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ARE OSHA HEALTH INSPECTIONS EFFECTIVE? A LONGITUDINAL STUDY IN THE MANUFACTURING SECTOR

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ABSTRACT

We examine the impact of OSHA health inspections on compliance with agency regulations in the manufacturing sector, with a unique plant-level dataset of inspection and compliance behavior during 1972-1983, the first twelve years of OSHA enforcement operations. Two major findings are robust across the range of linear and count models estimated in the paper: (1) the number of citations and the number of violations of worker exposure restrictions decrease with additional health inspections in manufacturing plants; and (2) the first health inspection has the strongest impact. The results suggest that prior research focusing on the limited impact of OSHA safety regulations may under-estimate OSHA's total contribution to reducing workplace risks.

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I. INTRODUCTION

The Occupational Safety and Health Administration has been controversial since it was established in 1970. Observers have challenged the agency's efforts on worker safety, arguing occupational disease presents a more serious case for government action[2] because workers experience greater difficulty collecting risk information for long-term disease hazards than for more immediate injury risks. Consequently, neither the wage-setting process nor the workers' compensation system internalize the costs of occupational disease as effectively as for occupational injuries.[3] Given the current regulatory approach to workplace health and safety, analysts further assert that OSHA health standards are more effectively designed to reduce future occupational disease than OSHA safety standards are designed to reduce accidents. Safety engineers have determined that the majority of injuries are not related to the violation of OSHA safety standards and would occur despite perfect compliance.[4] On the other hand, OSHA health standards establish

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2. See Cornell, Noll and Weingast (1976); Mendeloff (1979, 1988); and Nichols and Zeckhauser (1977).

3. See Boden and Jones (1987), and Barth and Hunt (1980).

4. Strains and over-exertion, for example, cause 1/4-1/3 of all lost-time injuries, but are unaffected by standards. See p. 26, Mendeloff (1979) for a discussion of the studies by safety experts.

worker exposure restrictions for most of the known disease threats in the workplace, and require medical exams, exposure monitoring, and warning signs.

Rule-making for OSHA health standards has not been exempt from controversy. Many of the 10 health standards promulgated through rule-making since 1972 have been challenged on cost-benefit grounds.[5] Though OSHA standard-setting does not explicitly incorporate cost-benefit principles, the Supreme Court decided in the benzene case[6] and affirmed in the cotton dust case[7] that, for each new standard, OSHA must show that "significant risks" currently exist and can be eliminated or reduced with the proposed regulation. OSHA also adopted Threshold Limit Values (TLV) for 400 chemical substances in 1971 and an additional 168 chemicals in 1988, by reference from the voluntary standards of the American Committee of Government Industrial Hygienists (ACGIH), a consensus-based organization. The goals for risk-reduction in ACGIH standard-setting appear to be less stringent than for OSHA standards promulgated through rule-making.[8]

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5. Mendeloff (1988) compiled and re-evaluated the historical record of cost and benefit studies for health standards. In his data (Table 2.1, p. 22), the accepted estimates of the willingness-to-pay for a life saved ($1.6-$8.3 million in 1985$; Fisher et al., 1989) fall within the range of costs per cancer prevented for all health standards (with cancer risks) promulgated through rule-making, except vinyl chloride. Employing an estimate of $2.5 million per life-saved, Mendeloff concludes that several standards are probably too stringent according to cost-benefit criteria, though the excess stringency is perhaps not as great as some critics have suggested. (p. xv)

6. Industrial Union Dept. v. American Petroleum Institute, 448 US 607 (1980).

7. American Textile Mfrs. Inst. v Donovan, 452 US 490 (1981).

8. In 1988, OSHA also lowered the TLVs for 234 of the 400 initially regulated chemicals, in accordance with ACGIH actions on the substances during the 1971-88 period. See Mendeloff (1988) for a more complete discussion of the ACGIH standards.

Despite greater expectations for OSHA's intervention to reduce health risks, lack of suitable data to measure health effects has restricted most statistical studies of OSHA to examining safety performance.[9] Though some early studies suggested OSHA had no effect on workplace injuries, current research with longitudinal plant-level data indicates that OSHA has had a small, salutary effect on reducing injuries.[10] Because the effect of the agency on workplace <u>health</u> risks has not been evaluated, however, the research to date may substantially under-represent OSHA's total effect on workplace quality.

Direct measurement of the incidence of occupational disease is extremely difficult because of the confluence of several factors: long latency periods (frequently 10-25 years) between initial workplace exposure to hazardous substances and the onset of disease; mobility of workers across establishments; and, sometimes, inaccurate diagnoses or inaccurate attribution of causation for diseases. As a result, there is no data series comparable to the BLS injury rate series for occupational diseases with long latency periods.[11] However, current worker exposure levels represent a useful proxy for the future incidence of occupational

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9. Exceptions include John Mendeloff's (1988) book focusing on the process of setting health standards, and a study of enforcement of the asbestos standard (Jones, 1984).

10. Analyzing a 7-year panel with plant-specific injury rates and OSHA inspection data, Gray and Scholz (1989) estimated that a 10% increase in inspections with penalties would have a cumulative effect lagged over 3 years of reducing total accident rates by 1-2%. Analyzing OSHA enforcement and compliance data, Gray and Jones (1989) showed that during the first twelve years of the agency, OSHA inspections reduced citations in ever-inspected plants by 3.0 citations or by 0.36 s.d., on average. For earlier statistical studies on safety effects, see Viscusi (1979, 1986); Bartel and Thomas (1985); Mendeloff (1979); Smith (1979); and McCaffrey (1983).

11. The BLS data series on workplace disease incidence mainly reports skin problems which manifest shortly after exposure.

disease because most of the diseases are characterized by dose-response relationships.

In this paper, we employ a unique plant-level dataset characterizing OSHA health enforcement and plant compliance, to study the impact of OSHA on reducing workplace health hazards. To solve the problem of measuring OSHA's effect on reducing health risks, we use data that document the worker over-exposures to regulated substances and citations for violating OSHA standards, recorded during OSHA health inspections. The longitudinal structure of the OSHA enforcement data allows us to estimate the determinants of plant-level health compliance patterns through the first 12 years (1972-1983) of the agency's enforcement operations. We implicitly assume that the future incidence of occupational disease will decline with (1) an increase in compliance with OSHA health standards, and (2) a reduction in violations of worker exposure restrictions.

