Final Project Report: Designing a Pilot Program for Strategic Mine Safety and Health Improvements Through the Use of Surveillance Data to Guide Targeted Inspection Activities*

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1 Introduction

From a regulatory perspective, the mining industry is unique. Unlike establishments in all other industries - which are inspected only infrequently by the Occupational Safety and Health Administration (OSHA) - each U.S. mine is inspected at least twice (and for underground mines, at least four times) per year by the Mining Safety and Health Administration (MSHA). Just as significantly, mine operators are the only private employers required by statute to report every worker injury, illness and fatality to MSHA on a quarterly basis. These twin advantages - MSHA's pervasive regulatory presence and the availability of comprehensive, timely data on hazardous conditions - make mining the ideal setting in which to develop innovative regulatory strategies.[1]

The second decade of the 21st century is a particularly opportune moment in which to pioneer such approaches. In the wake of several well-publicized mining disasters - including the explosion at Upper Big Branch Mine in April 2010 that claimed 29 miners' lives - MSHA has expressed a desire to put its scarce enforcement resources to better and more efficient use. In September of 2010, several months after the agency initiated the use of monthly impact inspections at mines deemed especially hazardous, Assistant Secretary Joseph A. Main explained, "We are striving to make our inspections more strategic, less predictable and more effective."[2]

To date, however, the agency has made only limited and sporadic use of its extensive historical data in carrying out its day-to-day enforcement activities. To be sure, a mine's past safety and compliance record are frequently used to calculate certain penalties and to identify mines that qualify for enhanced regulatory scrutiny (such as those exhibiting a potential *Pattern of Violations*, or POV). However, the agency has not yet applied statistical techniques to its enormously rich data in a systematic and thoroughgoing effort to channel inspection resources towards those mines that pose the greatest hazards. This project is a first step towards that ultimate goal. In helping the National Institute of Occupational Safety and Health (NIOSH) assess the viability of a statistical mine targeting algorithm, we hope to illustrate the potential benefits and probable challenges of strategic, data-driven enforcement – including tools that one day could be used to identify the nation's most hazardous mines and help avert mine disasters before they occur.

2 Executive Summary

This report presents our findings from NIOSH Research Contract No. 2008-N-10989: "Designing a Pilot Program for Strategic Mine Safety and Health Improvements through the Use of Surveillance Data to Guide Targeted Inspection Activities." The primary goal of the project was to use Bayesian time-series forecasting methods to develop a statistical algorithm for targeting high-risk mines that MSHA personnel might ultimately use as an enforcement tool. Although primarily reliant on MSHA's extensive historical data on each U.S. mine's

1. Alison Morantz, "Mining Mining Data: Bringing Empirical Analysis to Bear on the Regulation of Safety and Health in U.S. Mining," *W. Va. L. Rev.* 111 (2008): 45.

2. MSHA, *MSHA Announces Results of 5 Months of Impact Inspections*, news release, September 20, 2010, `http://www.dol.gov/opa/media/press/MSHA/MSHA20101321.htm`.

regulatory violations and reported injuries, the algorithm also incorporates some information collected by the Department of Energy's Energy Information Administration on large coal mines.

In the context of MSHA regulation, targeting can be defined as a systematic, data-driven effort to single out the most dangerous mines for inspection. The flexibility of Bayesian time-series forecasting makes this approach particularly well-suited to dynamic regulatory environments like mining, in which political, statutory, and technological factors may alter the mix of safety hazards and operators' incentives over time. The algorithm is constructed in a way that enables it to incorporate data on a mine's past behavior, update its predictions in real time based on new inspection data, and adjust its parameters to reflect changes in underlying conditions (such as a legislative reform or shift in technology).

First and foremost, the study highlights the overriding importance of specifying an appropriate "target" for regulatory targeting. It is not obvious, a priori, precisely which goal(s) the agency should be trying to further, and therefore which mines it should be seeking to target. We considered the following three goals and corresponding selection criteria:

1. Mitigate risks faced by miners at the nation's most dangerous mines by targeting mines with the highest predicted *injury rates*;

2. Save as many lives (and avert as many injuries) as possible nationwide by targeting mines with the highest expected *number of injuries*; and

3. Ensure that miners' remuneration reflects the level of hazards they face on the job by targeting mines in which compensation levels do not reflect miners' true levels of occupational risk (a situation suggestive of market failure).

In our view, all three of these criteria have strong theoretical and practical arguments to recommend them. The third criterion, however, cannot be implemented at this time because mine-level data on wages and fringe benefits do not exist. Therefore, we confined our analysis to the first two approaches: targeting mines with the highest predicted injury rates (a *rate-targeting algorithm*), and targeting mines with the highest predicted injury counts (a *count-targeting algorithm*).

We used three different metrics to evaluate each algorithm's performance: one that focuses on the algorithm's ability to select mines that report non-zero injuries; one that estimates the maximum number of injuries might be prevented; and one that compares average injury rates across targeted and non-targeted mines. At each stage of the analysis, we compared the performance of each algorithm to a "naive" predictive model based on each mine's average injury rate or count during the previous four quarters. Overall, our results are encouraging. Regardless of the metric examined, both algorithms mostly - although not universally - outperform their naive baselines. The critical factors that determine each algorithm's performance are the number of mines targeted and, to a lesser extent, the injury type examined (i.e., total, traumatic, or fatal injuries). A second important finding is that the rate-targeting and count-targeting algorithms have very different properties. The count-targeting algorithm almost universally outperforms the rate-targeting algorithm by every metric examined. However, the two algorithms outperform their respective naive baselines within different ranges and to varying degrees. Overall, we conclude that using statistical targeting techniques to prioritize mines for inspection would likely help MSHA make better use of its scarce enforcement resources, regardless of whether the agency chooses to target injury rates, injury counts, or some mixture of the two.

In addition to completing our primary task of designing and testing the statistical targeting algorithms, we investigated several other policy-relevant correlates of mine safety. These supplementary empirical analyses focused on four questions. First and most importantly, we probed the effect of unionization on coal mine safety and on the strength of regulatory enforcement. This line of inquiry was pursued extensively and yielded two academic publications. As described in Section 4.1 (page 25), unionization predicts a large and significant decline in traumatic injuries and fatalities, especially among large mines. Unionized mines also undergo longer, more frequent and more intense MSHA inspections, although this effect declines sharply with mine size. The remaining three questions - the relationship between mine size and safety, the impact of MSHA inspections on regulatory compliance, and the relationship between reported injuries and regulatory compliance - were explored in a much more cursory fashion. Nevertheless, as reported in Sections 4.2 through 4.4 these preliminary analyses did bring to light several puzzling patterns that we feel are sufficiently intriguing to warrant further investigation.

3 Targeting Algorithm

3.1 Theoretical Considerations: What is the Most Appropriate Criterion for Regulatory Targeting?

In designing the targeting algorithm, a critical threshold question that we confronted was which specific criterion to use as our measure of mine safety - in other words, how precisely to define our regulatory "target." We deemed all of the following to be plausible criteria:

1. Targeting mines with the highest predicted *injury rates* in order to mitigate risks facing vulnerable miners at the nation's most dangerous mines;

2. Targeting mines with the highest expected *number of injuries* in order to prevent as many injuries and fatalities as possible nationwide; and

3. Targeting mines in which miners' compensation levels do not seem to reflect their true levels of occupational risk (a situation suggestive of market failure) in order to improve the proportionality between remuneration and the severity of hazards miners face on the job.

In our view, all three of these criteria have compelling theoretical and practical arguments to recommend them, and all three merit serious consideration. In practice, however, the third approach cannot currently be implemented because mine-level data on wages and fringe benefits do not exist.[3] Consequently, we focused exclusively on the first two approaches: a *rate-targeting* algorithm that identifies mines with the highest predicted injury rates; and a *count-targeting* algorithm that identifies mines with the highest predicted injury counts. The choice of algorithm involves difficult policy tradeoffs to which there are no straightforward answers. For example, although a count-targeting algorithm may prevent the most injuries nationwide, it may also exacerbate inequalities across mines in the likelihood of a serious or fatal occupational injury. (This might occur, for example, if the algorithm exclusively targeted large mines because of their large expected number of injuries, even though miners at small mines face higher levels of occupational risk.) In practice, the agency may wish to implement a mixture of the two approaches. An important goal of our study is to clarify the likelihood of such tradeoffs and give policymakers some sense of their relative magnitudes.

3. In our view, the absence of any granular, mine-level data on miners' compensation and fringe benefits is a significant impediment to effective regulatory policy. The few national surveys that contain information on miners' wages - such as the Census and the Current Population Survey - contain very small samples, include no information on fringe benefits, and/or lack information on basic employer characteristics (such as mine type or union status). Availability of mine-level data on miners' remuneration would significantly enhance the potential effectiveness of regulatory enforcement, since it would enable the agency to target mines (or regions) in which miners are not being compensated for the risks they face on the job, presumably because of informational asymmetries and/or monopsonistic labor markets.

3.2 Methodology

3.2.1 Data Cleaning and Preparation

Our analysis rests on the comprehensive inspection and injury data contained in MSHA's historical database, encompassing the years 1983 through 2010. The database includes extensive information on each mine's controller and operator, quarterly inspections and violations, and reported injuries. We augmented this data with additional information on coal mines collected by the Department of Energy's Energy Information Administration (EIA), which contained information on union status, geological characteristics, economic constraints, and mining method.[4]

To create the final merged dataset, we first converted the raw data files that we received from MSHA and EIA into a format readable by Stata (a statistical software package on which we partially relied). We then cleaned each dataset - renamed variables, checked for data inconsistencies, dropped unnecessary variables, generated new variables, and so forth - to render each dataset suitable for analysis. Next, we merged multiple (cleaned) data files to create several comprehensive datasets encompassing all years, each of which relied on a different unit of observation (the individual inspection, the mine-quarter, or the mine-year). Once the final merged datasets were created, we could analyze all critical aspects of a mine's history - its operator and controller characteristics, production data, frequency and duration of inspections, magnitude of violations and assessments, and reported injuries and accidents - at the inspection, quarterly, and annual levels.

We included three different measures of mine safety as dependent variables: total injuries, traumatic injuries, and fatal injuries. We included *total* injuries because it is the broadest measure available and provides a useful point of comparison, notwithstanding its high susceptibility to reporting bias. We included *fatal* injuries because they are the least susceptible to reporting bias, even though their extreme rarity limits their utility for targeting purposes. Finally, we included *traumatic* injury rates because our supplementary empirical analysis suggested that they are less prone to reporting bias than total injuries yet sufficiently numerous to permit robust statistical inferences.[5]

Using these merged datasets to generate the targeting algorithms, however, required several further manipulations. As explained in greater detail in section 3.2.2 (page 9), an important preliminary task was to select - from among hundreds of possible candidates - those data fields most predictive of mine (total & traumatic) injuries and fatalities. To do so, we initially assembled a dataset with a list of potential candidates. We talked with mining consultant Ken Katen in an effort to include (at both the mine-quarter and mine-year levels) all variables that plausibly could be predictive of mine injuries. To account for possible lagged effects, we added lagged versions of each potential variable, except static variables such as county code, district, or office code. (Two lagged versions of each covariate were included: the average value reported in all active quarters during the preceding year,

4. Alison Morantz, "Coal Mine Safety: Do Unions Make a Difference?," *Industrial and Labor Relations Review* (forthcoming 2012 or 2013).

5. For a detailed discussion of the relative merits of these three safety measures and a description of how "traumatic" injuries were defined, see our forthcoming article on the relationship between unions and coal mine safety, presented in Appendix D.2 on page 91.

and a "linear contrast" of these same reported values.[6]) Finally, after splitting the merged datasets into two separate datasets - one for coal and one for noncoal - we dropped the quarter just before each mine closure, dropped the quarter immediately following each mine opening, and dropped mines with an unusually low number of hours worked. (Specifically, mine quarters were dropped for coal, metal, nonmetal, sand/gravel and stone mines if total hours worked per quarter fell below 100, 125, 90, 65 or 80, respectively. To determine the appropriate cutoff for each mine type, we confined our focus to mines that reported fewer than 2000 hours and used the smallest local maximum from a kernel density estimate of total hours.)

3.2.2 Feature Selection: Variable Transformations, and Classification and Regression Trees (CART)

Our Bayesian time-series modeling approach used to generate predicted injury rates and counts required a reduced set of variables from the approximately 300 that were available. In addition to improving interpretability of the resulting models and avoiding the use of variables that are not strongly associated with injury rates, a smaller set of injury rate predictors decreases the computational burden on an otherwise numerically intensive estimation algorithm. The goal of this initial stage of the statistical process was to winnow our list of approximately 300 predictors down to approximately 20-30. Please refer to Appendix B (page 39) for a list of the variables selected by CART for any targeting algorithm and Appendix C (page 43) for variable descriptions.

To select the list of the most promising candidate predictors, we fit *regression trees*, ignoring time-varying information in our data. A regression tree is a specific type of model in the class of Classification and Regression Trees (CART).[7] This procedure is carried out as follows: The algorithm first determines a predictor (among the approximately 300) that produces the greatest difference in injury rates/counts when divided at an automatically-chosen cut-point. This results in splitting the data into two groups. The procedure then finds a predictor variable (possibly the same as the first) that produces the greatest difference in injury rates/counts when applied to one of the two subsets at a determined cut-point, and this produces a further split in the data, resulting in three groups. This variable identification and splitting process is repeated recursively until little benefit is gained from further splitting. With our data, typically 20-30 variables used in the splitting was sufficient. Because it chooses the most predictive variables early in the recursion, CART is useful as a variable selection tool when many candidate predictor variables are available. Furthermore, CART is computationally efficient and can be performed quickly even on the very large data sets with which we were working. We used the `rpart` function ("recursive partitioning") in the statistics packages `R` to perform the regression tree algorithm. See Appendix E.1 (page 125) for an illustrative excerpt from the program that implemented CART.

Once we selected the most predictive variables through the regression tree procedure, we performed several different types of transformations of the variables to enable their efficient

6. The latter approach allows for a linear relationship between the quarterly predictor values and the logarithm of the mean injury rate.

7. Wei-Yin Loh, "Classification and Regression Trees," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 1, no. 1 (2011): 14–23.

use in our Bayesian time series models. Many of the predictor variables were a combination of a continuous range of values, along with many values equal to zero. This occurred most often in instances when data were not accumulated or gathered during particular quarters/years. In such cases, we created two separate variables out of the combined continuous/zero variables; one that indicated whether the variable was zero, and the other that gave the measured value if not zero. We also visually examined the relationship between the continuous ranges and the injury rate variables. In many instances, variable transformations were required before using the predictors in the Bayesian time series model. Most often, the logarithm (base ten) of a predictor variable was sufficient to ensure a meaningful relationship that satisfied the assumptions necessary for the Bayesian time series models. In cases where extremely large predictor variable values did not follow the pattern of the other predictor values in their relationships with injury rates, we created a separate variable to indicate an extreme value for that variable. Finally, when variables had missing values, we created an indicator variable signifying the lack of data which would then have its effect estimated in the Bayesian model fitting process. This entire process resulted in a manageable number of predictor variables for inclusion in the Bayesian time series models.

3.2.3 Using Bayesian Time-Series Forecasting to Generate our Predictive Algorithms

To predict future injury rates, we modeled our data using Bayesian Dynamic Generalized Linear models, a particular type of Bayesian time series modeling framework.[8] These models can be best understood as consisting of two components estimated simultaneously: (1) A model for injury rates during a fixed quarter as a function of the collection of the 20-30 predictor variables, and (2) a model for the change in the predictor variable effects over time. Thus, at any fixed point in time, a relationship is assumed between injury rates at a mine and the predictor variables depending on the time-specific coefficients. These coefficients, which measure the relationship between injury rates and the predictor variables, may be changing over time due to trends in business practices, mining regulations, and other factors which may influence the relationship between injury rates and our predictor variables. In our modeling framework, we can expect coefficients in successive quarters to be similar, but coefficients far apart in time could be noticeably different. Further specifics of our model are described in Appendix A (page 37).

We chose to use Bayesian time-series forecasting to generate predictive inferences for several reasons. First, unlike the classical framework, the Bayesian framework allows summarizing unknown quantities of interest using probability to describe uncertainty. For example, after fitting our Bayesian time series model, one can calculate a probabilistic range of values for the injury rate during a particular quarter, or the probability that an unknown true injury rate will increase from one quarter to the next. A second benefit is that fitting our complex time series model in a Bayesian framework permits computational tools that allow for straightforward analyses. Such tools are not available for classical analyses. In particular, we fit our models using Monte Carlo Markov chain (MCMC) simulation from

8. Mike West and Jeff Harrison, *Bayesian Forecasting and Dynamic Models*, 2nd ed. (Springer, 1997); Morantz, "Mining Mining Data: Bringing Empirical Analysis to Bear on the Regulation of Safety and Health in U.S. Mining."

the posterior distribution, a technique that has gained widespread use for Bayesian modeling since the early 1990s.[9] Lastly, our model assumes that the predictor coefficients can vary over time as a stochastic process, making them well-suited to the dynamic policy and regulatory environment in which MSHA operates.

We fit our Bayesian time series models via MCMC simulation using the software package `JAGS` implemented in the `R2jags` library in `R`.[10] (See Appendix E.2 on page 133 for an illustrative excerpt from the program that implemented the Bayesian algorithm in `R` and `JAGS`.) Rather than use all the data, we reserved the last quarter of data (Q4 of 2010) for predictive validation purposes. Thus, we fit our Bayesian time series models using all the data with the exception of the last quarter. We ran our MCMC algorithm in three parallel chains with overdispersed starting parameter values. Each chain was run for 20,000 iterations as a burn-in period, discarding the resulting simulated values, and every tenth iteration for the next 20,000 iterations was saved for model summaries. We retained only every tenth iteration's values to reduce the autocorrelation among successive parameter simulations that is common in MCMC. This process resulted in a total of 6000 sets of parameters to use for model summaries and predictions. To obtain predictions for injury rates for Q4 of 2010, we combined the 2010/Q4 coefficients predicted from our model with the predictor variable values in 2010/Q4. To obtain predicted injury *counts*, we simply multiplied the predicted rates by the predicted number of employee-hours for Q4-2010.[11]

3.2.4 Construction of the "Naive" Models

Comparing the performance of our targeting algorithms against randomly-generated predictions clearly would set too low a bar for success. However, we could not accurately test our algorithms' performance against the true status quo because detailed information on the agency's current mine selection practices (for example, the procedure being used to select mines for impact inspections) was unavailable. In an effort to construct more reasonable benchmarks, we generated "naive" predictions against which to compare each algorithm's performance. The naive rate-targeting model was defined as the average *injury rate* reported over the prior four quarters for a given mine. The naive count-targeting model was similarly defined as the average *number of injuries* reported over the prior four quarters. At each phase of the analysis described in Section 3.3, we compared the performance of each targeting algorithm against the performance of its corresponding naive model.

9. Mike West, "Mixture Models, Monte Carlo, Bayesian Updating, and Dynamic Models," *Computing Science and Statistics* (1993): 325–325.

10. Martyn Plummer, "JAGS: A Program for Analysis of Bayesian Graphical Models using Gibbs Sampling," in *Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003). March* (2003), 20–22.

