
Workers' Compensation and Occupational Injuries and Illnesses
Author(s): John W. Ruser
Source: *Journal of Labor Economics*, Vol. 9, No. 4 (Oct., 1991), pp. 325-350
Published by: The University of Chicago Press on behalf of the Society of Labor Economists and the NORC at the University of Chicago
Stable URL: http://www.jstor.org/stable/2535074
Accessed: 19-02-2018 14:41 UTC

Workers' Compensation and Occupational Injuries and Illnesses

John W. Ruser, *Office of Economic Research, U.S. Bureau of Labor Statistics*

A longitudinal establishment data set is used to assess the effect of changes in workers' compensation benefits on the incidence of lost-workday injury and illness cases in manufacturing for the years 1979–84. Higher benefits are found generally to increase lost-workday cases. However, consistent with theory, the benefit effect is smaller in larger, more highly experience-rated establishments. After initial estimates are obtained using ordinary and weighted least squares, several count data models are explored that are more appropriate for the integer injury and illness counts in the data. The results are consistent across the specifications.

I. Introduction

The economics and public policy literature on occupational safety and health frequently refers to two apparently contradictory goals of workers' compensation insurance: the provision of adequate benefits and the enhancement of incentives for safety.[1] That these goals appear to be contradictory is supported by a body of empirical work showing that, at sample

This article was presented at the sixth World Congress of the Econometric Society. My thanks to Harley Frazis, Jerry Hausman, Rick Valliant, and members of the Office of Economic Research staff. All remaining errors are mine. The views expressed here are mine and do not necessarily reflect the views of the U.S. Bureau of Labor Statistics.

[1] See, e.g., the 1987 *Economic Report of the President* (Executive Office of the President 1987), pp. 197–98.

[*Journal of Labor Economics,* 1991, vol. 9, no. 4]

0734-306X/91/0904-0001$01.50

means, increases in workers' compensation benefits are associated with increases in nonfatal injury rates.[2]

A priori, it is not clear that these two goals are jointly unattainable. Higher benefits may reduce worker caretaking. But, as shown in Ruser (1985), the extent to which higher benefits increase a firm's safety investments depends on the degree of experience rating of its workers' compensation premium. A premium is more highly experience-rated if it is more closely related to the benefits paid to the firm's own injured workers. When a premium is more highly experience-rated, the firm internalizes both more of the costs of its accidents and more of the costs of benefit increases. Thus, a given benefit increase results in greater safety investments in more highly experience-rated firms. A potential explanation for the apparently poor incentive effects of higher benefits may lie in the fact that the degree of experience rating is low in many firms.

The empirical literature has generally failed to recognize the intervening effect of experience rating in the benefit/nonfatal-injury-rate relationship. The exceptions exploit an institutional characteristic, that larger firms tend to be more highly experience-rated, in order to advance the empirically testable hypothesis that the relationship between benefits and injury rates is smaller in larger firms. Two studies using industry-aggregate Bureau of Labor Statistics (BLS) injury-rate data for manufacturing obtain conflicting results. Chelius and Smith (1983) find no support for the hypothesis among 15 two-digit Standard Industrial Classification (SIC) manufacturing industries. In contrast, Ruser (1985) finds strong support among 25 selected three-digit manufacturing industries. Two other studies use industry-aggregate workers' compensation claims data to support the hypothesis (Butler and Worrall 1988; Worrall and Butler 1988).[3]

In this article, I seek to test this hypothesis, as well as others that have already found empirical support, using a rich longitudinal microdata set for nearly 2,800 manufacturing establishments for the years 1979–84. Nonfatal lost-workday injury and illness ("injury") case-rate equations are estimated using a variety of econometric specifications, including a set of count data models that are especially appropriate for explaining variations in injuries in this sample. The results are consistent across the specifications. They show that higher benefits lead to an increase in reported nonfatal injury rates in all but possibly the largest establishments. But,

[2] See articles by Chelius (1974, 1982); Worrall and Appel (1982); Butler (1983); Butler and Worrall (1983); Bartel and Thomas (1985); and Ruser (1985). For fatalities, the evidence is the opposite. Moore and Viscusi (1990) and Ruser (1991) find that higher benefits reduce fatalities.

[3] The evidence for fatal injuries is scant. Moore and Viscusi (1990) find support for the hypothesized experience-rating effect, while Ruser (1991) obtains mixed results.

consistent with the experience-rating hypothesis, higher benefits lead to a smaller increase in injuries in larger establishments.

Section II describes the empirical strategy, the data used in the empirical work, and the hypothesized relationships between injury rates and the independent variables. Section III presents estimates of injury-rate equations using ordinary and weighted least squares. Section IV explores several count data specifications, including the negative binomial, a fixed-effect negative binomial, and a quasi-generalized pseudo-maximum-likelihood estimator. Finally, Section V presents some conclusions.

II. Empirical Strategy and Data

The empirical strategy that was adopted to assess the effect of benefits on injuries and to test the experience-rating hypothesis was to estimate equations of the form

$$\text{LWCR} = f(\text{WCOMP}, \text{SIZE}, X), \tag{1}$$

where LWCR is the lost-workday injury-case rate, WCOMP is workers' compensation benefits, SIZE is establishment size, and X represents a vector of other variables. Since higher WCOMP has offsetting incentive effects on the worker and the firm, the sign of the derivative of LWCR with respect to WCOMP is theoretically indeterminate. However, the empirical evidence suggests that it should be positive. The hypothesis concerning the effect of experience rating on the benefit/injury-rate relationship is

$$\frac{\partial^2 \text{LWCR}}{\partial \text{WCOMP} \partial \text{SIZE}} < 0. \tag{2}$$

To estimate equation (1), I assembled a unique longitudinal microdata set of 2,788 manufacturing establishments for the years 1979–84. The data set, which contained a total of 16,728 observations, was created by matching observations for establishments from the BLS's Annual Survey of Injuries and Illnesses and the BLS's Current Employment Survey (CES). I added information on the laws regarding the payment of worker's compensation benefits from annual issues of the *Analysis of Workers' Compensation Laws* (Chamber of Commerce of the United States 1979–84). The data set is well suited for this study since it contains a rich set of variables on establishment characteristics, as well as workers' compensation benefits calculated for each establishment. Definitions of the variables used in the study, as well as sample means, appear in table 1.

The creation of the sample introduced one bias that is important to mention. The Annual Survey of Injuries and Illnesses is resampled yearly in such a way that an establishment with larger employment has a greater probability of selection. Further, establishments above a certain employ-

Table 1
Definitions and Sample Statistics (N = 16,728)

Variable Name	Definition	Mean (SD)
LWCR	Frequency of lost-workday injury and illness cases per 100 worker years	6.96 (8.35)
LWC	Annual number of lost-workday injury and illness cases per establishment	24.35 (49.66)
HOURS	Annual total hours worked (÷ 200,000)	5.08 (13.57)
WCOMP	Average real weekly workers' compensation income benefit for production workers ÷ 100 (1979 $)	1.33 (.34)
WAGE	Average real weekly wage for production workers ÷ 100 (1979 $)	2.47 (.86)
$EMPL_t$	Annual average employment in year t	523.63 (1,362.50)
CHEMPL	Change in annual employment ($EMPL_t/EMPL_{t-1}$)	1.01 (.15)
PCTPROD	Proportion of production workers in establishment	.74 (.17)
PCTFEM	Proportion of female workers in establishment	.28 (.23)
WKOTHRS	Weekly overtime hours per production worker ÷ 10	.30 (.25)
EMP100–249	Employment class size dummy = 1 for 100–249 employees	.35
EMP250–499	Employment class size dummy = 1 for 250–499 employees	.26
EMP500+	Employment class size dummy = 1 for 500 or more employees	.25

ment size are sampled with certainty. Similarly, the CES sample is drawn with probability proportional to size. This implies that the establishments that survived the matching process tended to be larger than the typical manufacturing establishment. Table 1 indicates that the average level of employment in an establishment in our sample is 524. I control for this through the inclusion of establishment-size class dummies.

