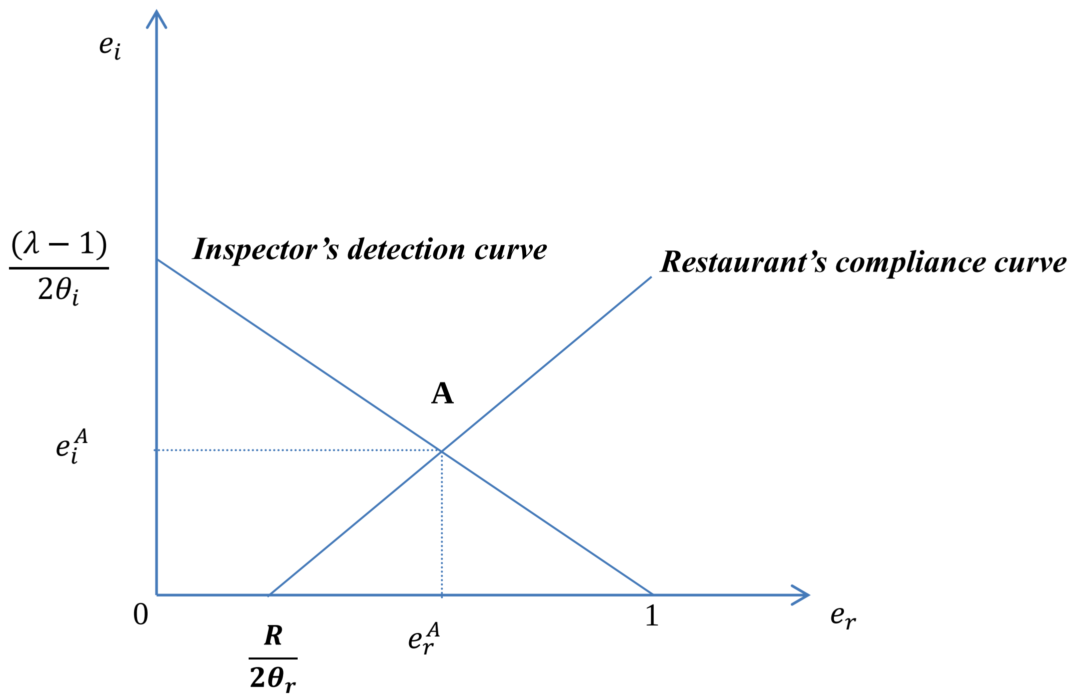


Figure 5. Comparative Statics by PDA Adoption ($\theta_i \rightarrow \theta_i^{'}, \theta_i > \theta_i^{'}$)

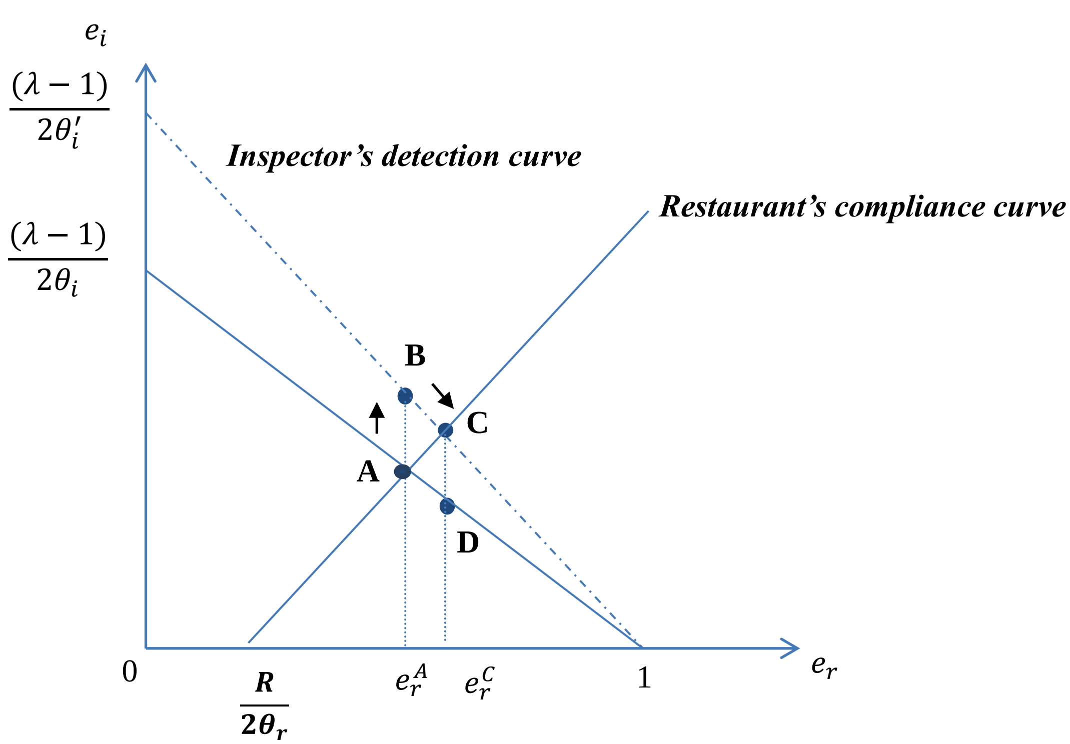


Figure 6. Changes in Detection Effects over Time

Notes: The horizontal axis represents the period from January 2004 to December 2009 by quarter. For each quarter, we run a regression of detected violations by PDA use. The squares represent the OLS estimates and the diamonds represent 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	7.89	6.99	0	111
Critical violations	4.85	4.53	0	66
Noncritical violations	3.04	3.24	0	47
Inspector characteristics				
New inspector (new to the current restaurant)	0.17	0.38	0	1
Number of inspections by previous inspector	3.62	2.91	1	36
Days since previous inspection	181	87	1	1754
Over one year since the last inspection	0.04	0.19	0	1
Inspector's past inspections	1830	1245	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	0.031	0	1
Restaurant age in years	4.11	2.65	0	14.19
Number of inspections done per day before the current inspection	1.85	1.70	0	36
First inspection today	0.25	0.43	0	1
Inspection during lunch time (12:00–2:00 PM)	0.38	0.49	0	1