11. Formally, our Bayesian model predicts only injury rates, not injury counts. Since many of the models that we estimated took several weeks to run - even on Stanford University's most powerful computing cluster - we did not have sufficient time to replicate the entire CART process and Bayesian modeling procedure using counts (instead of rates) as our dependent variable. Therefore, we used our model's predicted injury *rates* to compute estimated injury *counts* by multiplying a mine's predicted injury rate by its average hours worked during all active quarters during the prior year. Technically, in order to generate the most accurate count-targeting algorithm possible, one would need to re-run the entire CART process and Bayesian model using injury counts as the dependent variable. It is possible, therefore, that the performance of the count-targeting algorithm described in this report actually understates its true potential.

3.3 Results

To assess the performance of our algorithms, we used mine-level data from Q4 of 2010, which was deliberately omitted from our data sample to build our models. Table 1 records the number of mines of each type included in our sample in Q4 of 2010, as well as the numbers and percentages that reported zero injuries or fatalities. As noted in the table, most mines reported zero total, traumatic, and fatal injuries during this quarter.

Table 1: Mines with zero injuries in Q4-2010

Mine Type	Injury Type	# of Mines	# of Mines with Zero Injuries	% of Mines with Zero Injuries
Coal	Total	1238	882	71.2%
Coal	Traumatic	1238	998	80.6%
Coal	Fatalities	1560	1542	98.8%
Metal	Total	7181	6591	91.8%
Metal	Traumatic	7181	6841	95.3%
Metal	Fatalities	9465	9449	99.8%

As mentioned in Section 3.2.3, the estimation procedure for the Bayesian forecasting model returns 6000 simulated parameter draws for each variable in the model. Together these form a sample from the posterior distribution of model parameters. For each mine, we multiply simulated coefficients by their corresponding predictor variable values from that mine's Q4-2010 data. This process yields 6000 injury rate predictions for each mine for Q4-2010, which jointly comprise a sample from the posterior distribution of predicted injury rates for that mine-quarter.

To render the algorithms' predictions more amenable to comparative analysis, we streamlined them by fitting several unimodal distributions to the posterior distributions and used the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to assess goodness of fit.[12] Since the AIC and BIC identified the same distribution for fitting the posterior distributions, we decided to limit our attention only to the AIC when assessing the goodness of fit. The log-normal and gamma distributions, both of which contain two parameters, fit the best and enabled us to reduce the 6000 predictions for each mine-quarter to just four parameters.

Meanwhile, we explored several alternative methods of deriving our "best" estimate of each mine's predicted injury rate or count. We tried the mean, median, mode, as well as the 5th, 10th, 25th, 75th, and 90th percentiles from the fitted log-normal and gamma distributions, respectively. It made no difference in the targeting algorithms' performance (as determined by our three metrics specified below) whether injury predictions were based on the mean, median, mode, or other variant of the fitted distribution. For each mine, we computed the mean injury rate based on the distribution with the minimum AIC (indicating a better goodness of fit).

12. Hirotugu Akaike, "A New Look at the Statistical Model Identification," *IEEE Transactions on Automatic Control* 19, no. 6 (1974): 716–723; Gideon Schwarz, "Estimating the Dimension of a Model," *The Annals of Statistics* 6, no. 2 (1978): 461–464.

Using these estimated injury rates or counts, our next task was to rank all mines in the sample according to their predicted injury rate or counts, and target (or *flag*) n mines for $n = 1, 2, \ldots, N$, where N is the total number of mines in the sample. For example, setting $n = 1$ would target the one mine that the algorithm predicts to be most dangerous in the country in Q4 of 2010. Conversely, targeting N mines would (unrealistically) target *all* mines in the sample. Finally, we assessed the accuracy of our algorithms by comparing our predictions to the true injury data reported in Q4-2010. To undertake such comparisons, we chose three different evaluative methods, each of which offered a distinct perspective on the targeting algorithms' performance. Respectively, the three performance metrics were designed to shed light on:

1. each algorithm's capacity to distinguish mines with non-zero injuries from those with zero injuries (through comparison of nonzero classification curves);

2. the maximum number of injuries that could be averted by implementing each algorithm (through comparison of maximum injuries prevented); and

3. the typical disparity in reported injury counts (or rates) across targeted and non-targeted mines (through comparison of the Mann-Whitney U statistic).

Since each algorithm's performance depends on the number of mines flagged for inspection, how many mines to target is a crucial policy question. Between April 2010 and September 2012, MSHA conducted 477 impact inspections,[13] suggesting that it may be feasible for the agency to target at least 200 mines for inspection in a calendar year. Therefore, from a practical standpoint, the algorithms' performance up to and including this range may be of special policy interest.

3.3.1 Nonzero Classification Curves

We present three curves to evaluate each algorithm's capacity to predict which mines will report non-zero injuries. These curves are an adaptation of the ROC curve, which is designed to evaluate the performance of binary classification algorithms.[14] For example, email spam detection is a binary classification problem, since any given email is either spam or not spam, and a spam filter's performance can be measured by how accurately it classifies each incoming message. Predicting whether a tumor is benign or malignant poses a similar binary classification problem. The *confusion matrix*, presented in Table 2, offers a useful method of conceptualizing the performance of binary classification algorithms.

Unlike the examples given above, injury rates are continuous and therefore injury rate/count predictions do not, strictly speaking, pose a binary classification problem. However, for n mines flagged, we converted it into a binary classification problem by assessing how well our algorithms predicted which mines would report nonzero injuries (i.e., at least one injury) in Q4 of 2010. Since such a high proportion of mines reported zero injuries, this performance metric offered a useful perspective on the algorithms' relative performance (see Table 2).

13. MSHA, *MSHA Announces Results of July Impact Inspections*, news release, August 29, 2012, `http://www.dol.gov/opa/media/press/msha/MSHA20121757.htm`.

14. Andrew P. Bradley, "The Use of the Area Under the ROC Curve in the Evaluation of Machine Learning Algorithms," *Pattern Recognition* 30, no. 7 (1997): 1145–1159.

Table 2: The general format and notation of a confusion matrix

	Predicted = 0	**Predicted = 1**
Actual = 0	True Negative (TN)	False Positive (FP)
Actual = 1	False Negative (FN)	True Positive (TP)

To calculate this metric, we computed the True Positive Rate (TPR), the False Positive Rate (FPR), and the Positive Predictive Value (PPV) for each possible number of mines flagged, where

$$TPR = \frac{TP}{TP + FN}, \tag{1}$$

$$FPR = \frac{FP}{FP + TN}, \tag{2}$$

and

$$PPV = \frac{TP}{TP + FP}. \tag{3}$$

Loosely speaking, the TPR represents the "proportion of all dangerous mines that are flagged," the FPR represents the "proportion of all safe mines that are inappropriately flagged," and the PPV represents the "proportion of flagged mines that are dangerous."

Figures 1, 2, and 3 (pages 15, 16, and 17) plot the TPR, FPR, and PPV as a function of the number of mines flagged for total, traumatic, and fatal injuries, respectively. The rate-targeting models are presented in green, and the count-targeting models are presented in red. The Bayesian algorithms are depicted with solid lines and the naive models with dashed lines. For each set of figures, results for coal are shown on the left panels and noncoal on the right panels. The TPR, FPR and PPV graphs are vertically aligned so that for any given number of mines flagged, one can easily discern and compare each model's performance by all three criteria.

Careful scrutiny of the nonzero classification curves brings to light several important patterns. First, the FPR varies little across models; by far the two most informative criteria are the TPR (proportion of dangerous mines that are flagged) and PPV (proportion of all mines flagged that are dangerous). The remaining discussion therefore focuses exclusively on the latter two criteria. Secondly, both the Bayesian and naive count-targeting models almost universally outperform both of the rate-targeting models, often by wide margins. Since the nonzero classification curves are (by definition) designed to test each model's ability to predict nonzero injury *counts*, the count-targeting model's general superiority is not surprising in and of itself. However, some of the disparities observed - especially for traumatic injuries and especially when relatively few mines are targeted - are remarkably large. Third, both targeting algorithms outperform their naive baselines for at least some range of mines flagged, regardless of the injury type examined. (The sole exception is the rate-targeting algorithm for fatalities, which underperforms its baseline for virtually the entire range of mines flagged.[15])

15. The fact that the fatality algorithm underperforms not only the naive model, but also random chance, is puzzling. In our view, this is most likely a statistical anomaly driven in part by the scarcity of observations,

Figure 1: Nonzero classification graphs for total injury models

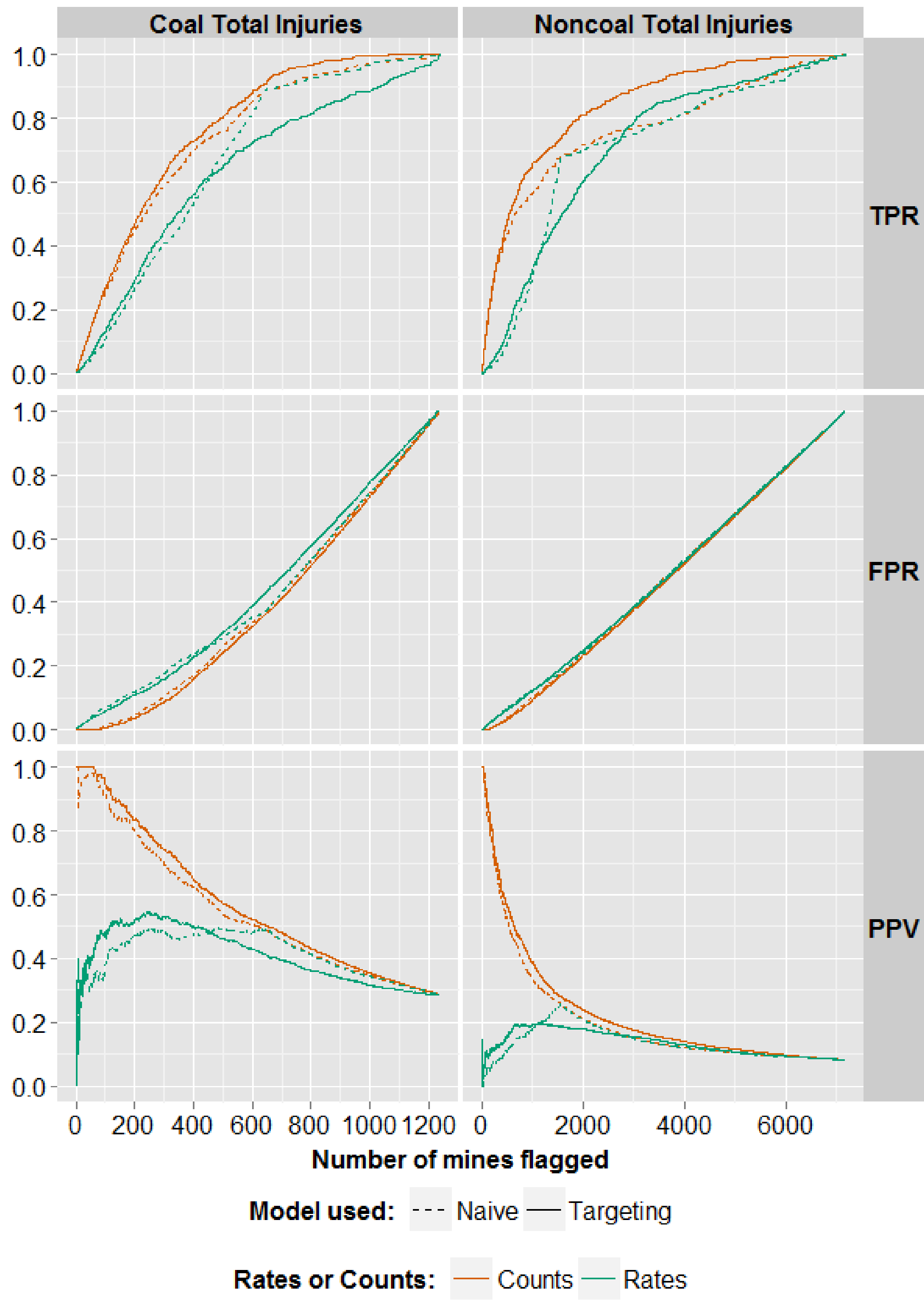


Figure 2: Nonzero classification graphs for traumatic injury models

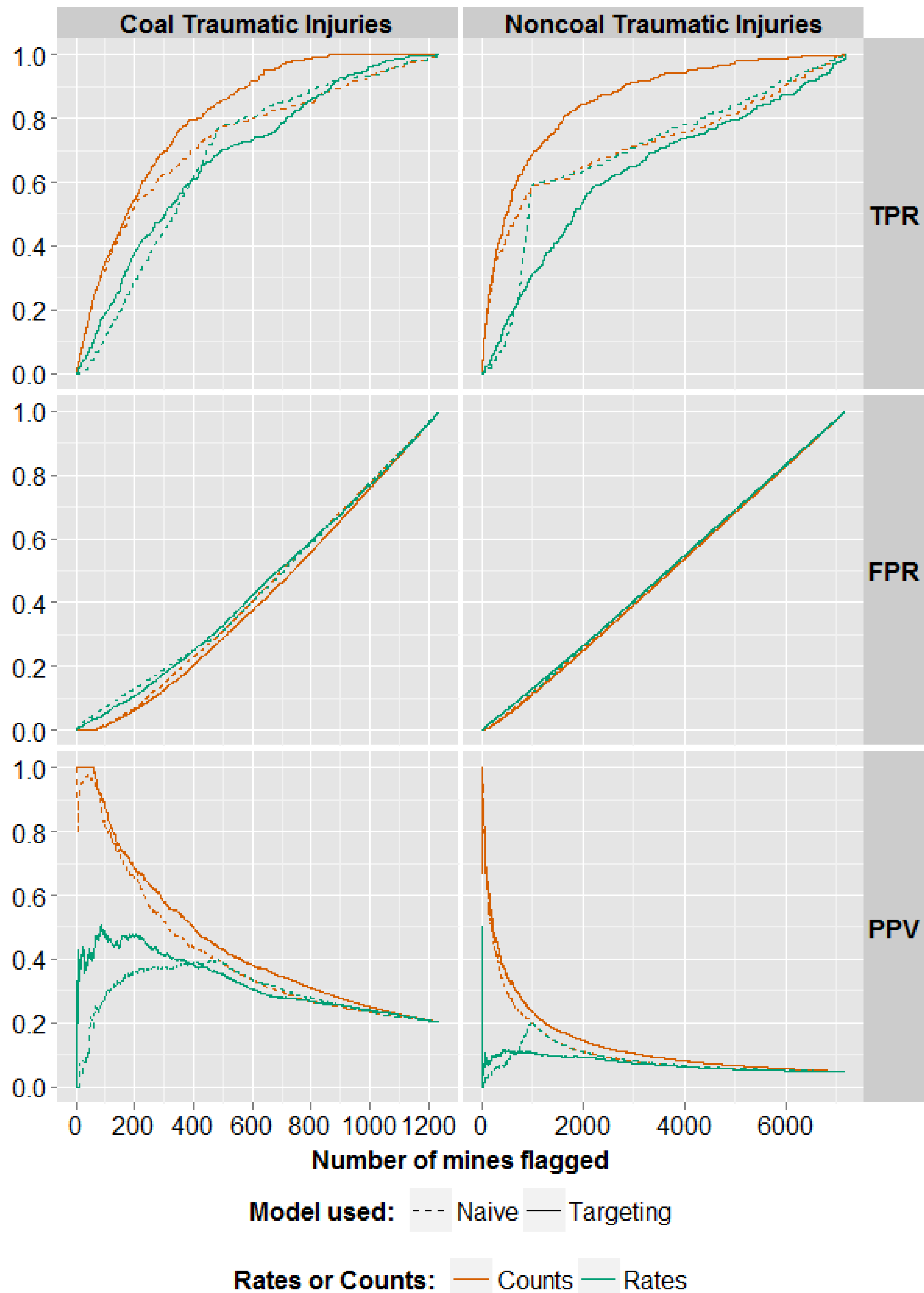
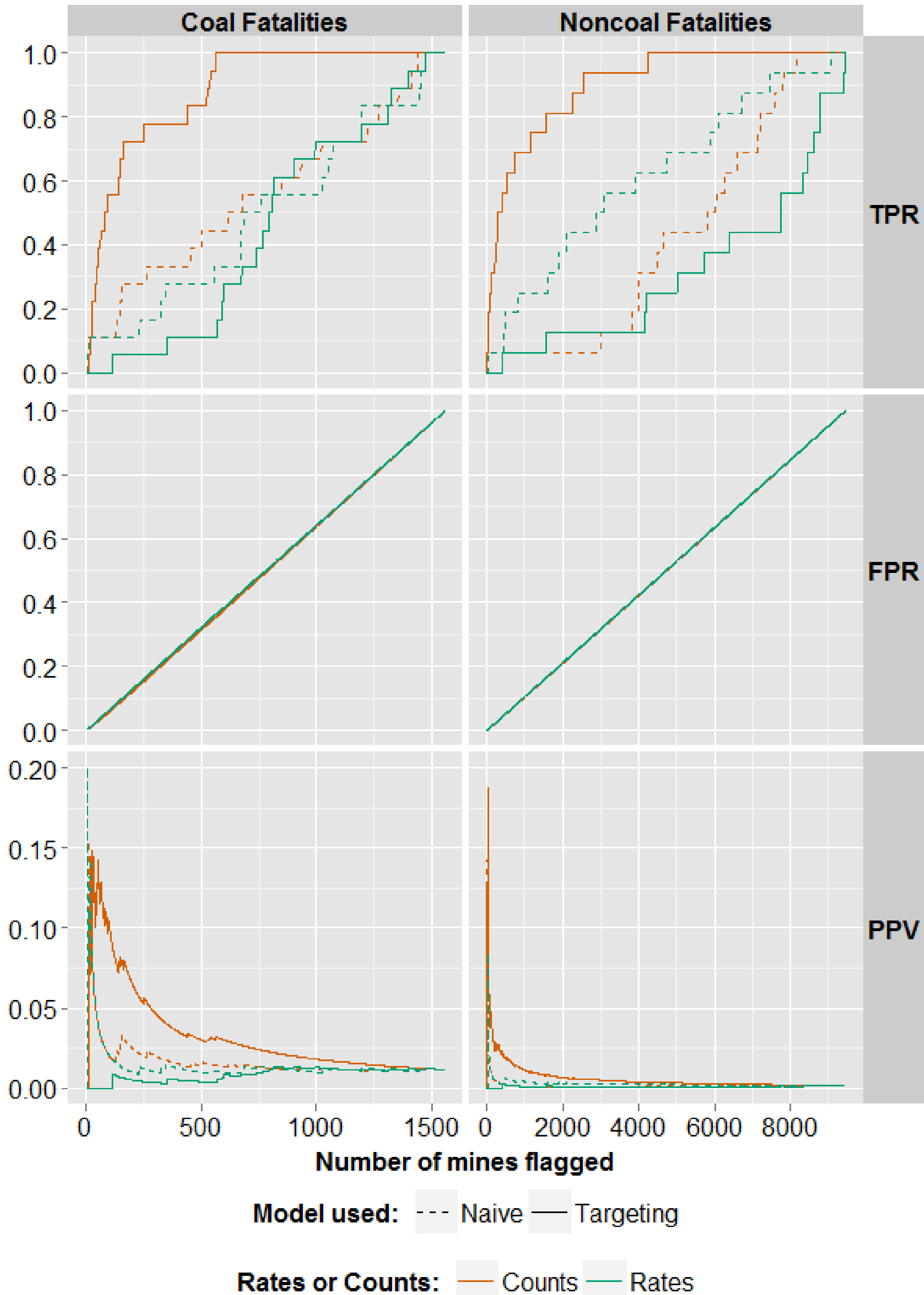


Figure 3: Nonzero classification graphs for fatality models



Finally, and more subtly, the TPR/PPV performance of the count-targeting algorithm relative to its naive model differs markedly from that of the rate-targeting algorithm relative to *its* naive model. The count-targeting algorithm invariably outperforms its naïve baseline when between 75 and 1200 coal mines, or between 104 and 7000 noncoal mines, are flagged for inspection – sometimes by sizable margins. However, the rate-targeting algorithm's performance is much less robust. To be sure, there are sizable ranges in which the rate-targeting algorithm outperforms its naive baseline - for example, when a modest proportion of mines are flagged in the total and traumatic injury models. However, there are also many ranges for which the rate-targeting algorithm lags behind its naive baseline.