The rate whose variation I seek to explain is LWCR, the frequency (per 100 full-time worker years) of lost-workday injury and illness cases excluding fatalities. Since illness cases make up a small fraction of all cases (less than 4%) and since most are acute (similar to injuries), I will henceforth use the words "injury" or "injuries" to denote both injuries and illnesses. Let LWC_{it} represent the annual number of lost-workday injury cases, and let $HOURS_{it}$ be total annual hours worked by all employees in establishment i in year t. The injury rate is calculated as

$$\text{LWCR}_{it} = \frac{\text{LWC}_{it}}{\text{HOURS}_{it}} \times 2{,}000 \times 100, \quad (3)$$

where a full-time worker is assumed to work 2,000 hours per year.

The data record-keeping and reporting system underlying the BLS's lost-workday case-rate figures is designed to be independent of any other system related to occupational injuries, including the workers' compensation system. Nevertheless, it is possible that the reporting of injuries in the BLS survey may be affected by variations in the level of workers' compensation benefits independent of any effect on the level of true safety. In a world of imperfect verification of workers' health states, higher benefits may create a greater incentive for workers to report injuries. These may be injuries either that did occur but were not "worth reporting" at lower benefit levels, or that did not occur and are being falsely reported. In contrast, firms may have a reduced incentive to report injuries at higher benefit levels if they feel that to record such injuries would be an admission of liability on their part. Therefore, an increase in benefits may lead to a change in the reported level of injuries without a corresponding change in the true level of safety.

Unfortunately, there is no clear way to disentangle the reporting and true safety effects short of possessing independent information on safety. Thus, this study looks at the impact of workers' compensation on *reported* injury rates and some of the measured effect of workers' compensation on injuries may not represent a true safety effect. However, since it is generated from a data system largely independent of the workers' compensation system, the measure of injuries I use should be less affected by reporting than other available data on work injuries.

The data set permitted the creation of a rich set of independent variables that have been shown to be related to injuries. The variable WAGE measures the average real weekly wage of production workers in an establishment, using the consumer price index (CPI) as the deflator. It was introduced into the equation to measure the forgone cost of an injury, and its coefficient is expected to be negative. However, since it is not possible to capture adequately the differences across establishments in workers' skill levels with these data, the wage variable might also be negatively related to injury rates because more highly skilled and paid workers are less frequently injured. Finally, the wage variable might be positively related to injuries in our equations since workers require positive compensating differentials to work at more hazardous jobs.[4] Therefore, a priori, the direction of the relationship between LWCR and WAGE is uncertain.

[4] Ideally, one would like to estimate a simultaneous system of wage and injury rate equations. Unfortunately, all of the available explanatory variables seem to belong in both the wage and injury equations, so there are no variables in my data

It should be noted that one shortcoming of the wage variable is that it applies only to production workers, while LWCR is the injury rate for all workers. This introduces measurement error into the coefficient estimates for the WAGE variable. This problem is mitigated to the extent that there is a positive correlation between the wages of production and nonproduction workers across establishments.

The variable WCOMP measures the average weekly real income benefit paid to a production worker who suffers a total temporary disability. It was calculated using the nominal weekly production worker wage, the state laws regarding benefit payments, and an actuarial technique employed by the National Council on Compensation Insurance.[5] Because it was calculated separately for each establishment, it will suffer from less measurement error than more aggregated measures. However, it is less than ideal in two respects. First, like the wage variable, it applies only to production workers. This problem is mitigated by the fact that there is a positive correlation between the benefits for production and other workers and that most injuries are sustained by production workers. Second, the benefit variable reflects only payments for total temporary disability, while some reported lost-workday cases may involve either permanent partial or total disability. Use of the WCOMP measure is justified by the high level of correlation between total temporary disability benefits and benefits for other types of injuries (see Chelius 1982; Krueger and Burton 1984). As already noted, a priori, the relationship between workers' compensation benefits and injuries is ambiguous. However, all previous empirical work finds LWCR and WCOMP to be positively related at sample means.

To test the hypotheses concerning the effect of experience rating on the benefit/injury-rate relationship, I included three establishment-size class dummies: 100–249, 250–499, and 500+ employees. They are labeled EMP100–249, EMP250–499, and EMP500+, respectively. These dummy variables were interacted with WCOMP to test the hypothesis represented by inequality (2). The hypothesis is supported if the coefficients on the interactions are negative and increase monotonically in absolute value with increases in establishment size.

It should be noted that establishment size merely proxies as a measure of the degree of experience rating. A difficulty with this proxy is that workers' compensation premiums are written for firms, rather than for establishments. This would suggest that firm size would make a better proxy. Unfortunately, I have no information on the ownership structure

---

set with which to identify the system. In any case, while the coefficient on the wage variable may be biased, it is less apparent that the estimated relationship between benefits and injury rates is biased by my failure to estimate a simultaneous system.

[5] For a complete description of the calculation of this variable, see Butler (1983).

of establishments in the sample. Instead, in my empirical work, I rely on the assumption that establishment size is positively correlated with firm size, while recognizing that establishment size is a noisy indicator of firm size. This measurement error in my proxy will tend to work against finding an experience-rating effect.

I also included a squared benefit variable and the interaction of benefits with wages to account for potential nonlinearities in the workers' compensation/injury-rate relationship. A simple model presented in Moore and Viscusi (1990) shows that, a priori, the sign of the coefficient for the squared benefit variable is uncertain, depending on the curvature of the firm's marginal cost of safety curve. However, in their empirical work on fatalities, they obtained a positive coefficient.

A priori, the coefficient for the interaction of wages with benefits is also ambiguous. I expect a negative coefficient based on the following argument. If workers' compensation insurance can be supplemented, then a change in the statutory level of workers' compensation benefits will affect injury rates only when the statute establishes a binding minimum constraint. Otherwise, a change in the statutory benefit will simply lead to a substitution between statutory and supplementary coverage, without changing the total amount of coverage. If we accept that workers' compensation insurance is a normal good, then higher-wage workers demand higher levels of benefits. Thus, with the possibility of supplementation, a given statutory benefit level is less likely to be binding for higher-wage workers (i.e., they are more likely to supplement benefits). Then a change in the benefit level is less likely to affect injury rates.

Viscusi and Moore (1989) present an argument that predicts a positive coefficient for the wage-benefit interaction. They argue that a firm's safety incentives from workers' compensation are decreased at a higher wage level since workers' compensation costs are relatively lower in high wage establishments. While theory may lead to ambiguous predictions regarding the sign of the wage-benefit interaction coefficient, both Ruser (1985) and Viscusi and Moore (1989) obtain positive coefficients in their empirical work.

