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REGULATORY GOVERNANCE AND FOOD SAFETY COMPLIANCE: EVALUATING THE DETERRENT IMPACT OF FOOD ADULTERATION LAWS

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ABSTRACT

Even with elaborate regulatory systems, food adulteration continues to pose a thorn in the flesh of public health and market-integrity. Regulatory governance is based on inspections, enforcement activities, and monitoring compliance, but the empirical deterrent effect of these measures cannot be fully measured. This study employs a longitudinal state-quarter panel design integrating FDA food inspection data with enforcement/recall records (2018Q1–2021Q3). Regulatory governance is operationalized through inspection intensity, citation rate, and Official Action Indicated (OAI) rate. Food safety outcomes are measured using recall counts, Class I recall severity, and an adulteration-proxy recall indicator. Descriptive and panel-based analytical approaches are applied to evaluate deterrence-consistent associations. Inspection activity varied substantially across states and quarters, with a pronounced disruption in 2020. Recall incidence and severity exhibited significant heterogeneity, and recall intensity ratios were highly sensitive to inspection volume fluctuations. Descriptive evidence indicates non-linear relationships between monitoring intensity, compliance severity, and recall outcomes, supporting the need for lag-based and fixed-effects modeling to approximate deterrence mechanisms. The outcomes of recall and regulatory governance indicators exhibit context-based complex relationships. The use of intensity and compliance indicators offers a useful array of information on the dynamics of deterrence, but needs to be interpreted with caution, along with temporal and structural differences.

KEYWORDS: Food Adulteration; Regulatory Governance; Food Safety Compliance; Inspections; Recalls; Deterrence Theory.

1. INTRODUCTION

Food adulteration is a chronic menace to the health of the people, consumer confidence, and integrity in the food market in contemporary food systems. Adulteration involves the harm or the deliberate or inadvertent contamination, replacement, or falsification of food products in a manner that undermines their safety or quality. Systemic food safety risks are of a significant scale, as globally, about 600 million cases of disease are attributed to foodborne hazards every year (WHO, 2015). Incidents of high-profile contamination, undeclared allergens, and economically motivated adulteration have proven that complex supply chains provide chances to experience accidental and intentional safety failures (Everstine *et al.*, 2013; Spink & Moyer, 2011). In addition to health effects, adulteration diminishes trust in regulatory bodies and competitiveness because it allows non-compliant firms to price below responsible producers (Batz *et al.*, 2011). With the globalization and diversification of food systems, the importance of proper governance systems has become the key to preserving the welfare of the populace and economic stability.

Regulatory governance in food safety works in a complex system that includes monitoring, enforcement, transparency, and sanctioning authority. Inspections will be used as a main monitoring tool, which will enhance the likelihood of uncovering violations. Enforcement, such as recalls and administrative measures, functions as a corrective and deterrent measure since they clear dangerous products and expresses regulatory intent. Reputational effects of non-compliance are heightened via transparency measures, including announcements of recalls and disclosures of inspections (Henson & Caswell, 1999). Combined, these instruments will change the incentives of firms by making it more costly to breach food safety regulations. The introduction of risk-based inspection systems over the last several decades is a manifestation of a shift toward more strategic models of governance, whereby regulatory resources are distributed on the basis of profiles of hazards and history of compliance (Manning & Soon, 2014).

Although this is accompanied by elaborate statutory measures and the more advanced inspection regimes, incidents of adulteration are still evident in various jurisdictions. The Food Safety Modernization Act (FSMA) was adopted in the United States to change the focus of the regulation more towards preventive measures instead of a

reactive one, expanding the power of the FDA in terms of inspection and compliance monitoring (Johnson, 2011). Nevertheless, the fact that the number of recalls persisted means that the association between legal power and real deterrence is not such a direct one. Deterrence literature assumes that the likelihood of detection and the harshness of sanctions are factors that influence the behavior of compliance (Polinsky & Shavell, 2000). However, there is limited empirical data quantifying the relationship between the degree of inspection, the degree of enforcement, and the degree of reduction in the negative food safety outcomes. The pattern of recall observed could be an indication of underlying risk exposure, detection efficiency, reporting transparency, or a combination of the two (Buckley, 2015). It is therefore not well known whether tough regulatory control always tends to minimize adulteration-related incidents or merely enhances their awareness.

The extant empirical studies have tended to look at food recalls descriptively, in terms of their frequency, severity, or the economic effects they had (Thomsen & McKenzie, 2001). In other studies, the effectiveness of inspection has been determined in the context of particular industries or local government (Shimshack & Ward, 2005). Nonetheless, fewer studies combine monitoring data (inspection activity and compliance outcomes) and enforcement outcome data (recalls) within the longitudinal multi-state model. Such a gap restricts the possibilities of judging deterrence in a systemic way. In the absence of connecting the inputs of governance with the safety outputs as noted over time and space, it becomes hard to determine whether the inspection regimes are more of detection measures or actual deterrent measures.