In recognition of the count form of the data series for both violation measures, we estimate several count-distribution models, along with the standard linear and log-linear models, to test the robustness of the results to model specification. Taking advantage of the longitudinal form of the dataset, we estimate the fixed-effects versions of the Poisson and negative binomial count models developed in Hausman, Hall and Griliches.

The following section of the paper presents a simple model of enforcement and compliance. The third section presents the statistical count models employed in the analysis. The fourth section describes the data. The fifth section presents the empirical results, and the final section summarizes the paper.

II. THE MODEL

The major actors in the model of workplace safety and health are OSHA and private companies. OSHA sets standards, inspects plants, takes samples measuring workers' exposures to regulated substances, and issues citations and penalties when violations are detected. Each company is assumed to choose a level of compliance with the standards for each of its plants. The compliance level, in turn, has implications for the levels of worker exposures to hazardous substances.

Following the tradition in the plant-level analysis in the OSHA literature, we employ a specific-deterrence framework to estimate the impact of an inspection of a plant on the subsequent compliance behavior of the plant. At any given point in time, the number of previous inspections signals the intensity of (past) enforcement. The initial inspections may disseminate information to firms about OSHA requirements and may provide a "management shock" to action. In addition, we implicitly assume that firms' responses to inspections are partially motivated by the trade-off between the anticipated future penalties for non-compliance and the costs of compliance. Though OSHA penalties for initial violations tend to be very low, the penalty schedules for repeat and willful violations cited in subsequent inspections are substantially higher.[12] To measure the intensity of agency enforcement, we employ dummy variables indicating the sequence number of the inspection for the first through the fifth inspection [SEQNUMj, j=1,...,5]. We do not have direct

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12. Other-than-serious penalties averaged $88 throughout 1977-84, while serious penalties averaged $276/citation (1977-80) and $192 (1981-84). However, willful penalties per citation averaged $3361 and $4389, and repeat penalties per citation averaged $395 and $365, during those two time periods, respectively. [Willful and repeat citations can be either serious or other-than-serious.] OTA (1985).

measures of the private costs of compliance. We assume that they vary with the employment size [SMALL] or are captured in the plant-specific dummy in the fixed-effects framework.

We employ two measures of plant performance with OSHA health standards. The number of worker exposure measurements violating OSHA permissible exposure limits [NUMBAD] serves as a proxy for plant performance in preventing (reducing) the future incidence of occupational disease.[13] The number of citations [NUMCITE] provides a measure of violations of all OSHA standards.

We control for several factors which may affect the consistency of the relationship between measured and "true" violations across inspections or through time. First, different Administrations may vary in the rate at which enforcement officers choose to sample various regulated substances, to cite different types of violations, or to impose penalties for repeat violations. We control for variations in agency enforcement policy across Administrations with dummy variables for the Nixon/Ford (1972-76) and Carter (1977-80) Administrations; the excluded dummy covers 1981-mid-83, the early part of the Reagan Administration. Second, the origin of each inspection (complaint, follow-up, general schedule, accident) affects how much of an establishment is inspected, and therefore affects the likelihood that violations will be detected. The dummy variable

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13. See the detailed study of the worker exposure data (Jones et al., 1986) for a discussion of sampling and reporting issues. An in-depth study of records in two OSHA offices indicated that compliance samples were taken in 48% and 61% of all health inspections, but samples were reported in approximately half of the inspections with samples taken. In the study the lack of reporting appeared to be random. Contrary to prior hypotheses, the distribution of severity levels for all compliance samples taken (as reported in area office files) was approximately the same as the distribution of severity levels for all compliance samples reported in the MIS by area offices.

identifies general schedule (targeted) inspections, which allow for the broadest coverage of the workplace.[14]

We observe the violation level only when an enforcement officer inspects an establishment. The criteria OSHA uses to select plants for repeated inspections will affect the choice of an appropriate estimation procedure. OSHA's policy of targeting high-hazard plants suggests that (re)inspection criteria conform to characteristics for which we can control in the analysis. Due to the longitudinal nature of the dataset, we also employ a fixed-effects framework to control for unobservable, permanent, plant-level effects.

III. STATISTICAL FRAMEWORK FOR COUNT MODELS

The dependent variable NUMCITE, measuring the number of citations detected in an inspection, equals 0 for 50% of the sample and has values of 3 or less for 75% of the sample. The other dependent variable [NUMBAD], measuring the number of exposure samples in violation of OSHA standards, equals 0 for 81% of the sample, and has values of 3 or less for 95% of the sample. (See Table A2 for a complete characterization of the distributions.) Given these distributions, count models, in which the dependent variable takes only non-negative integer values, seem more appropriate than the standard continuous approximations. Of particular interest are the fixed-effects versions of the Poisson and negative binomial models developed in Hausman, Hall and Griliches (1984) (hereafter referred to as HHG). The presentation below of the models we estimate is based on their discussion.

14. In accident, follow-up, and complaint inspections, inspectors are directed to focus on the specific factors originating the inspection.

For events that occur randomly and independently through time, the Poisson distribution is a natural starting point among count models. Denote the Poisson parameter as λ, and the number of violations identified by OSHA for plant j during inspection i, as v_{ij}. The basic Poisson probability distribution is:

$$(1) \qquad pr(v_{ij}) = f(v_{ij}) = [\exp(-\lambda_{ij})]\lambda_{ij}^{v_{ij}}/v_{ij}! \quad i=1,\ldots I_j;\ j=1,\ldots J.$$

The exponential functional form is conventionally used to incorporate exogenous variables, $\underline{X}_{ij}$, in order to restrict the range of possible values of the predicted Poisson parameter to positive real numbers:[15]

$$(2) \qquad \lambda_{ij} = \exp(\underline{X}_{ij}\underline{\beta})$$

HHG note that the advantages of the Poisson framework include (1) natural treatments of the integer property of the outcomes and of the zero-value case; (2) convenient time aggregation, which facilitates the implementation of a fixed-effect framework; and (3) ease of estimation by MLE due to global concavity of log-likelihood function.

