A SIMULATION MODEL OF OCCUPATIONAL INJURY AND ILLNESS CAUSATION AND REGULATION[1]

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Abstract. The United States Occupational Safety and Health Administration (OSHA) regulates the level of occupational safety and health within firms and inspects firms for violations of its regulations. Regression-based evaluations of occupational health and safety conditions in the United States generally conclude that OSHA's regulation fails to increase either the level of safety or safety-related investment. However, case studies and other forms of qualitative research suggest that regulation does increase both. Resolving this discrepancy requires a research strategy that combines elements of qualitative research and quantitative research. Simulation modelling can be used to bridge these two methods. Generally, the research project constructs a simulation model of accident generation within firms, generates synthetic data from variations of the model, and evaluates the sensitivity of regression methods to variations in the model. This paper presents the structure and base run behavior of the model used in this research project.

INTRODUCTION

This paper presents a system dynamics simulation model of the impact of safety inspections by the Occupational Safety and Health Administration (OSHA) on the safety performance within a single U.S.-based firm (Andersen, Crawford, Faerman and Mosekilde 1986). The model can simulate sequentially up to several thousand firms (each with some systematic and some random differences) for a period of three years. Hence, Monte Carlo-like simulations for several thousand firms can be produced in DYNAMO (Pugh 1983).

The results discussed below are of both substantive and methodological interest. From a substantive point of view, the model presents a unified and explicit causal theory of how OSHA inspections of an individual firm are or are not effective in reducing accidents. This theory is based on findings that have appeared previously in published case studies of OSHA effectiveness.

While mildly interesting in and of themselves, the substantive results of the work are perhaps of less interest than the methodological implications of the work. The Monte Carlo "synthetic" data generated by the model can be used as raw data in a regression equation designed to statistically test for the effectiveness of OSHA inspections in terms of reducing accidents. Quite obviously, since OSHA's effects are already perfectly known in a synthetic simulation environment, this test of OSHA's effectiveness becomes a test of the effectiveness of regression-based analyses to detect known effects and to fail to detect effects that are known to exist (Andersen 1982). In this methodological area, the model will be used to replicate a series of synthetic data experiments reported earlier (McCaffrey, Andersen, McCold, and Kim 1985) and to extend those results to the case where significant feedback is involved in the data generating model.

Overall, this paper is organized into several sections. First we discuss the discrepancies between OSHA effectiveness as measured by case versus regression studies. Next the paper explores the broad types of regression-based studies of OSHA effectiveness that have appeared in the literature. Next the structure of a model of how OSHA impacts on a single firm is presented, followed by a discussion of the model's base run behavior, including a discussion of how an OSHA inspection impacts on base run behavior. Finally, directions for further study are discussed, including a discussion of the proposed synthetic data experiments.

OSHA EFFECTIVENESS -- CASE VERSUS REGRESSION STUDIES

Studies of the impact of safety regulation on industrial firms have produced inconsistent results and have been a controversial topic for more than a decade now. While regression-based studies have consistently found that regulation does not improve safety performance, case studies have suggested otherwise.

The discrepancies between case studies and regression results are too common and systematic to reflect only the anomalous qualities of the cases. Just as likely, the differences in results can be attributed to the limitations of regression models. For instance, such models fail to incorporate a credible theory of how such regulatory systems work. And the data that may be used in an attempt to incorporate such a theory are usually gross surrogates for the theory they represent. Thus, although the various models may consistently fail to detect any significant net effects from the regulations, it is difficult to know what these results mean.

This article focuses on a dynamic simulation model of occupational safety regulation developed as a research strategy both to address the problem of improving theoretical models of regulatory systems and also to extend the use of regression analysis itself. It is essentially a theory-based model of the impact of regulation on a firm. Plausible theoretical and empirical implications have been built into the model, as well as non-linearities, multiple lags and feedback effects.

PREVIOUS REGRESSION STUDIES OF OSHA EFFECTIVENESS

Since 1971 the Occupational Safety and Health Administration (OSHA) has tried to reduce occupational injuries through a system of standards, inspections, and fines, as well as by information and technical assistance for managers and workers. The studies that seek to evaluate OSHA's effects on injury rates follow a common logic. A firm has certain characteristics that determine its injury rate over time. These characteristics are associated with the firm's industry type, the firm's employment size, recent changes in the firm's employment, and special traits of the firm. OSHA tries to lower the firm's "natural" injury rate by inducing the firm to invest in the capital and training required by OSHA standards. OSHA can increase these inducements by increasing the probability of inspection, by increasing the penalties associated with violations, or both. If OSHA does improve the level of safety in workplaces, then those firms that are inspected by OSHA ought to have lower injury rates than uninspected firms, controlling for the other characteristics of firms. Accordingly, studies of OSHA effects on injury rates use inspections as a proxy for the effects of OSHA as a whole.

One group of studies compares the injury rates of industries with relatively high rates of inspections to those industries experiencing lower rates of inspections. These studies generally conclude that high inspection rates in industries are not associated with lower injury rates, controlling for other factors. Furthermore, using cross-sectional regressions that are based on industry data for 1972-1975, one researcher reports that "there is no evidence of a direct or indirect effect of OSHA enforcement efforts on enterprise investment decisions. Given the negligible financial incentives created by the agency's regulatory efforts, this result is not unexpected" (Viscusi 1979).

Analysts conducting statistical studies at the individual firm level contend that OSHA's effects are relatively small and can only be detected if one analyzes individual firms (Smith 1979). Studying individual firms might reveal OSHA's effects because firms' injury rates vary a great deal more than aggregated injury rates. Thus, the statistical associations between injury rates and inspections would be more pronounced at the individual firm level than at the aggregated industry level. However, it is recognized that to compare directly inspected and uninspected firms is misleading, because inspected firms may be qualitatively different from uninspected firms before the inspection. Inspections can be triggered by employees' complaints, catastrophes, growing hazards, labor-management problems, and so forth; one cannot assume that inspected and uninspected firms function in the same way, with the only difference between them being an OSHA inspection. To identify the effects of an inspection, while only looking at comparable firms, the studies compare injury rates of firms that were inspected at different times of a given year (McCaffrey 1983). In principle, analysts could compare firms that were inspected in March-April ("early" inspectees) to those inspected in November-December ("late" inspectees). The late inspectees can be considered an "untreated" control group, similar in all important respects to early inspectees except one: the early inspectees would have been inspected early enough to show any decline in the injury rate that was induced by the inspection, while the late inspectees would have been inspected too late to show inspection effects. In practice, January-February inspectees are not used as the early group because these inspections might have been prompted by temporary increases in the prior year's injury rate. Instead, firms inspected in March and April are used as the early inspectees. Thus, the impact of an inspection on the annual injury rate can be estimated for the treated group (early inspectees) compared to the nontreated group (late inspectees). This early versus late experimental design is the one replicated in the data generating model discussed below.

The studies using data at the level both of the industry and of the individual firm appear to establish OSHA's ineffectiveness. However, there are two critical respects in which the regression-based studies of the impact of OSHA are not definitive. First, the data used to measure the variables are incomplete. In fact, in most cases the variables used are only proxies for other variables that are undefined but are suspected for various reasons to be important; thus, what the variables actually suggest about injury rates is unclear. Second, evidence from other sources, including cases studies and surveys, suggests that OSHA does improve the level of safety in firms, affecting firms through a process more complex than that implied in the regression studies. However, the data and variables used in regression studies are, for practical purposes, too weak to support more complex designs that might confirm or deny these discrepant findings.

In the work reported below, a simulation model of accident generation within firms of the manufacturing industry was created to bridge this methodological gap between the regression studies and case studies. The model does not purport to estimate the total impact of OSHA on these firms. Only impacts on occupational injury have been modeled, while the impact of OSHA on occupational disease has been excluded because of estimation difficulties. Also for reasons discussed earlier, the impact of OSHA on uninspected firms has been excluded.