Notes: Summary statistics for the restricted sample, excluding those inspections during the first six months after each restaurant's first appearance in the data and FY 2003. N = 290,179. The number of observations with non-missing restaurant age and non-missing inspection time is 261,128.

Table 2. Summary Statistics of PDA Variables

	Mean	SD
PDA	0.89	0.31
Number of previous PDA inspections	4.55	3.38
Restaurants with initial paper inspection in the sample*	0.16	0.37
Restaurants that experienced a switch back to paper**	0.30	0.46
No previous PDA inspection	0.07	0.25
One previous PDA inspection	0.11	0.31
Two previous PDA inspections	0.13	0.34
Three previous PDA inspections	0.13	0.33
Four previous PDA inspections	0.11	0.31
Five previous PDA inspections	0.10	0.29
Six previous PDA inspections	0.08	0.28
Seven previous PDA inspections	0.07	0.26
Eight previous PDA inspections	0.06	0.23
Nine previous PDA inspections	0.05	0.21
10 or more previous PDA inspections	0.10	0.30
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***	0.09	0.29

Notes: * represents the proportion of restaurants whose first inspection in the sample was a paper inspection of the 51,192 restaurants included in the regression analysis. ** represents the proportion of restaurants that experienced a switch back to paper inspections of those that were subjected to PDA inspection once. *** represents the proportion of paper inspections for those restaurants that were subjected to PDA inspection once. All the statistics are calculated from the restricted 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	20	21	Total
2	258	1,812	8,289	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10,359
3	32	257	1,227	4,369	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5,885
4	12	73	406	1,494	3,882	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5,867
5	0	24	100	397	1,316	2,910	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4,747
6	1	9	20	126	468	1,445	2,589	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4,658
7	0	29	41	34	159	612	1,440	2,046	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4,361
8	0	3	12	12	46	187	689	1,491	1,875	0	0	0	0	0	0	0	0	0	0	0	0	0	4,315
9	0	0	1	2	10	60	233	718	1,437	1,678	0	0	0	0	0	0	0	0	0	0	0	0	4,139
10	0	0	0	0	3	23	79	234	655	1,251	1,233	0	0	0	0	0	0	0	0	0	0	0	3,478
11	0	0	0	0	0	2	12	49	150	434	742	558	0	0	0	0	0	0	0	0	0	0	1,947
12	0	0	0	0	0	0	6	9	28	86	194	307	229	0	0	0	0	0	0	0	0	0	859
13	0	0	0	0	0	0	0	3	3	12	46	95	125	75	0	0	0	0	0	0	0	0	359
14	0	0	0	0	0	0	0	1	0	1	9	19	32	49	30	0	0	0	0	0	0	0	141
15	0	0	0	0	0	0	0	0	0	0	3	5	5	7	17	8	0	0	0	0	0	0	45
16	0	0	0	0	0	0	0	0	0	1	0	2	3	6	6	2	1	0	0	0	0	0	21
17	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	1	0	0	0	0	0	5
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	3
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Total	303	2,207	10,096	6,434	5,884	5,239	5,048	4,551	4,148	3,463	2,227	986	394	139	56	10	3	1	2	0	0	1	51,192

Notes: The number in each cell represents the number of restaurants. There are 51,192 restaurants in total in the restricted sample. For each restaurant, we count its frequency in the sample and the total number of PDA inspections. For example, the first cell shows that 258 restaurants appear twice in the sample and that they were not subjected to PDA inspection (i.e., both inspections were paper-based).

Table 4. Results from Fixed-Effect (FE) Poisson Models: Total Number of Violations

	Restricted Sample		Unrestricted Sample
	(1)	(2)	(3)
PDA	0.115***	0.113***	0.130***
	(0.009)	(0.012)	(0.011)
Number of Previous PDA inspections	-0.082***	-0.054***	-0.047***
	(0.003)	(0.003)	(0.003)
Number of Previous PDA inspections × PDA	-0.010***	-0.013***	-0.016***
	(0.002)	(0.002)	(0.002)
New inspector (new to the current restaurant)		0.094***	0.102***
		(0.005)	(0.005)
Inspections by the previous inspector × New inspector		0.007***	0.007***
		(0.002)	(0.002)
Inspections by the previous inspector		-0.008***	-0.009***
		(0.001)	(0.001)
Inspector's past inspections are fewer than the median		0.027***	0.026***
		(0.005)	(0.005)
Inspector's past inspections are 30 or fewer		0.200***	0.194***
		(0.018)	(0.017)
Number/inspections done before the current inspection per day		-0.030***	-0.030***
		(0.001)	(0.001)
First inspection today		0.005	0.000
		(0.005)	(0.005)
Missing inspection time		-0.044*	-0.038*
		(0.023)	(0.022)
Days since the last inspection		0.000***	0.001***
		(0.000)	(0.000)
More than one year since the last inspection		-0.079***	-0.102***
		(0.009)	(0.009)
Restaurant age in years		0.063***	0.052***
		(0.019)	(0.018)
Missing restaurant age		-0.193	-0.129
		(0.200)	(0.107)
Inspection performed in response to a citizen's complaint		-0.147***	-0.146***
		(0.008)	(0.007)
Inspection performed upon initial license or change of ownership		-0.399***	-0.375***
		(0.059)	(0.036)
Restaurant FE	Yes	--	--
Year-quarter FE	Yes	Yes	Yes
Inspection time hourly FE	No	Yes	Yes
Inspector-restaurant FE	No	Yes	Yes
Number of restaurants	51,192	51,192	61,861

