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Self-Correction versus Persistence of Establishment Injury Rates

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ABSTRACT

This article studies a panel of 1979 through 1984 plant-level manufacturing data for evidence of persistently high unexplained injury rates. Residuals are calculated from injury rate regressions. Statistically significant positive residuals (i.e., unexplained high injury rates) observed early in the time period tend to decline over time even in the absence of Occupational Safety and Health Administration inspections. There is less decline in the residuals over shorter time periods, for larger establishments, and when the residuals have been high for more than a year. These are situations when targeting safety inspections with plant-level injury data will be most successful.

Introduction

A cost-effective safety and health program requires the proper targeting of establishments for inspection. Until recently, the U.S. Occupational Safety and Health Administration (OSHA) targeted entire industries based on their lost workday injury rates. OSHA found that, as a result, it inspected many establishments that had low injury rates and few violations of safety standards. Some, including the National Research Council (NRC) (1987) and the General Accounting Office (GAO) (1990), have argued that a solution to this targeting problem is for OSHA to collect data on the accident experience of individual establishments. The NRC and GAO argue that, with these data, OSHA can concentrate its resources on high-risk establishments. Legislation recently intro-

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duced in the U.S. Congress would require collection of establishment-specific data that could be used to target inspections.[1]

In assessing the proposal to use establishment-specific data for inspection targeting, a variety of questions must be addressed about the goals of an inspection, the costs of collecting establishment injury rates, and how the use of these rates can further the inspection's goals.[2] Here, I address a question that is important to answer regardless of the goal: to what extent do the high observed injury rates of some establishments tend to persist over time? Unless there is enough persistence in injury rates, OSHA could still find itself inspecting many low-risk establishments even if it targets with establishment-specific data.

Several hypotheses raise doubts about injury rate persistence. One is that accidents occur somewhat randomly. An establishment with a high injury rate in a given period will tend to be one that experienced bad luck. Its rate will tend to regress back to the mean in subsequent periods even without an inspection.

Even if the establishment's high injury rate did not result from bad luck, it might not persist. Possibly, the cause of the high injury rate is only temporary. Or, if the cause is permanent, economic forces may come into play that penalize the firm for continuing to be excessively risky. These penalties include high workers' compensation premiums, compensating wage differentials, the costs of replacing damaged property, training replacement workers, and the implicit cost of foregone production. These costs create incentives for increased safety.

Consider, for example, a firm that finds itself riskier due to an increase in demand that is met in the short run by utilizing previously mothballed, less safe equipment. If the increase in demand is only temporary, then the injury rate will decrease as demand and production return to their previous levels and as the less safe equipment is retired. If the period of high demand is sufficiently short, an inspection based on the temporarily high injury rate will be too late to detect the use of the unsafe equipment. Alternatively, if the demand increase is permanent, the firm may make additional investments in safety over time to reduce accident costs, or it may invest in general capital equipment that is safer. These investments will be made at a rate that maximizes profits given adjustment costs (see Viscusi, 1979, for a partial adjustment model of safety investments).

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[1] The legislation is the Comprehensive Occupational Safety and Health Reform Act (H.R. 1280 and S. 575). Currently, establishment injury microdata collected by the U.S. Bureau of Labor Statistics are not given to OSHA because of confidentiality concerns.

[2] Some of these questions ask: Is the goal of an inspection to detect violations of safety standards, to detect generally unsafe working conditions, to educate high-risk employers about safety, or to create an incentive for safety investments through a general deterrence effect? If the purpose of an inspection is to detect either violations or generally unsafe working conditions, to what extent does an observed high injury rate correlate with violations or correctable unsafe conditions? (see Gray, 1988). If the purpose of an inspection is to educate firms on safety, to what extent are high-risk establishments run by managers who could benefit from this education?

Thus, to determine whether an inspection is warranted upon observing a high injury rate, one must determine whether and how fast the injury rate falls and to what level it settles. The longer it takes for the rate to decline and the higher the ultimate rate to which it falls, the more warranted is an inspection and the more useful is establishment injury microdata for inspection targeting.

Some previous empirical work bears on the subject of injury persistence. A number of studies of establishment microdata, including Hunt (1993), McCaffrey (1983), Ruser and Smith (1988, 1991), and Smith (1979), add a lagged dependent variable into an injury regression and show that this variable is strongly statistically significant. Similar results have been found in industry aggregate data (Viscusi, 1979, 1986). Hunt (1993), in particular, stresses the improved predictive performance of regressions that include a lagged dependent variable. Some of the research (McCaffrey, 1983; Ruser and Smith, 1991; Smith, 1979) also finds that the coefficient on the lagged dependent variable increases toward one with establishment size, suggesting greater persistence in larger establishments. Finally, in research that is most similar to this article, Scholz and Gray (1990) examine the intertemporal correlation of injury rate changes by estimating an autoregressive error structure for injury rate change residuals. Below, I make a detailed comparison of the Scholz and Gray findings with those presented here.

Identifying Especially Risky Establishments

This article takes a different view from the previous literature by focusing on the injury-rate behavior of establishments identified as being especially risky over a period of time. Previous work studied the persistence of injury rates among all establishments or inspected establishments, including many that had zero or low injury rates. But it is high-risk establishments that would be the focus of OSHA inspections, if establishment-specific data were available. These establishments should be studied by themselves, since their injury rate behavior could be quite different from that of all other establishments.

How would one identify an establishment that is especially risky and that is a candidate for an OSHA inspection? One approach would be simply to rank all establishments according to their injury rates and to inspect the worst first. This is a naive strategy that conceivably would lead relatively safe establishments in risky industries to be inspected before relatively risky establishments in safe industries. This shortcoming could be addressed by ranking establishments within industries and then inspecting the worst in each industry. Deciding which to inspect would require decisions about which industries to target and how far down each ranking to go.

This modified targeting strategy still does not utilize all available establishment-specific information. Establishments could be risky for a variety of observable reasons that are not of interest to OSHA. A more sophisticated strategy would determine the typical injury rate for an establishment with given observable characteristics, such as industry, employment size class, occupational distribution, and possibly other factors. The injury rate of any given establishment could then be compared against the rate for a typical establishment with the same characteristics to determine whether the establishment in question is a "bad actor" that should be inspected.

A potential criticism of this strategy is that bad actors are identified with respect to a group of establishments, whereas possibly all members of that group are bad actors. But if this is the case, then plant-specific injury data are not needed to target inspections, as the observable characteristics used to define the group signal an inspection.

A More Sophisticated Targeting Strategy

A sophisticated targeting strategy utilizes both establishment-specific injury rates and additional observable plant information. Establishments are targeted that have either certain observed covariate values or injury rates that are higher than expected. To identify the latter group, one could estimate a model for establishment injury rates based on the observed covariates and then use the residuals to target inspections. In such a scheme, the marginal value of establishment injury data comes from identifying plants that have high injury rates that are unexplained by the available covariates. The value of establishment injury data is greater when there is greater persistence in the unexplained component of injury rates.

In this article, I assume that a sophisticated inspection targeting strategy will be followed. Using the logic of the preceding paragraph, the targeting value of injury microdata is assessed indirectly by measuring the amount of persistence in the component of injury rates that cannot be explained by observed covariates. I utilize a panel of manufacturing establishment microdata for 1979 through 1984 to estimate injury rate regressions (not including a lagged dependent variable) to control for variations in injuries that can be explained by observed covariates.[3] The regression estimates are used to predict each establishment's expected injury rate for each year. The differences between the observed and predicted injury rates are then calculated. These residuals are the unexplained components of injury rates that are analyzed for evidence of persistence.

With each residual, I associate a p-value for the test that the residual is positive, that is, that the injury rate exceeds its expected value. I then focus on the behavior over time of the residuals for two groups of establishments: those with p-values less than 0.10 early in the panel and those with p-values less than 0.25 but greater than or equal to 0.10 early in the panel. The mean residuals of both groups tend to decline even in the absence of inspections, and a declining fraction of the residuals remains statistically significant. The declines are especially notable for establishments with fewer than 500 workers. The findings are consistent with regression to the mean, with a partial adjustment

[3] Unlike previous studies, I do not include a lagged dependent variable in the regressions. If I did so, then an unexplained high injury rate for a plant is defined only as high relative to the plant's previous level, not relative to a group of plants with the same characteristics.

model of capital investment, and with the unobserved causes of the high residuals being temporary but correlated over time.