MODEL STRUCTURE

Overview

The simulation model generates a simplified system of relationships within a manufacturing firm.[3] Each of the 1,000 firms simulated have been distributed among the twenty sectors that comprise the manufacturing industry.[4] The firms within each sector were then assigned to one of five size categories that represent the number of employees within a firm ranging from 1-49 employees at the low end to 500 plus at the high end.[5] The distribution of firms by size varies within each particular industry type and matches the distribution used in previous OSHA studies (McCaffrey 1983).

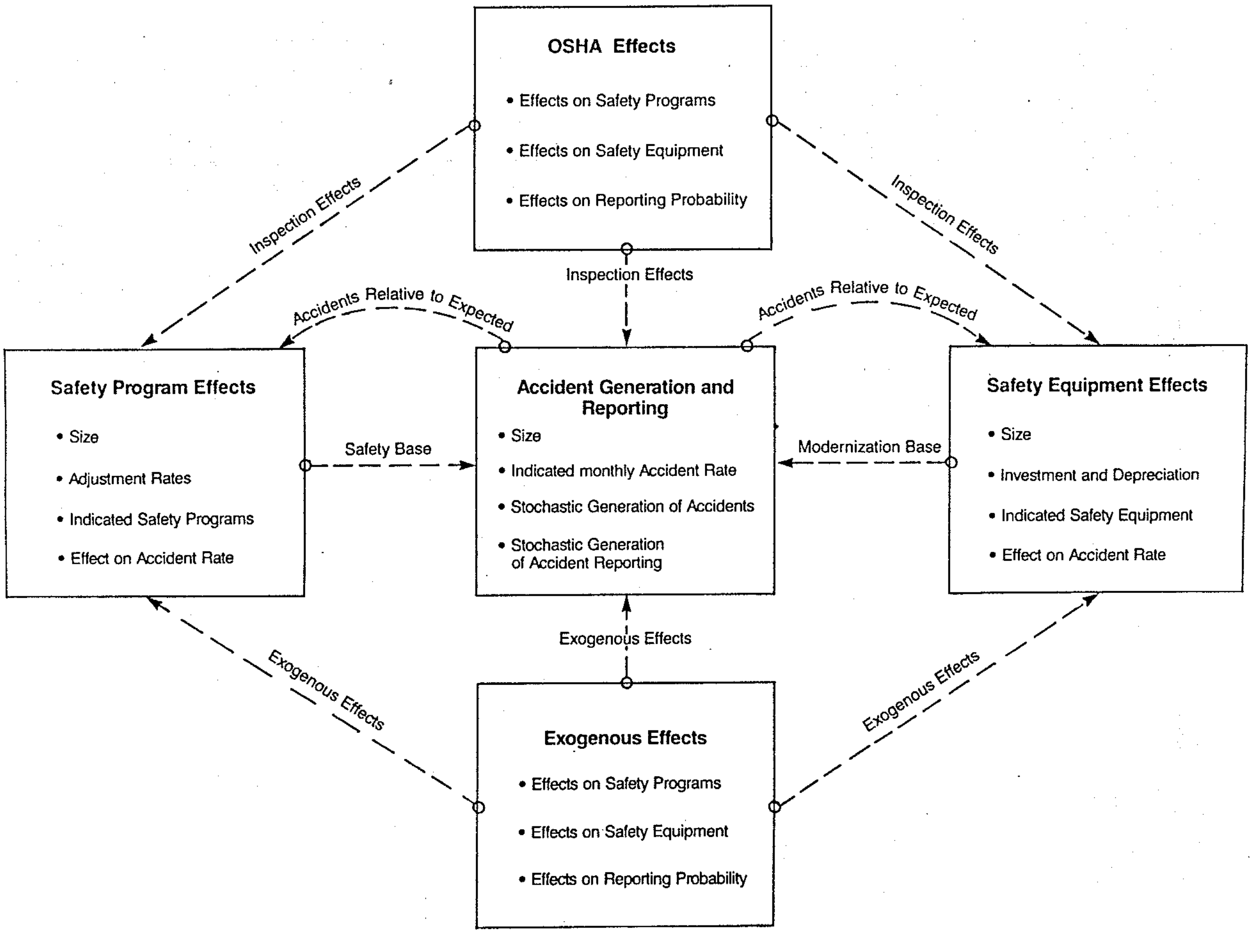
There are five major sectors within the model, with each sector representing assumed causal effects on a firm's accident rates, and interactions with other sectors. An overview of the relationship between the five model sectors is shown in Figure 1. Accident generation and reporting is the core sector, with the stochastic generation of accidents assumed to be influenced by the four other sectors. The OSHA sector models the impact of an OSHA inspection that will affect accident generation and both of the safety levels. Safety levels are divided into two sectors: safety programs and safety equipment. The exogenous effects sector can also influence accident generation and safety levels if it is activated during the simulated run.

The principal causal structure within the model is displayed in the flow diagram in Figure 2. Two negative feedback loops operate between the level of accidents within a firm and the safety equipment and safety program levels of that firm. Hence, the model essentially operates as a negative feedback system, with the endogenous effects between accidents, safety programs and safety equipment regulating the total number of accidents that occur within the system. Therefore, an increase in the level of accidents within a firm will raise the levels of safety equipment and safety programs. Subsequently, this increase will lead to a decrease in the level of accidents within that firm, producing a essentially self-regulated system.

Two separate exogenous effects can directly influence the safety levels and accident generation. If an OSHA inspection occurs, an increase in the levels of safety and the reporting probability within the inspected firm can occur. If the exogenous effects sector is activated, an increase or decrease in the safety levels and reporting probability can occur, depending upon the effect simulated. The gross causal structure of this regulatory system, then, shows that accidents are dependent on the levels of safety programs and safety equipment within the firm, as well as on a base accident rate. Safety programs and safety equipment are in turn influenced by the accident level and the two separate exogenous effects which can be activated during a simulation, OSHA inspections and exogenous effects.

Accident Generation Sector

The figures showing the principle causal structure within each model sector display more precisely the relationships assumed within the model. The glossary gives the variable acronyms for figures 3 through 7. The accident sector in Figure 3 displays the structure that stochastically generates two separate accident levels -- actual accidents (CACC) and reported accidents (RACC). The model assumes that a firm will compare itself to relevant


OSHA Effects
• Effects on Safety Programs
• Effects on Safety Equipment
• Effects on Reporting Probability
Inspection Effects
Inspection Effects
Inspection Effects
Accidents Relative to Expected
Accidents Relative to Expected
Safety Program Effects
• Size
• Adjustment Rates
• Indicated Safety Programs
• Effect on Accident Rate
Safety Base
Accident Generation and Reporting
• Size
• Indicated monthly Accident Rate
• Stochastic Generation of Accidents
• Stochastic Generation of Accident Reporting
Modernization Base
Safety Equipment Effects
• Size
• Investment and Depreciation
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• Effects on Reporting Probability