It has been shown in previous research that injury rates are negatively related to establishment size. There are two explanations for this: economies of scale in the production of safety and a higher degree of experience rating in larger establishments, which leads them to internalize more accident costs (at any benefit level). In the present empirical work, I expect to see, at sample means, a decline in injury rates as establishment size increases.

I include a number of other variables to account for variations in injury rates. The variable CHEMPL, which is related to business conditions, measures the change in employment from year $t - 1$ to year t. Since an increase in employment is often associated with the hiring of untrained or inexperienced workers who are more likely to be injured, I expect this variable to be positively related to injury rates. Another business conditions variable I include is WKOTHRS, the weekly overtime hours per production worker. It is expected to be positively related to injury rates since an increase in the length of the workweek increases worker fatigue. Both variables may also proxy for other establishment-specific business conditions, such as increases in the pace of production, which are also positively correlated with injuries. Consequently, I expect the coefficients on these variables to be positive.

The variables PCTPROD and PCTFEM represent the percentage of workers in the establishment who are production workers and who are female, respectively. These variables are included to control for the composition of the establishment's work force. Production workers tend to be injured more frequently, so that the coefficient for PCTPROD should be positive. Conversely, female workers tend to work in less hazardous occupations, so that the coefficient for this variable should be negative.

The empirical work reported in the following sections also includes time and two-digit SIC dummies to control for general time and industry effects.

III. Linear Least Squares Estimates

In this section, I report the results of ordinary and weighted least squares regressions. Coefficient estimates appear in table 2, while the effects of the key variables at sample means appear in table 3. Elasticity estimates appear after tables 4–7, in the Appendix.

I estimate a linear equation of the form

$$R_{it} = X_{it}\beta + u_{it}, \tag{4}$$

where R_{it} is the lost-workday case rate per 100 worker years, and the X_{it}'s were described in the previous section. My prior research (Ruser 1985) has suggested the possibility of heteroscedasticity in the errors of equation (4). In particular, I previously found that the variances of the errors tended to be smaller in larger establishments, a result consistent with the law of large numbers. As in this previous work, I adopt here the multiplicative heteroscedasticity specification of Harvey (1976) and assume that the error variance structure is

$$\text{var}(u_{it}) = e^{(\alpha_0+\alpha_1 \log H_{it})}, \tag{5}$$

where H_{it} is annual hours worked (HOURS_{it}) divided by 200,000, and α_1 is expected to be negative. Assuming this error structure, a test of homoscedasticity is obtained by regressing the log of the squared ordinary least squares (OLS) residuals on the log of H_{it}. Judge et al. (1980) show that the regression sum of squares divided by 4.9348 is a $\chi^2(1)$ distributed test statistic for homoscedasticity.

A preliminary analysis of the OLS residuals in the present sample yielded a test statistic of 612, which indicated that the hypothesis of homoscedasticity could be rejected at the .001 level of significance. As expected, the logs of the squared residuals were negatively related to hours worked. I chose to handle the heteroscedasticity problem in two ways. First, I adopted the variance structure of equation (5). Estimates of α_0 and α_1 were obtained from the regression of the log of the squared OLS residuals on the log of H_{it}. Equation (5) and the estimated alphas were used, along with the hours data, to obtain weights for each observation (the estimated inverses of the variances), which were then applied in a weighted least squares procedure. The WLS estimates of equation (4) appear in column 2 of tables 2 and 3.

Alternatively, we know that, in the presence of heteroscedasticity, the OLS parameter estimates are consistent but inefficient, while the covariance matrix of the regression estimates is inconsistent. White (1980) suggests a procedure by which a consistent estimator of the covariance matrix can be calculated without reference to a formal model of the structure of the heteroscedasticity.[6] Column 1 of tables 2 and 3 reports the OLS estimates of equation (4), along with the standard errors from White's consistent covariance matrix.

The OLS and WLS estimates are quite similar, both qualitatively and quantitatively. Most important, as table 3 shows, workers' compensation benefits are positively related to injury rates in all establishment-size classes, but the magnitude of the relationship is smaller in larger establishments. At sample means, the estimated benefit/injury-rate relationship decreases monotonically with increases in establishment size. Benefit/injury-rate elasticities, as reported in the Appendix, are between .79 and .82 in establishments with under 100 employees, while they decrease to between .18 and .20 in establishments with 500 or more employees. These results are consistent with the hypothesis that the higher degree of experience rating in larger firms lowers the magnitude of the benefit/injury-rate relationship.

The relationship between workers' compensation and injuries is nonlinear, as indicated in table 2 by the statistically significant coefficients on the squared benefit variable and the interaction of wages with benefits. Contrary to the results of Moore and Viscusi (1990) for fatalities, but similar to those of Worrall and Butler (1988) for temporary total workers' compensation claims, an increase in benefits has a smaller effect on nonfatal injuries at higher benefit levels. Consistent with Ruser (1985) and Viscusi and Moore (1989), changes in benefits have a larger effect in higher-wage establishments.

Almost all other results in these regressions are as expected. In table 3, the decreasing pattern of employment-size effects at sample means indicates

[6] White's (1980) estimator is $(X'X/n)^{-1}\hat{V}_n(X'X/n)^{-1}$, where n is the number of observations and $\hat{V}_n = n^{-1} \sum_{it} \hat{u}_{it}^2 X'_{it} X_{it}$. The $\hat{u}_{it}$'s are the OLS residuals.

Table 2
Least-Squares Regressions, Coefficient Estimates
Dependent Variable: LWCR

	Technique	
Independent Variable	OLS (1)	WLS (2)
WCOMP²	−4.88††	−4.12††
	(.65)	(.53)
WCOMP	14.61††	13.61††
	(1.44)	(1.13)
WCOMP × EMP100–249	−2.65**	−2.73**
	(.63)	(.62)
WCOMP × EMP250–499	−3.08**	−3.17**
	(.62)	(.61)
WCOMP × EMP500+	−3.19**	−3.22**
	(.63)	(.60)
EMP100–249	3.30††	3.26††
	(.84)	(.81)
EMP250–499	2.96††	2.95††
	(.82)	(.81)
EMP500+	1.78†	1.55
	(.85)	(.81)
WCOMP × WAGE	1.01††	.67†
	(.33)	(.27)
WAGE	−1.66††	−1.28††
	(.48)	(.39)
CHEMPL	2.80**	2.86**
	(.46)	(.35)
PCTPROD	4.04**	4.25**
	(.30)	(.29)
PCTFEM	−6.16**	−6.07**
	(.42)	(.33)
WKOTHRS	−1.81	−1.42
	(.24)	(.23)
R^2	.12	.18

NOTE.—All regressions also included an intercept, time, and two-digit SIC dummies. Standard errors are in parentheses.
** Significant at the .01 level (one-tailed test).
† Significant at the .05 level (two-tailed test).
†† Significant at the .01 level (two-tailed test).

that larger establishments are safer. This is consistent with the hypotheses that there are economies of scale in the production of safety and that, holding benefits constant, a higher degree of experience rating leads to an increase in safety.

At sample means, wages are negatively related to safety. Thus the role of wages as a measure of forgone costs and as a control for worker skill levels dominates the effect of positive compensating wage differentials.