For establishments with p-values less than 0.10 in 1979, the mean residuals are statistically significant even in the long run. But for plants with fewer than 500 workers, the 1984 means are at most one-third of the initial mean levels. Further, for establishments with fewer than 500 workers, less than 50 percent of the residuals that were significant at the 10 percent level in 1979 remain so after only two years.

There is somewhat more evidence of persistence for plants with 500 or more workers that have 1979 p-values less than 0.10. For these establishments, the 1984 mean residual is 50 percent of the 1979 mean. Further, 59 percent of the residuals that are statistically significant in 1979 are still significant in 1981. The text details many additional results, including those for establishments whose early residuals were between 0.10 and 0.25.

The findings of this article indicate that targeting with plant-level data will be most successful when the data are used soon after the reference period and for targeting larger establishments. Using multiple years of data will also improve the success of targeting.

Data and Estimating Equation

The data used in this study are quite similar to those in Ruser (1991). A panel of manufacturing establishment microdata from the Bureau of Labor Statistics (BLS) Annual Survey of Occupational Injuries and Illnesses was matched to other microdata from the BLS Current Employment Survey. The data span the period 1979 through 1984. Industry injury rates measured at the three- or four-digit SIC level and information regarding workers' compensation benefit laws were added. The resulting sample includes 15,690 observations for 2,615 plants. Details of the data set construction, as well as a discussion of its limitations, can be found in Ruser (1991).[4]

The variables used in the analysis and their sample statistics for four employment size classes are presented in Table 1. The injury rate measures the frequency of lost workday injuries per 100 full-time worker years. This injury category includes both injuries involving days away from work and those leading only to restrictions of work activity. It is the measure used by OSHA to target inspections.

Turning to covariates, two establishment-specific explanatory variables are included to capture variations in financial incentives. The wage is the average real weekly wage of production workers in the establishment, using the con-

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[4] In order to control as much as possible for industry effects, I felt that a highly disaggregated industry injury rate should be matched. Each observation was assigned its appropriate industry injury rate at the four-digit level. If this was not available, then the three-digit rate was matched. The establishment was deleted if neither a three- nor four-digit rate was available. Ruser (1991) controlled for industry only at the two-digit level (by means of dummy variables). As a result, the data set used for Ruser (1991) included observations for 173 more establishments.

Table 1
Sample Statistics for Four Employment Size Classes

	Number of Employees			
Variable	*Less than 100 (N = 2,160)*	*100-249 (N = 5,424)*	*250-499 (N = 4,158)*	*500 or More (N = 3,948)*
Lost Workday Cases	5.68	12.77	21.58	53.63
	(6.02)	(12.55)	(20.87)	(85.49)
Hours ÷ 200,000	0.65	1.58	3.38	14.53
	(0.27)	(0.54)	(1.00)	(25.72)
Lost Workday Case Rate	8.91	8.17	6.51	4.62
	(8.76)	(7.48)	(6.05)	(4.94)
Industry Lost Workday Case Rate	7.15	6.70	5.85	4.91
	(2.55)	(2.57)	(2.53)	(2.69)
Log(Hours ÷ 200,000)	-0.53	0.40	1.17	2.31
	(0.49)	(0.35)	(0.31)	(0.71)
Log(Industry Injury Rate)	1.90	1.82	1.66	1.45
	(0.38)	(0.43)	(0.50)	(0.54)
Workers' Compensation Benefit	1.27	1.29	1.31	1.45
(÷ 100)	(0.33)	(0.31)	(0.33)	(0.38)
Weekly Wage (÷ 100)	2.29	2.33	2.39	2.84
	(0.85)	(0.76)	(0.82)	(0.90)
$\text{Employment}_t \div \text{Employment}_{t-1}$	1.003	1.007	1.010	1.001
	(0.15)	(0.16)	(0.16)	(0.13)
Percentage of Production Workers	0.77	0.76	0.74	0.70
	(0.17)	(0.15)	(0.18)	(0.19)
Percentage of Female Workers	0.20	0.26	0.34	0.29
	(0.19)	(0.22)	(0.24)	(0.21)
Weekly Overtime Hours	3.17	2.96	2.96	3.11
	(2.85)	(2.45)	(2.49)	(2.28)

Note: Standard errors are in parentheses.

sumer price index as the deflator. The workers' compensation variable measures the average real weekly income benefit paid to a production worker who suffers a total temporary disability. It is calculated using the nominal weekly production worker wage for each establishment, the state laws regarding benefit payments, and a technique employed by the National Council on Compensation Insurance (NCCI). The wage and workers' compensation benefit variables represent, respectively, a cost and a benefit of an injury to the worker, while the workers' compensation benefit is a cost to the firm.

Two variables capture the characteristics of each establishment's workforce: the percentage of production workers and the percentage of female workers. Production work is more risky than nonproduction work, and women tend to hold safer jobs. These variables should be positively and negatively related to injuries, respectively.

Two variables proxy for plant-specific demand-related factors that affect injury rates. These are the change in employment and the weekly hours worked overtime by production workers. An increase in employment should be associated with an increase in less-experienced, more injury-prone workers, while an increase in overtime should increase worker fatigue. These variables might proxy for other demand-related variables such as line speed. Consequently, these two variables are expected to be positively associated with injuries. Time dummy variables are used to capture time-related effects common to all establishments.

Finally, two other explanatory variables included in the analysis are establishment size and the injury rate of each establishment's industry. For a more detailed discussion of the variables, see Ruser (1991).

The first step in the analysis incorporates an estimating equation approach of Liang and Zeger (1986) to estimate nonlinear models of injury rates. The approach is closely related to quasi-likelihood estimation. Previous empirical work with these data (Ruser, 1991) suggested that maximum likelihood estimation based on the negative binomial distribution was appropriate. However, as shown by the empirical work below, the intertemporal within-establishment residuals are correlated. Efficiency of the parameter estimates can be improved by accounting for this autocorrelation using the Liang and Zeger approach.

Let y_{it} be the number of injuries in establishment i in time t, let $Y_i = (y_{i1},\ldots, y_{iT})'$ be a T x 1 vector of injury counts for i, and let $X_i = (x_{i1},\ldots, x_{iT})'$ be a T x p matrix of covariates for i (i = 1,..., K). I assume that

$$E(y_{it}) = \exp(x_{it}/\beta), \text{ and} \tag{1}$$

$$\mathrm{var}(y_{it}) = \exp(x_{it}/\beta)/\phi_t. \tag{2}$$

The parameterization of the expected value in equation (1) differs from Ruser (1991) in that, here, the measure of worker-exposure hours H_{it} (hours/200,000) appears as an explanatory variable in log form, rather than outside the exponential function. This yields a slightly more flexible relationship between exposure and the count of injuries. In equation (2), I extend Liang and Zeger (1986) to permit a time varying scale parameter ϕ_t. The variance can either exceed or fall short of the mean depending on the value of this parameter. The relationship between the mean and variance is the same as the one in the negative binomial model that Cameron and Trivedi (1986) call Negbin I.

Let $\Delta = \mathrm{diag}\{\phi_t\}$ be a T x T matrix, let $S_i = Y_i - E(Y_i)$ be a T x 1 vector of residuals, let $A_i = \mathrm{diag}\{\exp(x'_{it}\beta)/\phi_t\}$ be a T x T diagonal matrix with the variances of y_{it} along the diagonal, let $\Phi = (\phi_1,\ldots, \phi_T)'$, and let $D_i = A_i\Delta X_i$. Further, let $R(\alpha)$ be a T x T symmetric matrix that fulfills the requirements to be a correlation matrix, where α is an s x 1 matrix that fully characterizes $R(\alpha)$. Then, define

$$V_i = A_i^{1/2} R(\alpha) A_i^{1/2}. \tag{3}$$

V_i will equal $\mathrm{cov}(Y_i)$ if $R(\alpha)$ is the true correlation matrix for Y_i.