Observations	290,179	290,179	332,010

Notes: The dependent variable is the number of violations per inspection. In Columns (1) and (2), we use the restricted sample. There are 19 quarter-by-year, 23 inspection time hour, and 79,270 inspector–restaurant fixed effects. For Column (3), we use the unrestricted sample. There are 24 quarter-by-year, 23 inspection time hour, and 88,700 inspector–restaurant fixed effects. Robust standard errors are clustered at the inspector–restaurant level. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 5. Impact of PDA Use by Period: Adoption and Earlier and Later Periods

Period	(1) Adoption	(2) Earlier	(3) Later
PDA	0.200***	0.148***	0.008
	(0.044)	(0.021)	(0.019)
Number of Previous PDA inspections	-0.012	-0.059***	-0.081***
	(0.023)	(0.007)	(0.004)
Number of Previous PDA inspections	-0.014	-0.025***	-0.002
× PDA	(0.014)	(0.004)	(0.003)
Control variables	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Inspection time hourly FE	Yes	Yes	Yes
Inspector-restaurant FE	Yes	Yes	Yes
Observations	30,851	106,867	166,586

Notes: The estimation results are obtained from FE Poisson models. The dependent variable is the number of violations per inspection. Robust standard errors are clustered at the inspector–restaurant level. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level. For Column (1), we use our unrestricted sample, including inspections during the first six months after each restaurant's first appearance in the data and FY 2003. The adoption period is from July 2003 to December 2004. For Columns (2) and (3), we use the restricted sample, excluding certain observations, as explained in Section 4.1. "Earlier" refers to the period from July 2004 to September 2006, and "Later" refers to the period from October 2006 to June 2009. All the control variables in Column (2) of Table 3 are included.

Table 6. Results by Violation Category Characteristics

	Critical vs. Noncritical		Number of Subcategories		
	(1)	(2)	(3)	(4)	(5)
	Critical	Noncritical	Large	Medium	Small
			20 or more	10–19	Fewer than 10
PDA	0.112***	0.117***	0.180***	0.087***	0.026
	(0.014)	(0.015)	(0.015)	(0.015)	(0.018)
Number of Previous PDA inspections	-0.064***	-0.040***	-0.051***	-0.063***	-0.048***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Number of Previous PDA inspections	-0.012***	-0.016***	-0.018***	-0.012***	-0.007***
× PDA	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Inspection time hourly FE	Yes	Yes	Yes	Yes	Yes
Inspector-restaurant FE	Yes	Yes	Yes	Yes	Yes
Observations	287,893	277,690	282,296	280,250	268,119

Notes: The main estimation results are obtained from FE Poisson models using the restricted sample. The dependent variable is the number of violations per inspection. Robust standard errors are clustered at the inspector–restaurant level. All the control variables in Column (2) of Table 3 are included. The cutoff numbers of subcategories were chosen so as to divide the sample as equally as possible. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level. Detailed results are available upon request.

Table 7. Detection and Compliance Effects over Repeated Uses of PDA

	(1) All	(2) Critical	(3) Noncritical
PDA	0.165***	0.144***	0.200***
	(0.019)	(0.021)	(0.023)
# of Previous PDA inspections = 1	-0.025	-0.058**	0.027
	(0.021)	(0.023)	(0.025)
# of Previous PDA inspections = 2	-0.086***	-0.140***	-0.000
	(0.022)	(0.024)	(0.027)
# of Previous PDA inspections = 3	-0.113***	-0.201***	0.020
	(0.024)	(0.026)	(0.029)
# of Previous PDA inspections = 4	-0.190***	-0.291***	-0.035
	(0.026)	(0.028)	(0.031)
# of Previous PDA inspections = 5	-0.195***	-0.305***	-0.024
	(0.027)	(0.029)	(0.033)
# of Previous PDA inspections = 6	-0.242***	-0.358***	-0.060*
	(0.029)	(0.032)	(0.037)
# of Previous PDA inspections = 7	-0.295***	-0.412***	-0.111***
	(0.032)	(0.035)	(0.040)
# of Previous PDA inspections = 8	-0.340***	-0.465***	-0.145***
	(0.036)	(0.039)	(0.046)
# of Previous PDA inspections = 9	-0.415***	-0.531***	-0.234***
	(0.040)	(0.044)	(0.051)
# of Previous PDA inspections = 10 or more	-0.461***	-0.602***	-0.239***
	(0.038)	(0.041)	(0.047)
PDA × (# of Previous PDA inspections = 1)	-0.047**	-0.031	-0.071***
	(0.020)	(0.023)	(0.025)
PDA × (# of Previous PDA inspections = 2)	-0.066***	-0.051**	-0.093***
	(0.020)	(0.022)	(0.025)
PDA × (# of Previous PDA inspections = 3)	-0.106***	-0.068***	-0.161***
	(0.022)	(0.024)	(0.026)
PDA × (# of Previous PDA inspections = 4)	-0.085***	-0.043*	-0.146***
	(0.022)	(0.024)	(0.027)
PDA × (# of Previous PDA inspections = 5)	-0.136***	-0.094***	-0.200***
	(0.022)	(0.024)	(0.028)
PDA × (# of Previous PDA inspections = 6)	-0.145***	-0.108***	-0.203***
	(0.025)	(0.026)	(0.031)
PDA × (# of Previous PDA inspections = 7)	-0.144***	-0.114***	-0.193***
	(0.027)	(0.030)	(0.033)
PDA × (# of Previous PDA inspections = 8)	-0.151***	-0.130***	-0.186***
	(0.031)	(0.032)	(0.039)
PDA × (# of Previous PDA inspections = 9)	-0.129***	-0.120***	-0.145***
	(0.034)	(0.038)	(0.045)