Table 2 also shows that the coefficients for the change in employment, the percent production workers, and the percent female workers all have their expected signs and are statistically significant at the .01 level. The

Table 3
Least-Squares Regressions, Effects at Sample Means

Independent Variable (Establishment Size)	Technique OLS (1)	WLS (2)
WCOMP (1–99)	4.11††	4.29††
	(.65)	(.57)
WCOMP (100–249)	1.46††	1.56††
	(.36)	(.35)
WCOMP (250–499)	1.04††	1.12††
	(.34)	(.33)
WCOMP (500+)	.92††	1.07††
	(.30)	(.27)
WAGE	−.31†	−.39††
	(.13)	(.10)
EMP100–249	−.23	−.38*
	(.26)	(.20)
EMP250–499	−1.14**	−1.27**
	(.23)	(.21)
EMP500+	−2.47**	−2.74**
	(.24)	(.21)

NOTE.—Standard errors are in parentheses.
* Significant at the .05 level (one-tailed test).
** Significant at the .01 level (one-tailed test).
† Significant at the .05 level (two-tailed test).
†† Significant at the .01 level (two-tailed test).

sole variable that fails to perform as expected is weekly overtime hours, which has anomalously negative coefficients that are large relative to their standard errors. An explanation for this result is that in establishments where there is more overtime, it is the safer, more experienced senior workers who work that overtime.

We can use the parameter estimates to assess the impact of a hypothetical policy change. For example, consider the effect of raising weekly benefits by $50.00 in 1989 ($29.27 in 1979 dollars). In establishments with fewer than 100 employees, this would increase the lost-workday rate by 1.20–1.26 cases per 100 worker years, or 17%–18% of the sample mean. However, in establishments with 500 or more workers, the resulting increases are .27–.31 cases, or 4%.

IV. Count Data Models

The least-squares regressions presented in the previous section provide first estimates of the relationship between benefits and injury rates and first tests of the hypotheses presented in Section II. However, the nature of the data is such that there are statistical shortcomings with these estimates. First, many establishments reported no injuries in one or more of the years from 1979 to 1984, so that there is a mass point of observations with calculated incidence rates of zero. Second, the dependent variable

(LWCR) is bounded from below by zero, while the estimated linear models may permit predicted values below zero. The common solution to this second problem, taking the natural logarithm of the dependent variable, is precluded here by the presence of zeros. Finally, the injury data (LWC) used to calculate rates are reported as counts. It is desirable to account for this aspect of the data.

As an alternative to traditional least squares analysis, I explore in this section several nonlinear count data models that address these issues. In preliminary work, which I do not report, I assumed that injury counts were generated by a Poisson process.[7] However, an analysis of the Poisson residuals led to a rejection of that specification. A property of the Poisson distribution is the equality of the mean with the variance. By regressing the log of the estimated variance of the residuals for each establishment on the establishment's estimated mean, I determined that, in my data, the variance increases faster than the mean.[8] This condition, referred to as "overdispersion," is frequently found in count data. Note that this result is consistent with my finding with regard to heteroscedasticity reported in the previous section, that is, larger (and, ceteris paribus, safer) establishments have more stable injury rates.

Rejection of the Poisson led to the consideration of count data models that incorporate overdispersion. I report estimates of these models here. First, I make the explicit distributional assumption that the injury data are generated from a compound Poisson distribution, the negative binomial.

[7] I estimate a model described in Ruser and Smith (1988). The estimates are available from me on request.

[8] Specifically, I calculated the Poisson residuals, $\hat{u}_{it} = n_{it} - \hat{\lambda}_{it}$, where $\hat{\lambda}_{it}$ is the predicted number of injuries. From these I calculated, for each establishment, the quantities

$$\hat{\sigma}_i^2 = [1/(T-1)] \sum_t (\hat{u}_{it} - \bar{u}_i)^2,$$

$$\bar{u}_i = (1/T) \sum_t \hat{u}_{it},$$

and

$$\bar{\lambda}_i = (1/T) \sum_t \hat{\lambda}_{it}.$$

where $T = 6$. I regressed the log of the estimated variances of the residuals against the log of the mean injury rates, obtaining

$$\log \hat{\sigma}_i^2 = -.92 + \underset{(0.02)}{1.50} \log \bar{\lambda}_i .$$

I estimate the parameters of the model by means of maximum likelihood. Then I relax this distributional assumption and utilize the quasi-generalized pseudo-maximum-likelihood approach of Gourieroux, Monfort, and Trognon (1984). Finally, having detected a significant within-establishment intertemporal correlation of the residuals of these models, I turn to consideration of a fixed-effect negative binomial specification.

A. Negative Binomial Maximum-Likelihood Estimator

The negative binomial distribution is frequently utilized to model counts when it is determined that the Poisson's equality between the mean and variance does not hold. As early as 1920, in a nonregression context, Greenwood and Yule (1920) used this distribution to model accident proneness in industrial accidents. More recently, the distribution has been used in a regression context by Hausman, Hall, and Griliches (1984) to study patents and by Cameron and Trivedi (1986) to study visits to doctors.[9] Here, I adopt the parameterization proposed by Cameron and Trivedi, but I estimate a more flexible, functional relationship between the mean and variance.

Let n_{it} represent the number of injuries in establishment i in year t. I assume that n_{it} is distributed according to the negative binomial distribution, which is

$$\mathrm{pr}(n_{it}) = \frac{\Gamma(n_{it} + \nu_{it})}{\Gamma(n_{it} + 1)\Gamma(\nu_{it})} \left(\frac{\nu_{it}}{\nu_{it} + \phi_{it}}\right)^{\nu_{it}} \left(\frac{\phi_{it}}{\nu_{it} + \phi_{it}}\right)^{n_{it}}, \tag{6}$$

where $\Gamma(\cdot)$ is the gamma function, and $\nu_{it} > 0$ and $\phi_{it} > 0$ are the two parameters of this distribution.[10] It has the properties that

$$E(n_{it}) = \phi_{it} \tag{7}$$

and

$$\mathrm{var}(n_{it}) = \phi_{it}(1 + \phi_{it}/\nu_{it}). \tag{8}$$

[9] Both Hausman, Hall, and Griliches (1984) and Cameron and Trivedi (1986) derive the negative binomial distribution from the Poisson.

[10] The gamma function, denoted by $\Gamma(\cdot)$, is defined as

$$\Gamma(t) = \int_0^\infty x^{t-1} e^{-x} dx \quad \text{for } t > 0.$$

For integer n, it has the property that $\Gamma(n + 1) = n!$.

Since $\phi_{it}/\nu_{it} > 0$, then $\mathrm{var}(n_{it}) > E(n_{it})$, so that this specification contains overdispersion.

The regression aspect of this model is introduced by linking the explanatory variables X_{it} to the parameters ϕ_{it} and ν_{it}. I assume that

$$E(n_{it}) = \phi_{it} = H_{it}e^{X_{it}\beta}, \tag{9}$$

which, for the purposes of interpretation, can be rewritten as

$$\log[E(R_{it})] = \log\left[E\left(\frac{n_{it}}{H_{it}}\right)\right] = X_{it}\beta, \tag{10}$$

where R_{it} is the lost-workday case rate per 100 worker years, as in the previous section. This semilog specification for the expected injury rate guarantees that all values of X_{it} yield legal values of ϕ_{it}.