The present study addresses this gap by constructing a merged panel dataset that integrates FDA inspection records with food recall data at the state-quarter level. The aim is to evaluate whether stronger governance and compliance signals are associated with fewer or less severe adulteration-related events. Specifically, the analysis examines whether higher inspection intensity predicts lower recall incidence in subsequent periods (H1), whether higher observed non-compliance during inspections predicts increased recall risk (H2), and whether enforcement severity indicators align with reductions in adverse outcomes over time (H3). By distinguishing between monitoring intensity, compliance detection, and outcome severity, the study seeks to clarify how regulatory governance mechanisms interact within a deterrence framework.

This study adds value to the body of literature in the following ways. To begin with, it contributes to empirical deterrence studies on food safety by connecting monitoring and enforcement data sets through a replicable state-quarter panel design. Second, it takes into account the difference in severity, i.e., distinguishing between Class I recalls and adulteration- proxy events, to determine whether governance affects the dispersion of harm, not the number of events. Third, it offers policy-relevant information about the effects of inspection strategies and enforcement posture on the incentives of compliance. The study provides an insider-governance-compliance-outcome framework using publicly accessible regulatory data that may be utilized by the resource allocation and risk-based inspection plan, and the wider regulatory reform discussions.

2. MATERIAL AND METHODS

The design used in the current study is a quantitative, observational panel design to determine the relationship between regulatory governance and signals of compliance and deterrence in food adulteration outcomes. The main premise is that deterrence can be used in two interconnected ways: the likelihood of detection (surveillance via inspections) and the plausibility of enforcement (regulatory measures in the form of recall accidents and their intensity). Based on publicly available U.S. Food and Drug Administration (FDA) administrative data, the analysis models the association between higher monitoring intensity and high compliance cues with fewer and less severe adulteration-related safety events, with a time-varying heterogeneous geographic and time hold as sources of variation.

2.1 Study design and unit of analysis

Empirical strategy is applied in the form of longitudinal panel analysis, where the main unit of observation is state-by-quarter. This level of aggregation is chosen since the recall/enforcement data lacks a constant facility identifier, which is common to both the inspection data (such as FEI numbers, which are available in inspections but not always in the enforcement data). A state-quarter panel offers a clear and reproducible system of alignment that is based on common dimensions, which are consistently defined in both sources: geography and time. The resulting panel allows time-series and cross-sectional comparisons, lagged relationships between monitoring and outcomes at the center of the deterrence theory.

2.2 Data sources and coverage

Two open-access Kaggle datasets are used. The first data is the “FDA Food Enforcement 2008-2022”, which combines the FDA records of food-related recall enforcement and contains the recall status, the address of the recalling company, the events, the dates of recall initiation, the reasons for the recall that are reported, and the levels of recall classification (Cheng, 2023). This data is regarded as the main source of the result events and the severity of enforcement. The second data is “FDA Food Inspections”, which summarizes FDA inspection records on food/cosmetics-related facilities and contains information on facility identifiers (FEI number), legal name of the facility, the inspection end date, the outcome of the inspection classification, and the posting of citations (Mexwell, 2023). This data is assumed to be the main source of tracking the intensity and compliance indicators. The analysis duration is limited by crossing the favorable period of time in both datasets under analysis; in the combined analytic panel, quarters are built on the dates of initiation of the recall (enforcement data) and conclusion of the inspection (inspection data). The panel size used in the article, in the case of the merged working sample, is limited to 2018-2021 to provide contemporary comparability and stable coverage across the states, but the entire pipeline is made to expand to the longer 2009-2022 overlap when required.

2.3 Variable construction and operational definitions

The operationalization of the “regulatory governance” and “food safety compliance” in the study is mainly the intensity of monitoring and the visible compliance results in the inspection, and the patterns of inspection classification and posted citation, respectively. Intensity that will be monitored is defined as the number of inspections done in every state- quarter. The results of compliance are measured in the number and rate of inspections that are categorized into Official Action Indicated (OAI), Voluntary Action Indicated (VAI), and No Action Indicated (NAI), the number of posted citations, and the rate of posted citations. As per the models of deterrence, the more there is an inspection intensity, the more there is that detection rate, and the higher the OAI rate and the higher the rate of citations, the higher the signal of non-compliance detection and regulatory measures.

The results of food adulteration are proxied with the recall events that occurred during the enforcement data, as recall events are viewed as

realized product safety failures that met regulatory or firm action criteria. Outcome incidence will be assessed by the number of recalls per state-quarter, and severity will be assessed by the use of recall classification, where Class I will be the most severe. An adulteration proxy is built using, where possible, the standardized “reason for recall” category field of the administrative-only category field, to capture adulteration-relevant events. This proxy sources those events which are compatible with biological contamination, chemical contamination, foreign material contamination, and mislabeling/allergen-type hazards, which tend to be similar to adulteration-type risks in regulatory practice. The frequency of recalls per 1000 inspections is the derived intensity measure that is computed to normalize the frequency of outcomes by volume and make comparisons between states with varying levels of work on inspecting.