PDA × (# of Previous PDA inspections = 10+)	-0.184***	-0.160***	-0.224***
	(0.029)	(0.031)	(0.036)
Control variables	Yes	Yes	Yes
Restaurant FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Inspection time hourly FE	Yes	Yes	Yes
Inspector-restaurant FE	Yes	Yes	Yes
Observations	290,179	287,893	277,690

Notes: The main estimation results are obtained from FE Poisson models using the restricted sample. The dependent variable is the number of violations per inspection. Robust standard errors are clustered at the inspector–restaurant level. All the control variables in Column (2) of Table 3 are included. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 8. Impacts of PDA Inspections on Foodborne Disease Outbreaks

Dependent variable (sample average)	Any restaurant foodborne disease outbreaks		Reported more than four restaurant foodborne disease outbreak cases		Non-restaurant foodborne disease outbreaks	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Data period starting July 2003	Mean = 0.045		Mean = 0.018		Mean = 0.022	
PDA $(t-1)$	-0.013**	-0.012**	-0.007*	-0.006*	0.003	0.004
	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
PDA $(t-2)$		-0.005		-0.004		-0.004
		(0.005)		(0.003)		(0.003)
Non-restaurant foodborne disease outbreaks	0.002**	0.002**	-0.0001	-0.0001		
	(0.001)	(0.001)	(0.0002)	(0.0002)		
Inspection rate	1.054	1.044	0.737	0.757	1.768	1.974
	(1.179)	(1.138)	(0.525)	(0.533)	(1.612)	(1.619)
Observations	10,385	10,318	10,385	10,318	10,385	10,318
R-squared (within group)	0.023	0.023	0.017	0.017	0.020	0.020
Panel B: Data period starting July 2004	Mean = 0.041		Mean = 0.017		Mean = 0.021	
PDA $(t-1)$	-0.009*	-0.009*	-0.005*	-0.005*	0.002	0.002
	(0.005)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
PDA $(t-2)$		-0.001		-0.000		-0.003
		(0.004)		(0.003)		(0.003)
Non-restaurant foodborne disease outbreaks	0.002**	0.002**	0.000	0.000		
	(0.001)	(0.001)	(0.000)	(0.000)		
Inspection rate	0.809	0.805	1.090**	1.090**	0.648	0.642
	(1.021)	(1.018)	(0.528)	(0.528)	(1.234)	(1.234)
Observations	8,844	8,777	8,844	8,777	8,844	8,777
R-squared (within group)	0.021	0.020	0.014	0.014	0.020	0.020
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time interval fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The time interval is 15 days. Linear probability models are used. The dependent variable is the indicator for any restaurant-related foodborne disease outbreaks in Columns (1) and (2), the indicator for whether there were more than four restaurant-related foodborne disease outbreaks in Columns (3) and (4), and the indicator for non-restaurant foodborne disease outbreaks in the bottom panel in Columns (5) and (6). The linear probability model is estimated with county-specific and time fixed effects. PDA (*t*-1) is the proportion of PDA inspections out of all inspections conducted in a county at time (*t*-1). The inspection rate is defined as the number of inspections done during a given time interval divided by the number of licensed restaurants in the year. Robust standard errors, clustered by county, are presented in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix

Appendix A. Derivation of Equilibrium

The restaurant's problem is the following:

$$\min_{e_r} W_r = \tau \cdot e_i \cdot (1 - e_r) + \theta_r e_r^2 + R \cdot (1 - e_r)$$

Taking the first-order condition of the restaurant's problem with respect to restaurant effort, we get the restaurant's optimal effort as $e_r = \frac{\tau \cdot e_i + R}{2\theta_r}$. The inspector's problem is the following:

$$\min_{e_i} \quad W_i = (1 - e_r)e_i + \lambda(1 - e_r)(1 - e_i) + \theta_i e_i^2.$$

Taking the first-order condition of the inspector's problem with respect to inspector effort, we get the inspector's optimal effort as $e_i = \frac{(\lambda-1)(1-e_r).}{2\theta_i}$

Putting the two first-order conditions together and solving for e_i and e_r, we have the following:

$$e_i = \frac{(2\theta_r - R)(\lambda - 1)}{4\theta_i\theta_r + \tau(\lambda - 1)}, \; e_r = \frac{2\theta_i R + \tau(\lambda - 1)}{4\theta_i\theta_r + \tau(\lambda - 1)}.$$