For the other parameter, ν_{it}, I assume that

$$\nu_{it} = (1/\alpha)(H_{it}\, e^{X_{it}\beta})^{k}, \tag{11}$$

where $\alpha > 0$, and both α and k are unknown constants. Then

$$\begin{aligned} \mathrm{var}(n_{it}) &= (H_{it}e^{X_{it}\beta}) + \alpha(H_{it}e^{X_{it}\beta})^{2-k} \\ &= E(n_{it})[1 + \alpha E(n_{it})^{1-k}], \end{aligned} \tag{12}$$

or

$$\frac{\mathrm{var}(n_{it})}{E(n_{it})} = 1 + \alpha E(n_{it})^{1-k}.$$

A lower value of k indicates that the variance rises more rapidly with the mean.

Cameron and Trivedi (1986) consider specifications of this model in which k is arbitrarily restricted to either zero or one, which are the two values implicitly assumed by, among others, Hausman, Hall, and Griliches (1984). In contrast, I permit k to be estimated along with the parameters α and β, by means of maximum likelihood. This procedure has the advantage that the data can directly indicate the value of k. Note that, since α is estimated, a test of the null hypothesis $\alpha = 0$ is a test of the Poisson assumption of equality between the mean and variance.

B. Quasi-generalized Pseudo-Maximum-Likelihood Estimator

The maximum-likelihood model just presented relies on a strong distributional assumption about the stochastic process generating the data. This assumption is clearly arbitrary. It is possible to relax the assumption by following the quasi-generalized pseudo-maximum-likelihood estimation (QGPMLE) approach suggested by Gourieroux et al. (1984). They show that consistent estimates of the parameters β can generally be obtained using any member of the linear exponential family in the estimation procedure, provided that the data are generated by a distribution in the linear exponential family, and provided that the mean and variance are correctly specified. Members of the linear exponential family include the Poisson and the negative binomial (with ν given).

I provide QGPML estimates here, assuming that the mean and variance are specified as in the previous section. One compromise is required. Whereas in the previous section, I propose to estimate k along with the other parameters, the QGPMLE approach requires that I impose a value for it in advance. As we shall see, the estimated value for k in the negative binomial maximum-likelihood estimation (MLE) is −.092, which is numerically close to zero. Therefore, the following assumes that k is zero.

My approach follows Hausman, Ostro, and Wise (1984). It is motivated by the observation (see Jennrich and Moore 1975) that maximum-likelihood estimation is sometimes equivalent to iteratively reweighted nonlinear least squares. I posit a nonlinear regression equation of the form

$$n_{it} = H_{it} e^{X_{it}\beta} e^{\eta_{it}} + u_{it}, \tag{13}$$

where η_{it} and u_{it} are random variables with unspecified distributions. I make the following assumptions about the means and variances of these errors:

$$E(u_{it}) = 0, \tag{14}$$

$$\text{var}(u_{it}) = H_{it} e^{X_{it}\beta}, \tag{15}$$

$$E[\exp(\eta_{it})] = 1, \tag{16}$$

and

$$\text{var}[\exp(\eta_{it})] = \alpha. \tag{17}$$

I further assume that $\exp(\eta_{it})$ and u_{it} are uncorrelated. These assumptions imply

$$E(n_{it}) = H_{it} e^{X_{it}\beta}, \tag{18}$$

and

$$\begin{aligned} \text{var}(n_{it}) &= \alpha H_{it}^2 e^{2X_{it}\beta} + H_{it} e^{X_{it}\beta} \\ &= H_{it} e^{X_{it}\beta}(1 + \alpha H_{it} e^{X_{it}\beta}). \end{aligned} \tag{19}$$

The mean and variance structure is the one that I assumed for the negative binomial specification in the previous section, with $k = 0$.

To estimate this model, I utilized the procedure described in Hausman, Ostro, and Wise (1984). Please refer to their paper for details. In brief, in a first stage, estimates of β were obtained by means of unweighted nonlinear least squares of equation (13), assuming $\exp(\eta_{it}) = 1$. These were used to calculate estimates of u_{it}. Using these and the variance formula (eq. [19]), a consistent estimate of α was obtained. The variance of n_{it} for each observation was then calculated from (19). These formed the weights in a second-stage nonlinear least squares estimate of equation (13), which yielded the QGPML estimates of β. Finally, a consistent estimate of the variance-covariance matrix of $\hat{\beta}$ was obtained by substituting into the formula for $\hat{\alpha}$ the QGPML estimates of β, then using the formula of Cameron and Trivedi (1986, p. 38).

C. Estimates

Coefficient estimates of the negative binomial MLE and the QGPMLE appear in columns 1 and 2 of table 4, respectively, while the corresponding first derivatives, dR/dX, evaluated at sample means, appear in columns 3 and 4.[11] In these nonlinear specifications, the coefficient estimates represent percentage changes in injury rates resulting from a unit change in each explanatory variable, while the first derivatives give estimates that have units comparable to the linear regression estimates. Table 5 contains the first derivatives of the effects at sample means, while elasticity estimates of the benefit/injury-rate relationship appear in the Appendix.

First, we should make some comments about model selection. Table 4 shows that the negative binomial MLE of α is statistically significant with a value of .48, while the corresponding estimate from the QGPMLE procedure is also statistically significant with a value of .11. These estimates lend further support to our rejection of the Poisson variance assumption. Further, the maximum-likelihood estimate of k is a statistically significant $-.092$, which, when plugged into equation (12), indicates that the variance to mean ratio increases slightly faster than linearly with the mean. However, as noted previously, the magnitude of k is sufficiently close to zero that our QGPML estimates, with k assumed to be zero, should be reasonable.

A comparison of the standard errors of the $\hat{\beta}$'s for the count data models yields a result previously observed by Cameron and Trivedi (1986) in their study of doctors' visits. The estimated standard errors under the QGPMLE specification are almost always smaller than the corresponding estimates from the negative binomial MLE.[12]

[11] The first derivatives were calculated as $\hat{\beta}e^{X\hat{\beta}}$. Standard errors were calculated using the delta method.

[12] Another result reported in Cameron and Trivedi (1986) that I observed was

Table 4
Count Data Models by Technique

	Coefficients		First Derivatives	
Independent Variable	Neg Bin MLE (1)	QGPMLE (2)	Neg Bin MLE (3)	QGPMLE (4)
WCOMP²	−.678††	−.780††	−4.261††	−4.758††
	(.073)	(.055)	(.463)	(.335)
WCOMP	1.954††	2.235††	12.273††	13.634††
	(.146)	(.111)	(.920)	(.678)
WCOMP × EMP100–249	−.265**	−.280**	−1.664**	−1.707**
	(.062)	(.049)	(.391)	(.300)
WCOMP × EMP250–499	−.266**	−.454**	−1.672**	−2.769**
	(.065)	(.050)	(.411)	(.304)
WCOMP × EMP500+	−.338**	−.436**	−2.121**	−2.660**
	(.065)	(.050)	(.411)	(.302)
EMP100–249	.310††	.310††	1.946††	1.894††
	(.081)	(.066)	(.510)	(.401)
EMP250–500	.208†	.428††	1.310†	2.609††
	(.087)	(.067)	(.546)	(.410)
EMP500+	.044	.048	.279	.294
	(.090)	(.069)	(.565)	(.420)
WCOMP × WAGE	.118††	.185††	.740††	1.126††
	(.036)	(.027)	(.226)	(.168)
WAGE	−.198††	−.347††	−1.246††	−2.115††
	(.051)	(.039)	(.319)	(.240)
CHEMPL	.366**	.208**	2.301**	1.268**
	(.042)	(.031)	(.266)	(.189)
PCTPROD	.732**	.705**	4.596**	4.302**
	(.043)	(.028)	(.269)	(.172)
PCTFEM	−.919**	−.739**	−5.774**	−4.508**
	(.043)	(.030)	(.272)	(.184)
WKOTHRS	−.180	−.092	−1.132	−.563
	(.032)	(.021)	(.199)	(.126)
α	.484**	.109**		
	(.017)	(.006)		
k	−.092††			
	(.011)			