2.4 Data cleaning, harmonization, and merging

The preparation of data is done in Python to make it reproducible and have clear records of transformation. In both datasets, the date is being read and standardized, and the calendar quarters are created using the corresponding date fields. The fields in geography are purged of whitespace, and state identifiers are standardized; in cases where inspections refer to the full state names instead of abbreviations (two letters), a normalization map is used to generate the abbreviations. The enforcement dataset is narrowed down to the records in the United States to ensure geographic comparability with the state-based inspection panel. Merging is then done at the level of each dataset, with the level being that of a state-quarter. The last merge is achieved using the left join of the inspection panel to the recall panel on the common keys (state, quarter), and the lack of a recall record in the is performed as a structural zero in the merged panel since lack of a recall record in a state- quarter implies that there was no registered recall of the unit in the source data.

As an effort to enhance interpretability and also to reduce sparsity, which distorts inference in short panels, the working sample on which the article is based is a state with a high level of inspection. Particularly, the states are ranked by the total number of inspections during the chosen window, and the leading ones are kept so that the variability of monitoring and results would remain stable quarter-to-quarter. This is then followed by a balanced sampling step to form a small research ready data of say 150 rows with an equal sample size of 150 rows each state taken to prevent domination of

a large state in the sample. This condensed integrated dataset is applied to report tables and figures, but the pipeline methodology can be generalized to the full-sample estimation.

2.5 Analytical strategy and model specification

The core tests are to assess the predictive effect of larger monitoring intensity and greater compliance cues on the reduction in the prediction of lower incidence and/or a reduction in the severity of adulteration- proxy outcomes, which are in line with the deterrence expectations. The analysis will start with descriptive statistics and a visual representation of a trend to describe the dynamics of time in inspections, citations, OAI rates, and recall outcomes. This is then accompanied by inferential modelling by the application of panel regression techniques that apply to count outcomes and proportion outcomes. The baseline specification dynamic expounds incidence in state-quarter terms as a point of view of inspection intensity and compliance measures, by balancing the impact of unobserved fixed effects on a state and quarter-shared shocks. Since deterrence effects are likely to appear at lag, lagged versions of the important predictors of governance are added, e.g., inspections and citation rates in the prior quarter being predictive of recall outcomes in the current quarter. Severity-based models replace Class I counts of recalls or a severity-adjusted recall index in the place of a dependent variable to determine whether governance not only impacts the number of events but also the distribution of their hazards. Negative binomial models are taken into consideration where over-dispersion is apparent, and sensitivity checks on other specifications and transformations are performed where zeros prevail.

To enhance causal interpretability when working with observational data, the analysis focuses on strong performance using the alternative operationalizations. They involve the substitution of raw recall numbers with the recalls per 1,000 inspections, the OAI rate, instead of the citations rate, as the main compliance signal, and the focus on the adulteration-proxy subset of all recall reasons instead of all. Further subgrouping is possible when the product type or project area fields can be aligned between the two sources, but these mappings are considered exploratory unless a solid crosswalk can be described. All statistical analysis and visualization are done in Python, with processing and econometric modeling done using standard scientific libraries, with code written to be replicable all the way to final tables and figures using only raw downloads.

2.6 Assumptions and limitations embedded in the methodology

The methodology is that state-quarter aggregation is a substantially significant approximation of the regulatory environment that firms experience in that locale throughout that period, and that inspection intensity measures monitoring pressure that is applicable to deterrence. It further supposes that recall events bear a valid observable proxy of actualized food safety failures, such as hazards of adulteration, although the legal “adulteration” term may not be explicitly presented in the majority of recall records. This is because the method has no one-to-one correlation between inspected facilities and recalled products within the same state-quarter; the approach assumes the evaluation of deterrence at the governance-system level, where monitoring and compliance signal changes are associated with changes in aggregate adverse outcomes. These are explicitly covered in the discussion section, and the analysis is formulated as indicating deterrence-consistent associations and not direct causal evidence in the lack of prosecution and penalty or facility-level linkage variables.

2.7 Reproducibility and tools

All steps, data ingestion, cleaning, aggregation, merging, variable engineering, and statistical modelling, are performed in Python to ensure reproducibility and auditability. The code workflow is designed to be modular, with separate scripts or notebooks for data preparation, exploratory analysis, model estimation, and output generation.