Taken as a whole, these results provide grounds for optimism, insofar as both models outperform - sometimes by sizable margins - their respective naive baselines for significant ranges of mines flagged. However, the nonzero classification curve analysis also highlights the fact that the count- and rate-targeting algorithms have very different properties. As a result, the question of "which target to target" is likely to be highly consequential.

3.3.2 Maximum Injuries Prevented

The second performance metric examined, the "maximum injuries prevented," is defined as the total number of injuries reported for Q4-2010 at each targeted mine. Our implicit assumption is that timely regulatory intervention could, at least in theory, have prevented all of the injuries that would otherwise have occurred. Figure 4 (page 19) depicts the maximum injuries prevented for all three injury types as a function of the number of mines flagged. As before, coal is shown on the left and noncoal on the right.

Once again, our findings are generally promising. It is not surprising that the count-targeting models (whether naive or Bayesian) nearly always outperform the rate-targeting models since the maximum injuries prevented is a tally of injury counts. Perhaps more surprising is the large size of such disparities, especially when one confines attention to the Bayesian algorithms. There remains a sizable range of mines flagged for which the Bayesian algorithms outperform their naive baselines, with the sole exception once again being the rate-targeting algorithm for fatalities. And also echoing the findings reported above, the relative performance of the two algorithms (as compared to their respective naive baselines) differs markedly. The count-targeting algorithm always outperforms its naive baseline, and this disparity grows as the number of mines flagged increases. In contrast, the rate-targeting algorithm only outperforms its baselines (in the total and traumatic injury models) when modest numbers of mines are flagged for inspection.

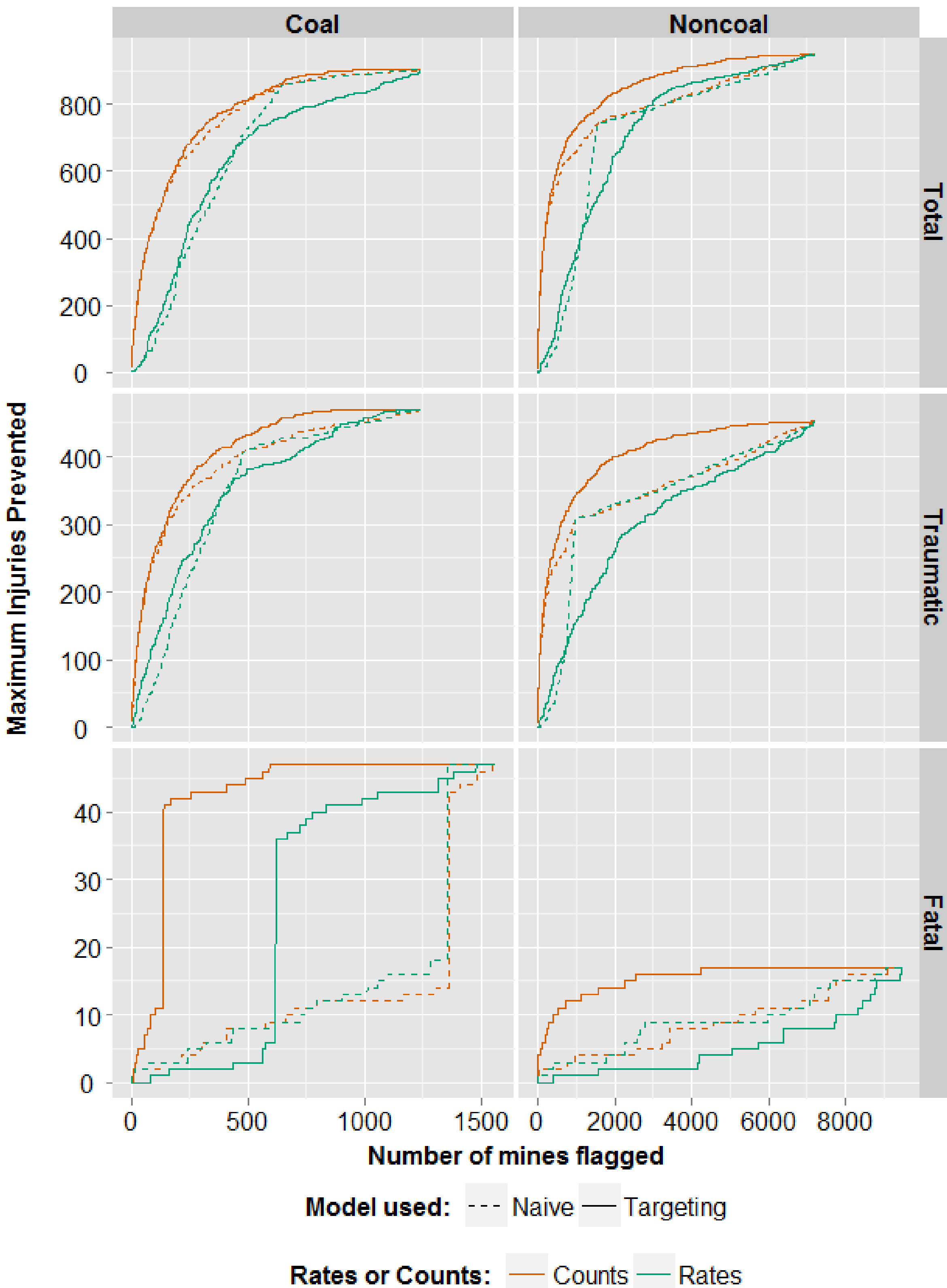
3.3.3 Comparing Real Injury Rates of Flagged and Non-Flagged Mines via the Mann-Whitney U Statistic

Using real injury data from Q4-2010, our third and final performance metric assesses whether injury rates among targeted mines are likely to be greater than among non-targeted mines. The Mann-Whitney U Statistic is a non-parametric statistical test where U estimates

$$P(\text{targeted mine's injury rate} > \text{non-targeted mine's injury rate}).$$

and in part by the fact that the model's performance is being tested against just one quarter of data.

Figure 4: Maximum injuries/fatalities prevented graphs for all models



U is computed as follows. First rank mines based on their *predicted* injury rates (or counts, as the case may be), and flag the top n most dangerous predicted mines. Then rank the mines in decreasing order by their real injury rates (counts) for Q4-2010, so that the least dangerous mine has rank 1 and the most dangerous mine has rank N, the number of mines. Let R be the sum of the *ranks* for the n flagged mines. Then

$$U = \frac{R - \frac{n(n+1)}{2}}{n(N-n)}.$$

The best-case scenario is $U = 1$, in which case all flagged mines had higher injury rates than all non-flagged mines. The worst-case scenario is $U = 0$, in which case all flagged mines had lower injury rates than all non-flagged mines. The average (uniform) random case is $U = 0.5$, in which case flagged mines are about equally as dangerous as non-flagged mines. Thus, U greater (less) than 0.5 indicates that a randomly-selected targeted mine's real injury rate or count is greater (smaller) than that of a randomly-selected, non-targeted mine. The closer U is to one, the more accurately the algorithm is targeting mines with higher injuries. We calculate U for each number of mines flagged $n = 1, \ldots, N$. The U statistic adds a new dimension to our analysis because it compares total reported injuries, as opposed to merely the likelihood of any injur(ies) being reported. Additionally, the U statistic is better equipped than binary classification schemes to handle ties in the data.

Our results are displayed in Figure 5 and 6 (pages 21 and 22). Figure 5 shows all possible numbers of mines flagged, while Figure 6 zooms in on a more plausible range of 0-500 mines flagged. Coal is shown on the left-hand panels and noncoal on the right-hand panels. Results are presented separately (by row) for total, traumatic, and fatal injuries.

Once again, our results are promising and largely echo those reported earlier. The count-targeting algorithm is globally the top performer - exceeding the performance of the rate-targeting models by a wide margin - and consistently, albeit modestly, outperforming its naive baseline for coal mines. (The count-targeting algorithm for non-coal mines also consistently outperforms its naïve baseline when more than 100 mines are flagged.) As usual, the performance of the rate-targeting model is much more variable: it only outperforms its naive baseline when up to several hundred mines are flagged for inspection. As usual, the rate-targeting results for fatalities are especially idiosyncratic: presumably because of the low frequency of fatalities, the model consistently lags behind its naive baseline.

3.4 Discussion

Overall, the three performance metrics examined present a consistent and nuanced picture of the prospects for using Bayesian time-series statistics to enhance strategic enforcement. First and foremost, both the rate- and count-targeting variants of the algorithm outperformed their (respective) naive baselines for at least some injury types and some ranges of mines flagged. This suggests that regardless of which variant MSHA adopts, an algorithm that was designed carefully and implemented effectively could appreciably enhance the agency's capacity to identify high-risk mines.

Secondly, our findings underscore the critical policy importance of deciding whether to target injury *rates* or injury *counts*. By all three metrics examined, the count-targeting

Figure 5: Mann-Whitney U statistic by number of mines flagged for all possible mines flagged

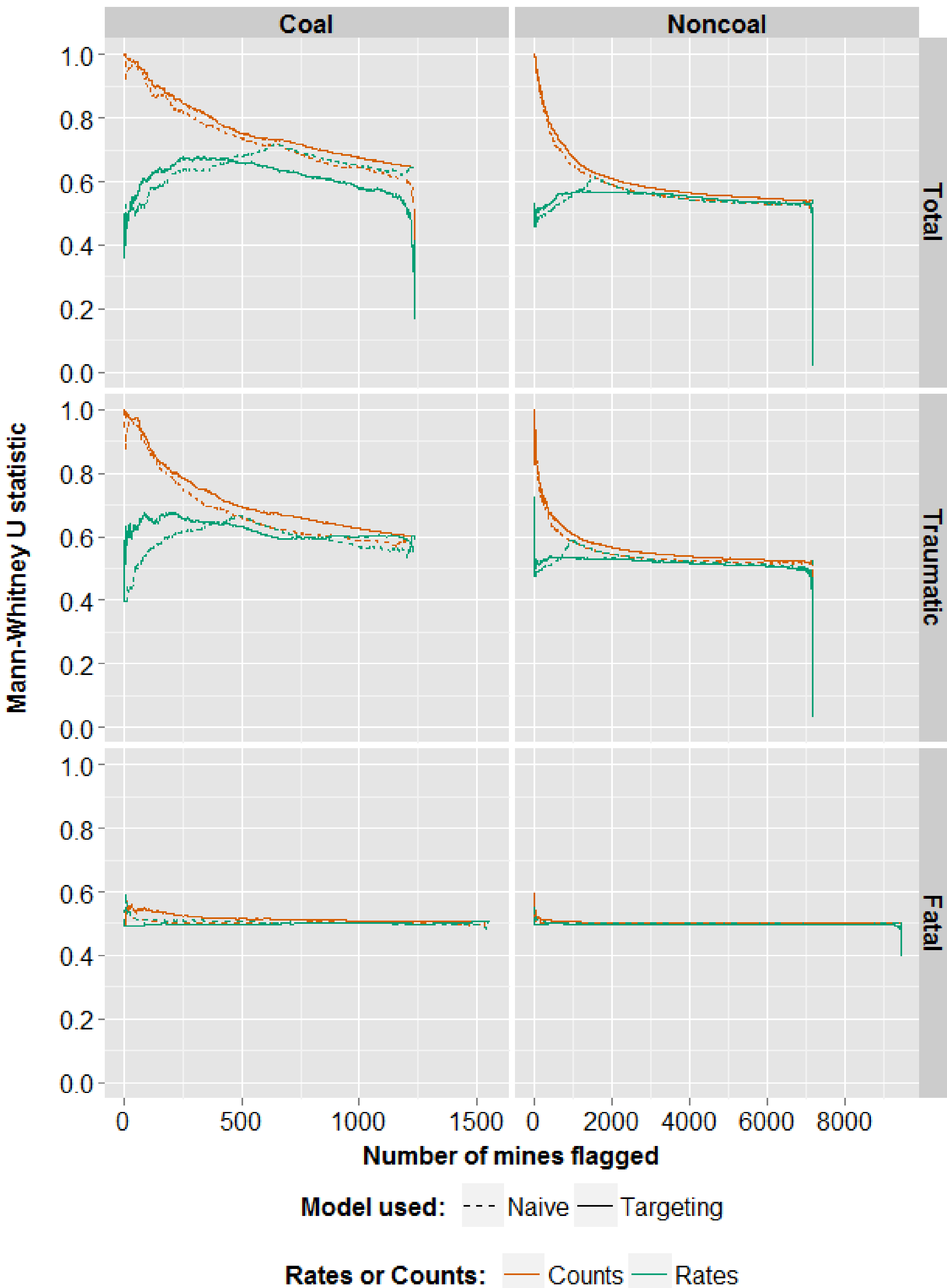
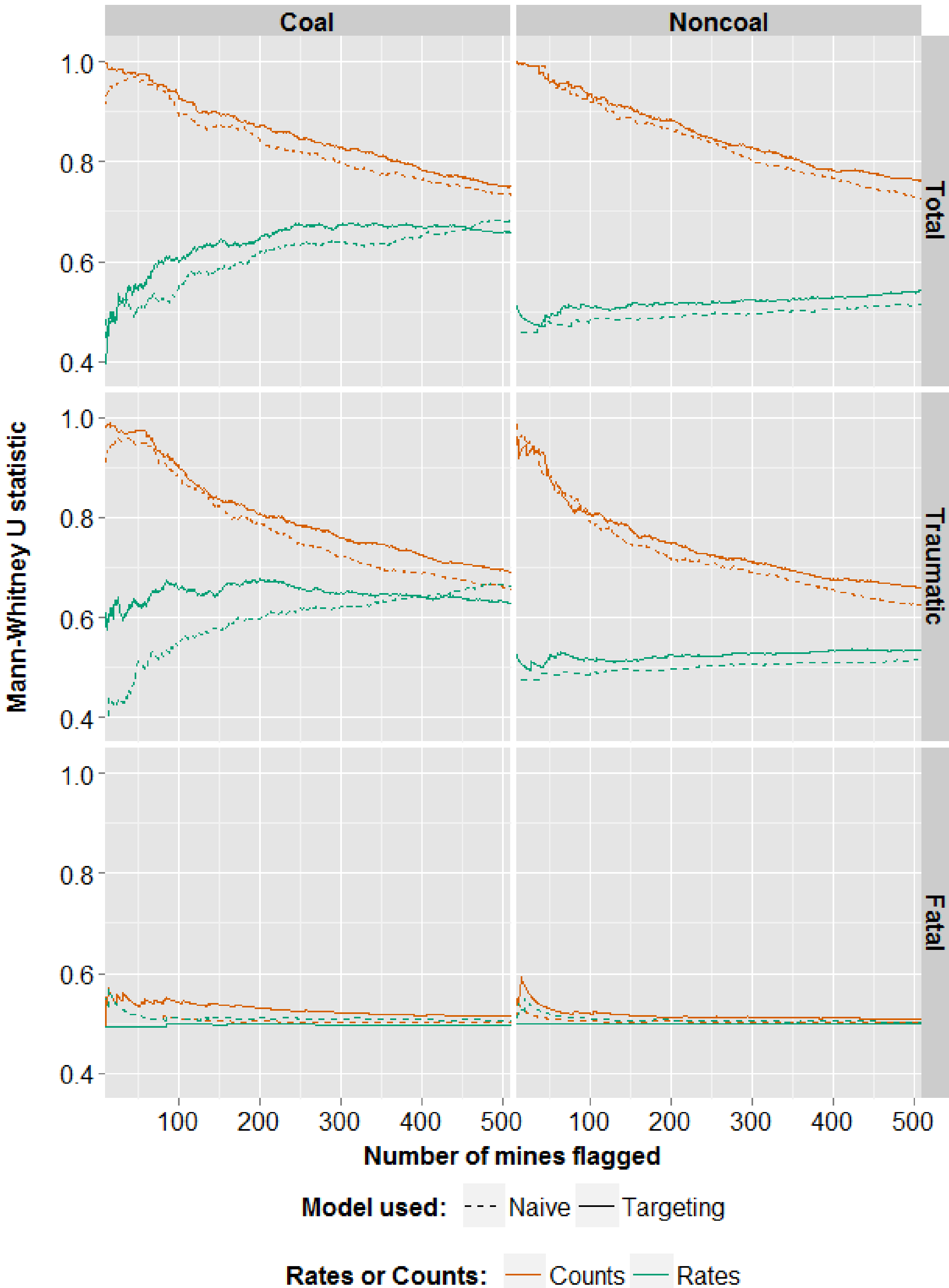


Figure 6: Mann-Whitney U statistic by number of mines flagged for 0-500 mines flagged



algorithm outperformed the rate-targeting algorithm, often by a substantial margin. In practice, implementing a pure count-targeting algorithm would probably compel the agency to focus mostly (if not exclusively) on large mines, where the greatest number of injuries can potentially be averted. Focusing its enforcement efforts on large mines, however, could exacerbate disparities in occupational risk facing miners at large versus small mines. Given the complexity of such tradeoffs, the agency should carefully weigh the costs and benefits of each approach, and possibly consider implementing some mixture of the two.

Third, our analysis suggests that despite their overriding importance from a policy perspective, overreliance on fatal injury rates (and counts) for targeting purposes is problematic. Because fatalities are such rare events, they produce a very "noisy" signal that is, at best, of only modest statistical value. As an alternative, the agency might consider focusing on traumatic injuries, which are less prone to underreporting than total injuries, yet still sufficiently numerous to be tractable from a statistical targeting perspective.

Finally, our findings indicate that in both a relative and an absolute sense, each algorithm's performance is highly variable and depends critically on how many mines are targeted for inspection. The optimal number of mines flagged cannot be discerned in isolation but can only be calculated with reference to the variant of algorithm employed (rate- vs. count-targeting), the type of mine inspected (coal vs. noncoal), and the type of injury examined (total vs. traumatic vs. fatal injuries).

Taken as a whole, our findings point in several potentially fruitful directions. Several properties of the targeting models that we did not explore in detail merit further inquiry. For example, it would be interesting to explore the extent to which algorithms that target traumatic injuries also help predict mine fatalities, which types of mines are most likely to be flagged, and whether the same "frequent flyers" are likely to be targeted year after year. To more thoroughly evaluate the algorithms' performance, one could test their predictions against recently-released closeout data from 2011. An even more realistic test could be developed by testing the algorithms' predictions against those mines actually singled out to receive POV letters and/or impact inspections since May of 2010.