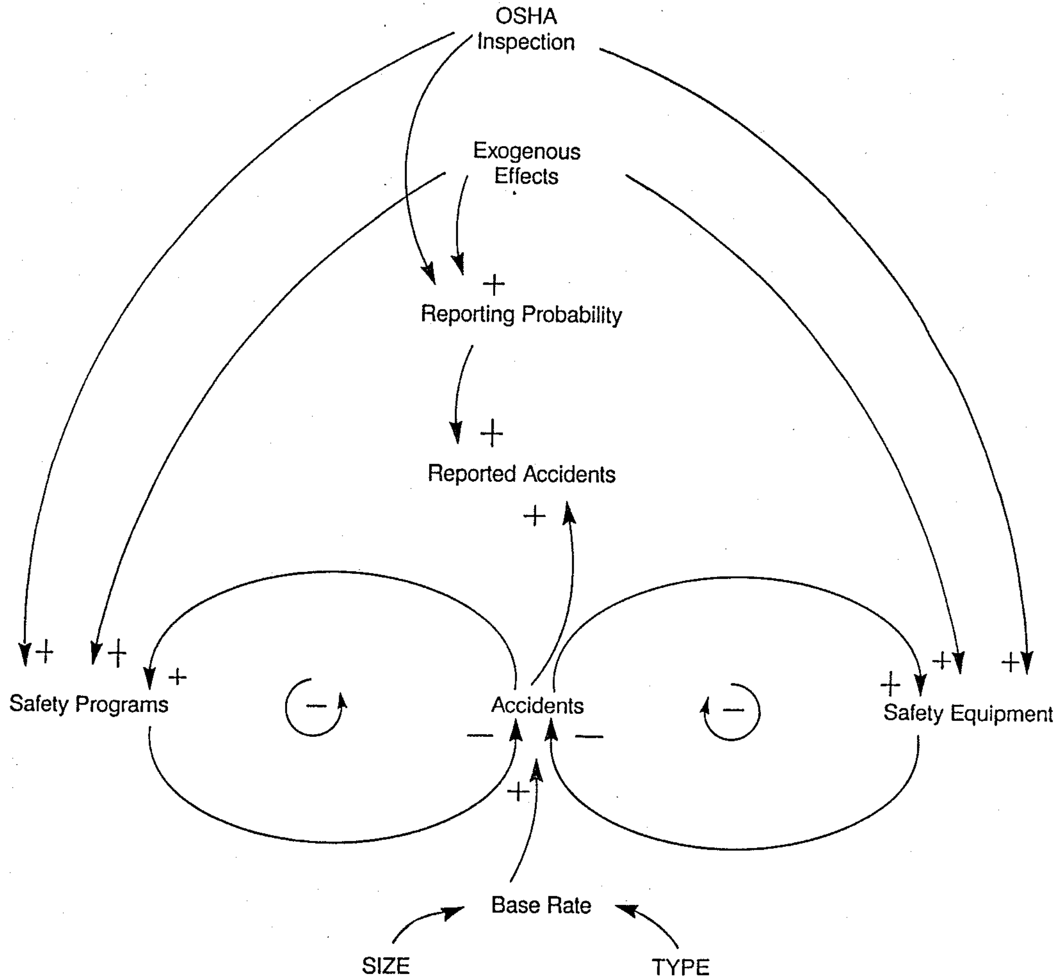

Figure 2. Principal causal structure within the simulation model.

industry data on accidents and make adjustments in its safety levels accordingly. Hence, as the accident ratio (ACREX) that compares actual accidents (CACC) to the indicated yearly accident rate (IYACR) increases, the relative safety program multiplier (RSAFT) and the relative safety equipment multiplier (RSFEQ) cause both levels of safety to rise. On the other hand, as the accident ratio (ACREX) decreases, the relative safety multipliers cause in both levels of safety to decrease.

According to the model, the accident rate within a firm is a function of a combination of factors related to that firm's size, industry type, and levels of safety. Monthly accidents are generated over a three-year period of simulation for each of the 1,000 firms simulated, with accumulated accidents observed at the end of each year. The generation of the actual accident rate (AR) and the reported accident rate (RAR) is based principally within the accident generation mechanism. Accident generation (AAA) is a discrete formulation with either 0, 1, or 2 accidents generated during each time increment (DT). The generation of an actual accident is dependent upon the indicated monthly accident rate (IMACR), which is a function of the firm's base accident rate (BASERN), the number of employees (EMP), the safety program effect (SAFACC) and the safety equipment effect (MODBAS). The base accident rates (BASERN) were derived from published accident data and correspond to the size and industry type categories used in this model (McCaffrey 1983).[6] The model assumes that the level of reported accidents (RACC) will generally be lower than the level of actual accidents (CACC). Therefore, the generation of a reported accident is determined by accident generation (AAA) and the reporting probability (RPROB). The reporting probability (RPROB) is a function of the initial reporting probability (RPROBN) and the reporting probability function (FTRP). The reporting probability function (FTRP) takes into account an OSHA effect (OSHARP) or an exogenous effect (EXRP) and adjusts the initial reporting probability (RPROBN) accordingly. The initial reporting probability (RPROBN) is assumed by the model to be a percentage of actual accidents and that percentage varies according to the size of a firm (SIZE).[7]

Safety Program Sector

The principal causal structure within the safety program sector is displayed in Figure 4. This sector impacts on accident generation through the safety program effect (SAFACC). The safety program effect is a function of a firm's relative safety (RSPROG), that is, a comparison between its actual level of safety programs (SAF) with the initial level of safety programs (SAFE). The level of safety programs (SAF) within a firm is determined by the safety program adjustment rate (SPAR), which is a function of the difference between the current level of programs and the indicated level of safety programs (INDSAF). This indicated level is a function of the firm's initial safety programs (SAFN), safety from size (SAFSZN), the relative safety program multiplier (RSAFT), OSHA effects on Safety (OSHASA) and exogenous effects on safety (EXSA).[8] The initial level of safety programs (SAFN) is a

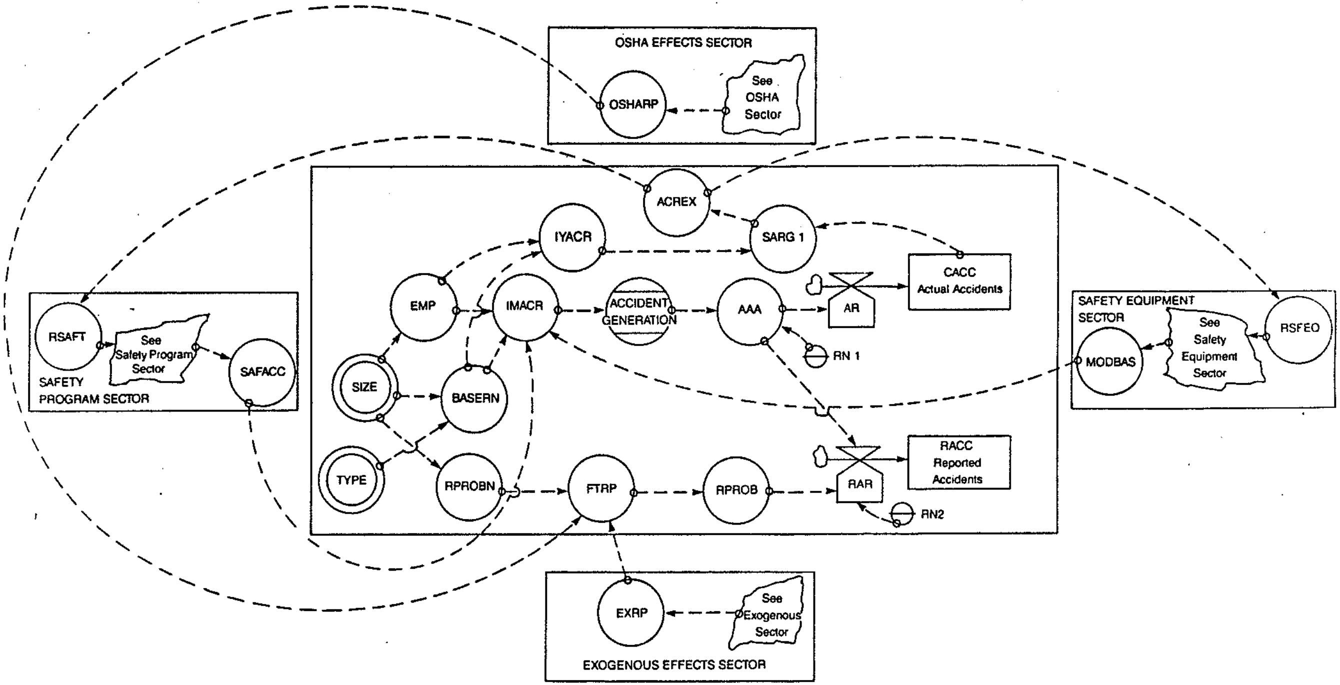

Figure 3. Principal causal structure within the accident generation sector.

