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# Economic Determinants of Workers' Compensation Trends

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## ABSTRACT

The upward trend in workers' compensation indemnity claims has been largely the result of two forces: changes in the program itself, particularly in the level of benefits and in the decline in the waiting period, and changes in the demography of the workforce, particularly the level of risky employment and the number of older workers. Consistent with previous research in workers' compensation, my research shows sizable increases in both the frequency and severity of insurance claims as the wage replacement rate increased and as the waiting period decreased. Comparisons with Occupational Safety and Health Administration data indicate that the increased benefit utilization comes from an increased propensity to report claims rather than a change in workers' or firms' risky behavior. This suggests that, even though current workplaces may be safer, the number of workers reporting an injury may increase as benefits are liberalized or as waiting periods continue to change.

## Why Costs Rose: Frequency and Severity Components

Estimates indicate that workers tend to increase the frequency and severity of workers' compensation claims as benefits increase and as the waiting period for receiving benefits falls. But this can be either because they are willing to undergo more risk ex ante which results in more injuries ex post—behavior that I call *risk bearing moral hazard*—or because higher benefits induce them to report more injuries and increase the duration of their claims—behavior that I call *claims reporting moral hazard.* This article adds to recent literature that aims to sort out the significance of these two types of behavior in explaining cost trends in compensation costs (Butler and Worrall, 1991b, for example) by looking at differential incentive responses in two different data sets.

Employee costs in workers' compensation have risen sharply in the last 15 years, escalating from something less than 1 percent of total payroll costs to over 2 percent. These average costs per employee can be factored into two

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components: claim frequency or the number of claims per employee, and claim severity or the average cost per claim.

This article examines indemnity costs from 1954 to 1984 for 39 states in a sample of National Council on Compensation Insurance (NCCI) states and all states reporting to the Occupational Safety and Health Administration (OSHA) (43 states) from 1976 to 1986 (though data for all states for all years are not available in either sample). This data set ignores medical costs, which are also reimbursed under the workers' compensation system but which deserve a separate treatment and do not enter into the actuarial "trend calculation" that is the focus here.

Indemnity costs per worker can be decomposed in a natural way as follows:

$$\frac{\text{Indemnity Costs}}{\text{Employees}} = \frac{\text{Indemnity Costs}}{\text{Number of Claims}} \cdot \frac{\text{Number of Claims}}{\text{Employees}}$$

$$= \text{Severity} \cdot \text{Frequency}.$$

Taking logarithms of the terms on both sides of the equation leads to

$$\ln \frac{\text{Indemnity Costs}}{\text{Employees}} = \ln(\text{Severity}) + \ln(\text{Frequency}).$$

The logarithms of frequency and severity will be the dependent variables in the statistical analysis employed in this article. The estimated coefficients from the regressions of these variables on the logarithm of benefits measure the percentage response in the dependent variable to a 1 percent increase in benefits. These estimates are, respectively, the benefits elasticity for frequency and severity.

## Review of the Literature

### *Severity Studies*

Much initial severity research has examined the transition from claimant to nonclaimant status using the NCCI's Detailed Claim Call data base. These transitions are modeled as a function of the wage, the worker's weekly compensation benefit, and other claim information. Worrall and Butler (1985) used proportional hazard models in their estimates, indicating benefits significantly increased claim severity. Since the technique they employed assumes nothing about the distribution of nonwork spells of disability except that they are separable in time, benefits elasticities are not immediately recoverable and were not calculated.[1] They found a significantly positive influence of benefits on the

[1] See Miller (1981, pp. 133-136) for information on how the distribution of time (what Miller describes as the "baseline survival" function) might be recovered from the proportional hazard estimates and spell data.

duration of claims but were unable to calculate the benefits elasticity. Hence, Butler and Worrall (1985) and Worrall et al. (1985) fit a general class of distribution functions to duration data, including controls for inherent differences in claims. Using general parametric and nonparametric controls for unobserved heterogeneity, Butler and Worrall (1991a) find benefit effects on duration elasticities consistent with their earlier research for the generalized gamma family of distributions. Other duration elasticities were provided by Meyer, Viscusi, and Durbin (1989) by looking at average durations before and after a real increase in benefits in a given state.

The principal finding of these studies is that the duration of disability varies directly with workers' compensation benefits and indirectly with the wage. The benefit elasticity in these studies is about 0.2 to 0.5, implying that a 10 percent increase in benefits yields about a 2 to 5 percent increase in the average cost per claim.

Johnson and Ondrich (1990) estimated the distribution of job absence spells for 1,040 workers with permanent partial claims from three states who were injured in 1970. Although not as detailed in the claim characteristics as the NCCI data base, their sample has better demographic information about the claimants, so that controls for union membership, education, and job experience are possible. They estimated severity elasticities of about 1.0, two to five times larger than those cited above. Even larger duration elasticities (between 1.5 to 2.0) were found by Krueger (1990), using various techniques on a large panel data set from Minnesota.

*Claim Frequency Studies*

A growing number of studies analyze the importance of benefit changes. Virtually all empirical analyses of workers' compensation find that claims frequency increases as workers' compensation benefits increase. These studies suggest that a 10 percent increase in benefits is accompanied by a 4 to 10 percent increase in the frequency of the claims (with an average elasticity of about 0.6 across the various studies).