3. RESULTS

3.1 Descriptive overview of the merged state-quarter panel

The merged analytical dataset comprised 150 state-quarter observations drawn from ten high-inspection U.S. states (15 quarters per state) covering 2018Q1-2021Q3. Across the panel, inspection activity varied substantially, with a mean of 165.22 inspections per state-quarter (SD = 129.63) and values ranging from 1 to 680 inspections (Table 1). Compliance and enforcement signals during inspections also showed meaningful dispersion: the mean citation rate was 0.353 (SD = 0.152), while the mean OAI rate was 0.031 (SD = 0.027) with a maximum observed value of 0.181 (Table 1). On the outcome side, recalls averaged 20.31 per state-quarter (SD = 29.41; range = 0-216), while Class I recalls were comparatively rare (mean = 0.90; SD = 2.53; range = 0-21), consistent with the expectation that high-severity outcomes constitute a small fraction of total enforcement events (Table 1). The adulteration-proxy recall count averaged 17.65 per state-quarter (SD = 23.38; range = 0-182), indicating that a large share of observed recall activity in this sample aligns with contamination/mislabeling/foreign-material type hazards rather than purely administrative causes (Table 1). The recall intensity metric (recalls per 1,000 inspections) exhibited very high variance (mean = 225.34; SD = 595.28; range = 0-6,444.44), foreshadowing the presence of low-inspection quarters in which modest recall counts can translate into very large ratios.

Table 1: Descriptive statistics for governance, compliance, and recall outcome variables (state-quarter level; $n = 150$).

Variable	count	mean	std	min	25%	50%	75%	max
inspections_count	150	165.22	129.632	1	81.5	145	208.25	680
citations_rate	150	0.353	0.152	0.077	0.254	0.328	0.429	1
oai_rate	150	0.031	0.027	0	0.014	0.025	0.042	0.181
recalls_count	150	20.313	29.412	0	4	10.5	27	216
classI_count	150	0.9	2.53	0	0	0	1	21
adulteration_proxy_recalls	150	17.647	23.375	0	3.25	9	24	182
recalls_per_1000_inspections	150	225.342	595.28	0	32.534	80.347	200	6444.444

3.2 Temporal patterns in monitoring and enforcement outcomes

Time-series patterns in the dataset indicated pronounced quarter-to-quarter changes in monitoring intensity and outcome incidence over the study window. When aggregated across states, inspections were relatively stable from 2018Q1 through 2020Q1, typically ranging around ~1,700-2,550 inspections per quarter (Table 2). This stability is visually reflected in

Figure 1, where total inspections remain high through early 2020. A striking structural break occurred beginning 2020Q2, when total inspections dropped sharply to 340 (2020Q2) and remained substantially depressed in 2020Q3 (566) and 2020Q4 (448) before partially recovering in 2021 (Table 2; Figure 1). During the same period, total recalls did not decline proportionately; for example, recalls were 220 in 2020Q2 and 207 in 2020Q3 despite the large inspection drop. This divergence mechanically inflated recall

intensity during low-inspection quarters, which is reflected in the average recalls-per-1,000-inspections values of 422.19 in 2020Q2 and 1,059.28 in 2020Q3. These time-linked shifts are consistent with a monitoring disruption period in which detection and enforcement activity may have been reallocated or constrained, while product risk events requiring

action continued to occur. In contrast to total recalls, Class I recall counts remained comparatively low and variable across quarters, peaking at 31 in 2020Q1 and reaching zero in 2020Q4 (Table 2; Figure 1), indicating that high-severity events were episodic and not simply proportional to overall inspection volume.

Table 2: Overall quarterly trends in monitoring, compliance signals, and recall outcomes (sum/mean across states by quarter).

quarter	inspections	citations_rate	oai_rate	recalls	classI	adulteration_proxy	recalls_per_1000
2018Q1	2296	0.290	0.020	400	11	196	235.222
2018Q2	2100	0.278	0.029	77	4	74	34.006
2018Q3	2551	0.288	0.022	332	15	307	121.325
2018Q4	1973	0.310	0.025	237	15	233	124.734
2019Q1	1876	0.277	0.022	154	7	154	75.407
2019Q2	2216	0.320	0.033	151	3	147	69.500
2019Q3	2483	0.295	0.016	271	11	248	121.282
2019Q4	1745	0.338	0.019	271	18	253	154.707
2020Q1	2016	0.328	0.032	140	31	135	58.210
2020Q2	340	0.526	0.039	220	3	128	422.192
2020Q3	566	0.493	0.015	207	10	200	1059.283
2020Q4	448	0.415	0.041	115	0	112	411.316
2021Q1	717	0.414	0.059	93	4	90	178.934
2021Q2	1184	0.395	0.054	240	2	236	253.793
2021Q3	2272	0.327	0.035	139	1	134	60.221