Given this notation, define a set of estimating equations as

$$\sum_{i=1}^{K} D_i' V_i^{-1} S_i = 0. \tag{4}$$

These p equations can be thought of as the score equations associated with maximizing a quasi-likelihood function. They implicitly define values of the parameters β given values for α and Φ. Now, let $\hat{\alpha}(Y,\beta,\Phi)$ be a $K^{1/2}$-consistent estimator of α when β and Φ are known, and let $\hat{\Phi}(Y,\beta)$ be a $K^{1/2}$-consistent estimator of Φ when β is known. Then, if we substitute these estimators for α and Φ back into equation (4), the equation becomes a function of β only. Let $\hat{\beta}_G$ be the solution to this equation. Liang and Zeger (1986) show (for time invariant ϕ) that $K^{1/2}(\hat{\beta}_G - \beta)$ is asymptotically multivariate normal with zero mean and covariance matrix V_G given by

$$V_G = \lim_{K\to\infty} K \left(\sum_{i=1}^{K} D_i' V_i^{-1} D_i\right)^{-1} \left\{\sum_{i=1}^{K} D_i' V_i^{-1} \operatorname{cov}(Y_i) V_i^{-1} D_i\right\} \left(\sum_{i=1}^{K} D_i' V_i^{-1} D_i\right)^{-1}. \quad (5)$$

Liang and Zeger state that a variance estimate $\hat{V}_G$ of $\hat{\beta}_G$ can be obtained by replacing $\operatorname{cov}(Y_i)$ with $S_i S_i'$ and by replacing α, β, and Φ with their estimates in equation (5). Liang and Zeger also note that consistent estimates of $\hat{\beta}_G$ and $\hat{V}_G$ depend only on a correct specification of the mean, not on the correct choice of R.

In order to compute $\hat{\beta}_G$, Liang and Zeger propose iterating between a modified Fisher scoring for β and moment estimation of α and Φ. Given current estimates $\hat{\alpha}$ and $\hat{\Phi}$, a new value of $\hat{\beta}_G$ can be obtained from

$$\hat{\beta}_{j+1} = \hat{\beta}_j + \left\{\sum_{i=1}^{K} D_i'(\hat{\beta}_j)\tilde{V}_i^{-1}(\hat{\beta}_j)D_i(\hat{\beta}_j)\right\}^{-1} \left\{\sum_{i=1}^{K} D_i'(\hat{\beta}_j)\tilde{V}_i^{-1}(\hat{\beta}_j)S_i(\hat{\beta}_j)\right\}, \quad (6)$$

where $\tilde{V}_i(\beta) = V_i\,[\beta,\hat{\alpha}\{\beta,\hat{\phi}(\beta)\}]$.

As suggested by Liang and Zeger, ϕ_t is estimated by

$$\hat{\phi}_t^{-1} = \frac{1}{K}\sum_{i=1}^{K} \frac{y_{it}-\exp(x_{it}'\beta_G))^2}{\exp(x_{it}'\beta_G)}. \quad (7)$$ [5]

In order to obtain the most efficient estimator for β in this class, I let R be unrestricted (Liang and Zeger's example number 5), estimating it by

$$\frac{1}{K}\sum_{i=1}^{K} A_i^{-1/2} S_i S_i' A_i^{-1/2}. \quad (8)$$

Since R is the true correlation matrix, $V_i = \operatorname{cov}(Y_i)$, so that the covariance matrix is

[5] This estimator also appears in Cameron and Trivedi (1986), except that they correct for degrees of freedom.

$$V_G = \lim_{K\to\infty} \left\{ \sum_{i=1}^{K} D_i' \operatorname{cov}^{-1}(Y_i) D_i / K \right\}^{-1}. \tag{9}$$

For the parameterization I choose, this has the form of Cameron and Trivedi's (1986, p. 38) covariance matrix.

Once $\hat{\beta}_G$ is obtained, the injury rate for establishment i in time t is predicted as

$$\hat{r}_{it} = \exp\,(X_{it}/\hat{\beta}_G)\; /\; H_{it} \tag{10}$$

and the injury rate residual as

$$\hat{\varepsilon}_{it} = n_{it} \;/\; H_{it} - \hat{r}_{it}. \tag{11}$$

Letting $G_i = \text{diag}\{1/H_{it}\}$ be a T x T matrix, a first-order approximation to the variance of the vector of residuals for establishment i is

$$G_i\left(V_i - D_i\left(\sum_{i=1}^{K} D_i' V_i^{-1} D_i\right)^{-1} D_i'\right) G_i. \tag{12}$$

The $\hat{\varepsilon}_{it}$ are the focus of the analysis.

Parameter Estimates

Table 2 reports the parameter estimates for separate injury regressions (equation (1)) for four employment size classes.[6] The coefficients largely conform to expectations and with results of Ruser (1991). However, since that study did not estimate a separate regression for each establishment size class and since there are some differences in equation specifications and the estimating technique, some discussion of the table is warranted.

The two variables with the most explanatory power in the regressions are the log of hours and the log of the industry injury rate. As expected, both of these variables have positive and statistically significant coefficients. The coefficients for the log of hours do not vary in any systematic way across size classes. They are consistently less than one, indicating that a 1 percent increase in total hours worked is associated with a less than 1 percent increase in the number of injuries. This implies that, within each establishment size class, injury rates decline with size. The coefficient on the log of the industry injury rate is also always less than one, with a tendency to increase with establishment size.

[6] Estimates of R and ϕ_t are not reported due to space limitations. They are available from the author upon request.

Table 2
Injury Regression Parameter Estimates of $E(y_{it}) = \exp(x_{it}/\beta)$ for Four Employment Size Classes

	Number of Employees			
Variable	*Less than 100*	*100-249*	*250-499*	*500 or More*
Log(Hours ÷ 200,000)	0.87*	0.73*	0.60*	0.83*
	(0.06)	(0.04)	(0.04)	(0.02)
Log(Industry Injury Rate)	0.62*	0.65*	0.64*	0.72*
	(0.08)	(0.05)	(0.05)	(0.04)
Workers' Compensation Benefit[2] (÷ 10,000)	-0.38*	-0.19*	-0.33*	-0.34*
	(0.18)	(0.11)	(0.12)	(0.09)
Workers' Compensation Benefit (÷ 100)	1.33*	0.62*	0.92*	1.08*
	(0.53)	(0.32)	(0.36)	(0.29)
Weekly Wage (÷ 100)	-0.002	0.02	0.05	-0.02
	(0.06)	(0.04)	(0.04)	(0.03)
$\text{Employment}_t \div \text{Employment}_{t-1}$	0.33*	0.37*	0.42*	0.32*
	(0.10)	(0.04)	(0.05)	(0.05)
Percentage of Production Workers	0.35*	0.63*	0.62*	0.67*
	(0.19)	(0.12)	(0.13)	(0.13)
Percentage of Female Workers	-0.27	-0.30*	-0.51*	-0.68*
	(0.20)	(0.12)	(0.13)	(0.16)
Weekly Overtime Hours (÷ 10)	0.44	-0.28	0.04	0.10*
	(0.89)	(0.54)	(0.59)	(0.06)
	Benefit Injury-Rate Elasticities			
	0.43	0.15	0.05	0.24
	(0.69)	(0.42)	(0.46)	(0.36)

Note: Standard errors are in parentheses. Regressions also include an intercept and time dummy variables.

* Statistically significant at the 5 percent level (one-tailed test).

The coefficients for the squared workers' compensation benefits variable are negative and statistically significant, while the coefficients for the benefit variable itself are positive and significant. The magnitudes of these coefficients are more similar to the fixed effect negative binomial results in Ruser (1991) than to those for the nonfixed effect specification. The benefit injury rate elasticities derived from the coefficients reported at the bottom of Table 2 are somewhat smaller than those reported in Ruser (1991) for the nonfixed effect specification and none are statistically significant.[7] As in Ruser (1991), the elasticities tend to decline with establishment size, with the exception that here the elasticity for the largest establishments is larger than those for the two middle size classes.

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[7] The regressions here differ in several ways from those in Ruser (1991): This sample is slightly smaller, the log of hours is entered as a regressor, the industry injury rate rather than industry dummy variables controls for industry effects, the regressions are estimated separately for establishment size classes, and a different estimating technique is used. The elasticity estimates are somewhat sensitive to all of these factors.