An early attempt by Chelius (1977) to estimate the frequency elasticity analyzed a cross-section of relatively homogeneous industries in 18 states. He estimated parameters for an injury rate equation, accounting for the fact that the level of wages may be related to job risk. Injury rates proxied job risk in his model. He found a positive, statistically significant relationship between workers' compensation benefits and injury rates (the benefit elasticity, although positive, was not reported). In another study, Chelius (1983) analyzed the injury rate of manufacturing industries in 28 states. His pooled cross-section (over states) time-series (over the 1972 through 1978 period) finding is that a statistically significant relationship exists between the percentage of income replaced by the expected workers' compensation indemnity benefits and the industry's injury rate. He tested his hypothesis using as the dependent variable the ratio of the number of injuries per 100 full-time workers in a given industry, time period, and state to the number of injuries nationwide. His independent variables are the ratios of income replacement and waiting periods (no elasticities are reported).

Butler and Worrall (1983) examine the frequency of temporary total and permanent partial disability claims over the period 1972 through 1978. They choose that time frame because it immediately followed the 1972 *Report of the National Commission on State Workmen's Compensation Laws,* which recommended that substantial benefit increases be adopted by the state workers' compensation programs. Perhaps because of a fear that the state systems might be federalized, states implemented many of the Commission's benefit recommendations.

Using data from 35 states, Butler and Worrall estimated the frequency elasticities accounting for both labor supply and labor demand adjustments in wages and hours of work using two-stage least squares. Although they observe only those firms in the aggregate that insured through the private market, they were able to account for this "selected sample" using well-known statistical corrections and get "representative" estimates of the elasticities. Even in the presence of controls for the secular increase in injury rates and real benefits, they find that the average benefit elasticity was about 0.4. The benefit elasticity for temporary total disability claims was a little less than 0.4, the benefit elasticity for minor permanent partial disability claims was about 0.4, and the benefit elasticity for major permanent partial disability claims was slightly over 1.0. Interestingly, the estimated frequency elasticity increased with the injury severity.

Butler (1983) also found a similar pattern of benefit elasticities. He examined 15 industries within one state over 32 years. The use of a single state holds constant some of the variation between states that can exist because of unobservable or difficult-to-quantify differences in state laws and program administration. Butler reported benefit elasticities generally around one, with the indemnity claim rate being higher for more serious claims. In an update of that study, Worrall and Butler (1990) found that elasticities may actually be greater than one. Their point estimates of the elasticities are 1.7, 2.8, and 1.1, respectively, for permanent total, permanent partial, and temporary total disabilities.

Bartel and Thomas (1982) examined the impact of the OSHA program on injury rates, while simultaneously looking at the frequency elasticity. The focus of their analysis was lost work days (for job injuries) per full-time employee, and their data are for 22 states for various industries during the period 1972 through 1978. Their estimated frequency elasticity of 0.626 lies in the middle of the 0.4 to 1.0 range from prior studies.

Ruser (1985) estimated the determinants of injury rates without regard to offsetting adjustments in wages or hours of work. This "reduced form" specification included wages and hours as independent factors, while the studies above treated them as being jointly determined. His sample consisted of pooled cross-section time-series data from 1972 through 1979 on 25 manufacturing industries in 41 states. The frequency elasticity was 0.35 for his preferred specification. One of the main differences between the Ruser specification and those cited above is his attempt to control for experience rating, perhaps accounting for his slightly smaller estimated benefit elasticity.

Three analyses of claim frequency use individual data sets. Data on individuals (instead of aggregated groups of workers or firms) allow for more demographic information about the individual claimant or claim, but they require the calculation of potential workers' compensation benefits for each individual (instead of a representative or "averaged" individual, as the aggregated analyses do). Leigh's (1985) logit analysis of workers' compensation recipients examines how benefit levels affect claim frequency. He finds a benefit elasticity of 0.4 when he did not control for year and state effects and an elasticity of 0.5 when he did, similar to the disaggregated analyses discussed above. Krueger (1988) used a matched 1983 through 1984 and 1985-1986 sample of workers from the Current Population Survey to estimate the correlates of claim participation in the workers' compensation system. Krueger estimated the frequency elasticity to be 0.535 for the entire sample, slightly more for manufacturing employees (0.569) than for nonmanufacturing employees (0.505) when they are estimated separately.

The other disaggregated analysis, a study by Moore and Viscusi (1990), imputed not only various measures of benefits to individuals in their sample, but imputed the risk variable as well on the basis of the employees' state of residence and reported industry. They found that, contrary to the studies listed above, an increase in benefits leads to a small but significant decrease in the frequency of injuries. They argue that employer responses are stronger than employee responses in workers' compensation; higher levels of workers' compensation payments actually save employers money since they promote workplace safety.

An interesting simulation by Knieser and Leeth (1989) suggests how Moore and Viscusi's results may be reconciled with the other studies mentioned above. Kneiser and Leeth simulated the workers' compensation system using a hedonic model and found that safety incentives actually do increase in their simulation (so that the number of real accidents fell), although in the same simulations the number of workers' compensation claims reported increased dramatically. Even if Moore and Viscusi's estimates are correct, they used a more "real" measure of safety in their analysis and not the reported number of claims used by Krueger and Leigh. Hence, it may not be altogether surprising to find that the number of actual injuries fall (Moore and Viscusi), while the number of reported injuries rises (all the other studies).

Articles by Butler and Worrall (1991b) and Butler, Gardner, and Worrall (1991) have suggested that Moore and Viscusi perhaps measured risk-bearing behavior, as contrasted with the other studies in the field, which measured claims filing behavior. Corroborative evidence on claims reporting moral hazard is provided by Ruser (1990). Ruser used firm level Bureau of Labor Statistics data and found that benefits do tend to decrease the number of fatal injuries (which he attributes to an absence of a claims reporting moral hazard effect) but actually increases the number of nonfatal injuries (for which claims reporting moral hazard is more important).