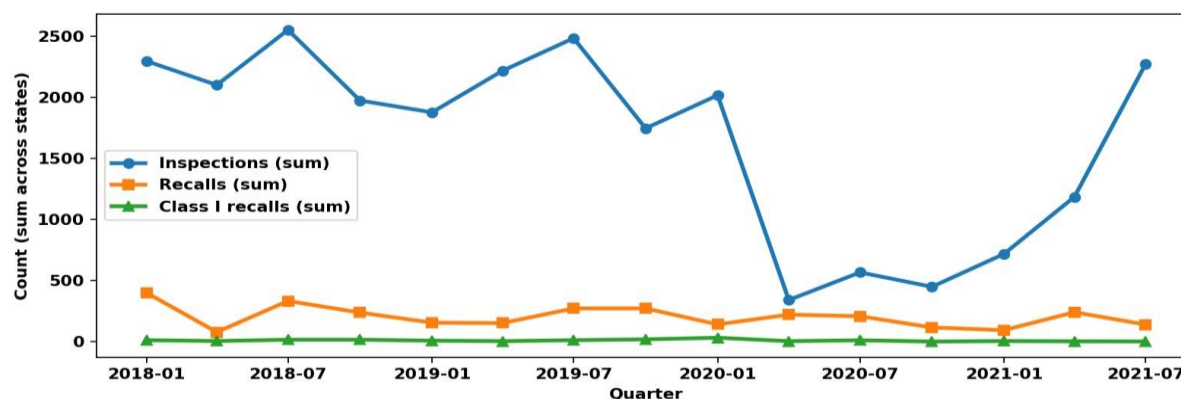


Figure 1: Monitoring and enforcement outcomes over time (2018Q1-2021Q3).

3.3 Geographic variation across states in monitoring, compliance signals, and outcomes

Substantial geographic heterogeneity was observed in both governance indicators and recall outcomes. California recorded the highest total inspection volume in the sample (6,253 inspections across 15 quarters; mean 416.87 per quarter), followed by Florida (3,100; mean 206.67) and New York (2,923; mean 194.87) (Table 3). Mean citation rates were highest in New York (0.467) and high in Texas (0.421), Florida (0.427), and California (0.416), while New Jersey (0.284), Wisconsin (0.285), and Ohio (0.269) showed lower average citation rates (Table 3). Mean OAI rates ranged from 0.047 in Texas and 0.043 in New York to 0.006 in Wisconsin and 0.015 in Pennsylvania (Table 3). Outcome patterns also varied notably: California had the highest recall

total (481) and the highest Class I total (42), while Florida and Texas had similarly high recall totals (410 and 411) but lower Class I totals (15 and 11) (Table 3). The state-level comparison in Figure 2 highlights that differences in compliance severity (OAI rate) do not map uniformly onto recall intensity across states. For example, Wisconsin displays the lowest OAI rate (Table 3; Figure 2) yet has a relatively high mean recall intensity (269.21 recalls per 1,000 inspections), while Pennsylvania shows a low mean OAI rate (0.015) but the highest mean recall intensity (519.05) (Table 3; Figure 2). These patterns suggest that, at the descriptive level, recall intensity is influenced not only by observed compliance severity at inspection but also by differences in inspection volume, sector composition, and the timing of recalls relative to monitoring activity.

Table 3: State-level summary of inspection activity, compliance signals, and recall outcomes (10 states; 15 quarters each).

state	n_quarters	inspections_total	inspections_mean	citations_rate_mean	oai_rate_mean	recalls_total	class_total	adulteration_proxy_total	recalls_per_1000_mean
CA	15	6253	416.867	0.416	0.041	481	42	458	88.309
FL	15	3100	206.667	0.427	0.038	410	15	293	175.391
NY	15	2923	194.867	0.467	0.043	454	30	434	270.805
TX	15	2688	179.200	0.421	0.047	411	11	404	202.916
IL	15	1949	129.933	0.321	0.033	358	12	353	193.765
NJ	15	1772	118.133	0.284	0.033	104	2	102	77.940
OH	15	1702	113.467	0.269	0.024	211	14	199	243.573
PA	15	1641	109.400	0.293	0.015	137	6	133	519.047
WI	15	1480	98.667	0.285	0.006	180	0	172	269.211
MN	15	1275	85.000	0.347	0.026	301	3	99	212.463