At the same time, the basic Poisson model is restrictive in several ways. First, it is based on the assumption that events are independently and identically distributed through time conditional on $\underline{X}$. Given the panel structure of the data, a primary alternative hypothesis is heterogeneity across plants, attributable to unmeasured differences such

15. Use of the exponential form requires adding 1 to the values of the dependent variable, to handle 0-value observations.

as plant technology, compliance costs, and management attitudes,[16] which we test with the fixed-effects Poisson framework.

Second, the Poisson is a single-parameter distribution in which the mean and variance of $(v_{ij}|\underline{X}_{ij})$ are equal. If this equality restriction is inappropriately imposed, the estimated standard errors of $\underline{\beta}$ may be spuriously small. Greater flexibility in the mean/variance relationship can be achieved by generalizing the Poisson model (which is deterministic in $\lambda|\underline{X\beta}$) to allow for unexplained variation in λ_{ij}. Under certain distributional assumptions, the resulting compound Poisson distribution yields the negative binomial distribution.

Figure 1 summarizes the models we estimate. For comparison with the count models, we also estimate 2 linear models. The first model is: $(v=\underline{X\beta}+\varepsilon)$, or $(v=\underline{X\beta}+\mu+\varepsilon)$ in the fixed-effects version. The first and second moments are: $(\underline{X\beta},\sigma_1^2)$ and $(\underline{X\beta}+\mu,\ \sigma_1^2+\sigma_\mu^2)$, respectively. The second model is the log-linear version, $\ln v=\underline{X\beta}+\varepsilon$, or $\ln v=\underline{X\beta}+\mu+\varepsilon$ in the fixed-effects form, with first and second moments $(\exp[\underline{X\beta}],\sigma_2^2)$ and $(\exp[\underline{X\beta}+\mu],\sigma_2^2+\sigma_\mu^2)$, respectively. The third and fourth models are the Poisson and negative binomial models, respectively. The assumed mean function is the same in models 2-4, $\exp(\underline{X\beta})$, which differs from the mean function in model 1: $(\underline{X\beta})$.

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16. Alternative violations of the independence hypothesis include the "true contagion" model, in which the occurrence of an event may increase the probability of subsequent occurrences, and the "spells" model, in which events occur in clusters, where clusters occur according to one probability law, and the events within a given cluster occur according to a different probability law. Given the long time between health inspections, it seems highly unlikely that either of these effects occur in the data. We estimated first-order serial correlations of error terms for the basic Poisson model and found them to be very small.

FIGURE 1. Models of Count Data

	Model	Distribution	Mean	Variance	Variance/Mean
1.1	Linear	Normal	$\bar{X}\beta$	σ_1^2	$\sigma_1^2/X\beta$
1.2	Linear-FE	Normal	$\bar{X}\beta+\bar{\mu}$	$\sigma_1^2+\sigma_\mu^2$	$(\sigma_1^2+\sigma_\mu^2)/(\bar{X}\beta+\bar{\mu})$
2.1	Log-linear	Normal	$\exp(\bar{X}\beta)$	σ_2^2	$\sigma_2^2/\exp(\bar{X}\beta)$
2.2	Log-linear-FE	Normal	$\exp(\bar{X}\beta+\mu)$	$\sigma_2^2+\sigma_\mu^2$	$(\sigma_2^2+\sigma_\mu^2)/\exp(\bar{X}\beta+\bar{\mu})$
3.1	Poisson	Poisson	$\exp(\bar{X}\beta)$	$\exp(\bar{X}\beta)$	1
3.2	Poisson-FE	Poisson	$\exp(\bar{X}\beta+\bar{\mu})$	$\exp(\bar{X}\beta+\bar{\mu})$	1
4.1	Negative binomial	Negative binomial	$\exp(\bar{X}\beta)/\delta$	$\exp(\bar{X}\beta)(1+\delta)/\delta^2$	$(1+\delta)/\delta > 1$
4.2	Negative binomial-FE	Negative binomial	$\exp(\bar{X}\beta+\bar{\mu})/\bar{\phi}$	$[\exp(\bar{X}\beta+\bar{\mu})/\bar{\phi}]\{1+[\exp(\bar{\mu})/\bar{\phi}]\}$	$[\exp(\bar{\mu})+\bar{\phi}]/\bar{\phi} > 1$

Note: In the fixed-effects models, the parameters μ and ϕ (in model 4.2) are plant-specific.

Poisson Distribution Models

The basic Poisson model (3.1 in Figure 1) yields the following log-likelihood function for a sample covering i_j inspections in plant j across j plants:

$$(3) \qquad \log L = \Sigma_j \Sigma_i [v_{ij}! - \exp(\underline{X}_{ij}\underline{\beta}) + v_{ij}(\underline{X}_{ij}\underline{\beta})]$$

The OSHA panel is unbalanced: plants vary in the total number of health inspections they have received. In the analysis sample, we truncate the number of inspections in plant j, i_j, to a maximum of 5.

Unobserved plant-specific effects can be incorporated by specifying $\tilde{\lambda}_{ij} = \lambda_{ij}\alpha_j$. Because $\tilde{\lambda}_{ij}$ needs to be positive, the following form is employed:

$$(4) \qquad \tilde{\lambda}_{ij} = \lambda_{ij}\tilde{\alpha}_j = \exp(\underline{X}_{ij}\underline{\beta} + \mu_0 + \mu_j)$$

where μ_j is the effect specific to plant j and μ_0 is the overall intercept. The fixed-effects framework does not require a distributional assumption for $\tilde{\alpha}_j$, and allows for correlation between the plant effect and the observed exogenous variables.[17]

HHG observe that the fixed-effects specification cannot be implemented simply by estimating separate μ_j parameters because, with I held fixed and J large, the incidental parameter problem occurs which may lead to inconsistency in ML estimators.[18] Instead they employ the

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17. This flexibility represents a major advantage relative to the random-effects framework, an alternative panel data model. However, inferences with the fixed-effects model are conditional on the plant error term; unconditional inferences are not possible without more specific distributional assumptions.

18. See Neymann and Scott (1948); Andersen (1973); and Haberman (1977).

conditional Maximum Likelihood techniques of Andersen (1970, 1972), and condition on $\tilde{\alpha}_j$ by conditioning on the sum of violations for plant j across its inspections, $\Sigma_i v_{ij}$.