## Unit Statistical Plan Results

Several regressions of workers' compensation frequency and severity were fit using Unit Statistical Plan (USP) data from the NCCI files. This cross-section time-series data base covers 39 states during the period 1954 through 1984 (not all states are represented in all years). The three specifications were as follows:

$$\ln(\text{Frequency}) = \ln(\text{Indemnity Claims per Nonagricultural Employee}) = X\beta + \varepsilon_f$$
$$\ln(\text{Severity}) = \ln(\text{Real Indemnity Costs per Claim}) = X\gamma + \varepsilon_s$$
$$\ln(\text{Real Indemnity Costs per Employee}) = X\theta + \varepsilon_t,$$

where $\beta + \gamma = \theta$, since real indemnity costs per employee is the product of severity and frequency. Estimates with these three dependent variables are presented in Tables 1 and 2.

**Table 1**
Unit Statistical Plan Results:
Basic Model Without Time Regressors

| | *Frequency Response* | | *Severity Response* | | *Total Response* | |
|---|---|---|---|---|---|---|
| *Independent Variable* | *No State Effects* | *State Effects* | *No State Effects* | *State Effects* | *No State Effects* | *State Effects* |
| Intercept | 5.906 | 5.572 | 9.634 | 10.787 | 15.540 | 16.359 |
| | (10.83) | (21.84) | (32.08) | (39.10) | (24.78) | (43.89) |
| Ln(Ben/Wages) | 0.484 | 0.325 | 0.671 | 0.825 | 1.155 | 1.149 |
| | (4.19) | (5.94) | (10.55) | (13.95) | (8.69) | (14.39 |
| Ln(Risk Empl) | 0.297 | 0.582 | -0.319 | -0.150 | -0.021 | 0.432 |
| | (6.66) | (21.12) | (12.97) | (5.04) | (0.42) | (10.73) |
| Monopolistic State Fund | --- | --- | --- | --- | --- | --- |
| No Self-Insurance | 0.597 | 0.546 | 0.316 | 0.392 | 0.913 | 0.938 |
| | (5.36) | (11.31) | (5.15) | (7.51) | (7.13) | (13.30) |
| Group Self-Insurance | -0.169 | 0.085 | 0.077 | 0.050 | -0.092 | 0.135 |
| | (2.30) | (2.71) | (1.90) | (1.46) | (1.09) | (2.94) |
| Waiting Period | -0.099 | -0.104 | 0.026 | -0.006 | -0.073 | -0.111 |
| | (8.72) | (14.36) | (4.11) | (0.82) | (5.61) | (10.43) |
| Time | --- | --- | --- | --- | --- | --- |
| $\text{Time}^2$ | --- | --- | --- | --- | --- | --- |
| State Effects | No | Yes | No | Yes | No | Yes |
| $R^2$ | 0.144 | 0.860 | 0.252 | 0.527 | 0.154 | 0.776 |

Note: See Butler and Worrall (1991b) for a description of the data and variables. The sample period is from 1954 through 1984. Ln(Ben/Wages) = the logarithm of the wage replacement rate. Ln(Risk/Empl) = proportion of nonagricultural workforce in manufacturing and construction (a measure of risky employment). Dependent variables are ln(frequency), ln(severity), and ln(indemnity costs per employee). Absolute t-statistics are in parentheses.

The basic model is presented in Table 1 with the log of the wage replacement rate; the log of a measure of risky employment (the proportion of the workforce in manufacturing and construction); and administrative dummy variables indicating whether a state does not allow any form of self-insurance, a state allows for group self-insurance, or a state has a monopolistic state fund (only in the OSHA data set).

**Table 2**
Unit Statistical Plan Results:
Basic Model with Time Regressors

| | *Frequency Response* | | *Severity Response* | | *Total Response* | |
|---|---|---|---|---|---|---|
| *Independent Variable* | *No State Effects* | *State Effects* | *No State Effects* | *State Effects* | *No State Effects* | *State Effects* |
| Intercept | 5.650 | 4.749 | 7.088 | 7.999 | 12.738 | 12.748 |
| | (8.62) | (14.95) | (22.51) | (28.15) | (17.36) | (30.93) |
| Ln(Ben/Wages) | 0.419 | 0.149 | 0.218 | 0.317 | 0.637 | 0.466 |
| | (3.06) | (2.23) | (3.32) | (5.29) | (4.16) | (5.37) |
| Ln(Risk/Empl) | 0.304 | 0.603 | -0.248 | -0.061 | 0.056 | 0.541 |
| | (6.65) | 21.68 | (11.32) | (2.47) | (1.10) | (15.02) |
| Monopolistic State Fund | --- | --- | --- | --- | --- | --- |
| No Self-Insurance | 0.582 | 0.499 | 0.209 | 0.245 | 0.790 | 0.744 |
| | (5.16) | (10.18) | (3.85) | (5.60) | (6.26) | (11.71) |
| Group Self-Insurance | -0.226 | 0.003 | -0.067 | -0.047 | -0.293 | -0.043 |
| | (2.63) | (0.10) | (1.62) | (1.45) | (3.05) | (0.93) |
| Waiting Period | -0.098 | -0.102 | 0.034 | -0.007 | -0.064 | -0.095 |
| | (8.59) | (14.04) | (6.29) | (1.06) | (4.97) | (10.09) |
| Time | -0.013 | -0.010 | 0.035 | 0.036 | 0.022 | 0.026 |
| | (1.37) | (2.59) | (7.96) | (20.78) | (2.19) | (5.43) |
| $Time^2$ | 0.0004 | 0.0005 | -0.0004 | -0.001 | 0.000 | -0.000 |
| | (1.46) | (3.62) | (2.94) | (4.40) | (0.04) | (0.24) |
| State Effects | No | Yes | No | Yes | No | Yes |
| $R^2$ | 0.145 | 0.863 | 0.433 | 0.684 | 0.201 | 0.827 |