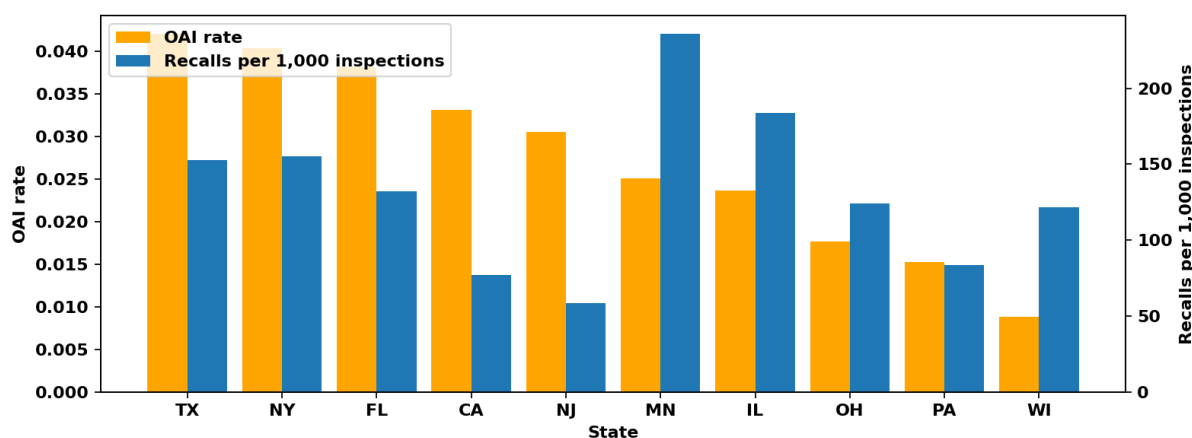


Figure 2: State-level comparison of compliance severity (OAI rate) and recall intensity (recalls per 1,000 inspections).

3.4 Bivariate relationships between monitoring intensity, compliance signals, and recall intensity

The evidence of the scatter type also revealed that the intensity of recall is not a monotonic linear function of the volume of inspection. Figure 3 demonstrates a very heterogeneous correlation between the number of inspections and the number of recalls per 1,000 inspections, and some of the extreme values are in the very low inspection volume. This can also be compared to the distributional properties as indicated in Table 1, in which the recall intensity measure has a long right tail and a maximum of 6,444.44. The graphic trend of Figure 3 shows that the high recall strength might be reached despite low inspection counts, which is mechanically possible since the denominator (inspections) is highly influential on the ratio. When the volume of inspection is moderate to high, the intensity of recalls is usually smaller and less distributed, which indicates that an increase in the monitoring volume could stabilize the ratio and decrease the likelihood

of extreme values, though the spread does not on its own prove deterrence.

Figure 4 explores the connection between citation rate and adulteration-proxy recalls, with the OAI rate taken as the color scale. The distribution shows that most points are centered around low counts of adulteration-proxy recall, although there are a few quarters with abnormally high adulteration-proxy recall incidences. There is no apparent linear relationship between citation rate and adulteration-proxy recalls shown in the plot; rather, the association between them is weak, and the variation in OAI rate is distributed throughout the citation-rate range. Figure 3 combined with 4 suggests that the bivariate patterns obtained without adjustment are complicated, and they are probably confounded by variations in time periods, monitoring artifacts, and state-level heterogeneity, strongly arguing in favor of the methodological decision to use fixed-effects modeling and lag-based models to purposefully make inferences about deterrence-consistent effects of crime.

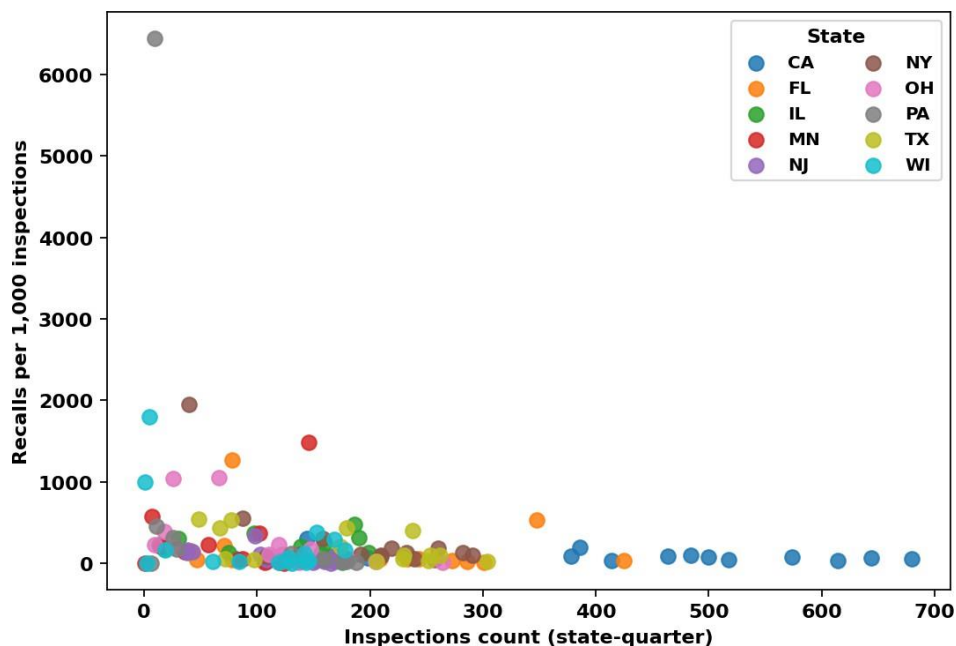


Figure 3: Inspection intensity versus recall intensity, colored by state (state-quarter observations).