Plugging them into y, we obtain the following:

$$y = e_i \cdot (1 - e_r) = \frac{2\theta_i(\lambda - 1)(2\theta_r - R)^2}{[4\theta_i\theta_r + \tau(\lambda - 1)]^2}.$$

To ensure that both e_i and e_r strictly lie between 0 and 1, we need $\theta_r > \frac{R}{2}$ and $\theta_i > (\lambda - 1)(\frac{1}{2} - \frac{\tau+R}{4\theta_r})$. The first condition implies that the restaurant's cleaning effort is costly enough for it to always have incentives to shirk if bad publicity is the only penalty for violations. The second condition implies that the cost of detection is sufficiently high relative to the perceived importance of detection such that the inspector will not exert his/her maximum effort of 1 even if he/she knows that the restaurant puts little effort into cleaning up. A more restrictive version of the first condition is $\theta_r \geq \frac{\tau+R}{2}$. In that case, cleaning up is so costly that the restaurant will not clean up completely even if it knows that the inspector will engage in full detection. In some range of the second condition $(\lambda - 1)(\frac{1}{2} - \frac{\tau+R}{4\theta_r}) < \theta_i < \frac{\lambda-1}{2})$, the intercept of the detection curve exceeds one, and therefore, the inspector will engage in full detection if restaurant effort is sufficiently low (i.e., $e_r < 1 - \frac{2\theta_i}{\lambda-1}$). This corner-solution range of the detection curve still leads to an inner solution in equilibrium as long as $\theta_i > (\lambda - 1)(\frac{1}{2} - \frac{\tau+R}{4\theta_r})$.

Figure A.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. Mark "X" in appropriate box for COS and/or R

IN = in compliance **OUT** = not in compliance **N/O** = not observed **N/A** = not applicable **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

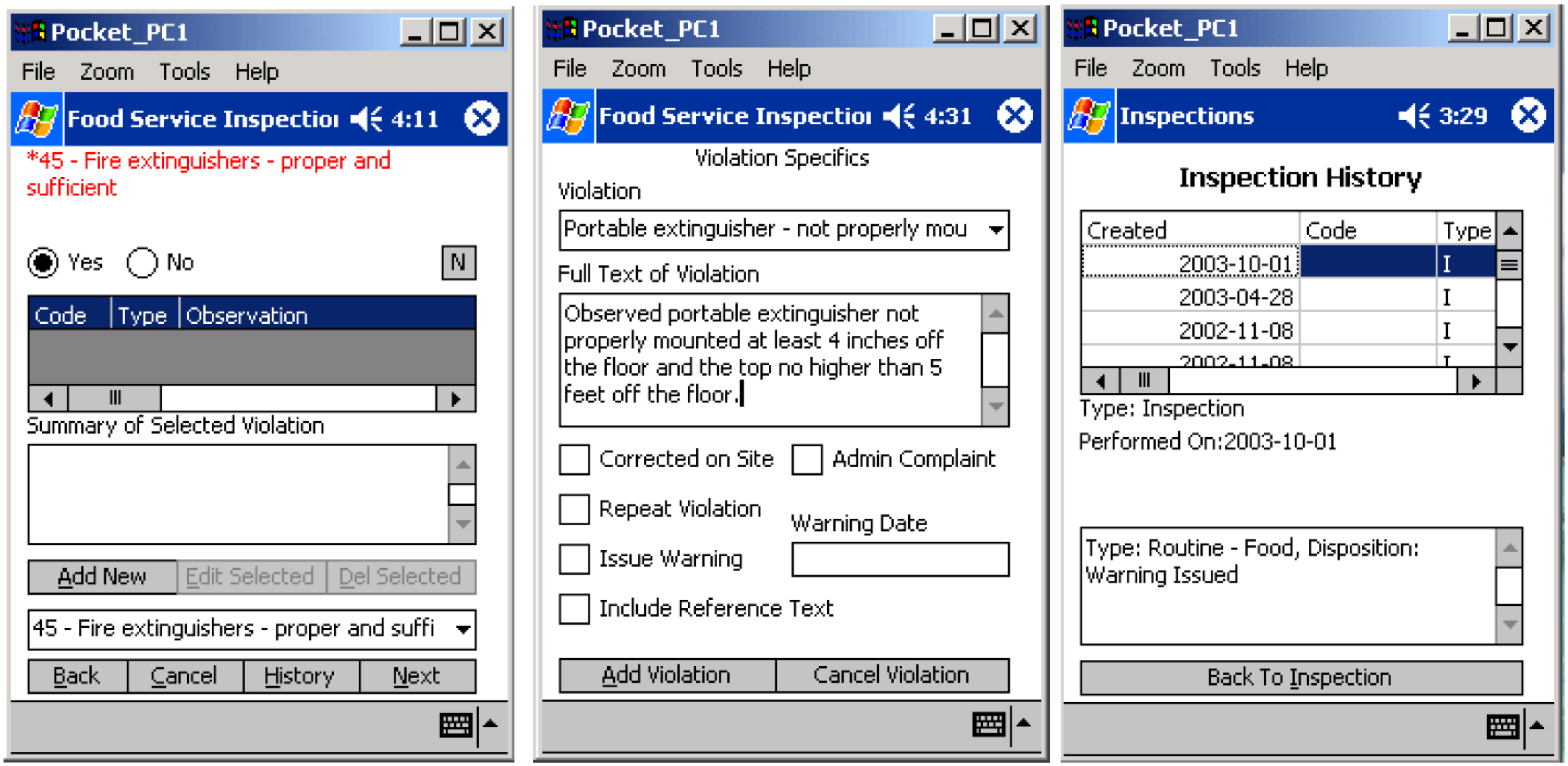
FAILURE TO COMPLY WITH THIS NOTICE MAY INITIATE AN ADMINISTRATIVE COMPLAINT THAT MAY RESULT IN SUSPENSION OR REVOCATION OF YOUR LICENSE AND FINES UP TO $1,000 PER VIOLATION.