The coefficients for the change in employment, the percentage of production workers, and the percentage of female workers variables have the correct signs and are generally statistically significant. The coefficients for the latter two variables increase with establishment size. The coefficients for the wage and weekly overtime hours variables generally are statistically insignificant.[8]

What is most important to note is that many of the explanatory variables, besides the establishment's hours worked and the industry injury rate, are statistically significant and are relatively large in magnitude. This indicates, of course, that these variables may explain why some establishments' rates are higher than others'. It demonstrates that an inspection targeting strategy should not rely solely on establishment injury rates, but also on the collection and proper use of injury covariate data.

Although these regression parameter estimates are of interest, the prime focus of this article is on persistence of the injury rate residuals for those establishments that are candidates for OSHA inspections. To identify these, I calculate the residuals and their variances according to equations (11) and (12). Candidates for inspections are those establishments that had positive residuals early in the panel that are statistically significant. The levels of significance chosen for this article—0.10 and 0.25—are admittedly arbitrary. They were chosen both to obtain those residuals most likely to be greater than zero and to ensure large enough samples for analysis. The significance level OSHA would use would depend upon the inspection resources available. However, the levels chosen here help focus attention on the groups of establishments most likely to include bad actors.

Graphical Analysis of Residuals

Figures 1 and 2 illustrate the central findings of this article. Figure 1 shows mean annual residuals for establishments whose 1979 residuals are positive and statistically significant at the 10 percent level (the residuals' p-values are less than 0.10). For each year from 1979 through 1984, there are separate bars for each of the four establishment size classes. Figure 2 contains similar information for establishments whose 1979 residuals are positive and statistically significant at the 25 percent level, but not at the 10 percent level (the residuals' p-values are between 0.25 and 0.10). As expected, the mean residual for a given year and establishment size is larger in Figure 1 than the corresponding mean residual in Figure 2.

For these establishments, the residuals tend to decline over time. However, the rates of decline seem to slow so that the long-run mean residuals appear to be above zero. For establishments with 1979 p-values below 0.10, the mean residuals cluster around five in 1984; for establishments with 1979 p-values

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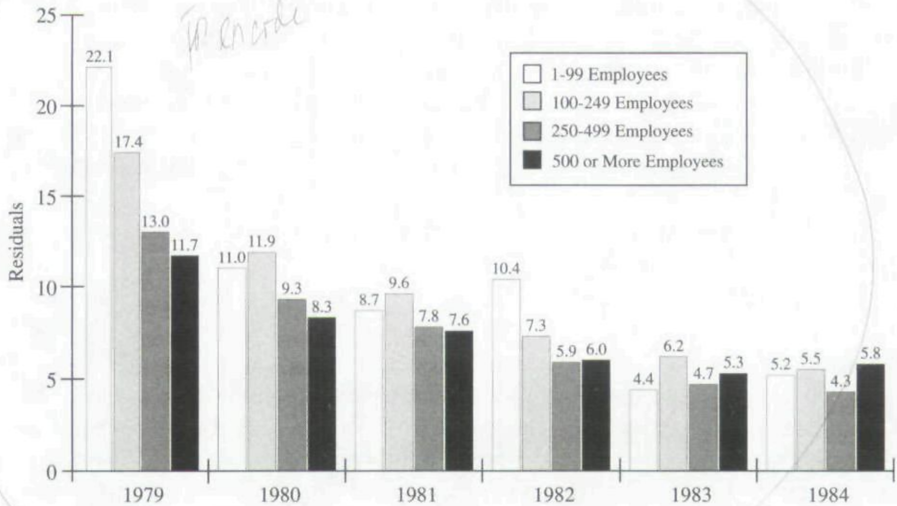
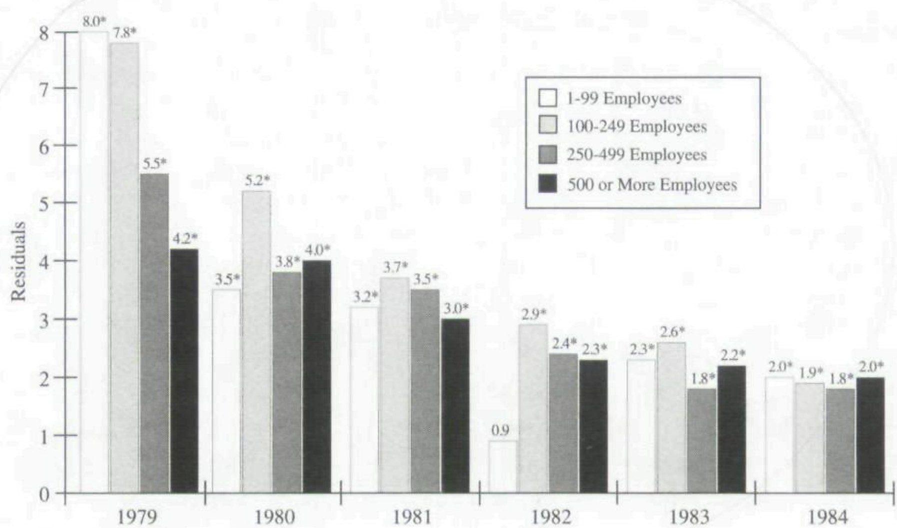
[8] Ideally, one would like to estimate simultaneous wage and injury rate equations. The wage equation should show that a higher wage is paid for more dangerous work. Unfortunately, I cannot estimate such a system with these data, because I lack variables with which to identify the system.

Figure 1
Annual Mean Residuals for Four Employment Size Classes:
Establishments with P-Values Less than 0.10 for 1979 Residuals



Note: All mean residuals are significant at the 5 percent level (one-tailed test).

Figure 2
Annual Mean Residuals for Four Employment Size Classes:
Establishments with P-Values Between 0.10 and 0.25 for 1979 Residuals



* Significant at the 5 percent level (one-tailed test).

between 0.10 and 0.25, they cluster around two. The close clustering of the means in 1984 is surprising given that the 1979 mean residuals are very different.

A number of hypotheses explain the observed declines in the mean residuals. Since safety capital is not observed directly and since the explanatory variables do not fully control for it, changes in that capital may affect the residuals. Also, unobserved investments in safer general capital equipment may also lead to gradual declines in the residuals. To the extent that this is the case, the profiles are consistent with a partial adjustment model for capital investment. The profiles are also consistent with the hypothesis that other factors that lead to unexplained higher rates, such as increases in demand, dissipate gradually. Importantly, the profiles are not consistent solely with the explanation that high injury rates are due to bad stochastic draws. If this were the case, the mean residuals would be zero in the years after 1979.

The greatest annual declines in injuries are between 1979 and 1980. This may occur because some of the establishments experienced bad luck in 1979 and their injury rates returned to expected values in 1980. These declines would be mixed in with the gradual declines of other plants. However, the continued declines after 1980 should be attributed to partial adjustment mechanisms or to temporarily persistent unobserved causes of injuries.

The profiles vary systematically across establishment sizes. It was shown in Ruser (1985) that the variances of errors in an injury rate equation are negatively related to establishment size. As is well known, the injury rate of a larger establishment can be measured with greater precision. In Figures 1 and 2, this is reflected in the larger mean residuals for smaller establishments in 1979. Since the mean residuals cluster together by 1984 in each figure, this implies that the declines are greater for smaller establishments.