Note: See Butler and Worrall (1991b) for a description of the data and variables. The sample period is from 1954 through 1984. Ln(Ben/Wages) = the logarithm of the wage replacement rate. Ln(Risk/Empl) = proportion of nonagricultural workforce in manufacturing and construction (a measure of risky employment). Dependent variables are ln(frequency), ln(severity), and ln(indemnity costs per employee). Absolute t-statistics are in parentheses.

Table 2 supplements this specification with a quadratic time trend specification—Time and $Time^2$, a linear time trend variable and its square—to allow for nonlinear trends in the injury rates. All were fit with and without individual state dummy variables to examine the importance of state specific effects. The state dummy variables allow each of the states to have a separate intercept in the specification, an adjustment to capture that part of the administrative environment that does not vary within a state but is different from state to state. The specifications that control for these state differences are called "state effects" models.

As a measure of the potential for benefit utilization by workers, the natural logarithm of the wage replacement ratio expected on the basis of the wage distribution in each state is included. This accounts for the minimum, maximum, and replacement rate differences between states based on a one-parameter wage distribution (as described in Butler, 1983).

Consistent with the above-mentioned studies of benefit utilization, rising benefits increase both the severity and frequency of claims. For every 10 percent increase in the wage replacement ratio, average claim costs (severity) increase by 7 percent (from the 0.7 average obtained from the two severity responses for the logarithm of the wage replacement rate coefficients), while frequency increases only by about 4 percent (from the 0.4 average of the coefficients in the two frequency response columns). The overall effect is fairly large: adding both effects together yields better than an 11 percent increase in costs per worker when the wage replacement ratio increases by 10 percent (see the total response columns for the logarithm of the wage replacement rate). These effects are only half as large as those shown in Table 2, when time trend and administrative control variables are included in the analysis. The overall effect of a 10 percent increase in the wage replacement rate is a 5 percent increase in average indemnity costs.

A proxy for inherent workplace dangers is the (natural logarithm of) the proportion of all nonagricultural employment in manufacturing and construction. Butler and Appel (1990) find evidence that this variable was highly correlated with OSHA injury and severity variables (in a time-series cross-section sample when both were available). The estimated impact of this variable is positive in the frequency models and negative in the severity model. Increased exposure to risk is always associated with an increased frequency of claims: claims increased 3 to 6 percent with a 10 percent increase in the proportion of risky firms. This increased frequency of claims is offset in the basic model by the severity effect—average claim costs tend to fall in the basic model specification as the proportion of workers in manufacturing and construction increases.

States that do not allow for self-insurance observe two injury rate effects: a reporting effect that tends to decrease the reported severity and frequency, and an economic effect that tends to increase it. The reporting effect is a sample selection phenomenon—where there is no self-insurance, all firms are observed in the sample, including the largest firms with lower-than-average frequency and severity. In states with self-insurance, those large firms tend to self-insure and disappear from the sample, leaving an insurance pool with relatively higher frequency and severity. The reporting effect implies a negative coefficient for the no self-insurance dummy variable.

Offsetting the negative reporting effect in states that do not allow self-insurance are the positive economic effects of self-insurance. Where self-insurance is an alternative, firms are more likely to be aware of their workers' compensation program and perhaps more attentive to workplace claims prevention. Self-insurance may also promote efficiency in the sense of increasing competition among insurers for those firms deciding whether to self-insure.

## OSHA Results

In order to complement the research done with the Unit Statistical Plan data, the USP analysis was replicated with injury "frequency" and "severity" from OSHA records. The OSHA data come from annual surveys of firms that report information from their injury logs on the number of accidents and the number of lost days of work due to accidents. The frequency measure is the total number of injury cases per 100 full-time employees (the number of injuries times

200,000—100 workers at 40 hours per week for 50 weeks—divided by the total number of hours worked).

The severity data is the number of lost work days per 100 full-time employees. The OSHA severity measure is much less satisfactory because it combines elements of frequency and severity (usually measured for claims with positive duration), and because it is generated from a truncated distribution of claims. All lost workday cases that are still in progress as of each calendar year are simply truncated on December 31. This does not affect frequency, but it does affect the severity measure. However, the measurement bias may be small for two reasons. First, only a small number of claims (relative to the yearly total) will be affected by the truncation. Second, to the extent that the degree of truncation does not change much from year to year for a given state, or is uncorrelated with the independent variables in the analysis, it will not affect the validity of the results.

## Expected Differences between OSHA and USP Data

The insurance (USP) data will reflect more claims reporting moral hazard than the OSHA data. The insurance data excludes self-insurers whereas OSHA includes them. Since self-insuring firms fully finance their own claims, they will be more responsive to benefit changes than firms that are only manually rated (that is, face a group price independent of their own claims experience). Self-insuring firms will therefore be more willing to spend resources to both reduce risk-bearing moral hazard and monitor claims-reporting moral hazard by workers. Hence, the OSHA data will more accurately reflect the claims reduction activities of the larger, self-insuring firms. However, due to controls for self-insurance in our empirical estimates, this effect may be dominated by other differences between the data sources.