Person in Charge (Signature) ____________________ Date ________

Inspector (Signature) ____________________ Date ________

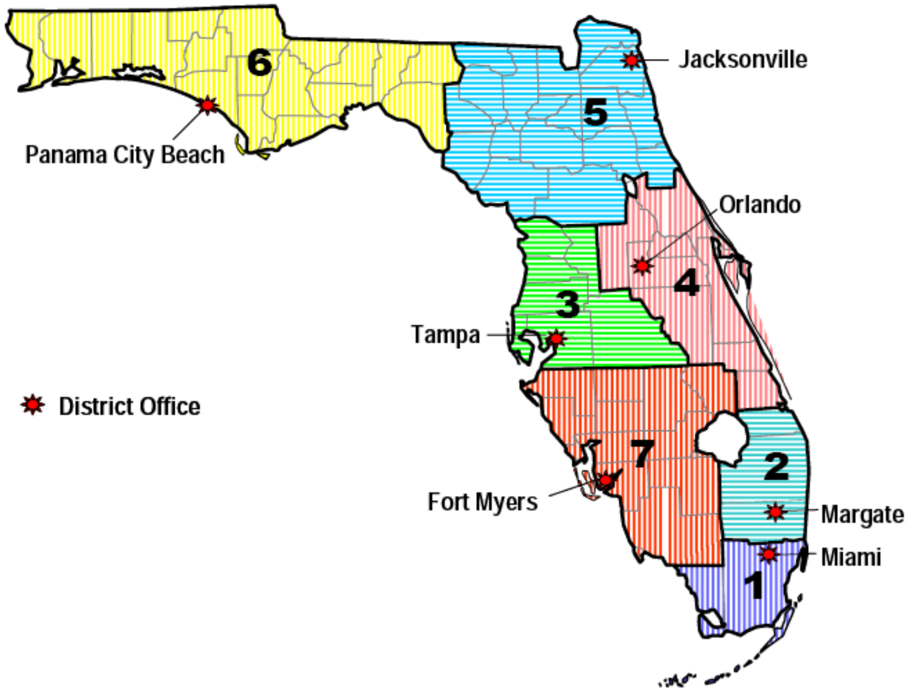
DBPR Form HR 5022-015 61C-1.002, FAC www.MyFloridaLicense.com/dbpr/hr/ 2009 October 1

Figure A.2. Screenshots of PDA Screens



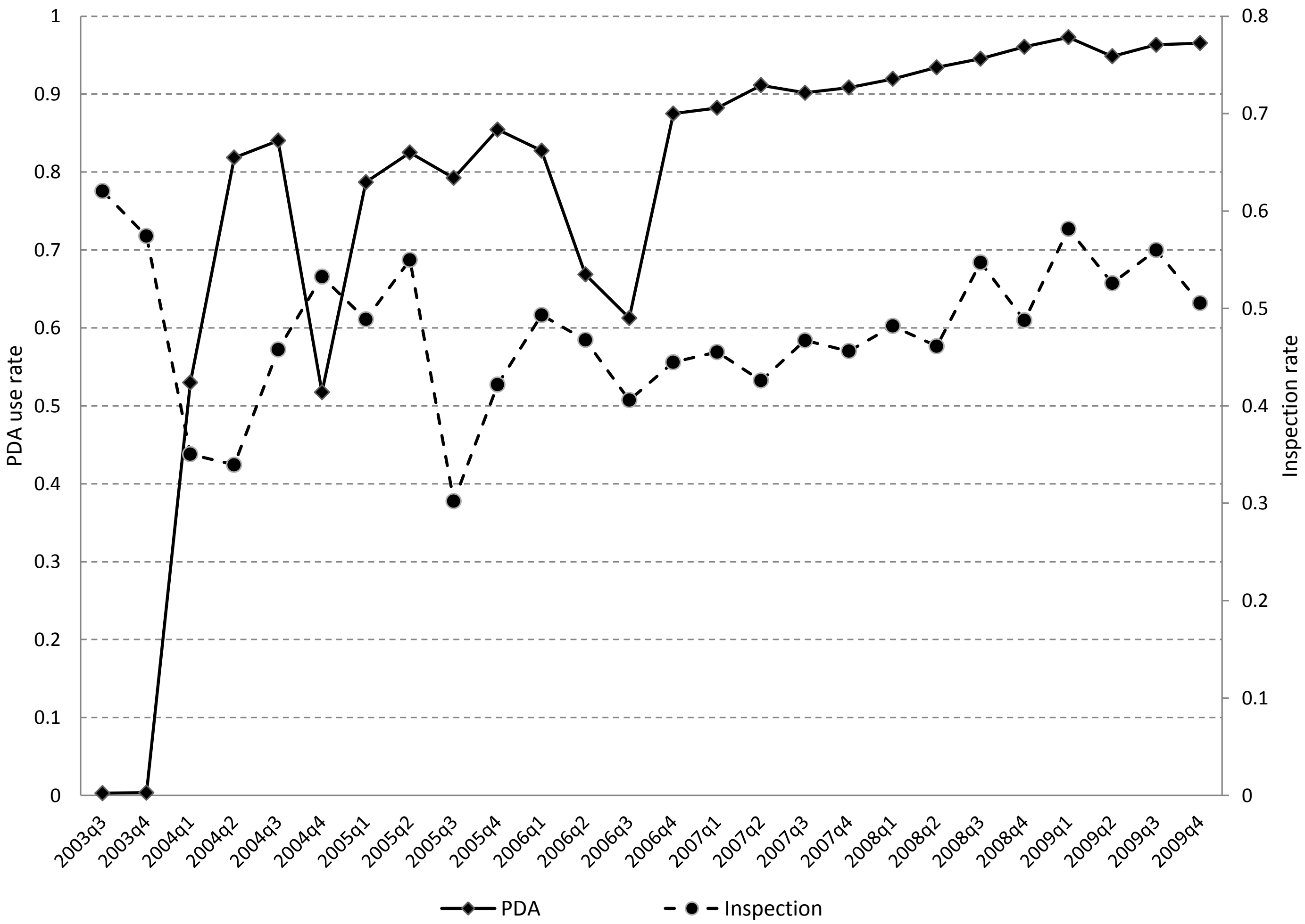
Source: Florida Department of Business and Professional Regulation, Division of Hotels and Restaurants, *Mobile Inspection User Manual*, November 12, 2003. The first image shows how to check a violation after accessing a dropdown menu at the bottom. The second image shows how to report the details of the violation. The last image shows how to retrieve the inspection history of the restaurant.