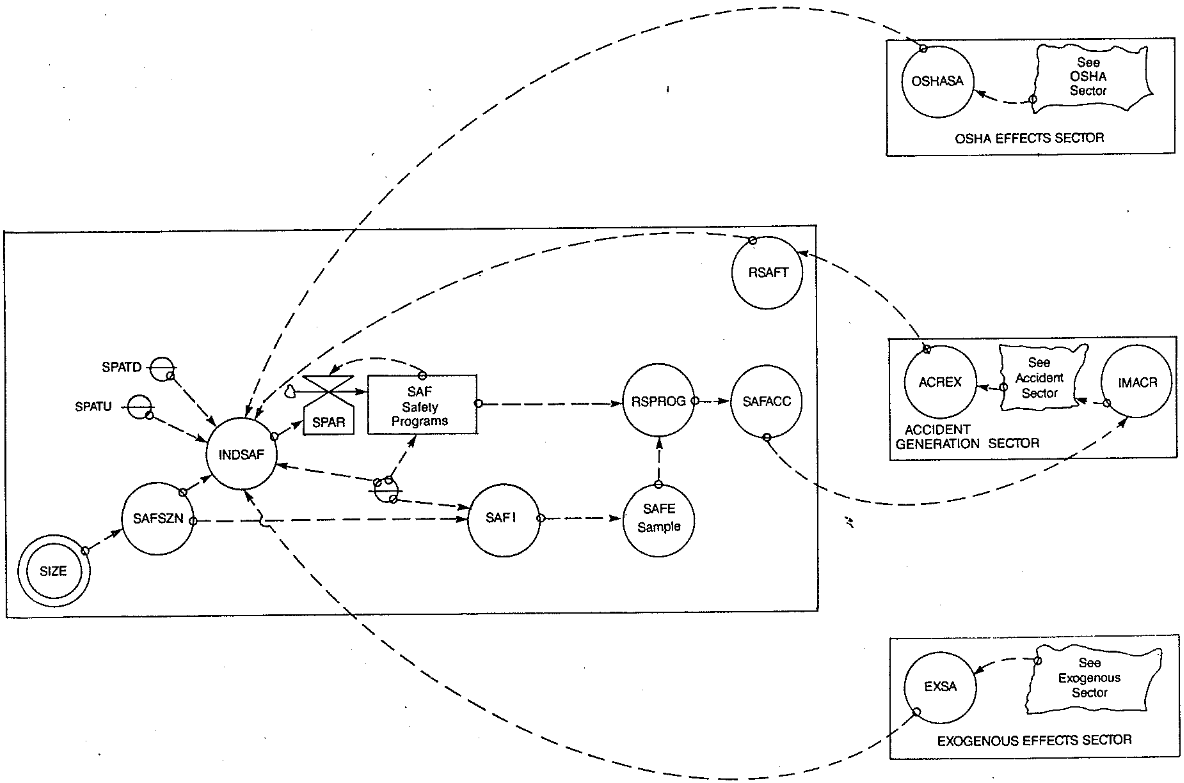

Figure 4. Principal causal structure within the safety program sector.

constant that is adjusted for safety from size (SAFSZN), that is basically an adjustment that assumes larger size firms will initially have more safety programs.[9] The relative safety program multiplier (RSAFT) is a function of the accident generation sector, with the level of safety programs increasing as the ratio of actual accidents to expected accidents (ACREX) increases.[10] Since the model also assumes that a safety programs will be implemented more rapidly than they will be dismantled, program adjustment time up (SPATU) and safety program adjustment time down (SPATD) adjust the indicated safety program level accordingly.

Safety Equipment Sector

The principal causal structure within the safety equipment sector is displayed in Figure 5. This sector impacts on the accident generation sector through a modernization base ratio (MODBAS), which compares the current level of a firm's safety equipment (SEQ) to its initial level of safety equipment (SEQE).[11] The current level of equipment is a capital investment loop that includes investment in safety equipment (INV) and the depreciation of that capital stock (DEP). The investment rate (INV) is determined by the current level of safety equipment (SEQ) and the indicated level of safety equipment (ISEQ). The four factors that influence indicated safety equipment (ISEQ) are the initial level of safety equipment (SEQI), the relative safety equipment multiplier (RSFEQ), the OSHA effect on safety equipment (OSHAEQ) and the exogenous effect on safety equipment (EXEQ).[12] The initial level of safety equipment (SEQI) is a function of the number of employees (EMP) and equipment adjusted for size (EQPSZN). The number of employees (EMP) and equipment adjusted for size (EQPSZN) are based upon the size (SIZE) of a firm.[13] The relative safety accident multiplier (RSFEQ) is a function of the ratio of actual accidents to expected accidents (ACREX) that operates within the accident generation sector.

OSHA Sector

The OSHA sector, shown in Figure 6, simulates an OSHA inspection (OSHA) of a firm. As discussed above, inspections occur either early on or late in the second year of a firm's simulation. Early versus late inspections are determined within the model by a random draw. Early inspections occur in the fifteenth month of a firm's run (third month of the second year), while late inspections occur in the twenty-forth month (end of the second year). An inspection activates the inspection impact variable (INSPIM) which then affects on the accident sector through the reporting probability function (FTRP), the safety program sector through indicated safety programs (INDSAF) and the equipment sector through indicated safety equipment (ISEQ). The model assumes that the level of impact (INSPIM) decays over a 24 month period of time.

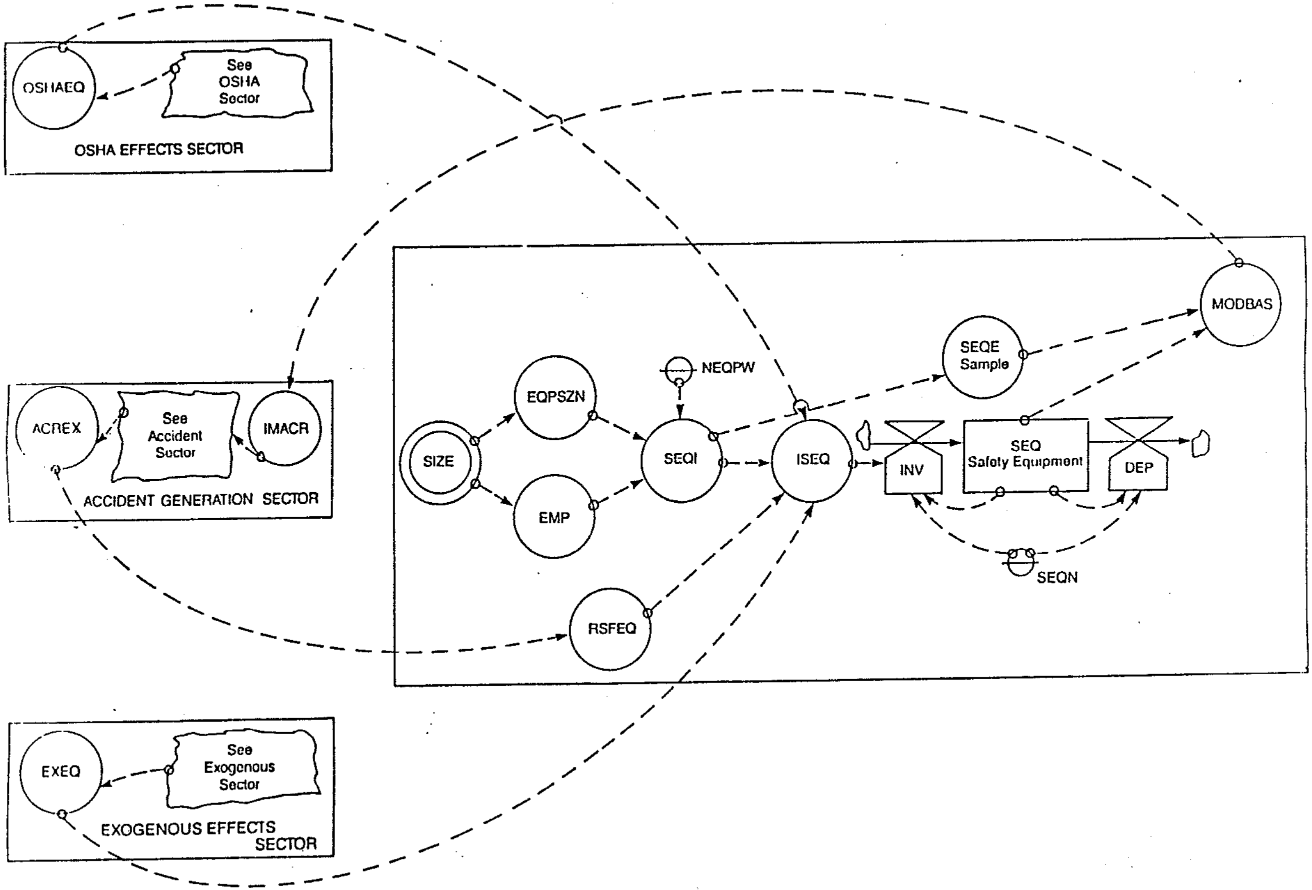

Figure 5. Principal causal structure within the safety equipment sector.