Ultimately, however, the best way to test the efficacy of the algorithm would be for MSHA to implement a pilot study using principles of experimental design. Agency personnel would use the algorithm on a limited basis (for example, for a limited period of time or among a subgroup of mines) and compare its efficacy against more conventional enforcement methods. If the promising findings reported in this study are borne out by the algorithms' performance in the field, then the use of Bayesian time-series forecasting to enhance regulatory targeting could become a key cornerstone of MSHA's strategic enforcement agenda and serve as a model for other agencies facing similar challenges.

4 Supplementary Empirical Analyses

4.1 Research Studies on the Effect of Unionization on Coal Mine Regulation and Safety

The first empirical question we investigated was the relationship between mine unionization and, respectively, regulatory enforcement and mine safety. The richness of the historical data and the availability of a viable identification strategy enabled us to explore both of these relationships in much more extensive and rigorous detail than the topics described in the remaining sections of this report. Both sets of findings were written up as research articles that were submitted to, and accepted by, academic journals. Although the following are short summaries of each article's main findings, copies of both papers are also appended to this report as Appendices D.1 and D.2 (pages 49 and 91).

The first article, "Coal Mine Safety: Do Unions Make a Difference?" is forthcoming in the *Industrial and Labor Relations Review*. The article begins with the perplexing observation that although the United Mine Workers of America (UMWA) has always advocated strongly for miners' safety, prior empirical literature contains no evidence that unionization reduced mine injuries or fatalities during the 1970s and '80s. The study uses a more comprehensive dataset and updated methodology to re-examine the relationship between unionization and underground, bituminous coal mine safety from 1993 to 2010. We find that unionization predicts a substantial and significant decline in traumatic mining injuries and fatalities, the two measures that we argue are the least prone to reporting bias. These disparities are especially pronounced among larger mines. Our best estimates imply that overall, unionization is associated with a 13-31% drop in traumatic injuries and a 27-83% drop in fatalities. Yet during the same period, unionization also predicts higher total and nontraumatic injuries. We interpret these results as suggesting not only that a real "union safety effect" probably exists, but also that injury reporting practices differ substantially between union and nonunion mines.

The second article, "Does Unionization Strengthen Regulatory Enforcement? An Empirical Study of the Mine Safety and Health Administration," appeared in Volume 14 of the *New York University Journal of Legislation and Public Policy* in 2011. The article examines the relationship between unionization and regulatory enforcement in underground, bituminous coal mines from 1995 to 2009. Specifically, we probe three closely intertwined questions. First, do the frequency, distribution, intensity and/or scope of MSHA inspections differ significantly across union and non-union mines? Second, do conventional metrics of regulatory enforcement stringency and compliance – such as the frequency of violations and the magnitude of penalties – vary by union status? Finally, do such disparities (if any) seem likely to explain the "union safety effect" reported in our prior study (summarized above)? The analysis reveals, first, that unionization predicts significantly greater frequency, duration, and intensity of MSHA inspections. Second, unionization correlates with a significant increase in the average fine assessed for non-trivial violations. However, both of these disparities diminish sharply with mine size. (In contrast, as noted above, the union/non-union disparity in traumatic and fatal injuries is the most pronounced among large mines.) Therefore, in answer to the third question, we conclude that the disparities in enforcement behavior that we have identified are unlikely to fully explain the "union safety effect" identified in the earlier study.

4.2 Preliminary Exploratory Analysis on the Relationship between Mine Size and Injury Rate

The second question that we investigated, and for which we conducted some preliminary exploratory analysis, was the relationship between mine size and injury rate. The conventional wisdom is that mine safety increases (so injury rate decreases) with mine size.[16] The rationale for this wisdom is that larger mines can afford capital improvements, institutional safety measures, offer more training, and that workers in larger mines are more likely to organize and know their rights.[17] If this is true, then we should see a generally decreasing trend in mean traumatic injury rates (recall that traumatic injuries are less prone to reporting bias than total injuries) as mine size increases.

To calculate the smoothed mean injury rate by mine size, we used a Generalized Additive Model (GAM).[18] We fit the GAM to injuries as a smoothed function of log(total employee hours), using the Poisson family with log(total employee hours) as an offset term. The GAM simultaneously fits a smooth function of the predictor variable and a generalized linear model (GLM) relating injury rate to mine size.

We used two different measures of mine size as explanatory variables: total hours worked and number of employees. These two variables are correlated, but not perfectly so. There are some mines with few employees but many hours worked, and also some mines with many employees but few hours worked.

The results of our exploratory analysis are presented in Figures 7 and 8 (pages 27 and 28, respectively). Surprisingly, the figures do *not* display the general downward trend that we expected. The figures for coal mines appear generally U-shaped, especially if one confines attention to underground mines. Although small mines are particularly hazardous (as expected) by most measures, injury rates do not consistently decrease - and sometimes even increase - with mine size. Indeed, judging from reported traumatic injury rates, surface mines that employ many workers are among the most hazardous mines in both the coal and noncoal samples. Although our choice of mine size measure (total hours worked vs. total employees) makes little difference among underground mines, it changes the picture drastically among surface mines. The "small mine problem" that emerges so dramatically from the left-hand panels of Figures 8a and 8b disappears entirely when one focuses on total employees in lieu of total hours. Perhaps some large mines (with a large number of employees on payroll) occasionally lay idle for days or even weeks at a time, leading to (deceptively) few hours worked and (misleadingly) high traumatic injury rates. Such mines might appear in the left tail of the distribution when the size measure is (logged) hours worked, but in the right-hand tail of the distribution when the size measure is total employees.

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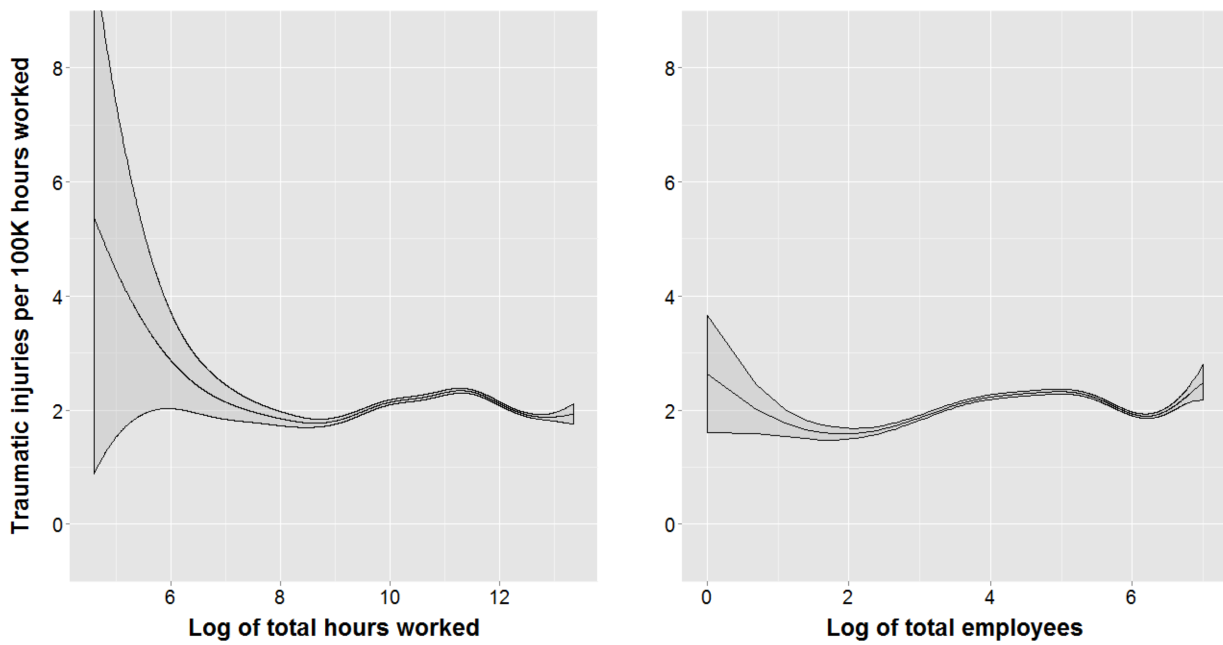
16. National Academy of Sciences/National Research Council/Institute of Medicine (NAS/NRC), *Toward Safer Underground Coal Mines* (Washington, DC: National Academy Press, 1982).

17. Susan E. Buskin and Leonard J. Paulozzi, "Fatal Injuries in the Construction Industry in Washington State," *American Journal of Industrial Medicine* 11, no. 4 (1987): 453–460; Katherine L. Hunting and James L. Weeks, "Transport Injuries in Small Coal Mines: An Exploratory Analysis," *American Journal of Industrial Medicine* 23, no. 3 (1993): 391–406.

18. T.J. Hastie and R.J. Tibshirani, *Generalized Additive Models* (Chapman & Hall/CRC, 1990).

Figure 7: Mean injury rate by mine size for underground mines

(a) Coal mines

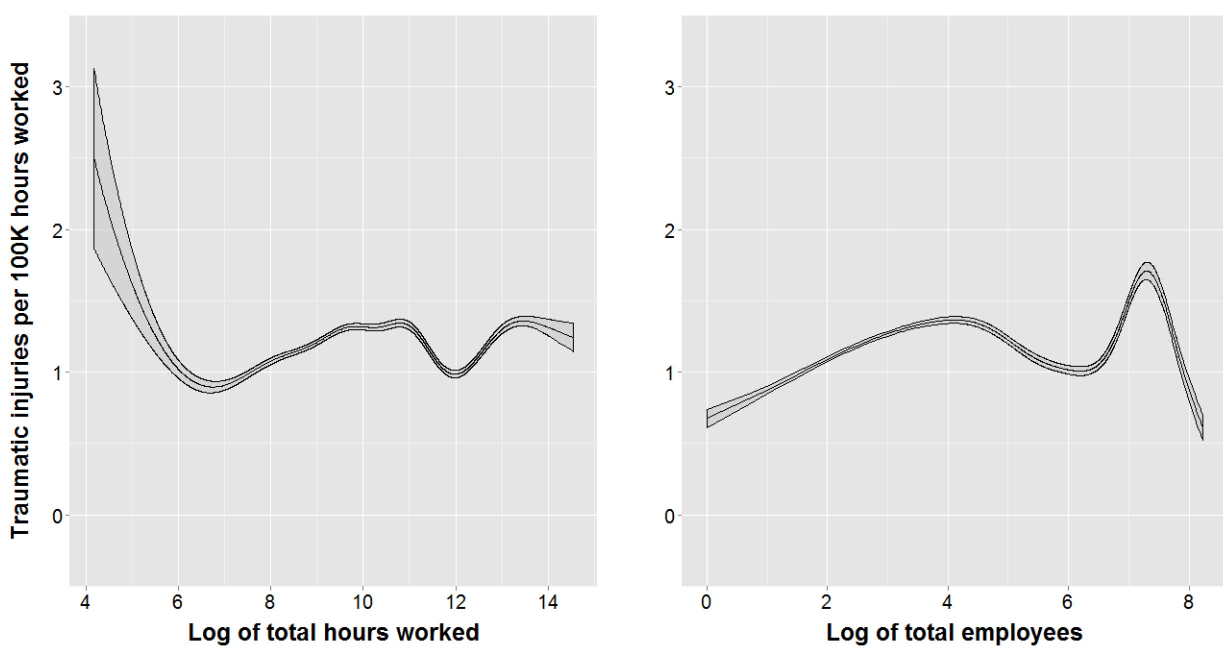


(b) Noncoal mines

Figure 8: Mean injury rate by mine size for surface mines

(a) Coal mines

(b) Noncoal mines



It is also worth noting that our preliminary exploratory analysis on the relationship between regulatory compliance and reported injury rates (summarized below in Section 4.3) also bears on the mine size question. (See Figure 12, page 36.) Surprisingly, we find that the correlation between regulatory compliance and mine safety is strongest among small mines. Here again, our preliminary findings are intriguing and seem to raise more questions than they answer.

In short, our preliminary analysis suggests that the correlation between mine size and occupational safety is more complex than previously has been understood. Exploring this relationship in greater detail would be a promising area for future inquiry.

4.3 Preliminary Exploratory Analysis of the Effect of Inspections on Safety

MSHA's primary activity is conducting on-site inspections, and the ultimate goal of each inspection is to prevent future worker injuries. One plausible way to evaluate the efficacy of MSHA's regulatory enforcement activities is to ask what effect, if any, inspections have on operators' subsequent behavior and mine safety. In academic parlance, this is known as the "specific deterrent" effect of MSHA inspections.

In practice, however, obtaining credible estimates of MSHA's specific deterrent impact is very challenging in this context because *all* mines are inspected with roughly equal frequency. Without plausibly exogenous variation in the frequency and/or intensity of inspections, it is difficult to find a statistically credible identification strategy to isolate the impact of an inspection on a mine's subsequent behavior.

Instead of trying to devise a rigorous identification strategy, we began to probe the issue informally by exploring two empirical relationships that might shed light (at least indirectly) on whether experiencing an MSHA inspection improves inspected mines' subsequent behavior. First, we used survival (event-history) analysis to examine how the number of elapsed days since a mine's most recent inspection relates to its reported injury rate. Our hypothesis was that a recently-completed inspection might, for behavioral reasons, affect the salience of occupational hazards and in turn the likelihood of workplace injuries. For example, if the memory of a recent inspection induces greater vigilance on the part of workers (and managers), one might observe a drop in injuries in the days immediately following an inspection, but such an effect would likely diminish as memories fade and safety concerns lose their salience. Secondly, we explored whether (and how) the frequency of regulatory violations and reported injuries, respectively, fluctuate across the life cycle of a mine. Since every U.S. mine is inspected at least twice per year, the longer a mine has been in operation, the more MSHA inspections it is likely to have undergone, and thus *ceteris paribus*, the safer and more compliant one might expect it to become.[19] To be sure, mine age is likely to correlate with many *other* factors that also affect both compliance and safety, such as geological conditions at the mine, average tenure and experience of mine personnel, operators' (and miners') familiarity with major hazards and how to mitigate them, etc. Thus, even if compliance and

19. Of course, even if inspections *do* impact safety and compliance, one might expect their marginal impact to diminish over time. However, it seems reasonable to assume that at least for some portion of a mine's life cycle, inspections do have a positive marginal impact - and that their impact remains positive (or at least non-negative) as long as a mine remains in operation.

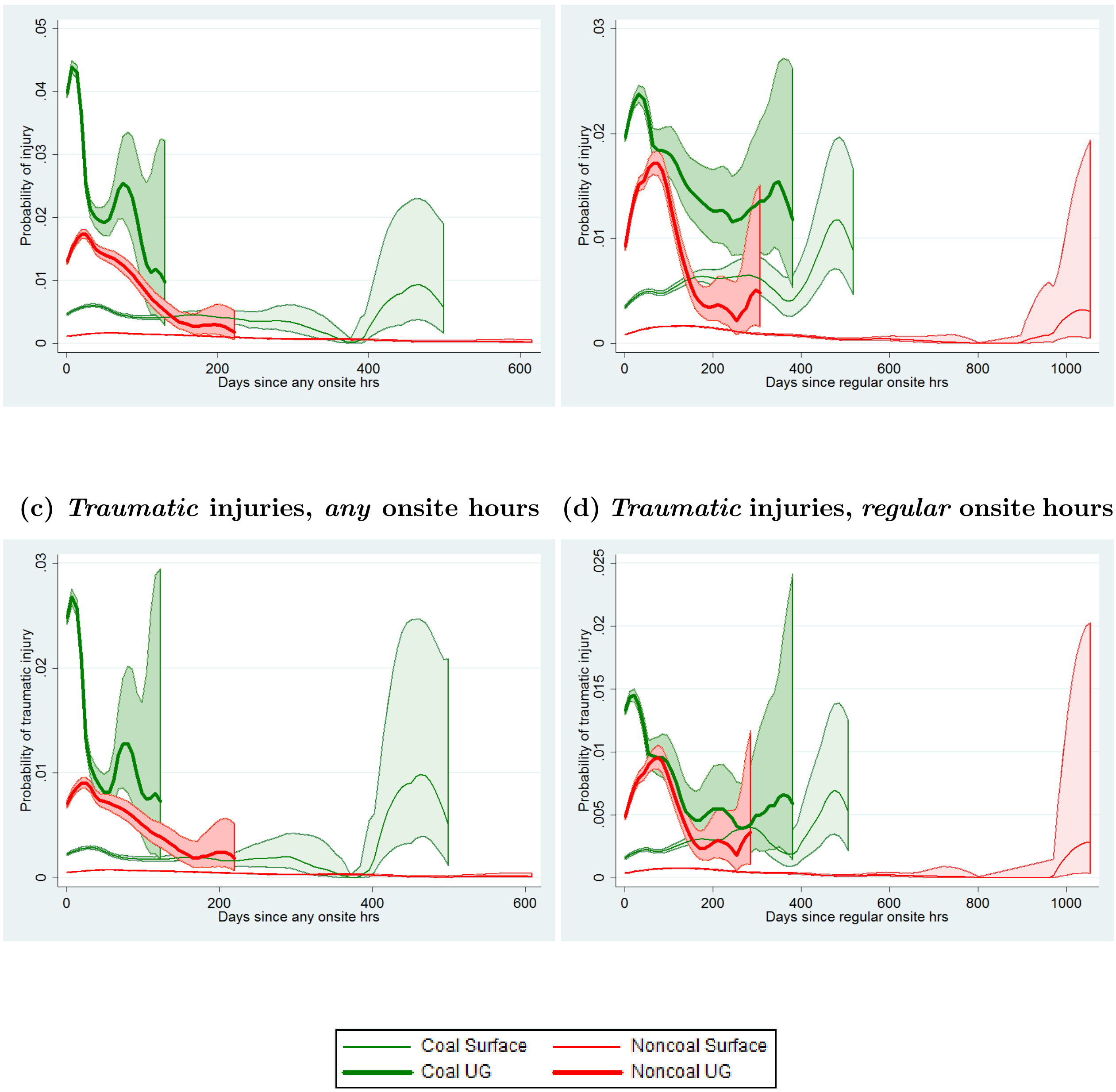
safety do improve with mine age, this would *not* indicate that regulatory enforcement is the (or even a) primary causal factor. On the other hand, if mine safety and compliance do *not* improve with age, this would raise intriguing (and disturbing) questions about the likely impact of regulatory enforcement. Although it is possible that countervailing factors (such as increasingly adverse geological conditions) are offsetting MSHA's beneficial impact, this explanation may not seem persuasive in all mining environments. At the very least, we felt that exploring such relationships could point the way toward promising follow-up studies.

To explore the first question - whether the elapsed days since an inspection affects a mine's likelihood of reporting an injury - we used unordered multiple-event hazard models (a variation of the Nelson-Aalen estimate using a kernel density smoother) in which the unit of observation was the inspection, and the elapsed time was re-set to zero each day that an inspector logged onsite inspection hours. (As a robustness check, we re-estimated the same models using *onsite* regular inspection hours.) Since we re-set the clock each time a new inspection began, the observations for any given inspection were right-censored (at the date that the next inspection began), and each injury was treated as an event linked to a single (prior) inspection. Injuries that occurred before the first inspection (i.e., immediately after a mine opened or re-opened after a temporary closure) were dropped from the analysis, since they could not be attributed to any inspection. We conducted the analysis for both total and traumatic injuries. Every inspection was linked to a non-negative number of injuries so unordered multiple-event survival analysis was the most appropriate modeling strategy.[20] Because the models are computationally expensive and time-consuming to estimate - and because the regulatory environment has changed considerably in the past quarter-century - we did not conduct our analysis for our entire data set, but confined our attention to the period since the MINER Act was signed into law (June 15, 2006).