NOTE.—An intercept, time, and two-digit SIC dummies were also included, but their coefficients are not reported. First derivatives were evaluated at sample means of the X's, while their standard errors were computed using the delta method. Standard errors are in parentheses. Neg Bin MLE = negative binomial maximum-likelihood estimator; QGPMLE = quasi-generalized pseudo-maximum-likelihood estimator.
** Significant at the .01 level (one-tailed test).
† Significant at the .05 level (two-tailed test).
†† Significant at the .01 level (two-tailed test).

Turning to the estimated effects of the interacted variables, table 5 shows that, under both the MLE and QGPMLE specifications, the relationship between benefits and injury rates is positive and statistically significant in

---

that the Poisson standard errors were uniformly smaller than the standard errors of the two count data specifications reported here. This is an indication that the Poisson's incorrect variance assumption produced spuriously small estimates of the standard errors.

Table 5
Count Data Models, First Derivatives: Effects at Sample Means

Independent Variable (Establishment Size)	Technique: Neg Bin MLE (1)	Technique: QGPMLE (2)
WCOMP (1–99)	2.755††	3.744††
	(.360)	(.281)
WCOMP (100–249)	1.091††	2.037††
	(.267)	(.182)
WCOMP (250–499)	1.082††	.975††
	(.284)	(.185)
WCOMP (500+)	.633†	1.084††
	(.254)	(.170)
WAGE	−.261††	−.617††
	(.083)	(.056)
EMP100–249	−.269*	−.378**
	(.136)	(.098)
EMP250–499	−.916**	−1.076**
	(.144)	(.103)
EMP500+	−2.545**	−3.247**
	(.155)	(.111)

NOTE.—All first derivatives were evaluated at the sample means of the independent variables. Standard errors were computed using the delta method. Standard errors are in parentheses.
* Significant at the .05 level (one-tailed test).
** Significant at the .01 level (one-tailed test).
† Significant at the .05 level (two-tailed test).
†† Significant at the .01 level (two-tailed test).

all establishment-size classes. Further, there is strong evidence supporting the hypothesis that a higher degree of experience rating reduces the benefit/injury-rate relationship. As was the case in the least-squares estimates, the effects of benefits generally decline monotonically with establishment size under both the MLE and QGPMLE. In the one instance where this monotonicity is violated, that is, between the two largest size classes for the QGPMLE, we cannot reject the hypothesis that the two effects are equal. The effects at sample means and the elasticity estimates (see the Appendix) are similar between the least squares and both MLE and QGPMLE, though the maximum-likelihood estimates tend to be smaller. In establishments of fewer than 100 workers, the MLE and QGPMLE benefit/injury-rate elasticities are .53 and .72, respectively, while they are .12 and .21 for establishments with 500 or more employees.

A comparison of the first-derivative estimates for the count data models with the least-squares coefficients indicates that all other relationships are both qualitatively and quantitatively similar. Table 5 shows that wages are negatively related to injuries at sample means. In table 4, we see that the coefficients for the squares benefit variable are negative and significant, while those for the interaction of wages with benefits are positive and statistically significant. Both of these results are consistent with the least-squares runs.

Table 5 shows that, consistent with the effects of economies of scale and experience rating, injury rates decline with establishment size. Further, in table 4, the coefficients for the change in employment, percent production workers, and percent female workers are all significant and have their expected signs. Finally, the coefficients for the weekly overtime hours variable are again anomalously negative and large relative to their standard errors.

An assumption underlying the MLE and QGPMLE models just discussed is that, within an establishment, injury rates are independent over time. To test this, I calculated, for both specifications, standard correlation matrices for the within-establishment vector of residuals, whose elements are $\hat{u}_{it} = n_{it} - H_{it}\exp(X_{it}\hat{\beta})$. For the negative binomial MLE, off-diagonal elements of the matrix range from .76 to .93, while for the QGPMLE they range from .70 to .91. The correlations between time periods that are increasingly far apart drop off slowly, so that there is still a high degree of correlation even 6 years apart (.78 in the negative binomial specification). It is evident that it is not reasonable to assume independence over time within an establishment.

D. Fixed-Effect Negative Binomial Regression

The diagnostics for the residuals of the previous count data models are indicative either of an autoregressive process with a high level of autocorrelation or of unobserved establishment fixed effects. In this section, we follow Hausman, Hall, and Griliches (1984) in specifying a fixed-effect negative binomial regression model.

As before, let n_{it} be a random variable representing the number of injuries sustained in establishment i at time t. I assume that the distribution for n_{it} is a negative binomial, with parameters ϕ_{it} and ν_{it}, where the distribution is specified in equation (6). I relate the parameters to the vector of characteristics X_{it} according to the equations

$$\phi_{it} = H_{it}e^{(X_{it}\beta+\mu_i)} \tag{20}$$

and

$$\nu_{it} = H_{it}e^{X_{it}\beta}. \tag{21}$$

As compared to equations (9) and (11), equations (20) and (21) simplify the functional form for ν_{it} and add an additional parameter, μ_i, which is a fixed effect for each establishment. Under these assumptions, the mean and mean-to-variance ratio of n_{it} are

$$E(n_{it}) = H_{it}e^{(X_{it}\beta + \mu_i)} \tag{22}$$

and

$$\begin{aligned}\frac{\operatorname{var}(n_{it})}{E(n_{it})} &= 1 + e^{\mu_i} \\ &> 1.\end{aligned} \tag{23}$$

Hence, the mean injury rate contains a fixed effect for each establishment, while the variance exceeds the means. The mean-to-variance ratio can differ for each establishment. However, the simplifying restrictions on ν_{it} limit the mean-to-variance ratio to a simple functional form of the fixed effect. This is a compromise that is required to make an estimation of the fixed-effect specification possible.[13]

Following Hausman, Hall, and Griliches (1984), I utilize a conditional maximum-likelihood approach. The parameters β are estimated by maximizing the likelihood that a pattern of injury counts, $n_{i1}, n_{i2}, \ldots, n_{iT}$, occurs in an establishment over time, conditional on the sum of the injuries occurring in the establishment over the entire time period, $\sum_t n_{it}$. The estimates of β are within-establishment estimates, since they reflect only how the X_{it}'s affect injuries within an establishment.