Figure A.3. Restaurant Inspection in the Seven Districts of Florida



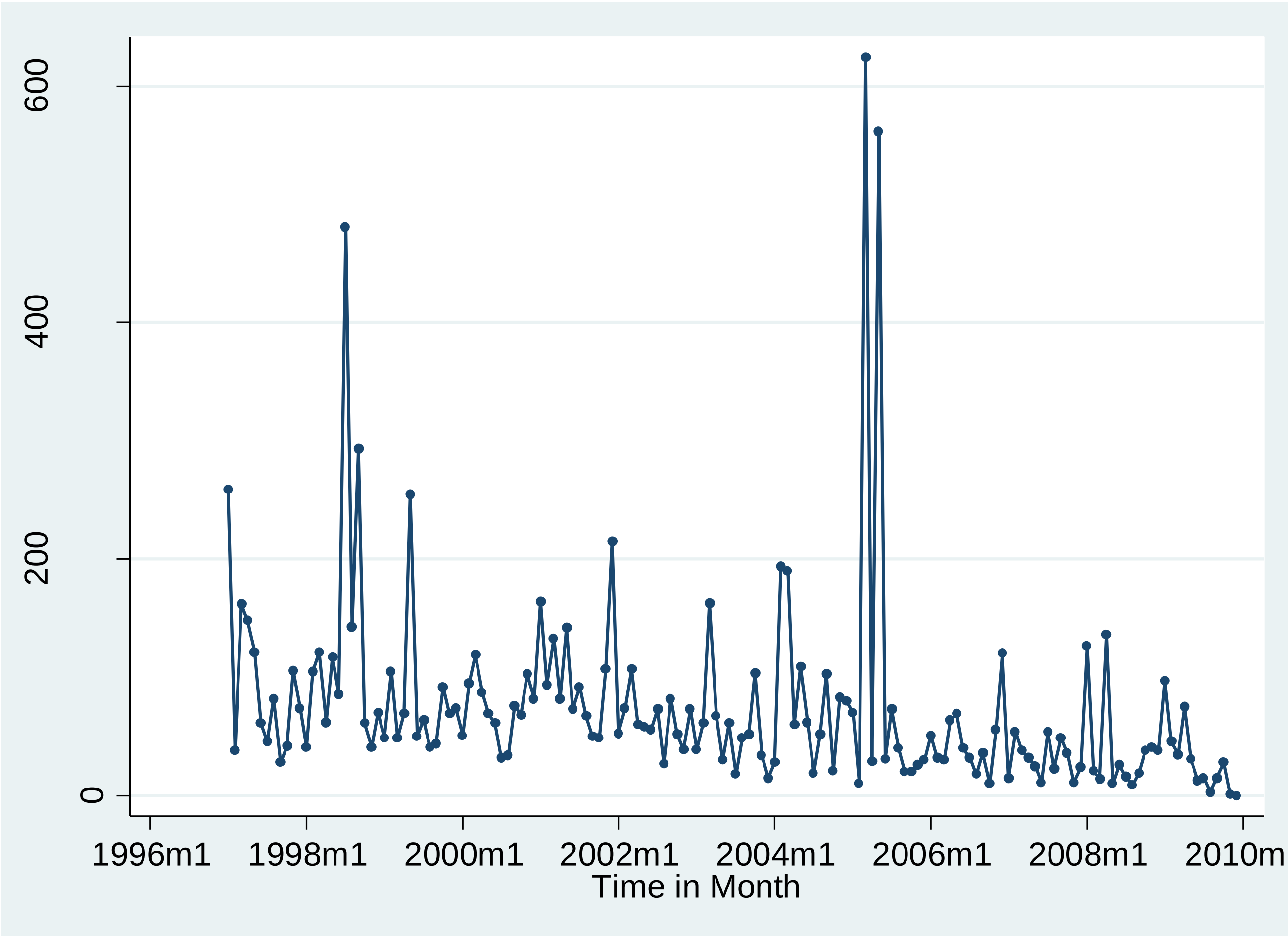
Source: Division of Hotels and Restaurants.