The estimated hazard rates for all four mine types and their 95% confidence intervals, shown in Figure 9 (page 31), are surprising. For all mine types, the probability of an injury *rises* for several weeks or months following a regular onsite inspection (quite dramatically so for underground mines); declines for a sustained period thereafter; and then rises again after considerable time has elapsed. (A roughly similar, although more muted and less robust, pattern emerges for *any* onsite inspection hours.) These puzzling findings raise a number of questions. Might the short-term spike in the probability of a reported injury reflect a reporting effect, whereby a recent inspection galvanizes workers to report even minor injuries? Or might it represent a form of moral hazard whereby mine personnel immediately let down their guard and become less vigilant as soon as the inspector exits the premises? Similarly, the declining hazard rate that follows could represent a real improvement in safety (as workers and supervisors abate hazards and apply insights gleaned from the inspection), it could be a reporting effect (as workers and/or operators become less willing to report workplace injuries), or it could represent a mixture of the two. The upward-sloping right tail of the hazard curves could indicate that either (or both) of these effects wears off after many months have elapsed. Although we cannot discern from our data which (if any) of these hypotheses has any merit, our counterintuitive findings do suggest that MSHA inspections have behavioral effects on inspected firms that are complex and time-variant.

20. Terry M. Therneau and Patricia M. Grambsch, *Modeling Survival Data: Extending the Cox Model* (Springer Verlag, 2000).

Figure 9: Injury hazard rate by days since last onsite inspection hour (by mine type). †



(a) ***Total*** **injuries,** ***any*** **onsite hours**

(b) ***Total*** **injuries,** ***regular*** **onsite hours**

(c) ***Traumatic*** **injuries,** ***any*** **onsite hours**

(d) ***Traumatic*** **injuries,** ***regular*** **onsite hours**

†. Only events between June 15, 2006 (the day the MINER Act was passed) and December 31, 2010 are included in the sample.

To probe the second question - the relationship between mine age, regulatory compliance, and reported injuries - we computed the mean traumatic injury rate and the mean significant and substantial (S & S) violation rate by mine *age* (in quarters of operation). The mean S & S violation rate by mine age is shown in Figure 10 (page 33), and the mean traumatic injury rate by mine age is depicted in Figure 11 (page 34). As is shown in the figures, the evolution of regulatory compliance and safety over a mine's life cycle is more complex than we anticipated, and differ significantly by mine size and type. Regulatory compliance generally improves with age among coal mines, although the same cannot be said for noncoal mines, whose S & S violation rates fluctuate repeatedly across the life cycle. Meanwhile, although reported traumatic injury rates tend to decline with age across all mine types, underground coal mines (especially medium-sized ones) are a salient exception. For all categories except noncoal underground mines, injury rates initially *rise* before starting to decline. The evolution of mine safety also varies markedly by mine size. For example, among small coal mines, the sustained decline in traumatic injury rates does not seem to start until a mine has been operating for at least 15 years (60 quarters). In contrast, the decline begins more rapidly (at about 8-10 years of age) for large coal mines. Most puzzling of all, such a decline *never* seems to occur among medium-sized underground coal mines. As always, it is important to stress that the relationships presented in Figures 11 and 12 are purely observational, and do not permit one to draw any credible inferences about cause and effect. Nevertheless, our analysis provides only qualified support (at best) for the notion that prolonged exposure to regulatory scrutiny necessarily improves mines' regulatory compliance and reported safety levels. Although by and large regulatory violations and reported (traumatic) injuries decline with age, the relationship is not monotonic and does not hold across all mine sizes and types. In fact, the decline in reported injuries emerges robustly only among mines that have been operational for a decade or more.

In short, our preliminary investigation into the impact of MSHA inspections raised more questions than it answered. The two lines of inquiry that we explored - how days elapsed since the last inspection affects the likelihood of an injury, and whether violation and injury rates decline across a mine's life cycle - revealed complex and intriguing patterns that merit further investigation.[21] We also feel that further efforts should be made to develop a rigorous identification strategy capable of isolating the specific deterrent impact of MSHA's inspection activities.

21. As an additional informal exploratory analysis we attempted to compare the traumatic injury rate on days when MSHA is present at a mine to days when MSHA is not present. Taken at face value, the results suggested that mines are *more* dangerous when an inspector is present. This surprising result was most likely due to the fact that MSHA does not know exactly which days a mine is open. That is, whether a mine is open is a confounding variable because it has a causal effect on both injury rate and an inspector's presence. To address this problem and correctly estimate the effect of inspector presence on mine safety, we would need to know which days a mine was open, and ideally how many hours were worked each day. However, MSHA does not currently collect this data.

Figure 10: Compliance by mine age, broken down by mine type and mine size.

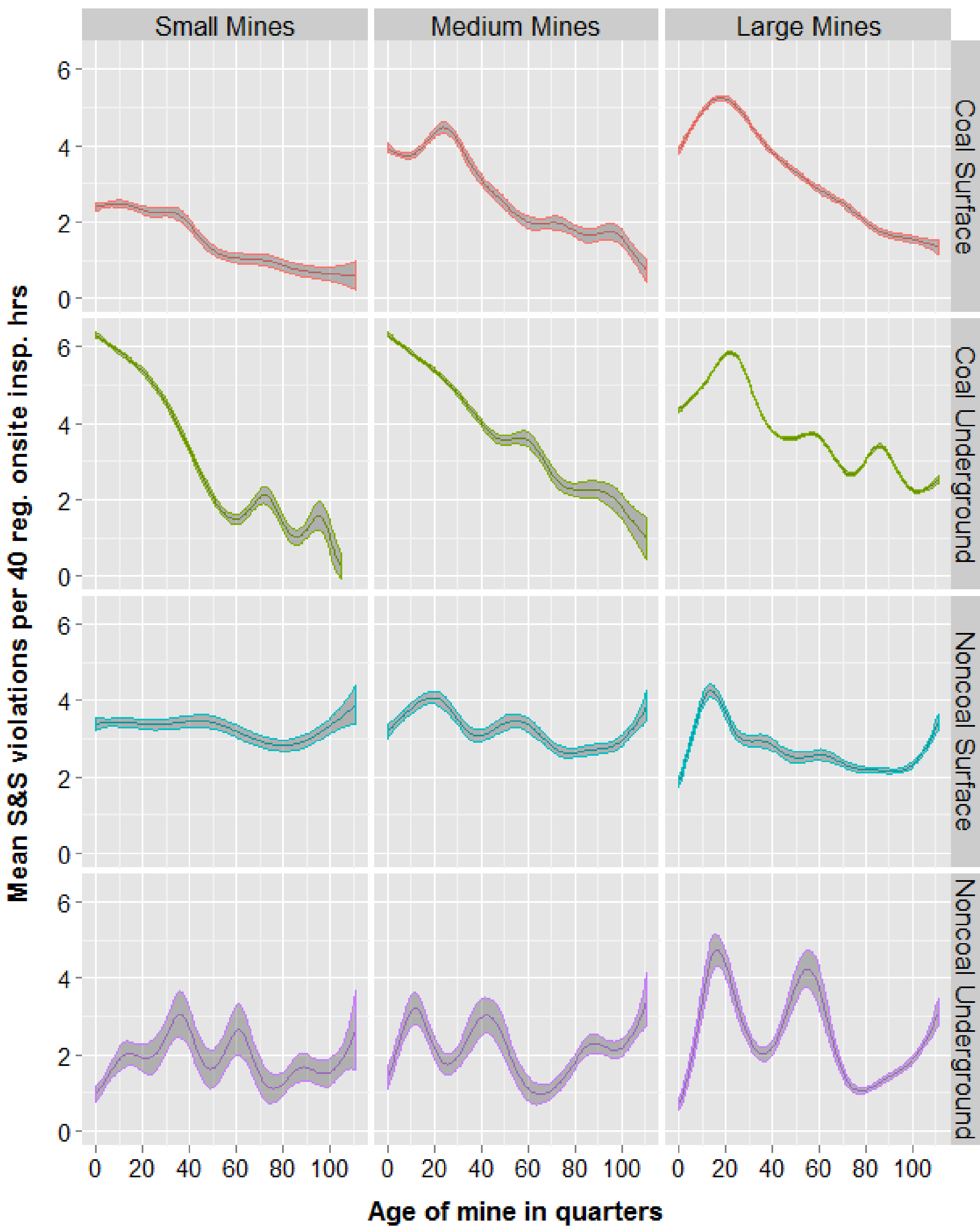
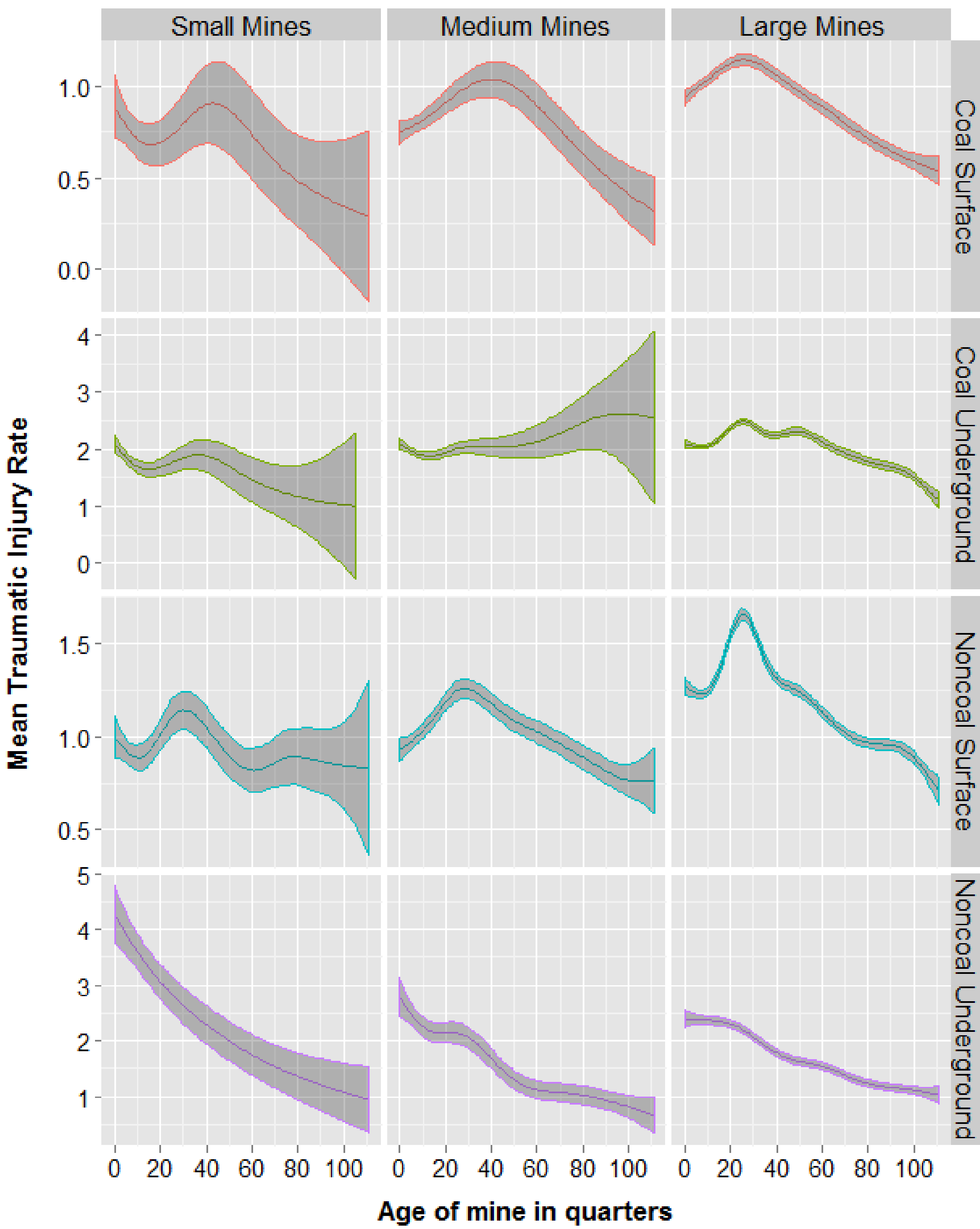


Figure 11: Mean traumatic injury rate by mine age, broken down by mine type and mine size.



4.4 Preliminary Exploratory Analysis on the Relationship between Regulatory Compliance and Reported Injuries

The final supplementary question we investigated in a preliminary fashion was the relationship between regulatory compliance and reported injury rates. A central goal of regulatory enforcement is to penalize operators for violating regulations designed to protect miners' safety and health, and thereby incentivize them to make needed safety improvements. Over the long term, then, one would expect higher regulatory compliance to translate into fewer and/or less severe mine injuries.

To determine whether such a correlation exists - i.e., whether more compliant mines are safer than those that frequently violate regulations - we estimated the mean injury rate as a function of a *compliance measure*. We chose the log of significant and substantial (S & S) violations per regular onsite inspection hours as a measure of regulatory compliance. (Although we tried several alternative measures as a robustness check, the choice of measure did not appreciably alter our results.) Specifically, let v_{ij} be the number of S & S violations for mine i in quarter j and h_{ij} be the number of regular onsite inspection hours for the same mine-quarter. Then the compliance measure c_{ij} is defined as

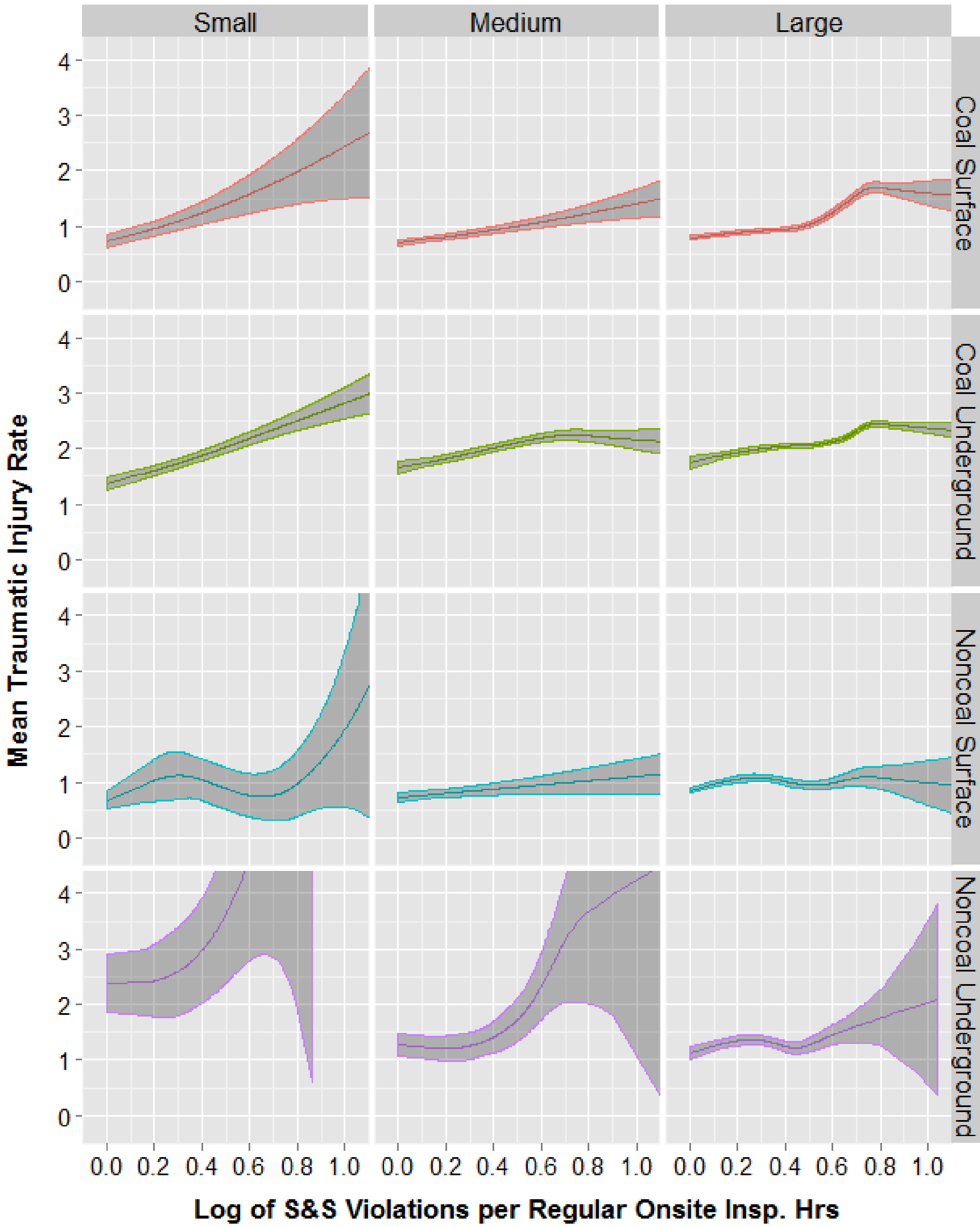
$$c_{ij} = \frac{\log(1 + v_{ij})}{\log(1 + h_{ij})}.$$

Thus, c increases as the number of S & S violations increases, but shrinks as the number of hours inspected increases. We constructed the compliance measure in this manner because it produced a less-skewed distribution than alternative methods.

Notice that $h = 0$ makes c undefined. This is intentional: if a mine is not inspected, there is no way of knowing what its compliance measure is. The model is similar to that for injuries: each mine has a latent S & S violation rate (which varies by quarter), and every hour an inspector is onsite (for a regular inspection), they discover violations at that rate. We observe how many violations they record and use this to estimate the mine's violation rate.

The results of plotting c against the estimated mean injury rate (plus 95% confidence intervals for the mean) are displayed in Figure 12 (page 36). Interestingly, the plots do not show a robust positive correlation between mean traumatic injury rates and the (logged) frequency of S & S violations per inspection hour for all mine types and sizes. For example, although the correlation is quite robust (and looks approximately linear) among small coal mines, it appears only weakly and sporadically among large mines and noncoal mines. Our exploratory analysis suggests that the correlation between compliance and safety is a complex one that varies by mine size and mine type. Exploring these relationships in greater detail - for example, by constructing more granular mine types (as opposed to our simple binary classification scheme) and using *lagged* measures of regulatory compliance - would be a promising area for future research.

Figure 12: Relationship between compliance and safety, broken down by mine type and mine size.



Appendix A Bayesian Time-Series Forecasting

The general Bayesian framework views probability as a measure of *belief*. Its methods are therefore designed to utilize both prior beliefs about a problem (represented by the prior distribution of model parameters) and information contained in the data (represented by the likelihood function) to produce a distribution representing the updated belief (represented by the posterior distribution). According to Bayes' Theorem, a posterior density is proportional to the prior times the likelihood:

$$P(\theta|\text{data}) \propto P(\theta)P(\text{data}|\theta)$$

Bayes' theorem allows us to update the prior distribution to a posterior distribution using our observed data.