The log-likelihood function for the fixed-effect Poisson model (3.2) is:

$$(5) \qquad \log L = \Sigma_j \{\log\Gamma[(\Sigma_i v_{ij})+1] - \Sigma_i \log\Gamma(v_{ij}+1) - \Sigma_i v_{ij} \log \Sigma_s \exp[-(\underline{X}_{ij}-\underline{X}_{sj})\underline{\beta}]\}$$

$$\text{where } s \in I_j$$

The log-likelihood function consists of different segments for plants with 2, 3, 4 or 5 inspections in the panel, respectively, with the segments linked by common parameters on shared variables.[19]

Negative Binomial Distribution Models

To relax the Poisson model restriction that the mean and variance of $(v_{ij}|\underline{X}_{ij})$ are equal, we allow for randomness in λ_{ij} by replacing (2) with the stochastic equation:

$$(6) \qquad \lambda_{ij} = \exp[\underline{X}_{ij}\underline{\beta} + \varepsilon_{ij}]$$

where the error term ε represents intrinsic randomness. It is well known that if the probability density of ε_{ij}, or equivalently of λ_{ij}, follows the gamma distribution, then the pr(v_{ij}) is distributed negative binomial.

HHG assume gamma-distribution parameters (γ, δ), with $\gamma_{ij}=\exp[\underline{X}_{ij}\underline{\beta}]$ and δ common both across firms and across time. Note the nature of the

19. In order to implement the fixed-effects framework, plants with only one inspection cannot be used in the analysis.

stochasticity in λ_{ij} in this model: λ_{ij} can vary over time even if $\underline{X}_{ij}$ remains constant (unlike with the Poisson model); however, there are no firm-specific effects, so the λ_{ij} are independent across inspections for a plant. With this formulation, the first and second moments of the distribution of v are: $E(v_{ij})=\exp[\underline{X}_{ij}\underline{\beta}]/\delta$ and $V(v_{ij})=\exp[\underline{X}_{ij}\underline{\beta}](1+\delta)/\delta^2$. With a variance/mean ratio for v of $(1+\delta)/\delta > 1$, the specification allows for over-dispersion (with the original Poisson as a limiting case with $\delta\to\infty$). However, it does not allow the variance to increase with the value of the dependent variable.

The log-likelihood function for model 4.1 is:

$$(7) \qquad \log L = \Sigma_j \Sigma_i \{-\log\Gamma(v_{ij}+1) - \log\Gamma[\exp(\underline{X}_{ij}\underline{\beta})] + \exp(\underline{X}_{ij}\underline{\beta})\log[\delta/(1+\delta)] - (v_{ij})\log(1+\delta) + \log\Gamma[v_{ij}+\exp(\underline{X}_{ij}\underline{\beta})]\}$$

In order to incorporate plant-specific effects in the negative binomial model, HHG again condition the estimation on the sum of citations across all inspections. The firm-specific effect is incorporated by setting the parameters of the underlying gamma function as follows: $(\gamma_{ij}, \delta_j) = (\exp[\underline{X}_{ij}\underline{\beta}], \phi_j/\exp[\mu_j])$, where δ_j now varies across plants. The moments of the corresponding unconditional negative binomial model are:

$$E(v_{ij}) = \exp[\underline{X}_{ij}\underline{\beta}+\mu_j]/\phi_j$$

$$V(v_{ij}) = (\exp[\underline{X}_{ij}\underline{\beta}+2\mu_j]/\phi_j^{\,2})(1 + \phi_j/\exp[\mu_j])$$

The variance/mean ratio for v in this specification is $(\exp[\mu_j] + \phi_j)/\phi_j$, which allows for both over-dispersion and a plant-specific variance/mean ratio. The log-likelihood function for the fixed-effects negative binomial model (4.2) is:

$$(8) \qquad \log L = \Sigma_j \{\log\Gamma[(\Sigma_i v_{ij})+1] - \Sigma_i \log\Gamma(v_{ij}+1) + \log\Gamma[\Sigma_i \exp(\underline{X}_{ij}\underline{\beta})] - \log\Gamma[\Sigma_i \exp(\underline{X}_{ij}\underline{\beta})+\Sigma_i v_{ij}] + \Sigma_i \log\Gamma[\exp(\underline{X}_{ij}\underline{\beta})+v_{ij}] - \Sigma_i \log\Gamma[\exp(\underline{X}_{ij}\underline{\beta})]\}$$

As with the fixed-effects Poisson model, the log-likelihood function consists of four separate segments with plants in each segment distinguished by total number of health inspections, $I_j=2,\ldots5$, but sharing the same coefficient matrix $\underline{\beta}$.

IV. DATA

The source of data for the analysis is OSHA's enforcement Management Information System (MIS), used by the agency to track agency enforcement and company compliance performance. The version of the MIS data obtained for this study includes the 63,383 federal health inspections performed in 37,639 manufacturing establishments between 1972 and the middle of 1983.[20] In order to create longitudinal records of plant inspection histories, Gray (1986) matched all inspections of individual establishments using

20. Not included in the data are those few inspections done in 1971 and 1972 before the MIS was operational, and inspections performed in "state plan" states, where state authorities have taken over responsibility for enforcement.

establishment-level identifiers.[21] In order to implement efficiently the conditioning procedure in the Andersen MLE technique, we only include up to the fifth inspection for a plant. This truncation does not result in the loss of any plants, but does eliminate 2909 health inspections of sequence order 6 and above (4.6% of all inspections) in 984 heavily health-inspected plants (2.6% of all plants), yielding a sample of 60,474 inspections.

In order to estimate the fixed-effect versions of the models, we restrict the analysis sample to the 35,427 health inspections in the 12,592 plants with two or more health inspections during the period. Table A1 compares the means and standard deviations of the variables for the full sample (I) with for the analysis sample (II). Across the full sample, inspectors wrote citations (NUMCITE) in 50% of the inspections, averaging 2.5 citations across all inspections and 5 citations in inspections with citations. Inspectors reported an average of .6 exposure samples violating exposure limits in each inspection, for an average of 3.2 violations in plants with exposure violations. In the analysis sample, the NUMCITE mean is almost identical; the mean of NUMBAD is 25% higher than the mean for sample I (.76 relative to .61).