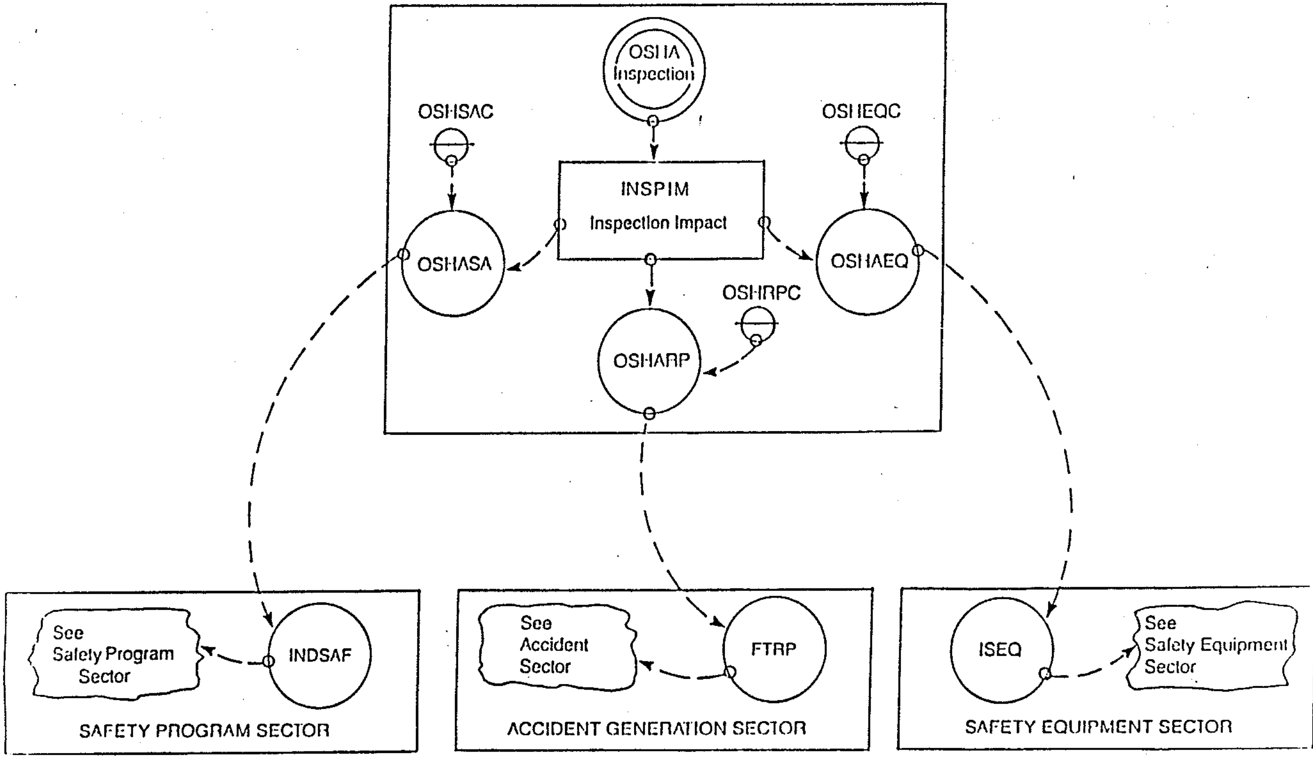

Figure 6. Principal causal structure within the OSHA sector.

Exogenous Sector

The exogenous effects sector, shown in Figure 7, can be activated during a run and will influence the accident sector through the reporting probability function (FTRP), the program sector through indicated safety programs (INDSAF), and the equipment sector through indicated safety equipment (ISEQ). The exogenous sector can be used to model the assumed influences of outside forces, such as public pressure to increase workplace safety.

MODEL BEHAVIOR

Base Run

A complete model run simulates 1000 firms in sequential time frames, with each firm's time frame contained within a 36 month period. The behavior of two firms in the lumber[14] and wood products industry is displayed in Figures 8 through 11. The base run of the model simulates an OSHA inspection occurring in each firm, but there is no impact on either the safety levels or reporting probability of a firm from that inspection. The behavior of the safety levels and accident levels of two firms in a base run is displayed in Figure 8. The levels of safety programs and safety equipment can be seen to accumulate yearly within each of the three years of a firm's run. Actual and reported accident incidence is shown as monthly step increases in the accumulated accident levels.

The behavior of the safety levels within each firm is also shown in two curves, safety programs and safety equipment. The safety levels for both firms have remained relatively stable in the first year, with relatively small increases occurring in both levels during the second year in response to changes in the actual accident level. For example, the accident level for the first firm at the end of the first year is quite high and both safety levels have adjusted accordingly within that firm by increasing over the next twelve month period.

The major internal dynamics of the safety sectors are displayed in Figures 9 and 10, with the behavior of each of the two firms again modeled sequentially within 36 month time frames. Figure 9[6] shows the causal relationships between the accident levels and Safety programs shown in greater detail. For the first firm (the first 36 months simulated) safety programs initially rise and then fall because of the level of actual accidents (and hence indicated safety programs) is initially high, but subsequently falls. The safety program multiplier multiplicatively adjusts actual safety programs as a function of indicated safety programs. This behavior results from the model's assumption that more safety programs within a firm increase the safety level of a firm, and increased safety levels within a firm result in fewer accidents.

Likewise, the level of safety programs responds directly to changes in the indicated level of safety. The indicated levels of safety programs shown in the figure remains stable over each of