The specific Bayesian time series model we assumed is described as follows. Letting i index a mine, and t index time (quarter), we assumed

$$Y_{it} \sim \text{Poisson}(\mu_{it})$$

where Y_{it} is the number of injuries (traumatic injuries) at mine i during quarter t, and μ_{it} is the expected number of injuries (not knowing the actual number). We further assume

$$\log \mu_{it} = \beta_{0t} + \log \text{emp.hrs}_{it} + \boldsymbol{x}'_{it}\boldsymbol{\beta}_t$$

where β_{0t} is an intercept at time t, emp.hrs_{it} is the number of employee-hours at mine i during quarter t, $\boldsymbol{x}_{it}$ is a vector of predictor values for mine i during time t (some of which may not depend on t), and $\boldsymbol{\beta}_t$ are the coefficients specific to quarter t. Note that emp.hrs_{it} is an offset term in this Poisson log-linear model to account for injury exposure. Finally, we assume a process on each element of $\boldsymbol{\beta}_t = (\beta_{1t}, \ldots, \beta_{Jt})$:

$$\beta_{jt} = \beta_{j,t-1} + \varepsilon_{jt}$$

for $j = 1, \ldots, J$, where $\varepsilon_{jt} \sim \text{Normal}(0, \sigma_j^2)$ is a normally distributed error term independent across predictor variables and over time. The model specification is completed by assuming a vague and proper prior distribution on the model parameters at $t = 1$ (corresponding to year 1983), and on the variance parameters σ_j^2.

We fit our model using Markov chain Monte Carlo (MCMC) to simulate draws from the posterior distribution of our model parameters. In our actual implementation, our posterior distribution is summarized based on 6000 simulated vectors of parameter values. To generate predictions, we determine $\log \mu_{it}$ for $t = $ 2010Q4 using the above specification.

Our model parameters can be updated due to regulatory and mining changes. Due to the widespread availability of MCMC simulation software, we can quickly draw from the posterior distribution. We use the MCMC simulation program JAGS,[22] called from within the software package `R`, to fit our Bayesian model.

22. Plummer, "JAGS: A Program for Analysis of Bayesian Graphical Models using Gibbs Sampling."

Appendix B Model Variables

	COAL			NONCOAL		
variable name	TOTAL	TRAUM	FATAL	TOTAL	TRAUM	FATAL
lg_total_injuries_rate_a4	x	x		x	x	
total_injuries_rate_a4_0	x	x		x	x	
cent_app_plus_il	x	x	x			
central_appalachia		x		x	x	
ug_subunit_dummy_a4_dum	x	x		x		
ctrl_light_inj_rt_a4_0	x			x		
ctrl_total_inj_rt_a4_0	x			x		
ctrl_traum_inj_rate_a4_0		x			x	
east_dum	x					x
inspection_rate_a4_0	x	x				
lg_controller_fte_a4		x		x		
lg_ctrl_light_inj_rt_a4	x			x		
lg_ctrl_total_inj_rt_a4	x			x		
lg_ctrl_traum_inj_rate_a4		x			x	
lg_inspection_rate_a4	x	x				
lg_rt_acc_class_code_12_L1			x			x
lg_rt_acc_class_code_9_L1			x			x
lg_total_hours_worked_A4				x	x	
lg_traum_injuries_rate_a4		x			x	
mine_age_active				x	x	
recovery_pct_a4	x	x				
rt_acc_class_code_12_L1_0			x			x
str_quar_subunit_dummy_a4	x	x				
traum_injuries_rate_a4_0		x			x	
traum_quot_a4		x			x	
traum_quot_a4_na		x			x	
accidents_rate_a4_0					x	
any_union		x				
any_union_L1			x			
cent_ap_IL_X_lg_ees_L1			x			
cent_ap_x_lg_tot_inj_rt_a4		x				
cent_ap_x_tot_inj_rt_a4_0		x				
ctrl_accidents_rate_a4_0		x				
ctrl_fatalities_rate_L1_0						x
ctrl_light_inj_rate_L1_0						x
ctrl_lost_day_inj_rt_A4_0				x		
ctrl_lost_day_inj_rt_L1_0						x
ctrl_num_inj_rate_a4_cart					x	
ctrl_pen_pts_rt_a4_0		x				
ctrl_pen_pts_rt_a4_na		x				
ctrl_reg_insp_hrs_a4_cart					x	
ctrl_total_inj_rt_a4_cart					x	
ctrl_traum_inj_rate_L1_0						x
east_X_lg_hrs_L1						x
east_x_lg_tot_inj_rt_a4	x					
east_x_tot_inj_rt_a4_0	x					
facility_dummy					x	
fatalities_rate_L1_0						x
higher_neg_prop_L1_0						x
higher_neg_prop_L1_NA						x
inspection_rate_L1_0			x			
intermed_inj_rate_L1_0						x
lg_accidents_rate_a4					x	
lg_controller_ees_a4	x					
lg_controller_fte_L1						x
lg_ctrl_accidents_rate_a4		x				

	COAL			NONCOAL		
variable name	TOTAL	TRAUM	FATAL	TOTAL	TRAUM	FATAL
lg_ctrl_fatalities_rate_L1						x
lg_ctrl_light_inj_rate_L1						x
lg_ctrl_lost_day_inj_rt_A4				x		
lg_ctrl_lost_day_inj_rt_L1						x
lg_ctrl_pen_pts_rt_a4		x				
lg_ctrl_traum_inj_rate_L1						x
lg_fatalities_rate_L1						x
lg_higher_neg_prop_L1						x
lg_inspection_rate_L1			x			
lg_intermed_inj_rate_L1						x
lg_light_injuries_rate_L1						x
lg_lost_day_inj_rt_L1			x			
lg_non_traum_inj_rate_L1						x
lg_num_affected_size_rt_A4				x		
lg_onsite_hours_a4	x					
lg_onsite_hours_L1			x			
lg_rate_high_risk_acc_L1			x			
lg_rate_injury_occured_L1						x
lg_rate_injury_unlikely_L1			x			
lg_rate_negligence_pts_L1			x			
lg_rt_acc_class_code_10_a4					x	
lg_rt_acc_class_code_10_L1						x
lg_rt_acc_class_code_13_L1			x			
lg_rt_acc_class_code_17_a4					x	
lg_rt_acc_class_code_17_L1			x			
lg_rt_acc_class_code_18_A4				x		
lg_rt_acc_class_code_18_L1						x
lg_rt_acc_class_code_31_a4	x					
lg_rt_acc_class_code_31_L1			x			
lg_rt_acc_class_code_5_L1						x
lg_rt_acc_class_code_6_L1			x			
lg_rt_acc_class_code_9_a4					x	
lg_rt_inj_like_viol_rt_L1			x			
lg_rt_injury_not_likely_L1						x
lg_rt_viol_per_day_pts_L1			x			
lg_sections_insp_rate_L1			x			
lg_ss_viol_onst_hrs_rt_L1			x			
lg_total_coal_prod_L1			x			
lg_total_employees_a4		x				
lg_total_employees_L1			x			
lg_total_hours_worked_L1						x
lg_traum_injuries_rate_L1			x			
light_injuries_rate_L1_0						x
lost_day_inj_rt_L1_0			x			
mean_bed_thickness_a4_dum		x				
mean_neg_A4_CART				x		
mill_prep_subunit_dummy_L1						x
mine_age_active_CART_L1						x
mine_age_contig_CART_L1						x
mine_age_first_op_CART_L1						x
non_traum_inj_rate_L1_0						x
num_affected_size_rt_A4_0				x		
onsite_hours_a4_0	x					
onsite_hours_L1_0			x			
rate_acc_class_code_5_L1_0						x
rate_acc_class_code_9_L1_0						x
rate_high_risk_acc_L1_0			x			

	COAL			NONCOAL		
variable name	**TOTAL**	**TRAUM**	**FATAL**	**TOTAL**	**TRAUM**	**FATAL**
rate_inj_like_viol_rt_L1_0			x			
rate_injury_occured_L1_0						x
rate_injury_unlikely_L1_0			x			
rate_negligence_pts_L1_0			x			
rate_negligence_pts_L1_NA			x			
rate_viol_per_day_pts_L1_0			x			
recovery_pct_a4_cart	x					
rt_acc_class_code_10_a4_0					x	
rt_acc_class_code_10_L1_0						x
rt_acc_class_code_13_L1_0			x			
rt_acc_class_code_17_a4_0					x	
rt_acc_class_code_17_L1_0			x			
rt_acc_class_code_18_A4_0				x		
rt_acc_class_code_18_L1_0						x
rt_acc_class_code_31_a4_0	x					
rt_acc_class_code_31_L1_0			x			
rt_acc_class_code_6_L1_0			x			
rt_acc_class_code_9_a4_0					x	
rt_acc_class_code_9_L1_0			x			
rt_inj_like_viol_rt_L1_NA			x			
rt_injury_not_likely_L1_0						x
rt_viol_per_day_pts_L1_NA			x			
sbsd_NA_X_lg_rsky_ac_rt_L1			x			
sbsd_NA_X_rsky_acc_rt_L1_0			x			
sections_insp_rate_L1_0			x			
sections_insp_rate_L1_NA			x			
sig_or_sub_viol_rate_L1_NA			x			
ss_viol_onst_hrs_rt_L1_0			x			
ss_viol_onst_hrs_rt_L1_NA			x			
subsid_NA_X_lg_ees_L1			x			
subsid_X_lg_ees_L1			x			
subsid_X_lg_rsky_acc_rt_L1			x			
subsid_X_risky_acc_rt_L1_0			x			
subsidiary_L1			x			
subsidiary_L1_NA			x			
total_coal_prod_a4_0		x				
total_coal_prod_L1_0			x			
traum_injuries_rate_L1_0			x			
traum_quot_L1			x			
traum_quot_L1_NA			x			
ug_subunit_dummy_L1						x
union_x_lg_prod_a4		x				
union_X_lg_prod_L1			x			
union_x_prod_a4_0		x				
union_X_prod_L1_0			x			
union_x_traum_qt_a4		x				
union_x_traum_qt_a4_na		x				

Appendix C Description of Model Variables

VARIABLE NAME	VARIABLE DESCRIPTION
lg_total_injuries_rate_a4	log of previous 4 quarters' average number of total injuries per 100,000 total hours worked
total_injuries_rate_a4_0	indicator whether previous 4 quarters' average number of total injuries per 100,000 total hours worked was zero
cent_app_plus_il	indicator for states VA WV KY PA IL
central_appalachia	indicator for states VA WV KY PA
ug_subunit_dummy_a4_dum	indicator whether more than half of the previous 4 quarters' average coal production in an underground subunit was nonzero
ctrl_light_inj_rt_a4_0	indicator whether previous 4 quarters' average controller light injury rate per 200 controller FTE was zero
ctrl_total_inj_rt_a4_0	indicator whether previous 4 quarters' average controller total injury rate per 200 controller FTE was zero
ctrl_traum_inj_rate_a4_0	indicator whether previous 4 quarters' average controller traumatic injury rate per 200 controller FTE was zero
east_dum	indicator for states AL CT DE FL GA IL IN KY ME MD MA MI MS NH NJ NY NC OH PA RI SC TN VT VA DC WV WI
inspection_rate_a4_0	indicator whether previous 4 quarters' inspection intensity (total inspection hours per total hours worked) was zero
lg_controller_fte_a4	log of previous 4 quarters' average quarterly FTEs by controller
lg_ctrl_light_inj_rt_a4	log of previous 4 quarters' average quarterly number of light injuries per 200 controller FTEs
lg_ctrl_total_inj_rt_a4	log of previous 4 quarters' average quarterly number of total injuries per 200 controller FTEs
lg_ctrl_traum_inj_rate_a4	log of previous 4 quarters' average quarterly number of traumatic injuries per 200 controller FTEs
lg_inspection_rate_a4	log of previous 4 quarters' average inspection intensity (inspection hours per total hours worked)
lg_rt_acc_class_code_12_L1	log of previous year's accident rate due to powered haulage
lg_rt_acc_class_code_9_L1	log of previous year's accident rate due to handling of materials
lg_total_hours_worked_A4	log of previous 4 quarters' average total hours worked
lg_traum_injuries_rate_a4	log of previous 4 quarters' average rate of traumatic injuries
mine_age_active	number of quarters since the mine opened minus quarters with no employment/production
recovery_pct_a4	previous 4 quarters' average percent of recoverable reserves at producing mines
rt_acc_class_code_12_L1_0	indicator whether previous year's powered haulage accident rate per 100,000 hours worked was zero
str_quar_subunit_dummy_a4	previous 4 quarters' average indicator of whether coal was produced at a strip, quarry, or open pit subunit
traum_injuries_rate_a4_0	indicator whether previous 4 quarters' average traumatic injury rate was zero
traum_quot_a4	previous 4 quarters' average traumatic quotient (traumatic injuries divided by total injuries)
traum_quot_a4_na	previous 4 quarters' average missing traumatic quotient (traumatic injuries divided by total injuries)
accidents_rate_a4_0	indicator whether previous 4 quarters' average number of accidents per 100,000 total hours worked was zero
any_union	indicator whether any part of the mining operation is unionized
any_union_L1	indicator whether any part of the mining operation was unionized the previous year
cent_ap_IL_X_lg_ees_L1	log of previous year's total employees for mines in states VA WV KY PA IL

VARIABLE NAME	VARIABLE DESCRIPTION
cent_ap_x_lg_tot_inj_rt_a4	log of the previous 4 quarters' average total injury rate per 100,000 hours worked for mines in states VA WV KY PA
cent_ap_x_tot_inj_rt_a4_0	indicator whether mine was in state VA WV KY PA and previous 4 quarters' average total injury rate was zero
ctrl_accidents_rate_a4_0	indicator whether previous 4 quarters' average controller accident rate per 200 controller FTE was zero
ctrl_fatalities_rate_L1_0	indicator whether previous year's average controller fatality rate per 200 controller FTE was zero
ctrl_light_inj_rate_L1_0	indicator whether previous year's controller light injury rate per 200 controller FTE was zero
ctrl_lost_day_inj_rt_A4_0	indicator whether previous 4 quarters' average rate of lost work days due to injuries per 200 controller FTE was zero
ctrl_lost_day_inj_rt_L1_0	indicator whether previous year's rate of lost work days due to injuries per 200 controller FTE was zero
ctrl_num_inj_rate_a4_cart	indicatory whether previous 4 quarters' average number of accidents resulting in an injury per 200 controller FTE was greater than 3.408661
ctrl_pen_pts_rt_a4_0	indicator whether previous 4 quarters' average controller penalty point rate per 1000 regular inspection hours was zero
ctrl_pen_pts_rt_a4_na	indicator whether previous 4 quarters' average controller penalty point rate per 1000 regular inspection hours was missing
ctrl_reg_insp_hrs_a4_cart	indicator whether previous 4 quarters' average controller regular inspection hours in a quarter was greater than 843.1562 hours
ctrl_total_inj_rt_a4_cart	indicator whether previous 4 quarters' average controller total injury rate per 200 controller FTE was greater than 2.179117
ctrl_traum_inj_rate_L1_0	indicator whether last year's controller traumatic injury rate per 200 controller FTE was zero
east_X_lg_hrs_L1	log of previous year's total hours worked for mines in state AL CT DE FL GA IL IN KY ME MD MA MI MS NH NJ NY NC OH PA RI SC TN VT VA DC WV WI
east_x_lg_tot_inj_rt_a4	log of previous 4 quarters' average total injury rate per 100,000 hours worked for mines in state AL CT DE FL GA IL IN KY ME MD MA MI MS NH NJ NY NC OH PA RI SC TN VT VA DC WV WI
east_x_tot_inj_rt_a4_0	indicator whether previous 4 quarters' average total injury rate was zero and mine was in states AL CT DE FL GA IL IN KY ME MD MA MI MS NH NJ NY NC OH PA RI SC TN VT VA DC WV WI
facility_dummy	indicator whether facility is present
fatalities_rate_L1_0	indicator whether previous year's fatalities rate was zero
higher_neg_prop_L1_0	indicator whether previous year's proportion of high negligence or reckless negligence violations out of the number of violations was zero
higher_neg_prop_L1_NA	indicator whether previous year's proportion of high negligence or reckless negligence violations out of the number of violations were missing
inspection_rate_L1_0	indicator whether previous year's inspection intensity (total inspections hours per total hours worked) was zero
intermed_inj_rate_L1_0	indicator whether previous year's fatality, permanent disability, and injury (resulting from roof/side falls, machinery, haulage, or electrical/explosive accidents) rate were zero
lg_accidents_rate_a4	log of previous 4 quarters' average accident rate
lg_controller_ees_a4	log of previous 4 quarters' average number of controller employees
lg_controller_fte_L1	log of previous year's quarterly FTEs by controller
lg_ctrl_accidents_rate_a4	log of previous 4 quarters' average quarterly number of accidents per 200 controller FTEs
lg_ctrl_fatalities_rate_L1	log of previous year's number of fatalities per 200 controller FTEs
lg_ctrl_light_inj_rate_L1	log of previous year's number of light injuries per 200 controller FTEs
lg_ctrl_lost_day_inj_rt_A4	log of previous 4 quarters' average quarterly number of lost work days due to injuries per 200 controller FTEs
lg_ctrl_lost_day_inj_rt_L1	log of previous year's number of lost work days due to injuries per 200 controller FTEs

VARIABLE NAME	VARIABLE DESCRIPTION
lg_ctrl_pen_pts_rt_a4	log of previous 4 quarters' average quarterly controller penalty points per 1,000 regular inspection hours
lg_ctrl_traum_inj_rate_L1	log of previous year's number of traumatic injuries per 200 controller FTEs
lg_fatalities_rate_L1	log of previous year's fatality rate per 100,000 total hours worked
lg_higher_neg_prop_L1	log of previous year's proportion of high negligence or reckless negligence violations out of all violations
lg_inspection_rate_L1	log of previous year's inspection intensity (inspection hours per total hours worked)
lg_intermed_inj_rate_L1	log of previous year's intermediate injury rate (fatality, permanent disability, and injury resulting from roof/side falls, machinery, haulage, or electrical/explosive accidents)
lg_light_injuries_rate_L1	log of previous year's light injury rate (first aid, accident, occupational or natural causes)
lg_lost_day_inj_rt_L1	log of previous year's number of lost work days due to injuries per 100,000 total hours worked
lg_non_traum_inj_rate_L1	log of previous year's nontraumatic injury rate
lg_num_affected_size_rt_A4	log of previous 4 quarters' average number of persons affected or potentially affected due to a violation per 100,000 total hours worked
lg_onsite_hours_a4	log of previous 4 quarters' average onsite inspection hours
lg_onsite_hours_L1	log of previous year's onsite inspection hours
lg_rate_high_risk_acc_L1	log of previous year's number of high risk accidents (codes 7, 9, 10, 12, 17, 18, 27) per 100,000 total hours
lg_rate_injury_occured_L1	log of previous year's number of gravity (injury occurred) violations per 100,000 total hours worked
lg_rate_injury_unlikely_L1	log of previous year's number of gravity (injury unlikely) violations per 100,000 total hours worked
lg_rate_negligence_pts_L1	log of previous year's number of negligence points per 1,000 total inspection hours
lg_rt_acc_class_code_10_a4	log of previous 4 quarters' average accident rate due to handtools (nonpowered)
lg_rt_acc_class_code_10_L1	log of previous year's accident rate due to handtools (nonpowered)
lg_rt_acc_class_code_13_L1	log of previous year's accident rate due to hoisting
lg_rt_acc_class_code_17_a4	log of previous 4 quarters' average accident rate due to machinery
lg_rt_acc_class_code_17_L1	log of previous year's accident rate due to machinery
lg_rt_acc_class_code_18_A4	log of previous 4 quarters' average accident rate due to slip or fall of person
lg_rt_acc_class_code_18_L1	log of previous year's accident rate due to slip or fall of person
lg_rt_acc_class_code_31_a4	log of previous 4 quarters' average accident rate due to disorders
lg_rt_acc_class_code_31_L1	log of previous year's accident rate due to disorders
lg_rt_acc_class_code_5_L1	log of previous year's accident rate due to falling/sliding/rolling materials
lg_rt_acc_class_code_6_L1	log of previous year's accident rate due to fall of face/rib/pillar/side/highwall
lg_rt_acc_class_code_9_a4	log of previous 4 quarters' average accident rate due to handling of materials
lg_rt_inj_like_viol_rt_L1	log of previous year's "likely injury" rate per 1,000 regular inspection hours per 100,000 total hours worked
lg_rt_injury_not_likely_L1	log of previous year's number of (injury not likely) likelihood violations per 100,000 total hours worked