In its early years, OSHA did not hire many industrial hygienists and so the agency conducted relatively few health inspections. The agency began to place greater priority on health inspections by the end of the

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21. This project used the Fellegi-Sunter technique of record matching, based on establishing the likelihood of agreement in the various fields. Because of the variation in coding of establishment data over time (including errors in data entry), there are almost certainly cases in which inspections of the same establishment are not identified as such. It is also possible (though less likely given the structure of the weights) that inspections of different establishments are mis-identified as repeat inspections of a single establishment.

Ford Administration, when a health professional was appointed head of the agency for the first time. In the full sample, health inspections are fairly evenly distributed across the years in the Carter (1977-80) and Reagan (1980-mid-83) Administrations (at 11% per year, with a slight bulge to 12.6% in 1980). Not surprisingly, after eliminating plants with only one inspection, the profile of sample II shifts slightly toward the earlier part of the panel. General-schedule targeting (aimed toward high-hazard workplaces) generated 44% of the inspections among all plants, dropping to 1/3 in the analysis sample. Slightly over half of the inspections (55%) in sample I were in plants with fewer than 100 employees; the share of small plants declines to 42% in the analysis sample.

Table A2 presents more detailed descriptive statistics for the two count variables, separately for the two samples. Given the patterns in the means, it is not surprising that the distribution for NUMCITE is almost identical for the two samples and the distribution for NUMBAD is shifted slightly upward in the analysis sample. We also show a 2x2 table indicating the joint outcomes on the 2 violation measures. It is reassuring that among plants with exposure violations, 88% received citations. Among plants with citations, 34% had documented exposure violations.[22]

22. Inspectors may cite plants for not having the appropriate control equipment to achieve exposure limits, without taking exposure measurements. Alternatively, citations may involve violations of other requirements such as exposure employer monitoring, warning signs, personal protective equipment, or medical exams.

V. EMPIRICAL RESULTS

The major issue considered in this paper is: do OSHA's enforcement efforts deter violations of OSHA health standards? To address this issue we estimate each of the four models developed above, both with and without plant-specific fixed effects. For the versions of the model without fixed effects, we control for the selection effect by incorporating the variable HNUMINSP, the total number of health inspections experienced by a plant, as a proxy for the plant fixed effect. As with the inspection-sequence series of variables [HSEQNUM], we create dummy variables for values of HNUMINSP equal to 1 through 5.[23]

Tables 1 and 2 report the estimates of the determinants of the total number of citations, NUMCITE, and the number of exposure violations reported, NUMBAD, respectively. Across all specifications for both variables, the results are consistent with the qualitative conclusions that (1) both measures of violation (worker exposure violations and citations of standards) decrease with additional inspections, and (2) the first health inspection has the strongest impact in reducing violations.

We first consider the results for NUMCITE presented in Table 1. In all four models, the fixed-effects framework cannot be rejected. The coefficients on the health inspection variables (HSEQNUMj) are somewhat larger (and the differences are statistically significant) in the fixed-effects versions. However, the estimates of the impact of OSHA enforcement throughout the sample, (summarized for fixed-effects models below in Table 3), are not greatly affected by the differences.

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23. With this model, the coefficients of the health inspection sequence variables [HSEQNUM], the focus of our inquiry, are estimated without bias. The coefficients on HNUMINSP are underestimated by a factor equal to the ratio of the variance of the "noise" in HNUMINSP (as a proxy for μ) to the total variance of HNUMINSP. Proof available from the authors.

TABLE 1. Alternative models of the determinants of citations (NUMCITE) in health inspections in plants with 2 or more health inspections.

Sample: 35427 inspections in 12,592 plants

Model	1.1 Linear	1.2 Linear-FE	2.1 Log-linear	2.2 Log-linear-FE	3.1 Poisson	3.2 Poisson-FE	4.1 Neg bin	4.2 Neg bin-FE
Constant	3.25 (.10)		.92 (.02)		1.12 (.004)		-.50 (.02)	-.14 (.03)
HSEQNUM2	-1.83 (.07)	-2.02 (.07)	-.50 (.01)	-.55 (.01)	-.69 (.003)	-.76 (.003)	-.58 (.01)	-.69 (.02)
HSEQNUM3	-.46 (.09)	-.71 (.09)	-.091 (.015)	-.15 (.02)	-.17 (.004)	-.38 (.004)	-.16 (.02)	-.060 (.020)
HSEQNUM4	-.22 (.12)	-.37 (.12)	-.058 (.021)	-.098 (.020)	-.095 (.006)	-.15 (.01)	-.14 (.02)	-.057 (.027)
HSEQNUM5	-.020 (.161)	-.15 (.15)	-.0076 (.027)	-.040 (.026)	.001 (.007)	-.088 (.008)	.018 (.030)	-.0047 (.0359)
HNUMINSP3	.59 (.08)		.13 (.01)		.21 (.003)		.19 (.02)	
HNUMINSP4	.78 (.09)		.18 (.02)		.26 (.004)		.15 (.02)	
HNUMINSP5	1.02 (.09)		.21 (.02)		.33 (.003)		.34 (.02)	
GENSCHED	1.19 (.06)	1.86 (.08)	.32 (.01)	.48 (.01)	.41 (.002)	.71 (.003)	.38 (.01)	.65 (.02)
SMALL	.28 (.06)		.083 (.010)		.13 (.002)		.090 (.011)	.058 (.024)
FORD	-.60 (.09)	-1.89 (.15)	-.11 (.02)	-.45 (.03)	-.27 (.004)	-.92 (.01)	-.27 (.02)	-.20 (.03)
CARTER	-.38 (.08)	-.37 (.11)	-.085 (.013)	-.14 (.02)	-.19 (.003)	-.24 (.01)	-.10 (.02)	-.055 (.021)
DELTA							.20 (.002)	
mean,sd	2.55 (5.21)	2.55 (5.21)	.74 (.91)	.74 (.91)	.74 (.91)	.74 (.91)	.74 (.91)	.74 (.91)
R_2	.05	.45	.12	.49				
$\sqrt{mse}$	5.08	4.84	.86	.82				
log L					-126,186	-53,989	-66,464	-28,375

TABLE 2. **Alternative models of the determinants of overexposures (NUMBAD) detected in health inspections, for plants with 2 or more inspections.**