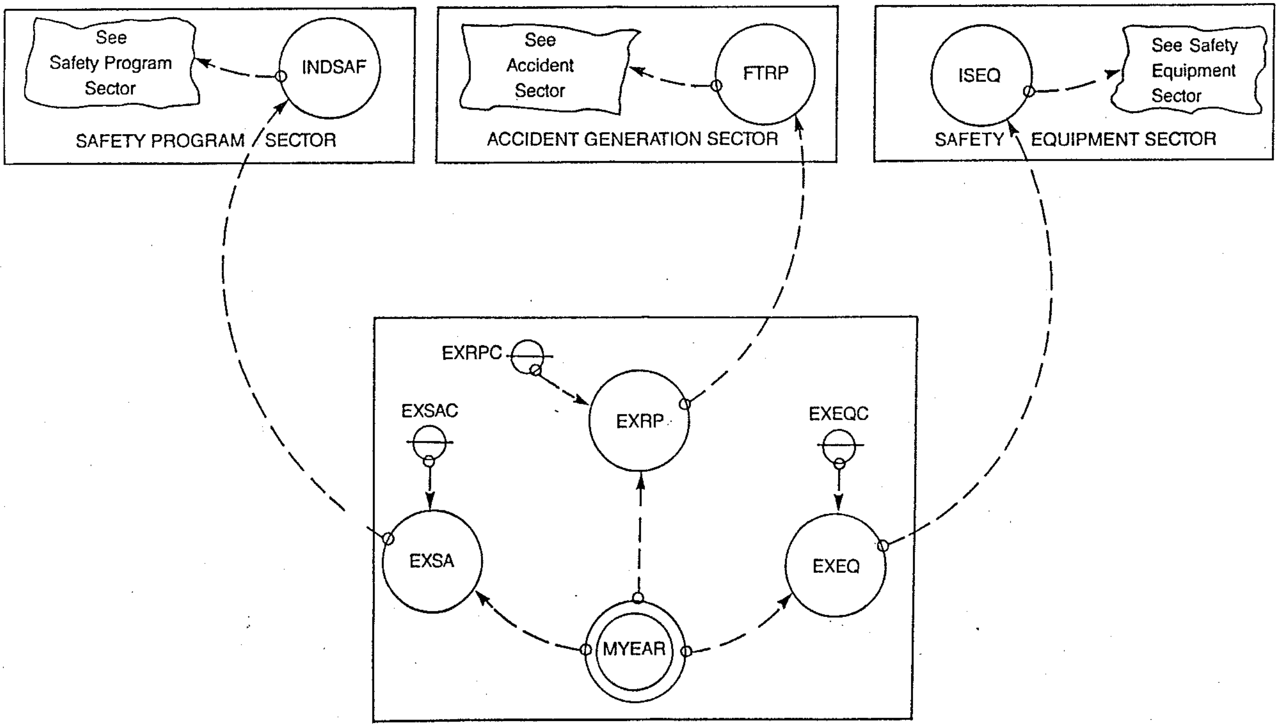

Figure 7. Principal causal structure within the exogenous effects sector.

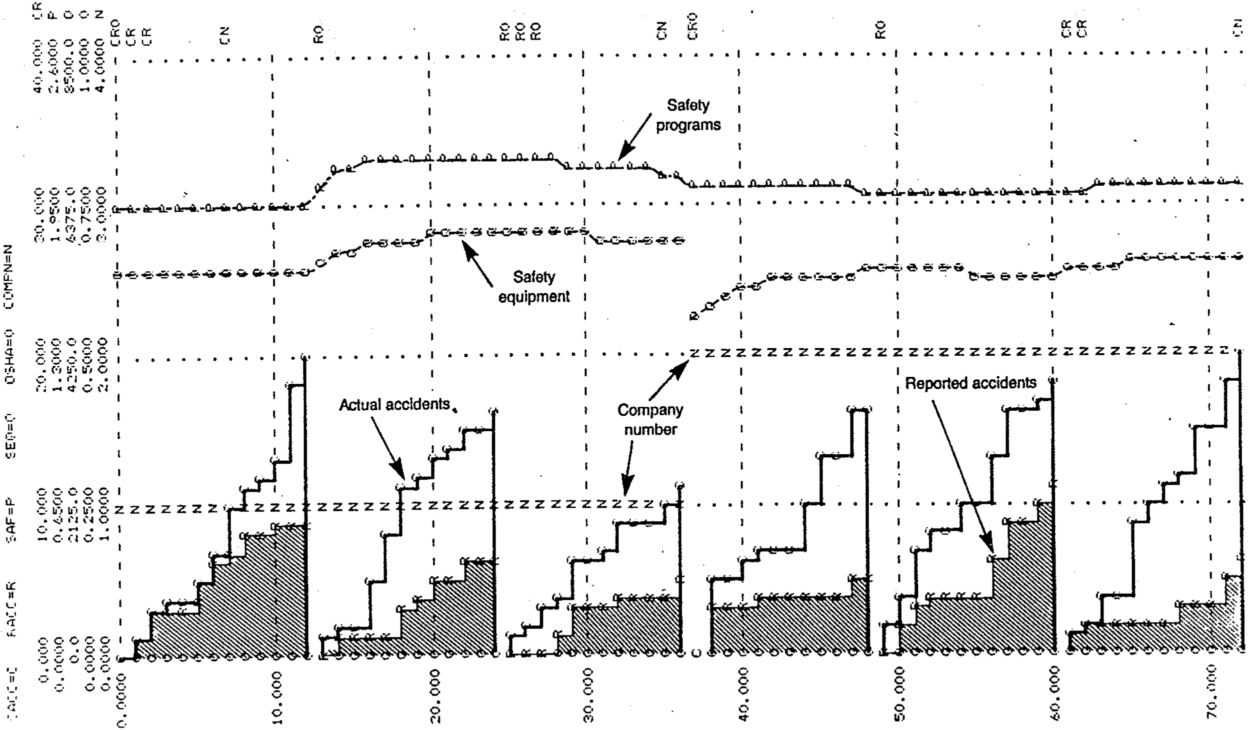

Figure 8. Base run of two firms in the lumber and wood products industry.

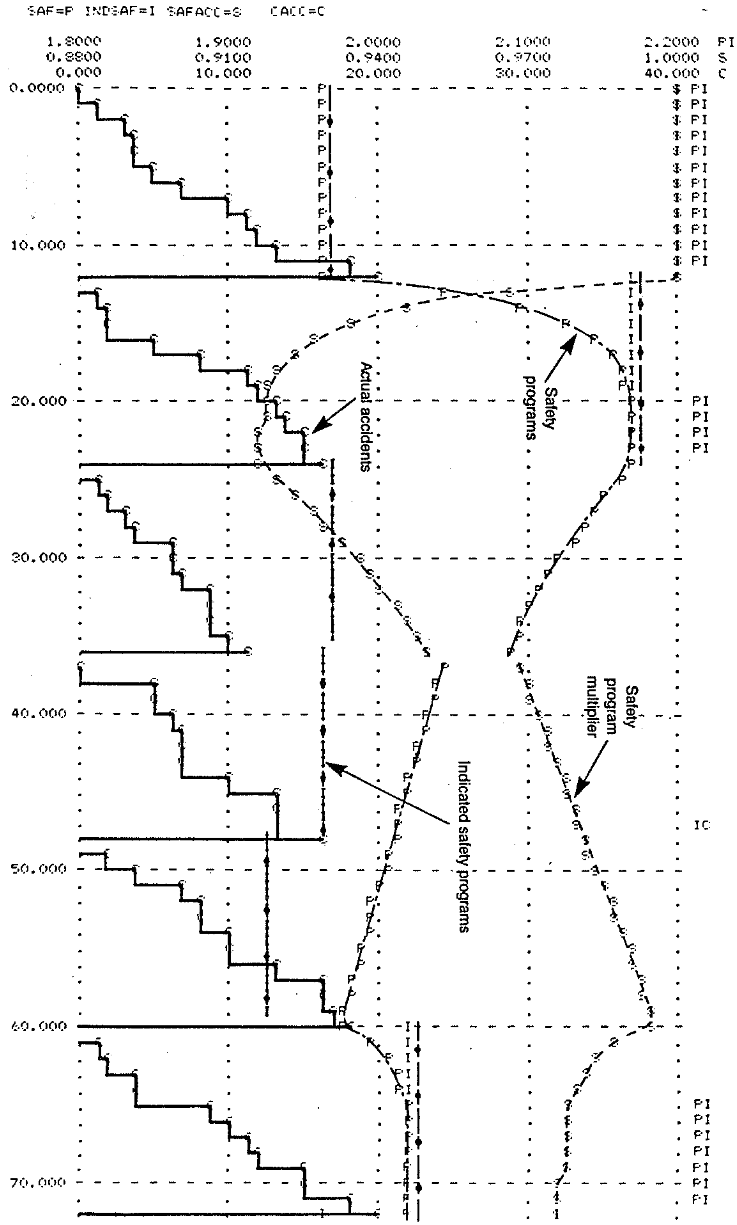

Figure 9. Internal dynamics of safety programs.