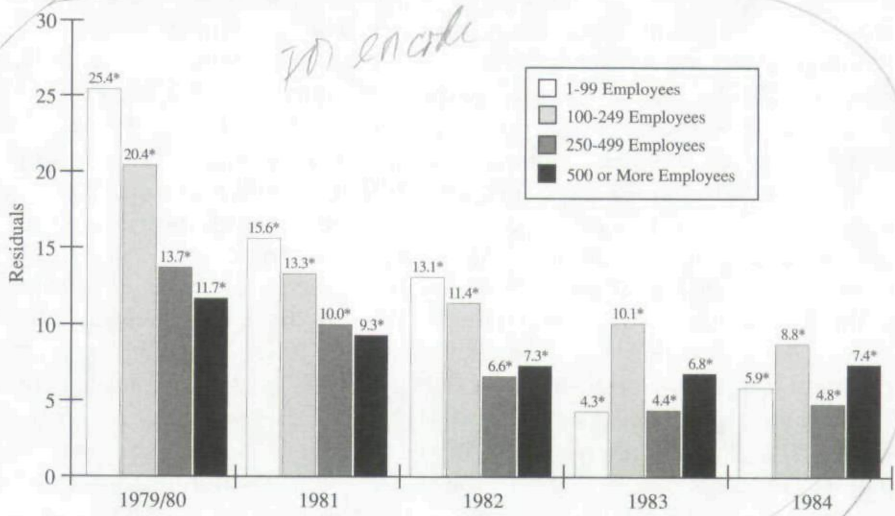
The declines in the means over the time period are relatively large, especially for smaller plants. To show this in relative terms, Table 3 presents the ratios of the means in each year to the 1979 mean. For any given year, the ratios generally increase with establishment size, indicating greater persistence in the residuals in larger plants. However, the declines are relatively large for all size classes. By 1982, the ratios exceed 50 percent only for the 500 or more employees size class, and, by 1984, the ratios are 0.33 or less for the three smallest size classes. Only in the 500 or more employees category are the ratios at or near 50 percent in 1984.

The sample exclusions underlying Figures 1 and 2 and Table 3 are based only on p-values in a single year. Next, the possibility is investigated that either the degree of persistence or the level to which the residuals decline is greater for establishments with statistically significant positive residuals in multiple years. The mean residuals for establishments whose residuals have p-values of less than 0.10 for both 1979 and 1980 are shown in Figure 3. Figure 4 shows the mean residuals for those plants with 1979 p-values between 0.10 and 0.25 and with 1980 p-values less than 0.25.

Table 3
Ratio of 1980 Through 1984 Mean Residuals to 1979 Mean Residual

	1980	*1981*	*1982*	*1983*	*1984*
1979 Residuals with P-Values Less than 0.10					
1-99 Employees	0.50	0.39	0.47	0.20	0.24
100-249 Employees	0.68	0.55	0.42	0.36	0.32
250-499 Employees	0.72	0.60	0.45	0.36	0.33
500 or More Employees	0.71	0.65	0.51	0.45	0.50
1979 Residuals with P-Values Between 0.10 and 0.25					
1-99 Employees	0.44	0.40	0.11	0.29	0.25
100-249 Employees	0.67	0.47	0.37	0.33	0.24
250-499 Employees	0.69	0.64	0.44	0.33	0.33
500 or More Employees	0.95	0.71	0.55	0.52	0.48

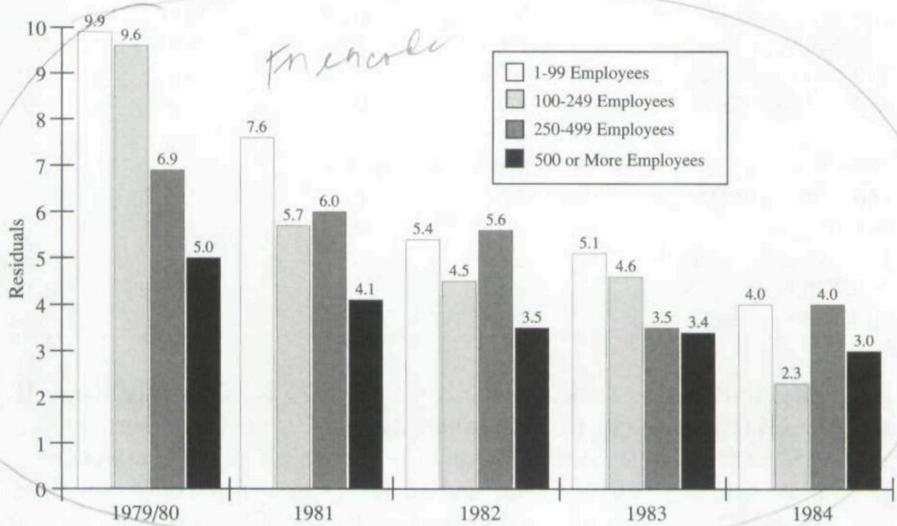
Figure 3
Mean Residuals for Four Employment Size Classes:
Establishments with P-Values Less than 0.10 for 1979 and 1980 Residuals



* Significant at the 5 percent level (one-tailed test).

Figures 3 and 4 continue to display the marked declining pattern of residuals that appears in Figures 1 and 2. However, as expected, the means tend to be larger in Figures 3 and 4 than their counterparts in the previous figures. To make valid comparisons, the 1979 means of Figures 1 and 2 should be compared with the 1979/1980 means of Figures 3 and 4, the means for 1980 in the earlier figures should be compared to the means for 1981 in the later figures, and so on. At the end of the time period, the means in Figures 3 and 4 have not declined to levels as low as those in Figures 1 and 2.

Figure 4
Mean Residuals for Four Employment Size Classes:
Establishments with P-Values Between 0.10 and 0.25 for 1979 Residuals
and Less than 0.25 for 1980 Residuals



Note: All mean residuals are significant at the 5 percent level (one-tailed test).

Table 4 contains the ratios of the future years' mean residuals to the 1979/1980 means. A comparison of this table with Table 3 suggests that there may be greater persistence of high residuals when multiple years of data are used to select establishments.[9] The data presented in Table 4 indicate, however, that within four years, the mean residuals for the two classes of smallest establishments declined to less than 50 percent of the 1979/1980 average. Although persistence does not increase monotonically with size (possibly due to small sample sizes), there is still evidence of less persistence in smaller establishments.

First-Order Autoregressions

The above analysis focuses on a relatively short time period after the sample selection years. It might be inferred that the mean residuals will continue to decline beyond the observed time period. This section presents the estimates of first-order autoregressions that are used to derive long-run levels for the mean residuals.

Table 5 presents the results of estimating first-order autoregressions for the residuals of establishments whose 1979 residuals have p-values less than 0.25.

[9] The 1981 column in Table 4 should be compared with the 1980 column in Table 3, etc.

Table 4
Ratio of 1981 Through 1984 Mean Residuals to 1979/1980 Mean Residual

	1981	*1982*	*1983*	*1984*
1979 and 1980 Residuals with P-Values Less than 0.10				
1-99 Employees	0.61	0.52	0.17	0.23
100-249 Employees	0.65	0.56	0.50	0.43
250-499 Employees	0.73	0.48	0.32	0.35
500 or More Employees	0.79	0.62	0.58	0.63
1979 Residuals with P-Values Between 0.10 and 0.25 and 1980 Residuals with P-Values Less than 0.25				
1-99 Employees	0.77	0.55	0.52	0.40
100-249 Employees	0.59	0.47	0.48	0.24
250-499 Employees	0.87	0.81	0.51	0.58
500 or More Employees	0.82	0.70	0.68	0.60

Panel A reports results for establishments with 1979 p-values less than 0.10, and Panel B reports results for establishments with 1979 p-values between 0.10 and 0.25. Each establishment contributed five observations to a regression: a 1979/1980 pair, a 1980/1981 pair, and so on up to a 1983/1984 pair. Even though the 1979 to 1984 time period is short, the regressions borrow strength by estimating across establishments. The table presents the coefficient estimates, the steady state values, the ratio of the steady state to the 1979 mean residual, and the time for convergence from 50 percent to only 5 percent above the steady state value. This latter convergence measure is somewhat arbitrary, of course, as it depends on the initial and final levels chosen. It is included to allow comparisons of relative convergence times across establishment size classes, rather than to determine absolute levels for these convergence times.

Let the regression equation for Table 5 be

$$\varepsilon_{it} = a + b\varepsilon_{it-1} + u_{it}, \tag{13}$$

where ε_{it} is the residual of plant i in time t, and u_{it} is a random error. The steady state value is that value such that, in the absence of any shocks u_{it}, the rate remains constant over time; that is,

$$s = a + bs. \tag{14}$$

The steady state is then

$$s = \frac{a}{1-b}. \tag{15}$$

The method described in Barkume and Ruser (1992) is used to calculate the convergence times in Tables 5, 6, and 7.[10] The time path (solution) to equation (13) in the absence of any random errors u_{it} is

[10] This method is due to Barkume.