A more important source of differential response between the USP and OSHA data will be the migration of claims from those that seek no indemnity payments for a claim but only medical treatment to claims for both medical and indemnity payments. An institutional feature of workers' compensation that favors such migration is the waiting period of at least three days. As real benefits increase, marginal injuries that previously went unreported for insurance claim purposes now get reported as workers find that the higher benefits offset the waiting period. (Or, alternatively, they choose to increase the length of stay on disability status at the margin as the cost of remaining on a claim is lowered by the higher benefits.) The best evidence on this type of claims migration is contained in Worrall and Appel (1982). They controlled for institutional variation by focusing on 20 years' of data from Texas, a state that did not allow private-sector self-insurance, and by using a time period during which the waiting period did not change. They found a substantial migration or shifting of claims from medical only to indemnity status (both in terms of frequency and in terms of dollars spent) as real benefits increase. Their estimates of claim elasticity of about 0.5 and severity elasticity of about 0.9

are very similar to those reported here, despite the differences in the empirical specification and data sets.

Moral hazard effects ought to be evident by comparing the estimated benefit elasticities between the two data sets. Clearly, claims reporting moral hazard will tend to increase claims frequency in the USP data over the OSHA data if the claims reporting effect is significant. When benefits increase substantially, not only will workers undertake more risk, but they also have greater incentive to report accidents. Marginal accidents or conditions that went unreported previously will now be reported. The USP data should reflect relatively more of this reporting effect than the OSHA data; therefore, it is expected that benefit elasticities for the USP data will be more positive than for the OSHA data. Indeed, if the OSHA data reflected only risk-bearing moral hazard (while the insurance data obviously reflect both), then we would expect the incentive response differences between these two data sets to represent the size of the reporting (claim reporting moral hazard) effect. In fact, the OSHA data also may reflect some claim reporting moral hazard effects, so that the difference between the USP and OSHA elasticities is probably a lower bound on the size of the reporting effect.

The effect of claims reporting moral hazard on reported severity is ambiguous because of offsetting effects. On one hand, the severity of the existing claims ought to increase as benefits rise, since the opportunity cost of remaining out of work falls with the increased benefits and each existing claim will increase in length or at best remain unchanged. This will unambiguously lead to higher levels of reported severity as benefits increase. However, since a rise in benefits will also increase claim frequency, a number of new claims will arise. If the distribution of these newer claims has a smaller mean than the distribution of existing claims, then the average reported severity may actually fall depending on the relative size of the two effects (it is more likely that reported severity will rise if the increase in the frequency of short claims is relatively small).

The changes in the magnitude and significance of the other variables between the two data sets is ambiguous: if the reporting and risky behavior effects work in the same direction, then the USP data will have larger and more significant coefficients; but if they go in opposing directions, then the OSHA data will have the larger coefficients. For example, to the extent that state effects measure fixed administrative differences in workers' compensation between states, then those effects ought to be more significant in the USP regressions. To the extent that they measure inherent risk differentials between states (unrelated to the workers' compensation administration), then state effects will be relatively more significant in the OSHA data set.

### *Empirical Results*

We observe much smaller benefit elasticities and waiting period effects in the OSHA data than in the USP data, suggesting that reporting effects are a significant factor in the recent increase in injury claims (see Table 3). A variable for retroactive periods and whether trials were tried de novo on appeal were excluded because they were generally not statistically significant and their exclusion did not change the empirical results.

**Table 3**
Occupational Safety and Health Administration Results:
Injury Frequency and Severity, 1976-1986

| | *Frequency of Claims* | | | *Severity of Claims* | | |
|---|---|---|---|---|---|---|
| | *No State Effects* | *State Effects* | | *No State Effects* | *State Effects* | |
| | *No Trends* | *No Trends* | *Trends* | *No Trends* | *No Trends* | *Trends* |
| Intercept | 2.430 | 3.358 | 3.302 | 4.262 | 4.690 | 5.175 |
| | (23.99) | (34.04) | (29.92) | (26.76) | (32.26) | (32.94) |
| Ln(Ben/Wages) | 0.034 | 0.006 | 0.005 | 0.032 | 0.003 | 0.004 |
| | (1.70) | (0.63) | (0.55) | (1.01) | (0.18) | (0.25) |
| Ln(Risk/Empl) | 0.008 | 0.648 | 0.551 | -0.079 | 0.019 | 0.423 |
| | (0.35) | (11.59) | (8.11) | (2.15) | (0.23) | (4.36) |
| Monopolistic State Fund | 0.054 | --- | --- | 0.200 | --- | --- |
| | (1.40) | | | (3.27) | | |
| No Self-Insurance | -0.006 | 0.182 | 0.132 | -0.121 | -0.118 | 0.061 |
| | (0.10) | (4.85) | (3.26) | (1.32) | (2.14) | (1.06) |
| Group Self-Insurance | -0.128 | -0.056 | -0.037 | 0.002 | 0.014 | -0.054 |
| | (7.09) | (4.69) | (2.71) | (0.07) | (0.81) | (2.81) |
| Waiting Period | -0.011 | -0.030 | -0.035 | -0.017 | -0.044 | -0.045 |
| | (2.61) | (3.87) | (4.55) | (2.72) | (3.82) | (4.10) |
| Time | --- | --- | -0.025 | --- | --- | 0.024 |
| | | | (4.83) | | | (3.20) |
| $Time^2$ | --- | --- | 0.002 | --- | --- | -0.000 |
| | | | (3.99) | | | (0.51) |
| State Effects | No | Yes | Yes | No | Yes | Yes |
| $R^2$ | 0.171 | 0.835 | 0.847 | 0.086 | 0.840 | 0.861 |

Source: U.S. Bureau of Labor Statistics, unpublished data by state for 1976 through 1986.
Note: Frequency of claims = logarithm of injury cases per 100 full-time employees. Severity of claims = logarithm of lost work days per 100 full-time employees. Ln(Ben/Wages) = the logarithm of the wage replacement rate. Ln(Risk/Empl) = the logarithm of the proportion of nonagricultural workforce in manufacturing and construction (a measure of risky employment). There are 374 observations in each specification. Absolute t-statistics are in parentheses.