Sample: 35427 inspections of 12,592 plants

Model	1.1 Linear	1.2 Linear-FE	2.1 Log-linear	2.2 Log-linear-FE	3.1 Poisson	3.2 Poisson-FE	4.1 Neg bin	4.2 Neg bin-FE
Constant	.77 (.05)		.26 (.01)		-.32 (.01)		-.98 (.02)	-.59 (.05)
HSEQNUM2	-.32 (.03)	-.34 (.04)	-.14 (.01)	-.16 (.01)	-.42 (.01)	-.45 (.01)	-.43 (.01)	-.49 (.02)
HSEQNUM3	-.12 (.05)	-.18 (.05)	-.048 (.010)	-.072 (.010)	-.098 (.007)	-.29 (.01)	-.21 (.01)	-.054 (.027)
HSEQNUM4	-.13 (.06)	-.17 (.06)	-.048 (.014)	-.063 (.013)	-.15 (.01)	-.14 (.01)	-.32 (.01)	-.044 (.034)
HSEQNUM5	-.031 (.080)	-.063 (.079)	-.021 (.018)	-.033 (.018)	-.009 (.011)	-.089 (.011)	.014 (.024)	-.026 (.042)
HNUMINSP3	.27 (.04)		.10 (.01)		.34 (.01)		.35 (.01)	
HNUMINSP4	.34 (.05)		.15 (.01)		.41 (.01)		.30 (.01)	
HNUMINSP5	.55 (.05)		.21 (.01)		.65 (.01)		.78 (.02)	
GENSCHED	.57 (.03)	.83 (.04)	.18 (.01)	.26 (.01)	.69 (.01)	.91 (.01)	.38 (.01)	.63 (.03)
SMALL	-.26 (.03)		-.047 (.006)		-.37 (.01)		.077 (.005)	.070 (.041)
FORD	-.19 (.05)	-.48 (.08)	.001 (.010)	-.13 (.02)	-.28 (.01)	-.78 (.01)	-.39 (.01)	.042 (.035)
CARTER	-.035 (.039)	.06 (.05)	.010 (.009)	-.0093 (.0122)	-.063 (.006)	-.035 (.009)	-.010 (.011)	.14 (.03)
DELTA							.483 (.004)	
mean, (sd)	.76 (2.55)	.76 (2.55)	.28 (.59)	.28 (.59)	.28 (.59)	.28 (.59)	.28 (.59)	.28 (.59)
R^2	.02	.40	.05	.43				
$\sqrt{mse}$	2.53	2.47	.58	.55				
log L					-60,408	-21,640	-36,344	-12,626

TABLE 3. Effect of health inspections on violation measures, NUMCITE and NUMBAD, estimated with the fixed-effects models.

Health inspection Sequence number:	NUMCITE: (Number of citations) 1.2 Linear-FE[a]	2.2 Log-linear-FE[b]	2 Poisson-FE[b]	4.2 NegBin-FE[b]	NUMBAD: (Number of over-exposures) 1.2 Linear-FE[a]	2.2 Log-Linear-FE[b]	3.2 Poisson-FE[b]	4.2 NegBin-FE[b]
2	-2.02	-1.95	-1.92	-1.75	-.34	-.28	-.34	-.40
3	-.71	-.54	-.97	-.15	-.18	-.13	-.22	-.04
4	-.37	-.35	-.39	-.15	-.17	-.11	-.11	-.03
5	-.15	-.14	-.22	-.01	-.06	-.06	-.07	-.02
TOTAL SAMPLE EFFECT[c]								
1) Assume no effect of plant's last insp								
Δ violations:	-1.56	-1.47	-1.58	-1.19	-.30	-.23	-.30	-.26
Δ violations/sd:	-.30 sd	-.28 sd	-.30 sd	-.23 sd	-.12 sd	-.09 sd	-.12 sd	-.10 sd
2) Infer effect of plants' last insp								
Δ violations:	-2.61	-2.42	-2.69	-1.89	-.51	-.40	-.53	-.41
Δ violations/sd:	-.50 sd	-.46 sd	-.52 sd	-.36 sd	-.29 sd	-.23 sd	-.30 sd	-.23 sd

NOTES

a Parameters for NUMCITE are from Col. 1.2, Table 1; parameters for NUMBAD are from Col. 1.2, Table 2.

b Calculated by multiplying the mean of the variable, (NUMCITE) or (NUMBAD), by the parameter estimates for the respective models appearing in Col. 2.2, 3.2, and 4.2 of Table 1 for NUMCITE, and of Table 2 for NUMBAD. [In models 2.2 we added +1 to the dependent variables to accomodate the log transformations.]

c Weighted averages of inspection sequence number effects. When an inspection j occurs we observe the effect of the prior inspection, j-1. Consequently, we have no direct observation of the effect of the last inspection for each plant, or of the fifth inspection for any plant.

1) is calculated based on the conservative assumption that the last health inspection in each plant has no effect on performance. HSEQNUMj parameters [measuring the effect of inspection j-1] are weighted by the values of HSEQNUMj variables (% of inspections of that order).

2) is calculated by assuming that the (unmeasured) expected effect of the last health inspection of a plant equals the effect measured for that sequence number in the subset of the sample receiving that order inspection. [We cannot estimate the effect of a fifth inspection.] The weights on b($HSEQNUM_j$) are the values of variables $HSEQNUM_{j-1}$. The values of HSEQNUM1-5 are: 1, .64, .29, .13, .05.