Table 5
First-Order Autoregression Estimates for Establishments with Residuals' P-Values Less than 0.25 in 1979

Establishment Size	*N*	*Constant*	ε_{t-1}	R^2	*Steady State*	*Ratio of Steady State to 1979 Mean*	*Convergence Time*
Panel A: 1979 Residuals with P-Values Less than 0.10							
All Establishments	1,215	1.81	0.58*	0.42	4.34*	0.28	4.3
		(0.27)	(0.02)		(0.52)		
1-99 Employees	170	3.66	0.38*	0.20	5.87*	0.27	2.4
		(0.94)	(0.06)		(1.20)		
100-249 Employees	415	1.47	0.63*	0.50	4.00*	0.23	5.0
		(0.49)	(0.03)		(1.12)		
250-499 Employees	340	1.64	0.58*	0.35	3.95*	0.30	4.3
		(0.49)	(0.04)		(0.91)		
500 or More Employees	290	0.69	0.76*	0.62	2.87*	0.25	8.3
		(0.37)	(0.03)		(1.24)		
Panel B: 1979 Residuals with P-Values Between 0.10 and 0.25							
All Establishments	1,130	0.56	0.62*	0.35	1.45*	0.23	4.8
		(0.16)	(0.03)		(0.37)		
1-99 Employees	130	0.28	0.59*	0.32	0.68	0.09	4.4
		(0.61)	(0.08)		(1.43)		
100-249 Employees	385	0.59	0.60*	0.33	1.47*	0.19	4.5
		(0.32)	(0.04)		(0.71)		
250-499 Employees	325	0.46	0.65*	0.37	1.32	0.24	5.3
		(0.27)	(0.05)		(0.68)		
500 or More Employees	290	0.52	0.70*	0.41	1.71*	0.41	6.4
		(0.22)	(0.05)		(0.55)		

Note: Standard errors are in parentheses.
* Significant at the 5 percent level (one-tailed test).

$$\varepsilon_{it} = (\varepsilon_{i0}-s)b^t + s, \tag{16}$$

where ε_{i0} is the initial value of ε_{it}. Then, given the time path (16), one can solve for the value of t for which ε_{it} traverses from $(1+\lambda)s$ as the initial condition to $(1+\delta)s$. To do this, use equation (16), substituting $(1+\lambda)s$ for ε_{i0} and $(1+\delta)s$ for ε_{it}; or,

$$(1+\delta)s = [(1+\lambda)s-s]b^t+s. \tag{17}$$

Canceling out s and taking logarithms of both sides, the time for convergence to $(1+\delta)s$ is

$$t_c = (\ln\delta-\ln\lambda)/\ln b. \tag{18}$$

The convergence times in Tables 5, 6, and 7 are derived by letting $\lambda = 0.5$ and $\delta = 0.05$. The numerator and denominator are both negative in equation (18), so that a value of b closer to one implies a larger value of t_c and more persistence in rates.

Turning to Panel A of Table 5, for all establishments pooled, the autoregression implies a steady state residual of 4.34, with a convergence time of 4.3 years. This steady state, which is only 28 percent of the 1979 mean residual, seems very plausible in light of Figure 1.

Looking across establishment size classes in Panel A, the coefficients on the lagged residuals and the R^2s generally increase with size, suggesting greater injury persistence in larger establishments. This is similar to the results in Ruser and Smith (1991) and other research that used a lagged dependent variable. The convergence times also generally increase with size, again consistent with greater injury persistence with size. However, the implied steady state residual is highest at 5.9 for establishments with 1 to 99 workers and it is lowest at 2.9 for establishments with 500 or more workers. Hence, in large plants, while it takes longer for the residuals to approach a steady state, they eventually approach a steady state that is closer to zero. All of the steady state values are 30 percent or less of the 1979 mean residuals. This indicates that, in the long run, there is a large drop in the residuals from their initial high levels. The especially short convergence time for establishments with fewer than 100 workers raises special doubts about the value of single-year microdata for targeting small plants.

Panel B of Table 5 replicates the analysis for establishments whose 1979 residuals have p-values between 0.10 and 0.25. As in Panel A, the coefficient on the lagged residuals and the R^2s rise with establishment size. The convergence times also rise with establishment size, though they are more similar across size classes than those in Panel A.

As expected, the steady state values are much smaller for establishments whose 1979 residual's p-values are between 0.10 and 0.25, and they are statistically significant for only two of the four employment size classes. The steady state values themselves do not vary in a systematic way by size; however, the ratio of the steady state to the 1979 mean residual increases with size. For establishments with fewer than 100 workers, the steady state is less than 10 percent of the 1979 mean residual, while it is over 40 percent for those plants that have 500 or more workers. This evidence again suggests that single-year site-specific data may be most useful for targeting inspections in larger establishments.

The sample exclusions in Table 5 are based on p-values for a single year. As in the previous section, I next investigate the possibility that either the degree of injury persistence or the steady state is greater for establishments with statistically significant positive residuals in multiple years. Table 6 reports the results of first-order autoregressions estimated for establishments with statistically significant residuals in 1979 and 1980. Panel A restricts the sample to establishments whose residuals have p-values less than 0.10 in both 1979 and 1980. Panel B includes those with 1979 p-values between 0.10 and 0.25 and with 1980 p-values less than 0.25.

The principal difference between this table and the previous one is in the steady state values. For all establishments pooled, in both panels, the steady state values are higher in Table 6 by about one injury per hundred workers. This result reinforces the evidence of the previous section and is consistent with the expectation that establishments that are unusually risky for two years

Table 6

First-Order Autoregression Estimates for Establishments with Residuals' P-Values Less than 0.25 in 1979 and 1980

Establishment Size	*N*	*Constant*	ε_{t-1}	R^2	*Steady State*	*Ratio of Steady State to 1979/1980 Mean*	*Convergence Time*
Panel A: 1979 and 1980 Residuals with P-Values Less than 0.10							
All Establishments	516	2.21	0.59*	0.41	5.37*	0.33	4.3
		(0.46)	(0.03)		(0.87)		
1-99 Employees	48	4.44	0.38*	0.18	7.11*	0.28	2.4
		(2.17)	(0.12)		(2.60)		
100-249 Employees	168	3.20	0.57*	0.40	7.39*	0.36	4.1
		(0.99)	(0.05)		(1.72)		
250-499 Employees	156	1.58	0.56*	0.33	3.59*	0.26	4.0
		(0.77)	(0.06)		(1.41)		
500 or More Employees	144	0.29	0.86*	0.73	2.00	0.17	14.7
		(0.49)	(0.04)		(2.92)		
Panel B: 1979 Residuals with P-Values Between 0.10 and 0.25 and 1980 Residuals with P-Values Less than 0.25							
All Establishments	444	1.04	0.58*	0.37	2.46*	0.33	4.2
		(0.28)	(0.04)		(0.53)		
1-99 Employees	44	1.20	0.59*	0.38	2.90	0.29	4.3
		(1.22)	(0.12)		(2.44)		
100-249 Employees	148	0.93	0.53*	0.31	1.98	0.21	3.6
		(0.58)	(0.06)		(1.05)		
250-499 Employees	108	1.09	0.64*	0.45	3.02*	0.44	5.1
		(0.55)	(0.07)		(1.16)		
500 or More Employees	144	0.80	0.65*	0.42	2.26*	0.45	5.3
		(0.33)	(0.06)		(0.66)		

Note: Standard errors are in parentheses.

* Significant at the 5 percent level (one-tailed test).