To the wage replacement rate and risky employment variables are added several other dimensions of the workers' compensation system: a linear time trend variable, the number of days in the waiting period for each state, and dummy variables for group self-insurance, no self-insurance allowed, and monopolistic state funds. All the OSHA specifications were fit with and without individual state dummy variables. These state dummy variables allow each state to have a separate intercept in the specification, an adjustment to capture all state-specific factors that do not change over time or change only very slowly.

The OSHA results for frequency mirror those for the USP fairly well (see Table 3). The substantial variation in frequency and severity rates between states is reflected in large and significant state effects. The $R^2$ is much higher in those specifications with the state effects, suggesting the wisdom in allowing for individual state differences when using these models to account for trend. Because of their significance, the discussion of the empirical results focuses on those specifications with the state effects included.

Increases in the wage replacement rate increase the frequency of injuries only very slightly in Table 3, although the increase associated with the proportion of all nonagricultural workers in construction and manufacturing is substantial. Injury frequency and severity remain virtually unchanged—again, increasing only slightly as the relative wage replacement rate increases. This does not mean that an increase in benefits will not be accompanied by an increase in claim frequency or claim severity; from the USP data we know that they will. What is suggested by the comparison of the USP results in Tables 1 and 2 and OSHA results in Table 3 is that higher benefits do not result in a significantly higher level of risk taking by employees. However, higher benefits do result in more reported injuries and a higher cost per claim—that is, benefit changes are accompanied by changes in *reported* injuries. Note also in Table 3 that the coefficient for severity is much smaller than the frequency coefficient, as with the severity results for the USP data set. A 10 percent increase in the proportion of risky employment results in about a 6 percent increase in the frequency of claims (the coefficient in the third column from the left is 0.55), and about a 4 percent increase in the severity of claims (the 0.423 coefficient of ln(risky employment) in the far right-hand column).

The other workers' compensation variables have the expected effects on injury frequency and severity. The waiting period variable provides another example of the incentive effects for risk taking: its negative coefficient implies that a 10 percent decline in the waiting period leads to a 3.5 percent increase in claims frequency. As discussed above, if the OSHA data set does reflect true changes in risky behavior, we would once again expect the OSHA coefficients to be uniformly smaller than the USP coefficients. This turns out to be the case (see the waiting period coefficients in Tables 2 and 3).

Declining waiting periods increase severity in the OSHA data but decrease severity in the USP data. This is the result of two potentially offsetting factors: an insurance truncation factor increases short-term claims that were formerly truncated by the previous, longer waiting period. This is only operative for the insurance data and explains why the waiting period has a positive coefficient in the USP data set (Tables 1 and 2 "no state effects" results). This truncation factor may be partially offset if the distribution of new claims induced by a shorter waiting period has a higher mean than the current distribution. Only this second factor would be operative in the USP data set and might explain why a decline in the waiting period increases claim severity there, even though it reduces it in the OSHA data (where the truncation factor is important).

To the extent that firms bear the full costs of their employees' claims (i.e., to the extent that they are fully experience rated or self-insuring), they will have greater incentives to prevent claims by providing a safer working environment, more carefully screening claims, etc. Not surprisingly, states that allow for group self-insurance seem to have a 4 percent lower frequency (third column in Table 3) and a 5½ percent lower severity (sixth column in Table 3) than states that do not allow group self-insurance. States that allow neither group self-insurance nor individual self-insurance have a 13 percent higher claims frequency and a 6 percent higher claims severity. Most interesting is the fact that, in monopolistic state funds, both frequency and severity are substantially higher, controlling for everything else.

Finally, the residual time trend in Table 3 indicates that, controlling for all other factors, frequency of claims follows a U-shaped pattern that falls to about 1981 and has been increasing since, while the severity is increasing at about 2½ percent per year throughout the sample period.

## Cost Trends and the Aging Workforce

Although the models of frequency and severity illustrated in Table 1 explain most of the variation in those variables when state effects are included, the statistical significance of the time and time-squared variables shown Table 2 indicates that a residual trend in the data persists even after controlling for relative benefits, waiting periods, the proportion of risky employment, and several institutional features of the workers' compensation system.

What explains this residual trend in the data? In order to address this question empirically, the trend analysis is extended to allow for various interactions with important demographic variables. That is, the basic specification of the quadratic time trend (suppressing the other regressors) can be written as follows:

$$\text{Injury} = \alpha_0 + \alpha_1\text{time} + \alpha_2\text{time}^2. \tag{1}$$

What factors help explain this trend? To look at this problem empirically, we allow the coefficients in equation (1) to be (affine) linear functions of demographic variables. Since many important demographic variables exhibit a strong serial correlation and may well influence either claims reporting or risk-bearing moral hazard, the time trend may be standing as a proxy for these omitted variables. A general way to test this (and more general models of trend) is to allow demographic variables to influence the trend specification as follows:

$$\alpha_i = \phi_{i0} + \phi_{i1}Z \quad \text{for } i = 0, 1, 2 \tag{2}$$

where Z is a vector of demographic variables. Substituting this vector back into equation (2) yields the following:

$$\text{Injury} = \phi_{00} + \phi_{01}Z + \phi_{10}\text{time} + \phi_{11}Z{*}\text{time} + \phi_{20}\text{time}^2 + \phi_{21}Z{*}\text{time}^2.$$

The trend in equation (1) now comprises two components: the pure trend in injuries (associated with the $\phi_{10}$ and $\phi_{20}$ coefficients) and the part of the trend associated with the vector of demographic variables Z (the $\phi_{i1}$ coefficients).