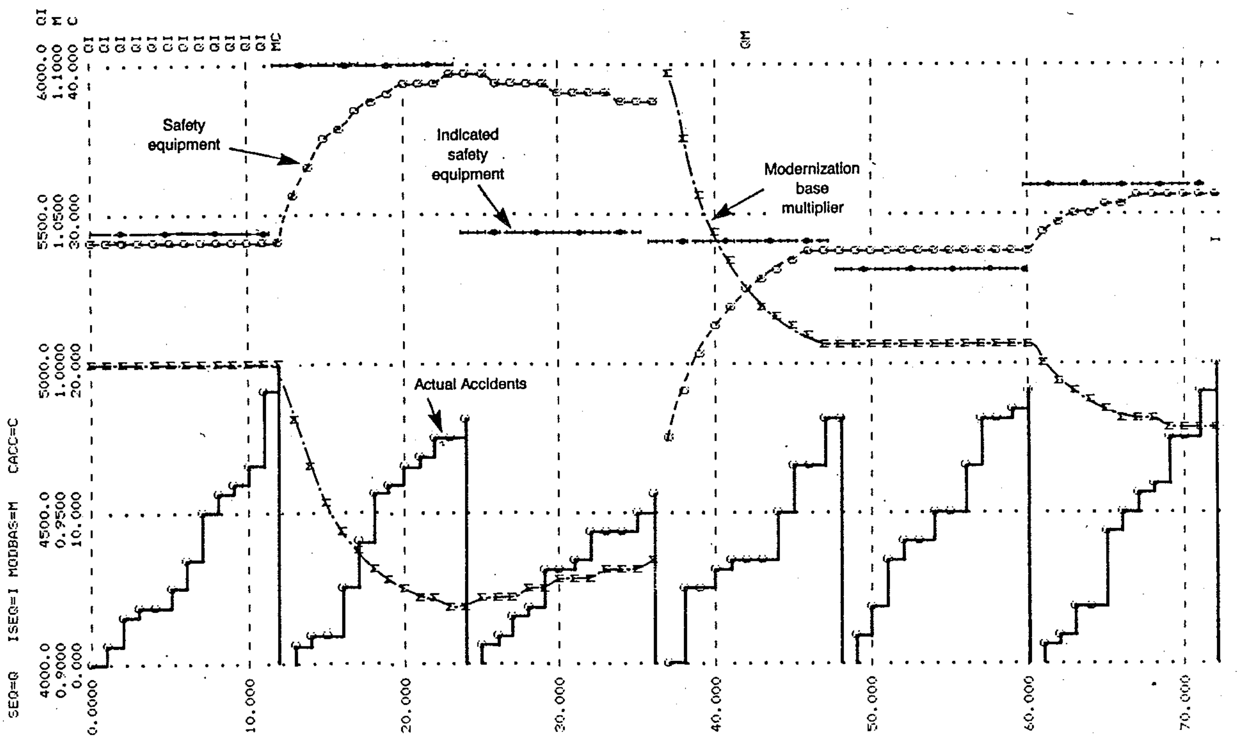

Figure 10. Internal dynamics of safety equipment.

the three years of a firm's run, with an annual adjustment occurring in the first month of each year using a SAMPLE argument in DYNAMO. A higher than average rate of actual accidents within a firm over the course of one year will increase its indicated levels of safety programs for the following year. This increase will cause the level of safety programs to rise. A decrease in the indicated level of safety will cause a decrease in the level of safety programs.

The internal dynamics of safety equipment within the same two firms are displayed in Figure 10. The causal relationships between accident levels and safety equipment are similar to those in the safety program sector. In this figure, however, the first firm modeled has had increases in the level of safety equipment, while the modernization base multiplier has decreased. Again, this behavior exhibits the model assumption that increases in the levels of safety equipment within a firm result in fewer accidents occurring within that firm. Further, the level of safety equipment also responds directly to annual changes in an indicated level of safety equipment which in turn is adjusted annually during the first month of each year using a SAMPLE argument. Hence, the level of safety equipment will increase or decrease as the indicated level of safety equipment increases and decreases.

A Sample Policy Run

While the base run simulates an OSHA inspection with no assumed impact on each of the 1000 firms, the policy run shown in Figure 11 simulates the impact of an OSHA inspection on each of the 1000 firms through three separate variables: safety programs, safety equipment and reporting probability. Figure 11 is identical to Figure 8 except that in Figure 11 the OSHA inspection was assumed to increase safety equipment and safety programs as well as a firm's reporting probability.

An early OSHA inspection has occurred in both firms. When compared to the base run in Figure 8, it can be seen that the inspections have affected both safety levels and both accident levels within each firm. For both firms, the actual accident level has decreased in the second and third years while the reported accidents has increased. Also, the levels of safety programs and safety equipment have responded to the changes in the accident level with increases occurring immediately after the inspection.

IMPLICATIONS AND FUTURE RESEARCH

The formal simulation model that has been constructed includes a number of features that are not to be found either in regression analysis or case studies. First, unlike regression analyses, much of the theoretical richness of the case study has been retained in this model. This is because the relatively flexible mathematical form of simulation models allows for the inclusion of a large number of "hard" and "soft" effects. Second, unlike case studies or regression analysis, this simulation model contains a

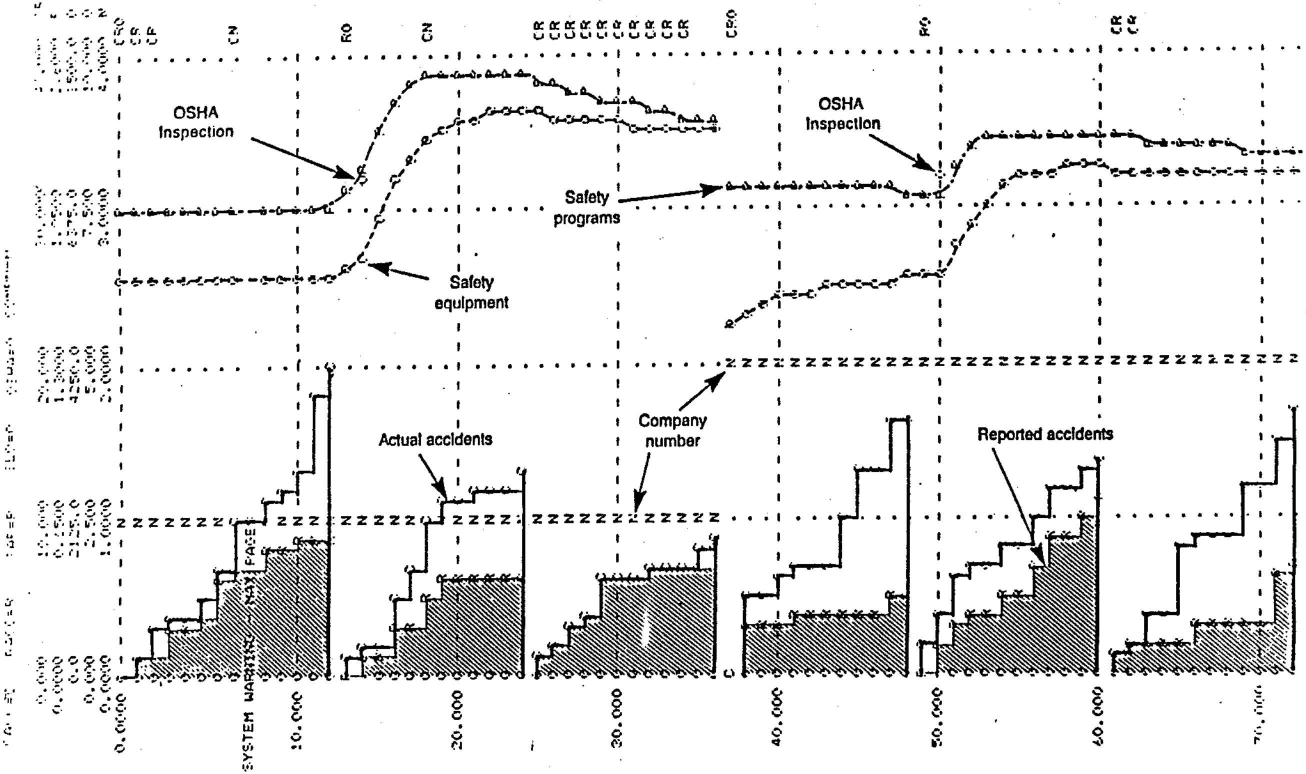

Figure 11. Policy run with OSHA inspections impacting on safety levels and accident levels.

mathematically explicit causal structure. Whereas case studies can be rich in descriptive detail, simulation models force the analyst to posit explicit causal hypotheses concerning how the policy system operates. A third feature of the simulation model is that all assumptions of the model are available readily for inspection since they have been cast into an unambiguous mathematical form. The model (and hence the causal theory being tested) must be absolutely consistent and logically complete, otherwise it will fail to produce the results demanded of it.