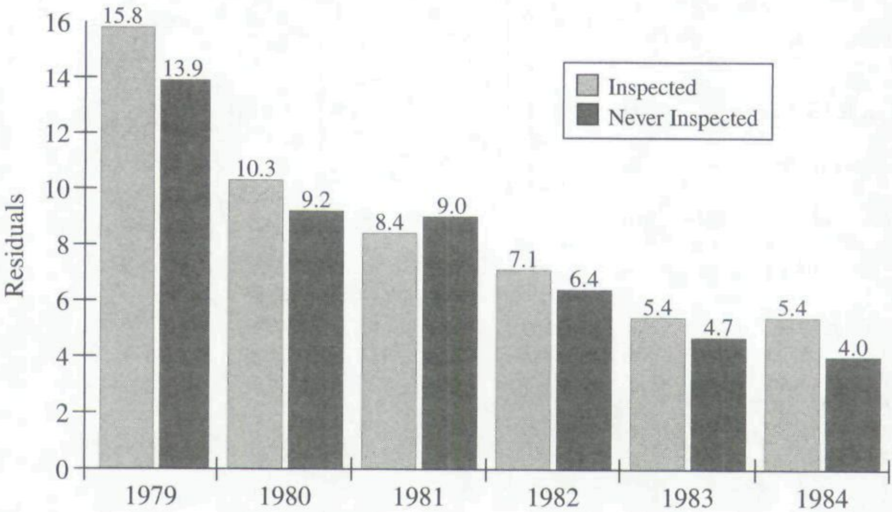
will tend in the long run to be riskier than those that are unusually risky for only one year. For establishments with 1979 p-values between 0.10 and 0.25, the ratios of the steady states to the 1979/1980 mean residuals are also higher in Table 6 than in Table 5. Note, however, that these ratios still imply a relatively large long-run drop from the initial 1979 level.

In Panel A, the higher steady state values appear only in the two smallest size classes. Surprisingly, they are lower in Table 6 than in Table 5 for the largest two size classes. This may be simply a statistical anomaly. In contrast, all of the steady states are higher in Panel B, as expected.

Many of the other results suggested by the data in Table 5 also appear in Table 6. The coefficients on the lagged residual, the R^2s, and the convergence times all increase with size in Panel A (though not in Panel B). More importantly, the convergence times are all relatively similar in magnitude between the two tables, with one exception.

Figure 5

Annual Mean Residuals for Establishments that Were and Were Not Inspected with P-Values Less than 0.10 for 1979 Residuals



Note: All mean residuals are significant at the 5 percent level (one-tailed test).

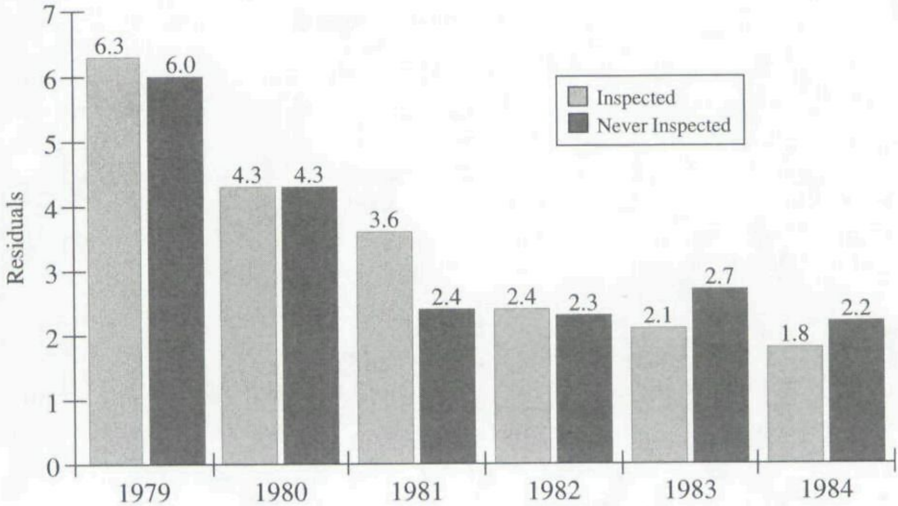
The Role of OSHA Inspections

The data indicate that the unexplained components of high injury rates tend to decline over time, attaining long-run levels that, for the establishments with low p-values, are less than one-third of initial levels. I have not addressed the issue of whether the observed declines are due to OSHA inspections. There is a variable in the data set that indicates the month of an inspection each year, if there was one. To see if the behavior of the residuals is due to OSHA inspections, I split the sample into those establishments that were and were not inspected in any of the years from 1979 to 1984. Figure 5 graphs the annual means of the residuals for establishments whose 1979 residuals had p-values less than 0.10, contrasting those plants that were and were not inspected in the 1979 through 1984 period. Figure 6 graphs the same means for those establishments with 1979 p-values between 0.10 and 0.25. The decline in injury rates is not a phenomenon associated only with establishments inspected by OSHA. The residuals for both inspected and never inspected establishments tend to decline together.

Table 7 presents some regression evidence on this point. Here estimates of first-order autoregressions for establishments that were inspected in the 1979 through 1984 period are contrasted with estimates for those establishments never inspected in the period. The restrictions imposed on the significance of the 1979 residuals are as before. The time series processes implied by these

Figure 6

Annual Mean Residuals for Establishments that Were and Were Not Inspected with P-Values Between 0.10 and 0.25 for 1979 Residuals



Note: All mean residuals are significant at the 5 percent level (one-tailed test).

Table 7

First-Order Autoregression Estimates for Establishments with High 1979 Residuals that Were and Were Not Inspected During 1979 Through 1984

Establishment Size	*N*	*Constant*	ε_{t-1}	R^2	*Steady State*	*Ratio of Steady State to 1979 Mean*	*Convergence Time*
Panel A: 1979 Residuals with P-Values Less than 0.10							
Never Inspected	170	2.16	0.52*	0.33	4.50*	0.32	3.5
		(0.75)	(0.06)		(1.26)		
Inspected	1,045	1.74	0.59*	0.43	4.30*	0.27	4.4
		(0.28)	(0.02)		(0.57)		
Panel B: 1979 Residuals with P-Values Between 0.10 and 0.25							
Never Inspected	210	0.73	0.58*	0.32	1.73*	0.29	4.2
		(0.35)	(0.06)		(0.72)		
Inspected	920	0.52	0.62*	0.35	1.39*	0.22	4.9
		(0.18)	(0.03)		(0.42)		

Note: Standard errors are in parentheses.

* Significant at the 5 percent level (one-tailed test).

estimates indicate that similar steady state values are approached for both inspected and uninspected plants, though the values for the never-inspected establishments are slightly higher. The steady states are all less than one-third of the 1979 means, supportive of relatively large long-run declines regardless of inspection status. Convergence times tend to be shorter for establishments never inspected.

Statistical Significance over Time

The previous sections have focused on the means of residuals of potentially bad actors. Another way to assess the usefulness of injury rates for targeting purposes is to determine what fraction of establishments that were bad actors in 1979 continue to have positive and statistically significant residuals over time. The larger this fraction is, the greater the value of establishment-specific data for targeting. Table 8 reports the results of such an exercise using 0.10 and 0.25 levels of significance (see Panels A and B, respectively).

Table 8
Percentage of Establishments with Positive Residuals
Remaining Statistically Significant Over Time

Number of Employees	*1980*	*1981*	*1982*	*1983*	*1984*
Panel A: Percentage of Establishments with P-Values Less than 0.10 Among Establishments with P-Values Less than 0.10 in 1979					
1-99 (N = 34)	35	44	47	17	29
100-249 (N = 83)	51	49	31	36	36
250-499 (N = 68)	57	44	43	32	31
500 or More (N = 58)	62	59	50	47	43
Panel B: Percentage of Establishments with P-Values Less than 0.25 Among Establishments with P-Values Less than 0.25 in 1979					
1-99 (N = 60)	55	60	47	42	45
100-249 (N = 160)	62	55	44	43	41
250-499 (N = 133)	62	51	51	43	34
500 or More (N = 116)	72	66	59	52	52

Two patterns are shared by Panels A and B. First, and most importantly, the percentages tend to decline over time for any given establishment size class. This is least apparent for the under-100-employees size class, for which there are small sample problems. Second, the percentages increase monotonically with establishment size in 1980, with the monotonicity largely disappearing after 1980. But, for each year, establishments with 500 or more employees have the largest fraction of statistically significant residuals.

The data presented in Panel A suggest that, for any given year, a sizable fraction of small plants no longer have statistically significant residuals. Only about one-third of establishments with fewer than 100 workers continue to have significant residuals in 1980, while the fraction is only one-half for the 100-to-249-employees category. By 1982, less than 50 percent of all establishments have significant residuals, and by 1984 the fraction is down to about one-third for all but the largest size class.