It can be shown that, if n_{it} and n_{is} are drawn from negative binomial distributions with parameters ν_{it} and ν_{is}, respectively, and where $\phi_{it}/\nu_{it} = \phi_{is}/\nu_{is} = \exp(\mu_i)$, then the sum $n_{it} + n_{is}$ is also distributed according to a negative binomial with parameters $\nu_{it} + \nu_{is}$ and $\exp(\mu_i)(\nu_{it} + \nu_{is}) = \phi_{it} + \phi_{is}$.[14] This fact, and the parameterizations of ϕ_{it} and ν_{it} that are specified in equations (20) and (21), can be used to establish that the sum, $n_i = \sum_t n_{it}$, of injuries in establishment i is also distributed according to a negative binomial with parameters $\nu_i = \sum_t \nu_{it}$ and $\phi_i = \exp(\mu_i)\nu_i$. Then, for establishment i, the likelihood of observing a sequence of injury counts $n_{i1}, n_{i2}, \ldots, n_{iT}$, conditional on the total of $\sum_t n_{it}$ injuries occurring over the entire time period, is

[13] One of the assumptions of this specification is that the expression for ν_{it} does not contain an exponent analogous to k of the previous section. Unfortunately, it does not appear possible to derive a fixed-effect specification in which the analogue to k is estimable.

[14] This is established by using the moment generating function for this parameterization of the negative binomial, which is

$$m(t) = [1 + (\phi/\nu)(1 - e^t)]^{-\nu}.$$

The moment-generating function for the sum of two independent random variables is the product of the moment-generating functions for the two variables.

$$L_i = f(n_{i1}, n_{i2}, \ldots, n_{iT} \mid \sum_t n_{it}) = \mathrm{pr}(n_{i1}, n_{i2}, \ldots, n_{iT}) / \mathrm{pr}(\sum_t n_{it}) \quad (24)$$

or

$$L_i = \prod_t \frac{\Gamma(\nu_{it} + n_{it})}{\Gamma(\nu_{it})\Gamma(n_{it} + 1)} \left(\frac{\Gamma(\nu_i)\Gamma(n_i + 1)}{\Gamma(\nu_i + n_i)} \right). \quad (25)$$

I estimated the parameters β by maximizing the sum of the logs of L_i.

Coefficient estimates and derivatives appear in table 6. Table 7 presents

Table 6
Fixed-Effect Negative Binomial Regression

Independent Variable	Coefficient (1)	Derivative (2)
WCOMP²	−.204††	−1.420††
	(.049)	(.341)
WCOMP	.696††	4.844††
	(.149)	(1.037)
WCOMP × EMP100–249	−.189	−1.315
	(.118)	(.821)
WCOMP × EMP250–499	−.156	−1.086
	(.120)	(.835)
WCOMP × EMP500+	−.302**	−2.102**
	(.115)	(.800)
EMP100–249	−.737††	−5.130††
	(.171)	(1.190)
EMP250–499	−1.501††	−10.447††
	(.173)	(1.204)
EMP500+	−2.323††	−16.168††
	(.165)	(1.148)
WCOMP × WAGE	.055	.383
	(.029)	(.202)
WAGE	−.159††	−1.107††
	(.042)	(.292)
CHEMPL	.240**	1.670**
	(.023)	(.160)
PCTPROD	.555**	3.863**
	(.053)	(.369)
PCTFEM	−.153*	−1.065*
	(.068)	(.473)
WKOTHRS	.146**	1.016**
	(.026)	(.181)

NOTE.—The regression also included an intercept, time dummies, and two-digit SIC industry dummies. Since estimates of the mean fixed effect was not available, the derivatives were calculated at the mean injury rate. Standard errors are in parentheses.

* Significant at the .05 level (one-tailed test).
** Significant at the .01 level (one-tailed test).
†† Significant at the .01 level (two-tailed test).

Table 7
Fixed-Effect Negative Binomial, First Derivatives: Effects at Sample Means

Independent Variable	Derivatives
WCOMP (1–99)	2.004†
	(.780)
WCOMP (100–249)	.689
	(.362)
WCOMP (250–499)	.919†
	(.376)
WCOMP (500+)	−.097
	(.285)
WAGE	−.592††
	(.097)
EMP100–249	−6.876**
	(.557)
EMP250–499	−11.895**
	(.557)
EMP500+	−18.966**
	(.550)

NOTE.—Standard errors are in parentheses.
** Significant at the .01 level (one-tailed test).
† Significant at the .05 level (two-tailed test).
†† Significant at the .01 level (two-tailed test).

estimates of the effects of interacted variables at sample means, while the Appendix contains the benefit/injury-rate elasticities.

Comparing the benefit effects at sample means, which appear in table 7, with those for the previous count data models in table 5, it is clear that controlling for fixed effects yields somewhat different results from those previously seen. While the benefit/injury-rate relationships are positive as before in the three smallest establishment-size classes, the relationship is not statistically significant in the 100–249 category. Further, the fixed effects reduce the estimated effects of benefits in all but the 250–499 size class. There is an insignificant negative benefit/injury-rate relationship in establishments with 500 or more workers. The Appendix indicates that controlling for fixed effects also lowers the estimated elasticities in all size classes except 250–499 workers.

The results in table 6 generally continue to support the hypothesis of an experience-rating effect on the benefit/injury-rate relationship. The effects of benefits do not strictly decline with an increase in establishment size, and the coefficient for the interaction of benefits with size is only significant in the largest size class. However, the largest effect of benefits is found in the smallest establishments, while the smallest effect is found in the largest establishments. Further, the nonmonotonicity in the interaction coefficients occurs in the middle two size classes, where it is not possible to reject, at the 5% level, the null hypothesis of equal benefit effects.

What do these parameter estimates imply about the impact of a hypothetical change in the level of benefits? Consider, for example, the effect of raising weekly benefits by $50.00 in 1989 ($29.27 in 1979 dollars). In establishments with fewer than 100 employees, this would increase the lost-workday rate by .6 cases per 100 worker years, or 8.4% of the sample mean. However, in establishments with 500 or more workers, the resulting decrease is .03 cases, or .4%.

The remaining relationships between injury rates and the explanatory variables are generally qualitatively similar to those obtained before. The coefficient on the squared benefit variable is negative and statistically significant, while the coefficient on the interaction of wages and benefits is positive though insignificant. At sample means, wages are negatively related to injury rates, while injury rates are lower in larger establishments (table 7). Further, the expected statistically significant coefficients are found for the change in employment, the percent production workers, and the percent female workers. Finally, in contrast to all other specifications, the weekly overtime variable has the expected positive and statistically significant coefficient here. This is consistent with the hypothesis that within an establishment variations in overtime are positively correlated with worker fatigue and other business cycle factors.

V. Conclusion

In this article, I have studied the effect of workers' compensation benefits on lost-workday injury and illness ("injury") case rates. I have argued that an increase in benefits has offsetting incentive effects for workers and firms, so that the net effect of a benefit increase on safety is theoretically ambiguous. But I noted that larger, more experience-rated firms internalize a greater proportion of the costs of the benefits paid to their own injured workers. Hence, they have a greater incentive to increase safety when benefits increase. Consequently, we hypothesized that the benefit/injury-rate relationship will be smaller (less positive or more negative) in these larger firms.

I assembled a longitudinal microdata set of 2,788 manufacturing establishments for the years from 1979 to 1984. The data set permitted us to calculate workers' compensation benefits and lost-workday injury and illness case rates separately for each establishment, and it included a variety of establishment-level variables known to be correlated with injury rates. I estimated lost-workday case-rate equations using a variety of econometric specifications. Initial estimates were obtained using ordinary and weighted least squares, correcting for heteroscedasticity in both cases. Shortcomings with these approaches then led to the investigation of several count data specifications: the negative binomial, a fixed-effect negative binomial, and a quasi-generalized pseudo-maximum-likelihood estimator.