However, the methodological advantages of dynamic simulation modeling are bought at a price. Such models are typically beset with complex questions: What is the basis for hypothesizing that A influences B? And what is the basis for fixing on the specific quantitative value that is supposed to reflect that influence? Nevertheless, there are various ways in which dynamic simulation models and regression models can be combined to exploit the relative strengths of both approaches. One way to combine these properties is through the use of synthetic data experiments. The basic ideas behind these experiments are, in principle, simple. First, the simulation model is run a large number of times under varying conditions in order to create a large number of observations. The range of conditions covered depends on what the experimenter thinks is plausible in the circumstances. Output from these runs then creates the synthetic data. Because the structure and character of the model is known, the characteristics of the data generated by the model are known as well. Having produced the data, the experimenter ought to be able to design a regression model -- relying on simultaneous equations, lagged variables, and variable transformations if necessary -- to recover the known structure and parameters of the data-generating model. Because the structure of the data-generating model is known, the experimenter can monitor in a mathematically precise way how well any given regression model -- corrupted by these various factors -- reproduces the simulation model's structure and parameters.

Synthetic data experiments already have demonstrated that even moderate amounts of measurement error can sometimes substantially distort the results that would be otherwise produced by a regression model (Senge 1977); that tests of statistical significance may be unreliable indicators of which variables are important and which are unimportant in determining the effects of programs (Mass and Senge 1980); and that the regression approach will sometimes fail to pick up program effects even when the effects are systematically built into the model that produced the synthetic data (McCaffrey, Andersen, McCold, and Kim 1985).

The work presented here will be used to extend and deepen those results. The hypothesis that we are investigating now centers on the relationships between negative feedback in a system's structure and multi-colinearity in observations of variables drawn from those negative loops. If negative feedback loops do tend to produce colinear variables, and if negative feedback structures are a common aspect of many social systems, then these same systems should be quite prone to unreliable estimation of program effects. The reasoning behind this claim is not complex. The colinearity produced by the feedback loops within the system, other things being equal, will tend to destabilize the estimated coefficients within a regression model (that is, will tend to increase the standard error of the estimate). If even minor amounts of measurement error do occur, then which of the colinear variables "explains" most of the variance can change dramatically.

The model described above will provide a laboratory setting for investigating the interactions between feedback structure and statistical estimation of program effects. By focusing on the OSHA case, these experiments can be carried forward in the context of the example where contradictions between regression and case study approaches are already known to exist, hopefully providing a rich example for exploring methodological points.

FOOTNOTES

1. The work presented in this paper was supported by a National Science Foundation Grant SES 84 1006. The opinions, findings, and conclusions expressed herein are those of the authors and do not necessarily reflect the view of the Foundation.

2. Authors are listed alphabetically for convenience; this paper is a fully collaborative effort.

3. For a complete listing of model code and a more detailed description of the model and the logic of the code, see David Andersen, Catherine Crawford, Sue Faerman and Erik Mosekilde, "A Dynamic Model of OSHA Regulation," working paper, Rockefeller College of Public Affairs and Policy, State University of New York at Albany, 1986.

4. The manufacturing sector was chosen since more than 40% of initial OSHA inspections between 1971 and 1975 occurred in the manufacturing sectors. For more information on inspection activity, see Nicholas A. Ashford, (1977) Crisis in the Workplace. MIT Press, Cambridge, MA.

5. As firm size moves from 1 to 5, the model assumes that the number of employees within a firm are: 30/80/200/400/1000.

6. The base accident rates (BASERN) were derived by assuming that the published data represents only that portion of all accidents that is reported. The portion is assumed to vary, depending upon firm size (see Footnote 7).

7. The initial reporting probability (RPROBN) is a table function. As firm size increases from smallest to largest (1-5), reporting probability also increases. The following percentages of actual accidents are assumed by the model to be reported, based upon size: .45/.75/.80/.85/.90.

8. There is an annual adjustment in the indicated level of safety programs (INDSAF) based upon the ratio of a firm's actual accident rate at the end of the preceding year to its initial base accident rate. The base rate is an industry average determined by the firm's size and industry type. As this ratio rises above 1, the indicated safety level will also rise. As the ratio drops below 1, the indicated safety level will also drop.

9. Safety from size (SAFSZN) is a table function that adjusts the initial value for safety programs according to firm size. As firm size increases from smallest to largest (1-5), the following values are used to make the adjustment: .50/.75/.80/.85/.90.

10. The relative safety program multiplier (RSAFT) is a table function that compares the level of actual safety programs to initial safety programs within a firm. As this ratio increases, the multiplier decreases and causes fewer accidents to be generated. As the ratio decreases, more accidents are generated.

11. The modernization base multiplier (MODBAS) is a table function that compares the level of actual safety equipment to the initial level of safety equipment within a firm. As this ratio increases, the multiplier decreases and causes fewer accidents to be generated. As the ratio decreases, more accidents are generated.

12. There is an annual adjustment in the indicated level of safety equipment (ISEQ) based upon the ratio of a firm's actual accident rate at the end of the preceding year to its initial base accident rate. As this ratio rises above 1, the indicated safety level will also rise. As the ratio drops, the indicated safety level will also drop.

13. Equipment from size (EQPSZN) is a table function that adjusts the initial value for safety equipment according to firm size. As firm size increases from smallest to largest (1-5), the following values are used to make the adjustment: 0.8/0.9/1.0/1.1/1.2.

14. The size of the two firms simulated for Figures 8-11 is small (1-49 employees).

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APPENDIX

GLOSSARY OF MODEL VARIABLES

AAA	Accident generation
ACREX	Actual accidents relative to expected accidents
AR	Actual accident rate
BASERN	Base accident rate
CACC	Actual accidents accumulated over 1 year
DEP	Depreciation
EMP	Employees
EQPSZN	Equipment size effect
EXEQ	Exogenous effect on safety equipment
EXEQC	Exogenous safety equipment constant
EXRP	Exogenous effect on reporting probability
EXRPC	Exogenous reporting constant
EXSA	Exogenous effect on safety programs
EXSAC	Exogenous safety program constant
FTRP	Function of reporting probability
IMACR	Indicated monthly accident rate
INDSAF	Indicated level of safety programs
INSPIM	Inspection impact
INV	Investment
ISEQ	Indicated level of safety equipment
IYACR	Indicated yearly accident rate
MODBAS	Modernization base multiplier
MYEAR	Year of a firm's run
NEQPW	Initial value safety equipment

OSHA	OSHA inspection
OSHAEQ	OSHA effect on safety equipment
OSHARP	OSHA effect on reporting probability
OSHASA	OSHA effect on safety programs
OSHEQC	OSHA safety equipment constant
OSHRPC	OSHA reporting constant
OSHSAC	OSHA safety program constant
RACC	Reported accidents accumulated over 1 year
RAR	Reported accident rate
RN1	Random number generator 1
RN2	Random number generator 2
RPROB	Reporting probability
RPROBN	Reporting probability initial
RSAFT	Relative safety program multiplier
RSFEQ	Relative safety equipment multiplier
RSPROG	Ratio of actual safety programs to initial safety programs
SAF	Safety programs
SAFACC	Safety program effect on the accident rate
SAFE	Sampling SAFI
SAFI	Safety programs initialization according to size
SAFN	Safety programs initial
SAFSZN	Safety programs adjusted for size
SARG1	Sample argument generating yearly variation of ACREX
SEQ	Safety equipment
SEQE	Sampling SEQI
SEQI	Safety equipment initialization according to size
SEQN	Safety equipment initial
SIZE	Size of firm
SPAR	Safety program adjustment rate
SPATD	Safety program adjustment time down
SPATU	Safety program adjustment time up
TYPE	Type of firm