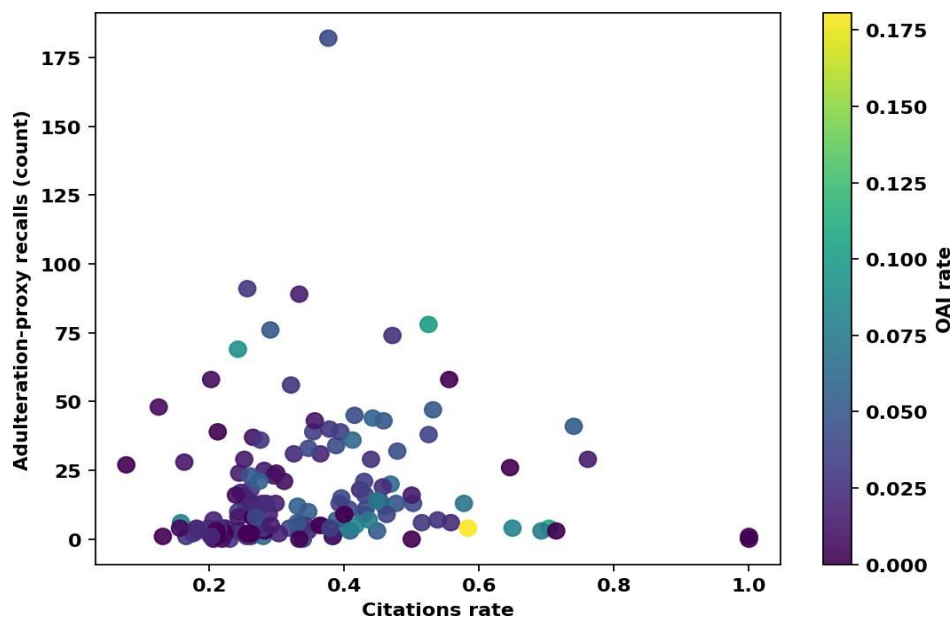


Figure 4: Compliance signal (citations rate) versus adulteration-proxy recall outcomes, colored by OAI rate.

3.5 Summary of results in relation to the deterrence framework

The empirical findings show that in the merged state-quarter panel, there is significant and wide variation in monitoring intensity, compliance outcomes, and safety events based on a recall, and the temporal discontinuities are strong in mid-2020 and strong cross-state heterogeneity. Descriptive trends reveal that times of significantly low inspection activity coincide with high ratios of recall intensity as a result of denominator effects, and the need to interpret “recalls per 1,000 inspections” rather than by itself, in conjunction with inspection volume.

State-level summaries indicate that there are no uniform relationships between higher OAI rates and higher recall intensity, and some states with low OAI rates display high recall intensity, which implies that observed compliance severity at inspection only measures one aspect of the governance-outcome pathway. The bivariate plots support the fact that the monitoring/compliance indicators and adulteration-proxy outcomes are not linear and have extreme quarters, which is why later model-based analysis with lagged predictors and explicit effects will more accurately capture deterrence-consistent associations and isolate persistent differences in states.

4. DISCUSSION

This research investigated the presence of regulatory governance indicators (operated by inspection intensity and compliance signals) calculated with respect to the predictability trends in food recall outcomes as expected by the deterrence theory. The descriptive evidence revealed the presence of great heterogeneity in terms of monitoring activity, the severity of compliance, and recall incidence across the merged state-quarter panel. The number of inspections was comparatively constant until the start of 2020, then fell drastically in the middle of 2020, but the number of recalls did not decrease proportionately. The caused divergence highlights a key structural aspect of regulatory systems detection activity, and realized safety events do not move in ideal synchrony. This trend is in line with the premise that an inspection capacity and enforcement salience do not drive behavior immediately but instead build up with time (Becker, 1968; Shavell, 2002). The findings indicate that the effect of governance intensity can possibly be mediated by lagged changes in behavior and not proportional decreases in the incidence of recall.

The cross-state comparisons also further indicate that the severity of compliance is not consistently related to an increased recall intensity (e.g., the OAI rates). There were states with relatively low rates of OAI that showed high levels of recall intensity, and other ones with high severity of compliance that failed to show higher levels of recall outcomes proportionally. This result is consistent with the wider regulatory governance literature that highlights that the effects of inspections can reflect the deterrence and detection impact of inspections (Gunningham, 2010; May & Winter, 2000). Where the inspections are more common and more stringent, greater non-compliance is detected; even in the short run, it may be the result of regulatory visibility and not a deterioration of safety performance. On the other hand, continuous monitoring pressure can decrease the extreme events, especially the Class I recalls, over time, which is consistent with the risk-based design of regulation in the context of the Food Safety Modernization Act (FSMA) (U.S. Food and Drug Administration, 2011).