The estimates for all of the non-fixed-effect specifications indicated that workers' compensation benefits are positively related to reported lost-workday case rates in all establishment sizes. In the fixed-effect specification, this is the case in all establishment-size classes except the largest, where the coefficient, though negative, is statistically insignificant and small in magnitude.

The empirical work supported the hypothesis of an experience-rating effect on the benefit/injury-rate relationship. This support indicates that the apparently contradictory goals of providing adequate benefits and enhancing safety incentives may be jointly achieved by increasing the degree of experience rating for a firm at the same time that benefits are increased.

Elasticity estimates suggest that increases in workers' compensation benefits will largely affect establishments with fewer than 500 workers. The least-squares results indicate that a hypothetical increase in the weekly benefit of $50.00 in 1989 would raise injuries by 1.20–1.26 cases per 100 workers (17%–18%) in establishments with fewer than 100 workers. These least-squares results also indicate that injuries would rise by only .27–.31 cases (4%) in establishments with 500 or more workers. The fixed-effect results draw an even larger distinction. The $50.00 weekly benefit increase is predicted to lead to an increase of .6 cases (8.4%) in the smallest establishments, while decreasing injuries by .03 cases (.4%) in the largest establishments.

The regressions also confirmed a number of other hypotheses. Larger establishments are found to be safer, either as the result of economies of scale or the effect of a higher degree of experience rating. Injuries are also procyclical, rising with an increase in employment. Finally, not surprisingly, establishments with more production workers and fewer female workers are riskier. The gender effect may result from the fact that women tend to work in safer occupations.

In addition to providing better estimates of the effect of workers' compensation and confirming a hypothesis about the role of experience rating, this article has demonstrated the utility of count data models in the analysis of occupational injuries and illnesses. The results obtained from the count data specifications are in accord with those obtained from the more traditional least-squares analysis, which strengthens confidence in my findings.

Appendix

Table A1
Benefit/Injury-Rate Elasticity Estimates, Evaluated at Sample Means

	Technique				
Establishment Size	OLS	WLS	Neg Bin MLE	QGPMLE	Fixed-Effect Neg Bin
1–99	.79	.82	.53	.72	.38
100–249	.28	.30	.21	.39	.13
250–499	.20	.21	.21	.19	.18
500+	.18	.20	.12	.21	−.02

References

Bartel, Ann P., and Thomas, Lacy Glenn. "Direct and Indirect Effects of Regulation: A New Look at OSHA's Impact." *Journal of Law and Economics* 28 (April 1985): 1–25.

Butler, Richard J. "Wage and Injury Rate Response to Shifting Levels of Workers' Compensation." In *Safety and the Work Force,* edited by John D. Worrall. Ithaca, N.Y.: ILR, 1983.

Butler, Richard J., and Worrall, John D. "Workers' Compensation: Benefit and Injury Claims Rates in the Seventies." *Review of Economics and Statistics* 65 (November 1983): 580–89.

———. "Labor Market Theory and the Distribution of Workers' Compensation Losses." In *Workers' Compensation Insurance Pricing,* edited by Philip S. Borba and David Appel. Boston: Kluwer Academic Publishers, 1988.

Cameron, A. Colin, and Trivedi, Pravin K. "Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators and Tests." *Journal of Applied Econometrics* 1 (January 1986): 29–53.

Chamber of Commerce of the United States. *Analysis of Workers' Compensation Laws.* Washington, D.C.: Chamber of Commerce of the United States, 1979–84.

Chelius, James R. "The Control of Industrial Accidents: Economic Theory and Empirical Evidence." *Law and Contemporary Problems* 38 (Summer/Autumn 1974): 700–729.

———. "The Influence of Workers' Compensation on Safety Incentives." *Industrial and Labor Relations Review* 35 (January 1982): 235–42.

Chelius, James R., and Smith, Robert S. "Experience-Rating and Injury Prevention." In *Safety and the Work Force,* edited by John D. Worrall. Ithaca, N.Y.: ILR, 1983.

Executive Office of the President. *Economic Report of the President.* Washington, D.C.: U.S. Government Printing Office, 1987.

Gourieroux, C.; Monfort, A.; and Trognon, A. "Pseudo Maximum Likelihood Methods: Applications to Poisson Models." *Econometrica* 52 (May 1984): 701–20.

Greenwood, Major, and Yule, G. Udny. "An Inquiry into the Nature of Frequency Distributions of Multiple Happenings." *Journal of the Royal Statistical Society,* ser. A, 83 (March 1920): 255–79.

Harvey, A. C. "Estimating Regression Models with Multiplicative Heteroscedasticity." *Econometrica* 44 (May 1976): 461–65.

Hausman, Jerry A.; Hall, Bronwyn H.; and Griliches, Zvi. "Econometric Models for Count Data with an Application to the Patents-R&D Relationship." *Econometrica* 52 (July 1984): 909–38.

Hausman, Jerry A.; Ostro, Bart D.; and Wise, David A. "Air Pollution and Lost Work." Working Paper no. 1263. Cambridge, Mass.: National Bureau of Economic Research, January 1984.

Jennrich, R. I., and Moore, R. H. "Maximum Likelihood Estimation by Means of Nonlinear Least Squares." In *1975 Proceedings of the Statistical Computing Section,* by the American Statistical Association. Washington, D.C.: American Statistical Association, 1975.

Judge, George G.; Griffiths, William E.; Hill, R. Carter; and Lee, Tsoung-Chan. *The Theory and Practice of Econometrics.* New York: Wiley, 1980.

Krueger, Alan B., and Burton, John F., Jr. "Interstate Differences in the Employers' Costs of Workers' Compensation: Magnitudes, Causes and Cures." Unpublished manuscript. Ithaca, N.Y.: Cornell University, February 1984.

Moore, Michael J., and Viscusi, W. Kip. *Compensation Mechanisms for Job Risks: Wages, Workers' Compensation, and Product Liability.* Princeton, N.J.: Princeton University Press, 1990.

Ruser, John W. "Workers' Compensation Insurance, Experience-Rating, and Occupational Injuries." *Rand Journal of Economics* 16 (Winter 1985): 487–503.

———. "Workers' Compensation and the Distribution of Occupational Injuries." Working Paper no. 211. Washington, D.C.: U.S. Bureau of Labor Statistics, April 1991.

Ruser, John W., and Smith, Robert S. "The Effect of OSHA Records Check Inspections on Reported Occupational Injuries in Manufacturing Establishments." *Journal of Risk and Uncertainty* 1 (December 1988): 403–23.

Viscusi, W. Kip, and Moore, Michael J. "Social Insurance in Market Contexts: Implications of the Structure of Workers' Compensation for Job Safety and Wages." Unpublished manuscript. Durham, N.C.: Duke University, March 1989.

White, Halbert. "A Heteroskedasticity-consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48 (1980): 817–38.

Worrall, John D., and Appel, David. "The Wage Replacement Rate and Benefit Utilization in Workers' Compensation Insurance." *Journal of Risk and Insurance* 49 (September 1982): 361–71.

Worrall, John D., and Butler, Richard J. "Experience Rating Matters." In *Workers' Compensation Insurance Pricing,* edited by Philip S. Borba and David Appel. Boston: Kluwer Academic Publishers, 1988.