Because the specification of the mean function is a critical component in the implementation of the count models, we are particularly interested in specification testing for models 1 and 2. The R^2 are not comparable in the two models (due to the data transformation). Alternatively, we use the Sargan test which indicates the log-linear model (2) is preferred to the linear version (1).[24]

Comparing the results for the two count-distribution models, we see the dramatic decline in the log-likelihood function for the negative binomial model[25] relative to the Poisson, from -126,186 to -66,464 for the non-fixed-effects version, and -53,989 to -23,375 for the fixed-effects version. Based on a χ^2 test, the negative binomial model is not rejected in either version. For the non-fixed-effects version, we can also examine the estimate of δ, which allows for over-dispersion in the negative binomial specification. In model 4.1, the estimated ratio of the variance to the mean is $(1+\delta)/\delta=6$, substantially different from the imposed ratio

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24. The statistic presented by Sargan (1964) is: $S=(\tilde{\sigma}_1/g\hat{\sigma}_2)^T$, where $\tilde{\sigma}_1$ is the root-mse from model 1, and $\hat{\sigma}_2$ is the root-mse from model 2, and g is the geometric mean of v. Based on the assumption that the errors from each model k, (k=1,2), are distributed iid $N(0,\sigma_k)$: if S>1, then model 2 is favored; if S<1, then model 1 is favored. [Maddala (1977, p. 317) proposed a comparable test.] The value of $(\tilde{\sigma}_1/g\hat{\sigma}_2) = 2.8$ for both the fixed-effects and the non-fixed-effects versions, which indicates that the log-linear model is preferred to the linear model.

25. Unlike the other fixed-effects models, the negative binomial allows estimation of coefficients for variables that are constant for a plant over time. Including the constant term had important implications: without it, the HSEQNUM2 coefficient in the NUMBAD equation was substantially (50%) higher in magnitude, yielding a much larger estimate of the effect of first inspections than with the other models. We also include the SMALL plant dummy in the reported results. The procedure would not converge when the HNUMINSP dummies were included, however, due to their high collinearity with the HSEQNUM dummies. When we incorporated HNUMINSP dummies with a range of pre-specified parameter values for the coefficients (rather than estimating them), the HSEQNUM parameter estimates were not greatly affected.

of 1 in the Poisson model. Note also that the standard errors are larger in the negative binomial model, consistent with the observation above that the standard errors estimated in the Poisson models may be spuriously small where over-dispersion occurs due to the imposed equality of mean and variance.

The HSEQNUM coefficients in the linear model (1, $v=\underline{X}\beta+\varepsilon$) indicate the change in the violation level with additional inspections. For the three other models (2-4) based on the log-linear form of the relationship, ($\ln v=\underline{X}\beta+\varepsilon$), the coefficients indicate the percentage change in the dependent variable with an additional inspection. In order to compare across models the estimated effect of inspections on the level of violations, we multiply the coefficients in models 2-4 by the mean of the dependent variables (v), which gives us the estimated inspection effect at the sample mean. In the following discussion we assume that the reduction in citations induced by an inspection is permanent, which yields a conservative interpretation of the incremental effects of repeated inspections.[26]

The first four columns of Table 3 summarize the impact of sequential inspections on citations. Due to the statistical dominance of the fixed-effects models, we report only those estimates of the inspection effects, in both numerical counts and standardized units (+ sd). Before turning to Table 3, we observe in Table 1 that the coefficients on the health

26. Alternatively, if the impact is short-lived, the effect of inspection j-1 equals the sum of the j^{th} coefficient plus all earlier HSEQNUM coefficients. A longer-term effect seems more appropriate when compliance predominantly involves making capital investments with long time horizons; the short-term effect seems more appropriate when compliance primarily requires the payment of operating expenses. Conventional wisdom suggests safety compliance is more oriented toward operating expenditures and health to capital expenditures.

sequence variables are all precisely estimated, with the exception of the HSEQNUM5 variables.

For NUMCITE [mean=2.5, sd=5.2], the pattern of inspection effects is very similar for models 1, 2, and 3. The log-linear results (Col. 2.2) indicate that the first-inspection effect is to reduce citations by -2.0, with subsequent inspections yielding reductions of -.5, -.4, and -.14 citations each, for an estimated total impact of the OSHA inspection pattern for the average manufacturing plant of -2.4 (-.5 sd). For the Poisson model, the estimated total effect is approximately the same, -2.7 citations (-.5 sd); with reductions declining across inspections, -1.9, -1.0, -.4, -.2. The negative binomial model estimates OSHA's total effect to be 20% lower than the other three models: -1.9 citations (-.2), with the reductions concentrated on the first inspection (-1.8 citations), with subsequent inspections yielding reductions of -.15, -.15, -.01 citations.

Note the effect of an inspection is observed in the subsequent inspection. The estimates of total effects cited above assume that the (unobserved) effect of the last inspection for each plant is equal to the effect measured for that inspection sequence number in the sub-set of the sample receiving additional inspections.[27] Alternatively, "more conservative" estimates of the effect of OSHA inspections during 1972-83, based on the assumption that there is no effect of the last inspection in any plant, range from -1.2 (-.2 sd) to -1.6 (-.3 sd) for the Poisson model. (See the notes to Table 3 for further details on the calculations.)

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27. It follows that we have no measure of the effect of the fifth inspection, and so we must assume a zero impact. The calculation attributes the estimated first-inspection effect to plants receiving only one inspection; these plants were not included in the analysis sample.

The results for the number of violations of worker exposure limits [NUMBAD] reported in Tables 2 and 3 follow similar patterns. In the fixed-effects versions (which are not rejected for any of the models), the coefficients tend to be slightly larger. The Sargan test, comparing the linear and log-linear forms, again indicates that the log-linear model is preferred.[28] Between the two count models, the negative binomial model is strongly preferred according to the χ^2 test. With NUMBAD, the estimated over-dispersion in the variance/mean ratio in model 4.1 is smaller: $(1+\delta)/\delta=3$. The parameter estimates for the HSEQNUM variables are significant except for the HSEQNUM5 variable (for all models) and for HSEQNUM4 with the negative binomial model.

The estimates of the total effect of OSHA health inspections on over-exposures [mean=.75, sd=2.5] are summarized in the last four columns of Table 3 for the fixed-effects version of the models. All four models again produce similar estimates of the total impact of OSHA: -.4 overexposures for the log-linear and negative binomial models, and -.5 overexposures for the linear and Poisson models. In the log-linear model, the inspection effects are -.3, -.1, -.1, and -.06, for a weighted average of -.4 over-exposures, (-.2 sd) or, according to the more conservative calculation, -.2 over-exposures (-.1 sd). In the negative binomial model (4.2), the estimates of individual inspection-effects are -.4, -.04, -.03, and -.02, for a total impact of -.4 citations (-.2 sd) or, more conservatively, -.3 citations (-.1 sd). Though all models indicate large first-inspection reductions with smaller effects from subsequent

28. The value of $(\bar{\sigma}_1/g\hat{\sigma}_2)$ was 3.4 for the fixed-effects model and 3.3 for the non-fixed-effects model.

inspections, it is notable how much more pronounced the effect is with the negative binomial model.