VARIABLE NAME	VARIABLE DESCRIPTION
lg_rt_viol_per_day_pts_L1	log of previous year's number of violation points per day per 100,000 total hours worked
lg_sections_insp_rate_L1	log of previous year's total number of sections inspected per 1,000 total inspection hours
lg_ss_viol_onst_hrs_rt_L1	log of previous year's S&S violations per 1,000 onsite hours
lg_total_coal_prod_L1	log of previous year's total coal production
lg_total_employees_a4	log of previous 4 quarter's average total non-office employees
lg_total_employees_L1	log of previous year's total non-office employees
lg_total_hours_worked_L1	log of previous year's total hours worked
lg_traum_injuries_rate_L1	log of previous year's rate of traumatic injuries
light_injuries_rate_L1_0	indicator whether previous year's light injury rate was zero
lost_day_inj_rt_L1_0	indicator whether previous year's number of lost work days due to injuries per 100,000 total hours worked was zero
mean_bed_thickness_a4_dum	indicator whether previous 4 quarters' mean bed thickness was greater than or equal to 1.743056 yards
mean_neg_A4_CART	indicator whether previous 4 quarters' mean negligence was greater than 1.23125
mill_prep_subunit_dummy_L1	indicator whether previous year's subunit contained a mill operation/preparation plant
mine_age_active_CART_L1	indicator whether previous year's mine age (years since mine opened minus quarters with no employment/production) was greater than 24.5 years
mine_age_contig_CART_L1	indicator whether previous year's contiguous mine age (restarted mine age after a year or more of zero production) was greater than 10.5 years
mine_age_first_op_CART_L1	indicator whether previous year's difference between mine's first production year and operator's earliest start year was greater than 15.5 years
non_traum_inj_rate_L1_0	indicator whether previous year's nontraumatic injury rate was zero
num_affected_size_rt_A4_0	indicator whether previous 4 quarters' average number of persons affected or potentially affected due to a violation per 100,000 total hours worked was zero
onsite_hours_a4_0	indicator whether previous 4 quarters' average onsite hours was zero
onsite_hours_L1_0	indicator whether previous year's onsite hours was zero
rate_acc_class_code_5_L1_0	indicator whether previous year's falling/sliding/rolling materials accident rate per 100,000 hours worked was zero
rate_acc_class_code_9_L1_0	indicator whether previous year's handling of materials accident rate per 100,000 hours worked was zero
rate_high_risk_acc_L1_0	indicator whether previous year's high risk accidents (codes 7, 9, 10, 12, 17, 18, 27) per 100,000 total hours worked was zero
rate_inj_like_viol_rt_L1_0	indicator whether previous year's (injury likely) violations per 1,000 regular inspection hours per 100,000 total hours worked was zero
rate_injury_occured_L1_0	indicator whether previous year's number of likelihood violations for injury occurred (likelihood ==5) per 100,000 hours of total hours worked was zero
rate_injury_unlikely_L1_0	indicator whether previous year's number of likelihood violations for unlikely injury (likelihood ==2) per 100,000 hours of total hours worked was zero
rate_negligence_pts_L1_0	indicator whether previous year's number of negligence points per 1,000 total inspection hours was zero
rate_negligence_pts_L1_NA	indicator whether previous year's number of negligence points per 1,000 total inspection hours was missing
rate_viol_per_day_pts_L1_0	indicator whether previous year's number of violation points per day per 100,000 total hours worked was zero
recovery_pct_a4_cart	indicator whether previous 4 quarters' average percent of recoverable reserves at producing mines was greater than 75.375

VARIABLE NAME	VARIABLE DESCRIPTION
rt_acc_class_code_10_a4_0	indicator whether previous 4 quarters' average handtools (nonpowered) accident rate per 100,000 hours worked was zero
rt_acc_class_code_10_L1_0	indicator whether previous year's handtools (nonpowered) accident rate per 100,000 hours worked was zero
rt_acc_class_code_13_L1_0	indicator whether previous year's hoisting accident rate per 100,000 hours worked was zero
rt_acc_class_code_17_a4_0	indicator whether previous 4 quarters' average machinery accident rate per 100,000 hours worked was zero
rt_acc_class_code_17_L1_0	indicator whether previous year's machinery accident rate per 100,000 hours worked was zero
rt_acc_class_code_18_A4_0	indicator whether previous 4 quarters' average slip or fall of person rate per 100,000 hours worked was zero
rt_acc_class_code_18_L1_0	indicator whether previous year's slip or fall of person rate per 100,000 hours worked was zero
rt_acc_class_code_31_a4_0	indicator whether previous 4 quarters' average disorders (repeated trauma) rate per 100,000 hours worked was zero
rt_acc_class_code_31_L1_0	indicator whether previous year's average disorders (repeated traumatic) rate per 100,000 hours worked was zero
rt_acc_class_code_6_L1_0	indicator whether previous year's fall of face/rib/pillar/side/highwall accident rate per 100,000 hours worked was zero
rt_acc_class_code_9_a4_0	indicator whether previous 4 quarters' average handling of materials accident rate per 100,000 hours worked was zero
rt_acc_class_code_9_L1_0	indicator whether previous year's handling of materials accident rate per 100,000 hours worked was zero
rt_inj_like_viol_rt_L1_NA	indicator whether previous year's number of violations that are highly likely to cause injury or did in fact cause an injury per 1,000 regular inspection hours per 100,000 total hours worked was missing
rt_injury_not_likely_L1_0	indicator whether previous year's number of likelihood points for injury not likely per 100,000 total hours worked was zero
rt_viol_per_day_pts_L1_NA	indicator whether previous year's number of violation points per day per 100,000 total hours worked was missing
sbsd_NA_X_lg_rsky_ac_rt_L1	log of previous year's high risk accidents (codes 7, 9, 10, 12, 17, 18, 27) per 100,000 total hours worked for mines that are missing a subsidiary indicator
sbsd_NA_X_rsky_acc_rt_L1_0	indicator whether previous year's high risk accidents (codes 7, 9, 10, 12, 17, 18, 27) per 100,000 total hours worked was zero for mines that were missing a subsidiary indicator
sections_insp_rate_L1_0	indicator whether previous year's total sections inspected per 1,000 total inspection hours was zero
sections_insp_rate_L1_NA	indicator whether previous year's total sections inspected per 1,000 total inspection hours was missing
sig_or_sub_viol_rate_L1_NA	indicator whether previous year's significant or substantial violations per 1,000 total inspection hours was missing
ss_viol_onst_hrs_rt_L1_0	indicator whether previous year's number of significant or substantial violations per 1,000 onsite inspection hours was zero
ss_viol_onst_hrs_rt_L1_NA	indicator whether previous year's number of significant or substantial violations per 1,000 onsite inspection hours was missing
subsid_NA_X_lg_ees_L1	log of previous year's total employees for mines that were missing a subsidiary indicator last year
subsid_X_lg_ees_L1	log of previous year's total employees for mines that were a subsidiary last year
subsid_X_lg_rsky_acc_rt_L1	log of previous year's high risk accident (codes 7, 9, 10, 12, 17, 18, 27) rate per 100,000 total hours worked for mines that were a subsidiary last year
subsid_X_risky_acc_rt_L1_0	indicator for a subsidiary previous year and for a high risk accident (codes 7, 9, 10, 12, 17, 18, 27) rater per 100,000 total hours worked that was zero
subsidiary_L1	indicator whether a mine was a subsidiary the previous year
subsidiary_L1_NA	indicator whether the subsidiary indicator was missing for the previous year
total_coal_prod_a4_0	indicator whether previous 4 quarters' average total coal production was zero
total_coal_prod_L1_0	indicator whether previous year's total coal production was zero

VARIABLE NAME	VARIABLE DESCRIPTION
traum_injuries_rate_L1_0	indicator whether previous year's traumatic injury rate was zero
traum_quot_L1	previous year's traumatic quotient (traumatic injuries divided by total injuries)
traum_quot_L1_NA	indicator whether previous year's traumatic quotient (traumatic injuries divided by total injuries) was missing
ug_subunit_dummy_L1	indicator whether previous year's coal production in an underground subunit was nonzero
union_x_lg_prod_a4	log of previous 4 quarters' average total coal production at unionized mines
union_X_lg_prod_L1	log of previous year's total coal production at unionized mines
union_x_prod_a4_0	indicator whether previous 4 quarters' total coal production was zero for unionized mines
union_X_prod_L1_0	log of previous year's total coal production at mines with unions last year
union_x_traum_qt_a4	previous 4 quarters' average traumatic quotient (traumatic injuries divided by total injuries) at unionized mines
union_x_traum_qt_a4_na	indicator whether previous 4 quarters' average traumatic quotient was missing at unionized mines

Appendix D Articles on the Effect of Unionization on Coal Mine Regulation and Safety

D.1 Alison Morantz, *Coal Mine Safety: Do Unions Make a Difference?* Industrial and Labor Relations Review (forthcoming 2012 or 2013)

(Full text begins on next page.)

Coal Mine Safety: Do Unions Make a Difference?

Alison D. Morantz‡

ABSTRACT:

Although the United Mine Workers of America (UMWA) has always advocated strongly for miners' safety, prior empirical literature contains no evidence that unionization reduced mine injuries or fatalities during the 1970s and '80s. This study uses a more comprehensive dataset and updated methodology to examine the relationship between unionization and underground, bituminous coal mine safety from 1993 to 2010. I find that unionization predicts a substantial and significant decline in traumatic injuries and fatalities, the two measures that I argue are the least prone to reporting bias. These disparities are especially pronounced among larger mines. My best estimates imply that overall, unionization is associated with a 13-30% drop in traumatic injuries and a 28-83% drop in fatalities. Yet unionization also predicts higher total and nontraumatic injuries, suggesting that injury reporting practices differ between union and nonunion mines.

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Empirical literature on the relationship between unionization and workplace safety presents a curious puzzle. On one hand, lscholars have documented numerous ways in which unions help to promote safe work practices. For example, unions typically play a critical role in educating workers about on-the-job hazards; incentivizing workers to take greater care on the job; attracting more safety-conscious workers; inducing employers to abate known hazards; increasing regulatory scrutiny; and developing safety-related innovations. Yet most empirical studies of the relationship between unionization and important safety outcomes, such as injuries and fatalities, have failed to find statistically significant evidence of a "union safety effect" (Morantz 2009).

Prior research on the coal mining industry typifies this perplexing pattern. Coal miners' unions, especially the dominant United Mine Workers of America (UMWA), have advocated vigorously for improved worker safety since their inception. When the UMWA adopted its first constitution in 1890, for example, three of its "Eleven Points" called for improvements in the safety and health conditions of miners (Fox 1990:22-25). Organized labor was also instrumental in the passage of the Mining Safety and Health Act of 1969 (the "Coal Act"), the statute that paved the way for comprehensive federal enforcement of occupational safety regulations at all surface and underground coal mines (Fox 1990:470-73). More recently, the UMWA played a critical role in broadening the provisions of the Coal Act and encouraging the formation of state regulatory agencies (Fox 1990:462-470, 474, 504). By the 1980s, the UMWA's Health and Safety Department had developed an extensive tripartite structure including a Washington, D.C.-based international staff; regionally-based health and safety representatives tasked with liaising with Mining Safety and Health Administration (MSHA) District Offices; and mine-level health and safety committees that surveil day-to-day mine conditions. The myriad activities of mine-level health and safety committees include advocating on behalf of individual miners; conducting independent inspections; accompanying MSHA inspectors during inspections; participating in pre- and post-inspection meetings; tracking MSHA appeals; providing various forms of safety training; and, in extreme cases, shutting down hazardous sections of a mine, a power conferred by the UMWA's collective bargaining agreement with the Bituminous Coal Operator's Association (BCOA) (Weil 1987: 117). Nevertheless, most empirical studies focusing on the 1970s and '80s have reported, if anything, a counterintuitive *positive* relationship between a union's presence at a mine and the frequency of reported injuries and accidents.

This paper re-examines the link between unionization and mine safety using more recent data, a broader set of control variables, and updated statistical techniques. Highly granular MSHA data on injuries and mine characteristics, combined with data from the National Institute for Occupational Safety and Health (NIOSH) and confidential data obtained from the Department of Energy, enable me to examine whether several discrete safety outcomes differ significantly between union and nonunion mines. Focusing on underground mines that extract bituminous coal, I find that unionization is robustly associated with lower levels of traumatic injuries and fatalities, the two safety outcomes that I argue are the least prone to reporting bias. My best estimates imply that overall, unionization predicts a 13-30% drop in traumatic injuries and a 28-83% drop in fatalities.[1] These effects are especially pronounced among larger mines and, for traumatic injuries, after the mid-1990s. At the same time, however, unionization is associated with a significant *increase* in total and non-traumatic injuries, measures that are highly susceptible to reporting bias. Taken together, these findings lend credence to concerns that injury reporting practices vary significantly across union and nonunion settings.

Literature Review

In the past few decades, scholars have examined the relationship between unions and workplace safety in a wide range of industries, such as the U.S. construction sector (Dedobbeleer, Champagne, and German 1990), U.S. manufacturing (Fairris 1995), British manufacturing (Reilly, Paci, and Holl 1995, Nichols, Walters, and Tasiran 2007), forest product mills in British Columbia (Havlovic and McShane 1997), and the New Jersey public sector (Eaton and Nocerino 2000). Most such studies have failed to find a statistically significant negative relationship between unionization and the frequency of workplace accidents. Similarly, empirical scholarship relying on aggregate cross-industry data from the U.S., Canada, and Great Britain has rarely reported any robust evidence of a salutary union effect. (Morantz 2009).

Given its inherent dangers, the mining sector has attracted a disproportionate share of scholarly attention. Several recent historical studies suggest that if anything, unions improved miners' safety during the early twentieth century (Fishback 1986; 1987:324; Boal 2009). However, empirical scholarship focusing on the decades after the passage of the Coal Act (1969)

[1] These ranges represent 95% confidence intervals for the coefficients on the "union" indicator variables in the public-fields version of the baseline (hours worked) specification presented in Table 2.

has reached very different conclusions. Boden (1977:116) and Connerton (1978), the first two empirical studies focusing on the latter part of the twentieth century, examine data from 1973-75 and 1974-75, respectively. Although neither study focuses specifically on unionization, both include union status as a control variable and report that union mines experienced significantly more disabling injuries, *ceteris paribus*, than their nonunion counterparts. A landmark study on underground coal mines sponsored by the National Research Council (1982), examining data from 1978-80, also briefly addresses the relationship between unionization and mine safety. The authors observe that the positive statistical relationship between union status and disabling injuries disappears when they confine attention to a measure of injuries that is less prone to reporting bias than total injuries, and that a (negative) correlation between unionization and mine fatalities also vanishes when one accounts for mine size.[2] On these grounds, the authors suggest that there is no relationship at all between unionization and underground coal mine safety (NRC 1982:95-96).

Appleton and Baker (1984), the first study to focus squarely on the effect of union status, analyzes cross-sectional data from a single year (1978) culled from 213 mines in eastern Kentucky and western Virginia. Controlling for several mine-specific covariates, the authors report that both total injuries and relatively serious injuries are significantly higher at union mines. They hypothesize that the union job-bidding system and/or union miners' postulated lower job motivation and productivity could explain these results. Several later commentators (Bennett and Passmore 1985; Weeks 1985) critique Appleton and Baker's conclusions by pointing out limitations in their data and methodology.

In sum, scholars have generally reported a *positive* relationship, if any at all, between union status and reported mining inuries since the New Deal. There are, however, several

[2] "Intermediate" injuries, adjudged by the study's authors to be the least prone to reporting bias, are defined to comprise "all fatal and permanent disability injuries as well as all injuries resulting from roof/side falls, machinery, haulage, or electrical/explosive accidents" (NRC 1982:82). The report states, "The rationale for defining [the intermediate injury rate] rested on the belief that reporting inconsistencies would occur most frequently for the degree 3-5 material handling and slipping/bumping injuries. Consequently, for consistency in reporting, [the intermediate injury rate] is felt to lie somewhere between the [fatality and permanent disability rate], where reporting differences are felt to be negligible, and the [disabling injury rate], where they might not be. We thus regard [the intermediate injury rate] as a compromise measure of safety that includes ample numbers of injuries for most statistical purposes and provides for reasonably good consistency between mines in the reporting of injuries" (NRC 1982:83-84). As a robustness check, this paper's *Companion Website* (http://amorantz.stanford.edu/papers/union-coal-mine-safety/) reports results from models in which the dependent variable is the number of intermediate injuries. Although the estimated coefficients are not dissimilar from those presented for traumatic injuries in Table 2, none is statistically significant at the 5% level.

compelling reasons to question the accuracy and contemporary relevance of these findings.

First, as Appleton and Baker (1984:140) point out, the accident reporting system in use before 1978 suffered from extremely poor reporting practices, and therefore underreporting of injuries by nonunion mines could have biased the results of Boden (1977) and Connerton (1978).

Second, most prior scholarship relies upon data that is geographically restricted, highly aggregated, time-invariant, and/or prone to small-sample bias. For instance, the 213 mines analyzed in Appleton and Baker (1984) were restricted to a single geographic region and comprised less than 10% of all coal mines that were active in 1978.

Third, all of the statistical analysis in prior studies consists of ordinary least squares regression modeling. Under standard assumptions, Poisson and negative binomial models yield less biased estimates, and therefore have become the preferred approach for analysis of "count data" such as injuries and fatalities (Cameron and Trivedi 1998:1-3).

Finally, the labor strife that characterized most of the 1970s, which included periodic strikes and work stoppages, may have limited unions' capacity to improve safety practices. Although Appleton and Baker limit their study of bituminous mining to what they characterize as a single "non-strike year" (1978) in the hopes of circumventing this problem, government statistics indicate that 414 bituminous coal mine strikes took place in 1978 and that the national labor-management climate remained highly adversarial (Staats 1981: 12-25; Darmstadter 1997: 27-31). Moreover, even if unions were relatively ineffectual during the 1970s, their impact may have changed in recent decades, as the UMWA become more familiar with MSHA's regulatory procedures and expanded the scope of its internal health and safety programs (Weil 1994: 197).