Making this substitution, and including the demographic variables available in the data set, yields the specification in Table 4. Of special interest are two variables that reflect nonmarket opportunities that might affect market claim behavior: per capita nonlabor income and the proportion of the population not in the work force. The nonlabor income variable was not statistically significant in the analysis and is excluded here. Its presence in the specification did not make any quantitative difference in the other coefficients.

**Table 4**
Unit Statistical Plan Results:
"Residual" Trend Depends Largely on Age of Workforce

| | *Frequency Response* | | *Severity Response* | | *Total Response* | |
|---|---|---|---|---|---|---|
| *Independent Variable* | *No State Effects* | *State Effects* | *No State Effects* | *State Effects* | *No State Effects* | *State Effects* |
| Intercept | 4.107 | 4.382 | 7.637 | 7.278 | 11.744 | 11.660 |
| | (12.60) | (11.31) | (25.98) | (21.07) | (28.04) | (23.49) |
| Ln(Ben/Wages) | 0.176 | 0.175 | 0.332 | 0.307 | 0.507 | 0.484 |
| | (2.67) | (2.63) | (5.58) | (5.19) | (6.00) | (5.66) |
| Ln(Risk/Empl) | 0.065 | 0.608 | -0.044 | -0.052 | 0.561 | 0.556 |
| | (21.94) | (21.98) | (1.78) | (2.11) | (15.83) | (15.69) |
| No Self-Insurance | 0.523 | 0.518 | 0.253 | 0.256 | 0.776 | 0.774 |
| | (10.87) | (10.74) | (5.83) | (5.95) | (12.55) | (12.53) |
| Group Self-Insurance | -0.025 | -0.032 | -0.066 | -0.009 | -0.092 | -0.041 |
| | (0.71) | (0.84) | (2.05) | (0.26) | (1.99) | (0.84) |
| Waiting Period | -0.090 | -0.090 | 0.008 | 0.010 | -0.083 | -0.080 |
| | (12.40) | (12.33) | (1.16) | (1.58) | (8.83) | (8.53) |
| Time | 0.003 | -0.022 | 0.044 | -0.0001 | 0.046 | -0.022 |
| | (0.62) | (0.65) | (11.51) | (0.00) | (8.56) | (0.51) |
| Time$^2$ | -0.0001 | 0.0003 | -0.001 | 0.001 | -0.001 | 0.002 |
| | (0.81) | (0.29) | (6.07) | (1.48) | (4.89) | (1.26) |
| Ln(Old) | -0.799 | -0.452 | -0.523 | -0.807 | -1.322 | -1.259 |
| | (6.21) | (1.44) | (4.51) | (2.89) | (8.00) | (3.14) |
| Time*Ln(Old) | --- | -0.032 | --- | -0.048 | --- | -0.081 |
| | | (0.76) | | (1.29) | | (1.49) |
| Time$^2$*Ln(Old) | --- | 0.0006 | --- | 0.002 | --- | 0.003 |
| | | (0.49) | | (2.32) | | (2.00) |
| State Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.869 | 0.869 | 0.693 | 0.700 | 0.838 | 0.839 |

Note: Ln(Ben/Wages) = the logarithm of the wage replacement rate. Ln(Risk/Empl) = the logarithm of the proportion of nonagricultural workforce in manufacturing and construction (a measure of risky employment). Ln(Old) = the logarithm of the porportion of the population under 18 or over 64 years old. Time*Ln(Old) = linear time trend multiplied by Ln(Old). Time$^2$*Ln(Old) = linear time trend squared multiplied by Ln(Old). Absolute t-statistics are in parentheses.

Surprisingly, only the single variable for nonworkers (the proportion of the population over 64 or under 18) was necessary to explain the trend. That is, comparing the trend coefficients from Tables 2 and 4, it is clear that including the nonworkers variable in the specification removes the pure trend effect—that is, the time and time-squared variables are no longer statistically significant. The fact that the coefficient has a negative impact on both claim frequency and severity is straightforward. For the older group, social security is an excellent alternative to workers' compensation, especially at moderate and lower wage levels (social security benefits are highly regressive). Also as the proportion of the youngest age group increases, the relative cost of an injury is arguably higher because families on average have more dependents to support.

## On-Level Adjustment Factors

Although the research tools employed above are economic rather than actuarial, in this section I bridge the gap between the two disciplines somewhat by comparing the actual levels of indemnity losses with levels that would be predicted with on-level adjustments (defined below) as a function of the four variables that were found to be important: the wage replacement rate, the waiting period, the proportion of risky employment in the market, and various institutional features of the workers' compensation system.

For ease of interpretation of the results, I will speak of the inverse of the on-level factor for indemnity payments as the "predicted" level of workers' compensation indemnity losses. The on-level adjustment is an actuarial adjustment used to inflate the indemnity losses in previous years to current levels (so that, with increasing benefits, prior years' on-level factor will be much larger than the factor for the recent past). The inverse of this ratio is the predicted level of indemnity losses (relative to a base year), and its trend is the predicted degree of inflation in indemnity benefits based on actuarial analyses of the benefit increases.