VI. SUMMARY AND DISCUSSION OF RESULTS

In this paper, we provide the first estimates of the impact of OSHA health-related enforcement on compliance throughout the manufacturing sector. We resolved the lack-of-data impediment to research on OSHA's health effects by creating violation measures from the data on exposure samples and citations recorded by OSHA inspectors in the agency enforcement MIS.

Two major conclusions are robust across the range of linear and count models estimated in the paper: (1) both the number of citations of OSHA standards and the number of violations of worker exposure limits decrease with additional health inspections in manufacturing plants; and (2) the first health inspection has the strongest impact. The best estimates, based on the fixed-effects negative binomial models, suggest that in ever-inspected manufacturing plants, OSHA health inspections during the first twelve years of the agency operation have reduced the number of citations on average by -2 or -.4 sd and have reduced the number of detected exposure violations by -.4 or -.23 sd.[29] The ranges of estimates across the models are for reductions from -1.9 to -2.7 citations and for reductions of -.4 to -.5 worker over-exposures samples. The methodology does not allow us to estimate the

29. The estimated reduction in citations induced by health inspections presented in this paper is of comparable magnitude to the estimated reduction reported in our earlier study, focusing on safety inspections (80% of all OSHA inspections). With a Tobit model, we estimated inspection effects on citations of (-2.3, -.6, -.5 and -.3); with a linear fixed-effects model, the estimated inspection effects were somewhat larger (-2.9, -1.4, -.8, and -.9). The average effect of OSHA inspections throughout the 12-year panel period (based on the Tobit coefficients), was to reduce citations by -3 or -.36 sd.
Because the dataset involved in the safety analysis was substantially larger, we did not employ the difficult-to-estimate count models.

indirect or general deterrent effects of inspections on other non-inspected plants, for example in the same industry or the same geographical area. Also the analysis is strictly limited to federal OSHA inspections: it does not necessarily measure the impact of enforcement efforts in states with federally-approved state enforcement programs.

We assume that the future incidence of occupational disease will tend to decline with an increase in compliance with OSHA standards and a reduction in violations of worker exposure restrictions. Based on this assumption, the results demonstrating OSHA's efficacy in promoting compliance with health standards suggest that OSHA is making a valuable contribution to the reduction of workplace risks. By focusing on the limited impact of safety regulations, prior evaluations of OSHA may have substantially under-estimated OSHA's workplace impact.

To make recommendations for future enforcement policy would require extrapolations beyond the plants ever-observed in the sample. Nonetheless, one particularly robust result observed in both our previous safety inspection study and the current health inspection study deserves comment. Within the 12-year panel period, the large reduction in citations and exposure violations following the first inspection of a plant contrasts greatly with the small measured effect of later inspections. The results suggest that, on the margin, substantial gains could occur if inspection resources were reallocated from the intensive margin to the extensive margin of OSHA's inspection strategy.

TABLE A1. Descriptive statistics for the analysis sample

Sample I = Health inspections (1 - 5), N = 60,474.
Sample II = Health inspections (1 - 5) in plants receiving at least 2 health inspections, N = 35,427.

Name	Description	I Mean (s.d)	II Mean (s.d)
NUMCITE	Number of citations in this inspection	2.518 (4.954)	2.545 (5.214)
NUMBAD	Number of worker exposure samples violating exposure restrictions.	.614 (2.233)	.759 (2.551)
HSEQNUM	Health sequence number of this inspection of this establishment (Dummy variables).		
HSEQNUM1	=1 if [Sequence number ≥1]	1.000	1.000
HSEQNUM2	≥2]	.378	.645
HSEQNUM3	≥3]	.169	.289
HSEQNUM4	≥4]	.076	.130
HSEQNUM5	≥5]	.028	.047
HNUMINSP	Number of total health inspections of this establishment (Dummy variables).		
HNUMINSP1	=1 if [Total inspections = 1]	.413	0
HNUMINSP2	= 2]	.231	.393
HNUMINSP3	= 3]	.133	.226
HNUMINSP4	= 4]	.085	.145
HNUMINSP5	≥ 5]	.138	.236
GENERAL	=1 if origin of inspection was a general schedule (targeted) inspection	.437	.335
	0 if origin was complaint, accident or follow-up	.563	.665
FORD	=1 if inspection occurred in 72-76 0 otherwise	.261	.282
CARTER	=1 if inspection occurred in 77-80 0 otherwise	.456	.519
REAGAN	=1 if inspection occurred in 81-mid83 0 otherwise	.283	.199
SMALL	=1 if Number of employees < 100	.549	.420
	0 if Number of employees ≥ 100	.451	.580

TABLE A2. Detailed descriptive statistics for the violation variables.

	NUMCITE		NUMBAD	
Sample:*	I	II	I	II
Mean	2.518	2.545	.614	.759
Std. dev.	(4.954)	(5.214)	(2.232)	(2.551)
N	60,474	35,427	60,474	35,427
Frequency counts:				
	cum%	cum%	cum%	cum%
0	49.8	51.4	80.9	77.2
1	62.0	63.2	88.5	85.9
2	71.2	72.0	92.6	90.9
3	77.8	78.1	94.9	93.7
4	82.3	82.2	96.4	95.6
5	85.7	85.5	97.4	96.7
6	88.4	88.1	98.0	97.5
7	90.4	90.1	98.5	98.1
8	92.1	91.7	98.8	98.5
9	93.4	93.1	99.0	98.8
10	94.4	94.1	99.2	99.0
Highest extremes:	88	85	64	64
	88	88	67	67
	99	99	71	71
	115	115	75	75
	123	123	88	88

* Sample definitions: I refers to health inspections 1-5 for all plants
II refers to health inspections 1-5 for all plants with 2 or more health inspections

TABLE A2 - cont'd

Sample I:

		NUMBAD = 0	> 0	Total
NUMCITE	= 0	28,750	1,359 (11.8%)	30,109
	> 0	20,187 (66.5%)	10,178 (88.2%) (33.5%)	30,365 (100.0%)
	Total	48,937	11,537 (100.0%)	60,474

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