The percentages are higher in Panel B since the test for statistical significance is less stringent. However, at least one-third of establishments with fewer than 500 workers no longer have statistically significant residuals in 1980, and the fraction is more than 50 percent for these establishments by 1982. By 1983, even the largest size class has a fraction close to 50 percent.

Reconciliation with Scholz and Gray

The results presented thus far are consistent with a partial adjustment mechanism for capital and with temporarily persistent causes of high injuries. Scholz and Gray (1990) proposed a "fire-fighting" model to explain evidence of self-correcting injury rates in their data. In this section, the empirical results of Scholz and Gray are shown to appear in my data, and their results are shown to be entirely consistent with a partial adjustment model of safety capital. I also argue that their fire-fighting model may or may not be consistent with my results.

Table 9
Reconciliation with Scholz and Gray

Variable	*Coefficient*	*T-Statistic*
Panel A: Scholz and Gray Autoregression		
One-Year Lag	-0.489	-49.8
Two-Year Lag	-0.316	-29.5
Three-Year Lag	-0.127	-9.8
Panel B: Estimates of Third-Order Autoregression, Changes in Errors ($\Delta\varepsilon_{it} = \alpha_1\Delta\varepsilon_{it-1} + \alpha_2\Delta\varepsilon_{it-2} + \alpha_3\Delta\varepsilon_{it-3} + u_{it}$)		
One-Year Lag ($\Delta\varepsilon_{it-1}$)	-0.441	-32.7
Two-Year Lag ($\Delta\varepsilon_{it-2}$)	-0.216	-15.3
Three-Year Lag ($\Delta\varepsilon_{it-3}$)	-0.045	-3.5
Panel C: Estimates of Fourth-Order Autoregression, Levels of Errors		
One-Year Lag (ε_{it-1})	0.437	31.6
Two-Year Lag (ε_{it-2})	0.164	10.9
Three-Year Lag (ε_{it-3})	0.130	8.7
Four-Year Lag (ε_{it-4})	0.017	1.4

Scholz and Gray estimate a *percent-change* injury equation on microdata for 6,842 establishments for the period 1979 through 1985. They estimate a third-order autoregressive process for the errors of this equation, obtaining negative coefficients on all of the lags. The coefficients decline in absolute value with the length of the lag. Scholz and Gray's results—interpreted as being consistent with a model of "putting out fires"—are reproduced in Panel A of Table 9. In this model,

> an unexpected increase in accidents will cause managers to pay more attention to safety. This should lead to a reduction in accidents in later years until the firm's attention turns back to other areas.... The implication is that surprising changes in the number of accidents over time should be negatively correlated, which implies that the error term in the equation estimating current risk should be negatively correlated with past error terms (p. 286).

To show that the Scholz and Gray finding is consistent with a partial adjustment model of safety capital, I first replicated their essential result in my data. Using the estimated residuals, ε_{it}, from my regressions (the ^ over ε is dropped in this section for convenience), the change in the residual, $\Delta\varepsilon_{it}$, is calculated for each observation in my data set (including those with negative residuals in any given year):

$$\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}. \tag{19}$$

The current year change for t = 1983 or 1984 is then regressed on three lags of the change; that is, I estimate

$$\Delta\varepsilon_{it} = \alpha_1\Delta\varepsilon_{it-1} + \alpha_2\Delta\varepsilon_{it-2} + \alpha_3\Delta\varepsilon_{it-3} + u_{it}. \tag{20}$$

The coefficient estimates for this regression appear in Panel B of Table 9. Qualitatively, these are the same results as Scholz and Gray, in that the coefficients are negative, statistically significant, and declining in absolute value with length of lag.

One can mathematically transform the change equation estimated into an equation of residuals:

$$(\varepsilon_{it}-\varepsilon_{it-1}) = -0.44(\varepsilon_{it-1}-\varepsilon_{it-2}) - 0.22(\varepsilon_{it-2}-\varepsilon_{it-3}) - 0.05(\varepsilon_{it-3}-\varepsilon_{it-4}),$$

or

$$\varepsilon_{it} = 0.56\varepsilon_{it-1} + 0.22\varepsilon_{it-2} + 0.17\varepsilon_{it-3} + 0.05\varepsilon_{it-4}. \tag{21}$$

Thus, the change equation can be written in nonchange form, yielding a declining pattern of positive coefficients.

With these same data, a fourth-order autoregression of the residuals is estimated; that is, I directly estimated an equation like (21). The estimates appear in Panel C of Table 9. The coefficients are similar qualitatively to those derived above from the change equation, though smaller in magnitude. The derivation in equation (21) from the change to nonchange form is plausible. Thus, I have shown that Scholz and Gray's results appear in my data.

How does a partial adjustment model account for the pattern of changes in the residuals observed here? Let K_t represent the actual safety stock and K^* be the desired stock. Assume that, due to a shock, the desired capital stock rises; that is, $K^* > K_t$, so that the firm will invest in more safety. In the partial adjustment model, investment I_t is a fraction λ of the divergence between actual and desired capital:

$$I_t = \lambda(K^*-K_t) \tag{22}$$

with $0 \leq \lambda \leq 1$. Equation (22) implies that

$$I_{t+1} = \lambda(K^*\text{-}K_t\text{-}\lambda(K^*\text{-}K_t)) = \lambda(1\text{-}\lambda)(K^*\text{-}K_t) \tag{23}$$

so that $I_{t+1} < I_t$. Thus, in this model, investments in safety decline as the capital stock approaches the desired level. If we assume that changes in safety are proportional to changes in the capital stock, this implies a decline in the change in safety, precisely what is observed by Scholz and Gray.

Whether my empirical findings and the partial adjustment model are consistent with the fire-fighting model depends on the assumptions supplied to the fire-fighting model. Suppose that, when managers give their attention to safety, they invest in either physical or human safety capital. As their attention wanes, they invest less in that capital. This is precisely what happens in a partial adjustment model. The data are completely consistent with such a fire-fighting model. But if the managers' attention is in the form of greater supervision effort (or something else that is not durable in nature), then one would not observe the pattern of residuals shown in Figure 1. Rather, one would see initially low residuals followed by increasing residuals caused by the loss of interest in safety. Such a fire-fighting model is inconsistent with my findings.

Conclusion

The evidence in this article suggests that injury rates that are high for reasons unexplained by observed covariates tend to decline over time even without inspections. The declines seem to be especially large and rapid for smaller establishments. However, the long-run residuals for even the largest establishments are small relative to initial values. The results suggest that inspection targeting with plant-specific injury data will be most successful for larger establishments and for inspections that occur soon after the data's reference period. Targeting with multiple years of data may also improve success.

I provide three explanations for the high residuals' declines. An initial drop may result from regression to the mean of the injury rates of plants that had experienced bad luck. However, the observed continuing gradual declines are explained by two other hypotheses. First, it is possible that investments, either in safety equipment or in safer general capital, are made according to a partial adjustment model. Since investments are not observed in these data, their effect on injuries appears as a gradual decline of the residuals, to the extent that the investments are not correlated with the observables. Second, there may be other factors for which the observables do not control that lead injury rates to be temporarily high. If these factors decline only slowly, then again we would observe the gradual decline of the residuals found here. Finally, I argue that Scholz and Gray's (1990) fire-fighting model is consistent with the data, provided that managers' attention to safety takes the form of investments in safety capital.

The statistical significance and magnitude of the explanatory variables in the injury equations show that covariates can aid in understanding why certain establishments have injury rates that consistently exceed their industry means.

The fact that there is some persistence in injury rate residuals may indicate an incomplete set of covariates. With a more complete set, particularly one that included information about the occupational structure of each plant, the role of injury rates themselves as a targeting tool might be clarified. Persistence of residuals above zero might become stronger, in which case the value of injury rates themselves to target inspections would be strengthened. However, the persistence might decline, consequently reducing the targeting value of injury data.

In deciding whether establishment injury data should be used for targeting, more must be considered than whether the data appear to support its use for that purpose. Ruser and Smith (1988) find evidence that inspection targeting based on firm-reported injury rates leads firms to under-report injuries in order to avoid inspections. If proper safeguards (such as injury log audits and stiff penalties for under-reporting) are not established to counteract this under-reporting, firm-reported injury rates will not be reliable guides for targeting and the present statistical system will be undermined.

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