A major actuarial trend problem is that the actual level of indemnity losses in recent years has frequently exceeded the predicted level. By making the (logarithmic) difference between them a function of the same variables employed above, it can be determined whether benefit utilization and risky employment can explain any of the recent increases in the trend.

The dependent variable in this analysis is the percentage difference between actual and predicted levels of indemnity losses (that is, the log differences). The predicted levels of losses are indexed by the inverse of the on-level factor as explained above. A comparable index of "actual" losses is created by dividing all the nominal average indemnity losses in a given state by its 1981 value.[2]

The positive coefficient for the wage replacement variable indicates that a 10 percent increase in benefits is associated with an additional 4 to 11 percent increase in the actual level of indemnity losses over the predicted level of losses (see the first two columns of Table 5). Note that this falls within the range of the combined frequency and severity results of Tables 1 and 2 and the empirical results of other researchers. On-level adjustments apparently do not adequately account for the change in frequency and severity when benefits rise, and they systematically underpredict the size of the indemnity increases.

[2] 1981 is the base year for the actual index, and 1988 is the base year for the on-level, "predicted" index. The difference in base years was necessitated by the data and is inconsequential for the conclusions drawn about trend.

**Table 5**
Actual Versus Predicted (from On-Level Factors) Premium Level Changes

$$\textit{Dependent Variable} = \log \frac{\textit{Average Cost}_t}{\textit{Average Cost}_{1982}} - \log \frac{1}{\textit{Indemnity On-Level Factor}_{1986}}$$

| | No State Effects | State Effects | |
|---|---|---|---|
| *Independent Variable* | *No Trends* | *No Trends* | *Trends* |
| Intercept | 2.758 | 5.203 | 1.145 |
| | (4.26) | (11.52) | (2.48) |
| Ln(Ben/Wages) | 0.398 | 1.128 | 0.311 |
| | (2.94) | (11.67) | (3.16) |
| Ln(Risk/Empl) | 0.466 | 0.202 | 0.351 |
| | (9.21) | (3.62) | (7.53) |
| No Self-Insurance | 0.600 | 0.790 | 0.489 |
| | (5.14) | (9.80) | (6.96) |
| Group Self-Insurance | 0.488 | 0.399 | 0.102 |
| | (5.31) | (6.72) | (1.83) |
| Waiting Period | -0.100 | -0.001 | 0.019 |
| | (7.05) | (0.08) | (1.74) |
| Time | --- | --- | -0.003 |
| | | | (0.46) |
| $\text{Time}^2$ | --- | --- | 0.001 |
| | | | (5.11) |
| State Effects | No | Yes | Yes |
| $R^2$ | 0.221 | 0.718 | 0.801 |

Note: Ln(Ben/Wages) = the logarithm of the wage replacement rate. Ln(Risk/Empl) = the logarithm of the proportion of nonagricultural workforce in manufacturing and construction (a measure of risky employment). Absolute t-statistics are in parentheses.

Beyond benefit utilization, other coefficient patterns found in Tables 1 and 2 seem to be reflected in Table 5 as well. The proportion of risky employment increases the overall average indemnity costs (Tables 1 and 2), and risky employment also leads to an underprediction of actual losses. The same is true of the no self-insurance variable, although the results for the group self-insurance and waiting period variables are mixed.

The sizable improvement in regression fit when state effects are included indicates that state-specific administrative differences are very important in analyzing the prediction error. About 70 percent of the variation of the prediction error is explained by the regressors (the $R^2$ in the middle column with state effects). But the other regressors are jointly significant and generally have the expected sign pattern. The time coefficients are also interesting (right-hand column), showing a small but statistically significant convex trend that becomes substantial in the post-National Commission era. Perhaps this reflects the impact on the compensation system of the 1972 report of the National Commission on State Workmen's Compensation Laws.

## Conclusion

This research demonstrates that the upward trend in workers' compensation indemnity claims has been largely the result of two forces: changes in the program itself—particularly in benefit levels and the waiting period—and changes in workforce demography—especially in the amount of risky employment and among the oldest and youngest members of society.

To address the empirical magnitude of these changes, the research employed two data sets. The first and primary source of information was the NCCI's Unit Statistical Plan data. The second data set came from the Occupational Safety and Health Administration, results from which added considerable insights to the interpretation of the USP data.

Consistent with previous research in workers' compensation, I found sizable increases in both the frequency and severity of claims as the replacement rate (benefits) increased, and as the waiting period to receive benefits decreased. Comparisons with the OSHA data indicate that this is a reporting effect rather than a change in workers' or firms' risky behavior. It is quite possible, and consistent with the results reviewed and reported here, that liberalization of workers' compensation benefits led firms to provide safer working environments while it led workers to file more claims. As benefits increase, firms have incentives—depending on the degree of experience rating—to reduce risk-bearing moral hazard in order to minimize insurance costs. On the other hand, in the face of liberalized benefits, workers have more incentive to engage in claims reporting moral hazard. More injuries are reported, but the workplace may in fact be safer than before. However, after controlling for these incentives, a residual trend remains that is explained by the proportion of the nonworking population.

These results indicate that actuarial procedures that do not account for benefit utilization, in the sense of higher claims frequency and severity as benefits increase, will likely underestimate the cost consequences of any given change in the structure of future benefits. This is shown to be the case by comparing actual increases in the indemnity costs with the on-level (predicted) increases in those costs. The frequency and severity models presented here capture this differential reasonably well.

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