Figure A.4. Time Trends of PDA Use Rates and Inspection Rates



Notes: The PDA use rate is defined as the proportion of PDA inspections out of all inspections done during a certain quarter. The inspection rate is defined as the number of inspected restaurants during a certain quarter divided by the total number of licensed restaurants in the quarter's year.

Figure A.5. Monthly Trends of Restaurant Foodborne Disease Outbreaks (1997–2009, Number of Reported Cases per Month)



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

[1] 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).

[2] Unfortunately, we do not know the exact reasons for the variations in PDA use after 2007. It is conceivable that the PDAs did not work or that the online system was out of order on a certain day. The data show that in most cases, PDAs were either used for all inspections in a given day or not used at all.

[3] This result is further confirmed by a regression. In particular, for restaurant i inspected in week t, we regress the restaurant's previous violation on a dummy for whether the district has adopted PDA in week t, a cubic polynomial of t, and an interaction between the two, where t lies between -10 and 10, with 0 corresponding to the week of the massive PDA adoption. The dummy of after-PDA adoption has a coefficient of -0.19 and a standard error of 0.561. This suggests no discontinuity immediately before and after the massive adoption.

[4] The incentive to hide perfectly observable violations has been the focus of many theories on inspector–firm collusion.

[5] We may assume that consumers have no information on restaurant hygiene, and therefore, cleaning up does not directly affect restaurant revenue. In fact, 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 had no restaurant hygiene report card even though inspection outcomes had been posted online only since 2009. This implies that concerns over negative publicity should be minor. Still, our model incorporates the risk of publicity for the sake of generality.

[6] The first condition implies that the restaurant's effort is so costly that bad publicity alone is not sufficient to motivate a complete cleanup operation. The second condition implies that the inspector's effort cost must be high enough relative to his/her view of undetected violations such that he/she may choose a lower-than-maximum detection effort even if the restaurant puts little effort into cleaning up.

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

[8] Restaurants are not immediately sanctioned after initial inspections. Usually, follow-up inspections (callbacks) are scheduled. In addition, restaurants can request a hearing (OPPAGA 2005). This suggests that the incentive for restaurants to comply for initial inspections should be low.

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

[10] The original inspection files include 386 inspectors and 97,990 restaurants. After we apply our sample selection criteria, there remain 334 inspectors. Of these, 63 inspectors are additionally dropped because of inspector–restaurant fixed effects. In terms of the number of inspections, this drops 3,793 observations, about 1% of the sample.

[11] 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," whereas other subcategories are identified as "other critical violations." We consider category 08 to belong to "risk factors." Further, note that distinction among the three groups is made at the subcategory level. However, our group distinction is made at the category level because we do not observe subcategories in our data.

[12] The average number of regular inspections was 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, and 2.14 in FY 2008. The corresponding proportion of restaurants that were inspected only once is 50.6%, 22.4%, 39.9%, 26.2%, and 15.2%, respectively.

[13] In fact, time indicates the order of the inspection in our sample. We use year-quarter fixed effects to control for common time trends. Using year-month fixed effects generates very similar results.

[14] These results utilize variations in PDA use related to the initial massive PDA adoption as well as the PDAs' temporary mechanical and software problems, while controlling for Florida's introduction of a new classification in March 2004. If we consider the data up to February 2004 (that is, strictly before the classification change) and compare inspection results before and after the massive PDA adoption, the number of detected violations increased 1.19 after the massive PDA adoption. The magnitude of the initial detection effect is very similar to what we found in Figure 2A.

[15] In particular, the coefficients of the three key PDA variables are 0.086 (with standard error 0.010) for the dummy of PDA, -0.100 (0.005) for the number of previous PDA regular inspections, and -0.009 (0.004) for their interaction term.

[16] In a robustness check, we include a quadratic term of the number of previous inspections by that inspector in the same day and find it to be significant and negative, whereas the linear term remains negative and significant. This suggests that the fatigue effect increases during the day. Separately, the hour-of-day dummies suggest more violations if the inspection is done during lunchtime,

which may reflect a higher food safety risk at lunchtime.

[17] This effect was suggested by our contact in the DHR.

[18] The net effect of PDA use at 10+ previous PDA inspections is negative (-0.019 = 0.165 - 0.184). However, it is not significantly different from zero. This is also true for Columns (2) and (3).

[19] To check this more formally, using county-level panel data, we run a regression of inspection rate on PDA use rates after controlling for county, year, and month fixed effects. We find that PDA use is significantly correlated with an increase in the inspection rate over time.

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

[21] Without county fixed effects, the incidence of foodborne disease outbreaks is positively correlated with the average number of reported violations per inspection. However, this correlation becomes negative when we control for county fixed effects. These results are reasonable because across counties under similar detection technology, more violations imply dirtier restaurants, and thus, a greater likelihood of an outbreak. However, over time, changes in reported violations within a county could be driven by enhanced detection, which in turn motivates better compliance.

[22] Given the limited amount of inspection resources available in the DHR, increased restaurant inspections might decrease inspection rates for non-restaurant facilities (OPPAGA 2007). As long as this indirect effect matters, our placebo test is limited.