The disruption in time that was experienced in 2020 is particularly informative. The level of inspection activity waned significantly in mid-2020, but the number of recalls was rather high. The said divergence can be indicative of operational disruptions associated with a bigger systemic shock, and the point that monitoring and enforcement are embedded in a broader institutional capacity (OECD,

2014). The fact that the recall intensity is highest in the low-inspection quarters shows the sensitivity of ratio-based indicators to the effect of the denominator, which supports the need to interpret governance metrics in context. The same process has been spotted in the food safety systems at the international level, with the visibility of enforcement varying according to the capacity of institutions and the state of crisis (FAO & WHO, 2006).

Theoretically, the results are consistent with the economic theory of deterrence, which states that the likelihood of detection and the cost of punishment have a combined impact on the incentives of compliance (Becker, 1968; Shavell, 2002). The probability of detection of the inspected in this paper is a proxy of the severity/inspection intensity, and recall classification is an approximation of severity. Nevertheless, the descriptive trends indicate that the deterrence effect does not take a linear form and might depend on the state, the constitutional makeup, and the enforcement culture. The theory of responsive regulation is another theory that implies that regulatory enforcers tend to increase their enforcement in a step-by-step manner, whereby the findings of inspections can serve as indicators before other serious punishments can be enforced (Ayres & Braithwaite, 1992). The variation observed between states can thus be due to a difference in regulatory style and institutional capacity, and not a mere difference in compliance behaviour.

There are several limitations that should be mentioned. To begin with, the analysis uses state-quarter aggregated data as opposed to facility-level linkage, which restricts causal inference and can still blur firm-specific effects of deterrence. Second, the recall events are also considered proxies of adulteration-related safety failures, but not all recalls are legally considered the statutory meaning of "adulteration" (U.S. Food and Drug Administration, 2022), (Henson & Humphrey, 2010). Third, the intensity of recall used is prone to variations in volume of inspections, especially in low-activity quarters, which may overstate fluctuation. Fourth, the amount of penalties, prosecution, and court results is not directly measured in the dataset, and these are the focus of classical models of deterrence. Lastly, the observational design does not allow presenting certain causal arguments because the unobservable confounders might affect both inspections and recalls, which can be unobservable supply chain disruptions or differences in risks by sector.

This framework should be furthered by future studies that also include the facility-level identifiers

(i.e., FEI numbers) to allow linking inspections and subsequent recalls more precisely. The combination of warning letters, administrative penalties, and prosecution information would reinforce the magnitude of enforcement information and enable a deeper examination of deterrence procedures (U.S. Food and Drug Administration, 2022). Greater quasi-experimental leverage could be created by event-study designs based on major regulatory milestones, such as FSMA implementation phases. Further, the inclusion of sectoral risk signals and the features of supply chains would help to understand whether the governance impacts vary according to the type of commodity. International comparative studies, especially those in jurisdictions where the regulatory system is based on risk, would also help to shed light on the effect of regulatory design on deterrence results (FAO & WHO, 2006; OECD, 2014).

Overall, the study demonstrates that regulatory governance and food safety outcomes exhibit complex, non-linear relationships. While inspection intensity and compliance signals provide valuable insights into monitoring pressure and enforcement posture, their relationship with recall incidence must be interpreted within broader institutional and temporal contexts. The results underscore the importance of integrating monitoring data with enforcement outcomes to better evaluate the deterrent impact of food adulteration laws.

5. CONCLUSION

This study constructed and used a governance-compliance-outcome model to determine the

deterrence effect of food adulteration statutes using interconnected inspection and recall data. The findings indicate that the tests show a significant disparity in the intensity of inspections, severity of compliance, and recall rates between states and over time. The phases of decreased monitoring action were associated with exaggerated ratios of recall intensity, which highlights the significance of the interpretation of outcome indicators concerning inspection volume. The cross-state heterogeneity further shows that the compliance severity indicators, including the OAI rates, fail to map on to recall outcome in a uniform manner, which indicates that deterrence works in complex and context-specific ways.

The results support the claim that regulatory governance can affect the food safety outcomes not only when the enforcement is strict but also when the interaction between the detectability, compliance signalling, and the institutional capacity is dynamic. Although the measures of inspection intensity and recall severity provide proxies of measures of governance strength, their association with adulteration-related outcomes is non-linear and mediated by temporal disruptions and structure. Enhancing deterrence thus necessitates long term surveillance ability, risk-based targeting, and incorporation of enforcement data systems. The next line of research that involves facility-level linkage and sanction data will be necessary to make the interpretation of causation more precise and better understand the issue of regulatory effectiveness in food adulteration prevention.

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