In short, analysis of recent data may not only bear more directly on unions' contemporary relevance, but may also yield more credible estimates of their long-term effect. To my knowledge, no study has directly investigated the relationship between unionization and mine safety since 1980.[3]

The goal of the present article is to fill this gap in the literature by examining the 1993-2010 period with comprehensive, granular data and up-to-date econometric methods. I pose, in turn, a series of questions regarding the relationship between unionization and mine safety during this period. First, are there statistically significant disparities, *ceteris paribus*, between the rates

[3] Reardon (1996) analyzes coal mining data from 1986-88, but he does not compare the probabilities of accidents occurring across union and nonunion settings. Rather, he focuses on the probability that a *reported accident* has already resulted (or will likely result) in a fatality or permanently disabling injury.

of occupational injuries in union and nonunion coal mines? Second, do such disparities persist if one focuses on measures of injury rates that are relatively impervious to reporting bias? Third, have the disparities remained constant, or have they fluctuated over time? Finally, what might explain these empirical findings?

Data

The analysis presented here relies primarily on MSHA's historical database from 1993-2010. This database includes quarterly data on the characteristics of each coal mine under MSHA's purview and on each accident or injury that was reported to MSHA during this period. Although enormously detailed, the dataset has two important limitations. First and foremost, it contains little information on the union status of individual mines. Although MSHA originally collected data on unionization, the survey fell into disuse by the 1990s and historical records on union status were not preserved.[4] In 2007 MSHA conducted a one-time survey of mines in an effort to identify which ones were operating under union contracts, and in what year those mines became unionized. Using these data, one can obtain a snapshot of the union status of U.S. mines in 2007. However, it is impossible to determine whether any given mine was unionized in prior years and, if so, for how long. Secondly, although the MSHA database contains comprehensive data on coal production and employment, it lacks information on each mine's geological characteristics (such as mean coal bed thickness), economic constraints (such as whether it is a subsidiary of a larger firm), and predominant extraction methods (such as the relative prevalence of longwall, shortwall, continuous, and conventional mining).

To remedy these shortcomings, I supplement the MSHA database with information obtained from NIOSH and the Department of Energy's Energy Information Administration (EIA). The EIA database encompasses every mine in the U.S. that produces an appreciable amount of coal.[5] Most importantly for my purposes, the EIA database contains a "union ID" field indicating whether each mine was unionized in a given year and, if so, by which union.[6]

[4] Phone conversation with MSHA's George Fesak, Director of Program Evaluation and Information Resources, on 8/14/08.

[5] According to the EIA Coal Production and Preparation Report (Form EIA-7A), the EIA collects data annually on mines with operations that "produced and/or processed 10,000 or more short tons of coal and/or worked 5,000 hours or more during the reporting year." Of our sample (from MSHA) of underground, bituminous coal mines with active production for the years 1993-2010, 0.41% of mine-years do not have corresponding EIA data. These observations were dropped from the dataset.

[6] The EIA considers this data unreliable prior to 1993 (Phone Conversation with Vlad Dorjets, Lead Economist at

The data also contain detailed information on the geological and economic characteristics of each mine, including the number of coal beds, the thickness of each coal bed, the value of captive and open production, productive capacity, recoverable reserves, and (for underground mines) the share of production attributable to conventional, continuous, longwall, shortwall, and other mining methods.[7] Finally, the NIOSH dataset contains an alternative (binary) measure for whether or not a mine utilizes longwall mining.[8] Merging the MSHA, EIA, and NIOSH datasets allows me to assemble a detailed picture of safety-related outcomes at each union and nonunion coal mine in the country between 1993 and 2010. (Precise definitions of the variables included in this final dataset, along with their respective sources, are presented in Appendix C.)

I restrict the sample in several ways to ensure that the attributes of the union and nonunion mines being compared are as similar as possible.[9] First, like most previous scholars, I confine my analysis to underground coal mines. (Surface coal mines, which have very different risk profiles and production characteristics, are also much less likely to be unionized.) Secondly, since none of the underground anthracite and lignite coal mines in the dataset operated under a union contract, I restrict the sample to bituminous coal mines. Third, I drop any mine-quarters in which a mine reported zero coal production and/or zero hours worked.[10]

Once these restrictions are imposed, the final sample contains 2,635 mines,[11] each of

EIA, on 2/25/2010). Since the EIA's union data are reported annually, whereas MSHA's injury data are reported quarterly, I make the simplifying assumption that the union status recorded for a particular year applies to all four quarters of that year.

7 Since some of these variables are considered trade secrets by the mines that provide them, I obtained these data on a confidential basis. EIA staff indicated that two of these variables, recoverable reserves and percent captive production, are unreliable before 1998 (E-mail correspondence with William Watson, EIA, 12/7/2010). Results including these confidential fields are presented in the "confidential-fields" specifications for 1998 onwards.

8 Because of the uncertainty surrounding which way of coding each mine's extraction method is more accurate – the multifaceted approach used by MSHA, or the binary approach used by NIOSH – I estimate models that include (respectively) each measure as a regressor.

9 As a robustness check, I refine the sample further using matching methods and re-estimate the models. The purpose of this procedure, as described by Ho et al. (2007), is to balance the distributions of the covariates across the "treatment" and "control" groups. The "balanced" sample consists of 11,378 mine-quarters for which the estimated likelihoods of unionization are similarly distributed across the union and nonunion subsamples. Although results for this sample, available on the *Companion Website* (http://amorantz.stanford.edu/papers/union-coal-mine-safety/), generally echo those presented in the Results section, all of the coefficients in the fatality models lose statistical significance.

10 While injuries occur occasionally when a mine is not producing coal, the underlying causes of such accidents are likely to differ from those that occur during active production. Out of 42,586 initial mine-quarters, 3,696 (8.7%) reported zero coal production and/or zero hours worked; these were dropped from the analysis.

11 Because a mine that is unionized for part of the sample period and nonunionized for part of the sample period is counted in Appendix Table A1 as both a union mine and a nonunion mine, some mines are double-counted, for a total of 2,799 mines. The total number of mines used in the baseline regressions is 2,635. The difference between these two numbers, 164 mines, represents the number of mines that switched union status at some point during the

which was active, on average, for 15 of the 72 quarters under observation.[12] Figure 1 shows the geographical distribution of the mines in the sample. While the mines are spread across 17 states, 89% are located in the coal mining regions of Kentucky, Pennsylvania, West Virginia, and Virginia. Figure 2 displays the percentage of active mines that were unionized in each quarter. Mirroring the general trend for most U.S. industries, the unionization rate declined steadily, from 18.7% in 1993 to 9.2% in 2010.

Each injury report submitted to MSHA contains information on the nature and source of the injury, the body part(s) affected, the activity in which the employee was engaged when the incident occurred, and the severity of the injury (ranging from "first aid" to "fatality"). Using these fields, I tabulate four different injury counts: fatal injuries ("fatalities"), "traumatic" injuries,[13] "non-traumatic" injuries,[14] and total injuries. For each tabulation, I include only injuries that occurred in the underground subunit of a mine.[15] Table 1 presents injury counts (and percentages) for both union and nonunion mines. Although fatalities uniformly comprise a very

sample period. The latter group of 164 mines comprises the sample in the fixed effects models in Appendix Table A3. Also, because the historical variables (lost-work injuries and penalty points) are summed up for the previous four *quarters* for the non-traumatic, total, and traumatic injuries regressions, but are summed up for the previous *calendar year* for the fatality regressions, some mines are excluded from the fatality models but included in the other models. (For example, if a mine is open for all of only one calendar year, it will have no historical data at the *yearly* level, but it will have historical data for three of the four *quarters* it was open.) For this reason, the sample used for the fatality models contains only 2,568 mines.

[12] The underground coal mining industry exhibits high rates of entry and exit due to fluctuating demand and costs of production. For example, out of 884 mines that were active in the first quarter of 1993, only 16% were still active in the first quarter of 2000 and only 6% remained active in the final quarter of 2010. Similarly, out of 421 mines that were active in the final quarter of 2010, only 22% had been active in the first quarter of 2000, and only 11% had been active in the first quarter of 1993.

[13] Because a "traumatic" injury, by definition, is caused by a discrete accident that a miner sustains during working hours, its work-relatedness is rarely in dispute as long as the miner's account of the incident is deemed credible. In contrast, the diagnosis of non-traumatic injuries, such as cumulative or repetitive-motion injuries, often relies on the patient's self-report of subjective symptoms. Because the existence – let alone the work-relatedness – of the latter injuries may be difficult to verify using "evidence-based medicine," the frequency with which such claims are filed and approved can vary widely across employers. The category of "traumatic" injuries, intended to encompass the subset of injuries that are the least prone to underreporting, was defined in consultation with Professor Mark Cullen, M.D., the Chief of Stanford University's Division of General Internal Medicine. According to Dr. Cullen, the critical determining factor in determining whether or not an injury is reported is not the triggering *cause* of the injury, but rather the characteristics of the injury itself. More specifically, injuries of at least moderate severity, whose effects are readily visible, that are "traumatic" (rather than cumulative) in nature are generally the least prone to reporting bias. The following injuries were deemed by Dr. Cullen to meet these criteria: amputations; enucleations; fractures; chips; dislocations; foreign bodies in eyes; cuts and lacerations; punctures; burns/scalds; crushings; and chemical, electrical, and laser burns. Fatalities of any type are also treated as traumatic injuries. So defined, "traumatic" injuries account for 37.5% of the injuries reported during the period of observation.

[14] All injuries that are not classified as "traumatic" injuries are classified as "non-traumatic" injuries.

[15] As a robustness check, I also estimate models that include *all* injuries occurring at underground mines, including those that take place above ground. Presented on the *Companion Website*, these results do not materially change my findings.

small fraction (0.3-0.6%) of total accidents, the fraction of non-traumatic injuries is typically higher at union mines than at nonunion mines (69.9% versus 58.1%).

Figure 3 provides a preliminary comparison of recent trends across union and nonunion mines by plotting, respectively, the frequencies of total and traumatic injuries (per 2,000 hours worked) from 1993 to 2010. Two general patterns are apparent. First, regardless of union status, the frequency of traumatic injuries has remained relatively constant over time, whereas the frequency of total injuries has declined steadily since the early 1990s. Secondly, although the direction and magnitude of the union-nonunion disparity fluctuated by year and injury type in the early 1990s, by the turn of the millenium, union mines were reporting lower injury rates than nonunion mines regardless of the metric examined.

Methodology

To explore the relationship between union status and safety outcomes, I estimate negative binomial regression models in which the dependent variables are, respectively, total injuries, non-traumatic injuries, traumatic injuries, and fatalities.[16] The total number of hours worked is used as an exposure term, and standard errors are clustered at the mine level. In addition to a dummy variable indicating the presence of a union, I include several other covariates (listed in the Appendix) that, based on prior literature and/or conversations with industry stakeholders, are deemed likely to affect mine safety. This article presents results from several leading models. Two different versions of three model specifications were estimated, for a total of six specifications. The two versions differ in that the "public-fields" version relies solely on public data, whereas the "confidential-fields" version incorporates confidential data from EIA.[17] The first model specification uses full-time equivalents (FTEs)[18] as the measure of mine size. Since it is conventional to use FTEs to calculate the frequency of workplace accidents, this is designated as the "baseline" specification, as in Morantz (2012). The second and third specifications use employees[19] and coal tonnage[20] as alternative measures of mine size.

[16] Tests of overdispersion consistently indicate that a negative binomial model is preferable to a Poisson model.
[17] See Appendix B for a complete description of model specifications.
[18] Yearly FTEs are defined as 2,000 hours worked, and quarterly FTEs are defined as 500 hours worked.
[19] MSHA defines employees as the average number of persons working during each pay period of a given quarter, rounded to the nearest whole number (see http://www.msha.gov/stats/part50/rptonpart50.pdf). Results presented here include only employees working in the underground subunit. On the *Companion Website*, I present results from a robustness check in which I include all injuries at underground mines, regardless of whether the injuries occurred

Several studies by Weil (1987:181-84; 1991:23; 1992:124-25) suggest that unions' effects on workplace safety vary by employer size. For example, unions at large and small facilities may differ in their respective capacities to exercise their "walk around" rights during MSHA inspections; to form powerful health and safety committees; to independently conduct inspections; and to enforce open-door policies among safety and health personnel. To explore whether unions' impact varies by mine size, I fit several models including interaction terms between union status and mine size quartiles.

The final public-fields specification includes the following regressors: union dummy, mine size, union-size interaction term(s), logged controller size, mine age, mine productivity, number of lost-work injuries (in hundreds) in the previous four quarters (or in the previous year for fatality regressions), total penalty points (in thousands) in the previous four quarters (or in the previous year for fatality regressions), a constant term, dummies indicating presence of each type of mine subunit, quarter dummies, MSHA district dummies, and a longwall indicator. The confidential-fields version replaces the longwall indicator with mining method percentages and adds as regressors the number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, and recoverable coal reserves. Appendix Table A1 presents descriptive statistics for each included covariate.

For total, traumatic, and non-traumatic injuries, I use the most granular time period available, the "mine-quarter," as the unit of analysis. However, because fatalities are such rare events, using quarterly data is problematic when modeling fatality counts. (There is often too little variation across observations to yield valid estimates.) Therefore, I use the "mine-year" as the unit of analysis in all fatality regressions.

By including a broader set of covariates than has been used in previous studies, I hope to minimize omitted variable bias. Nevertheless, there are several potentially confounding characteristics of union and nonunion miners – such as disparities in miners' demographics and remuneration levels – for which I cannot control. These limitations, including their implications for the interpretation of my findings, are discussed in the Interpretation section.

Other types of unobservable, mine-level heterogeneity could also bias my analysis. For

above or below ground. For purposes of these models, I consider all employees in the mine – not just those working in the underground – when calculating mine size.

[20] Tonnage is defined here as the total tons of coal produced in the underground subunit of a mine. On the *Companion Website*, I present robustness checks in which all injuries (regardless of subunit) are included in the model; for these purposes, I similarly define tonnage as total tons produced across all subunits.

example, unusually hazardous geological conditions may affect a mine's injury rate as well as the likelihood that its employees will vote for unionization. In theory, a promising way to control for unobservable heterogeneity across mines is to use (mine-level) fixed effects to explore whether a given mine's safety record changes in predictable ways when it ceases (or begins) operating under a union contract. In practice, however, estimating fixed-effects models in this context creates more identification problems than it solves. First, only a handful of underground coal mines (6.2%) changed union status during the period examined. Second, these mines are highly unrepresentative of the population as a whole.[21] Any identification strategy predicated upon this idiosyncratic subgroup would likely yield biased estimates of unionization's true effect. In short, despite its intuitive appeal, a fixed-effects modeling approach is ill-suited to the peculiarities of the mining industry during this period.[22]

Importantly, most of the statistical biases identified in prior literature will tend, if anything, to attenuate unionization's measured effect. For example, virtually all scholars that consider the possibility of selection bias have argued, on both theoretical and empirical grounds, that inherently hazardous mines are *more* likely to unionize (Brown 1995; Leigh 1982; Worrall and Butler 1983; Hirsch and Berger 1984; Hills 1985; Robinson 1988b; Robinson 1991). If this is correct, then because I cannot control for each mine's intrinsic perilousness, any estimates of unions' beneficial impact will likely be biased *downward*.[23]

Another type of bias that has received much attention in the literature, often referred to as "reporting bias," stems from the fact that injury reporting practices may differ across union and nonunion environments. For example, nonunion miners may fail to report legitimate injuries due to a fear of reprisal from their employers. At the same time, some unions may facilitate or even

[21] Industry stakeholders recounted that, in recent decades, mines that underwent changes in union status typically did so in the wake of adverse economic shocks, such as sudden changes in the regulatory environment. The data seem to bear out this claim. At least 19% of coal mines that de-unionized and 76% of mines that became unionized during the sample period experienced major disruptions (defined as production, employment, or hours worked dropping by over 50%; a year or more of inactivity; and/or a change of the mine operator or mine controller) during the year when the transition took place. Such operational discontinuities are likely to have exerted an independent effect on mine safety, making it difficult to empirically isolate the impact of unionization. Moreover, the unusually precarious environment in which unions were forced to operate before or after these transitions may have limited their capacity to influence workplace behavior.

[22] Notwithstanding these significant methodological concerns, for the benefit of the interested reader, Appendix Table A3 presents results from mine-level fixed-effects models.

[23] One might imagine, alternatively, a form of adverse selection in which the *most* dangerous mines are the *least* likely to unionize. For example, mine operators that invest the least in workplace safety may invest the most in (or become especially skilled at) defeating union certification elections. Although this form of adverse selection seems plausible – especially in monopsonistic or oligopsonistic labor markets – I am unaware of any prior literature that confirms its existence.

encourage the reporting of fraudulent or exaggerated claims (Hirsch, MacPherson, and Dumond 1997; Morse et al. 2003). Even in the absence of outright employer intimidation or employee fraud, institutional norms may differ regarding what "counts" as a compensable occupational injury. For example, Azaroff, Levenstein, and Wegman (2002) suggest that attitudinal barriers that impede the detection and reporting of injuries are weaker in unionized workplaces, especially for injuries that are relatively minor and/or hard to diagnose. In apparent support of this hypothesis, Hirsch, MacPherson, and Dumond (1997) and Morse et al. (2003) find that even among those who self-report similar rates of occupational injuries, union workers are more likely to receive workers' compensation benefits. In short, reporting bias may also diminish the measured impact of unionization.

Fortunately, my data enable me to explore the magnitude of reporting bias indirectly by examining four different injury categories that vary in their relative susceptibility to such bias: non-traumatic injuries, total injuries, traumatic injuries, and fatalities. As illustrated in Figure 4, non-traumatic injuries are hypothesized to be the most prone to reporting bias because they (by definition) include cumulative injuries whose work-relatedness is often difficult to confirm. At the opposite end of the continuum are workplace fatalities, which are virtually impossible to hide from authorities and regulators. The remaining two measures – total and traumatic injuries – fall in between these two extremes. Total injuries are less prone to reporting bias than non-traumatic injuries because they include fatalities and severe traumatic injuries. Traumatic injuries are hypothesized to be even less susceptible to reporting bias than total injuries since they exclude cumulative injuries.

If there is significant reporting bias across union and nonunion mines, the union safety effect (if any) should appear strongest in the fatality rate models; weaker in the traumatic injury rate models; weaker still in the total injury rate models; and weakest of all in the non-traumatic injury rate models. In other words, union status should predict more and more injuries as the focus of inquiry shifts from fatalities, to traumatic injuries, to total injuries, and finally to non-traumatic injuries. The following section summarizes my main findings, but space constraints preclude me from presenting detailed results from each and every model specification and robustness check that was performed. For the benefit of the interested reader, the *Companion Website*[24] presents a variety of extra specifications and robustness checks.

[24] See http://amorantz.stanford.edu/papers/union-coal-mine-safety/

Results

Tables 2-4 present the study's main findings for the four different outcomes examined: non-traumatic injuries, total injuries, traumatic injuries, and fatalities. For ease of interpretation, I transform each coefficient into an incident rate ratio (IRR), whereby a coefficient of 1 indicates no change at all in predicted injuries; coefficients between 0 and 1 represent a predicted fall in injuries (e.g. a coefficient of 0.97 represents an approximate 3% decline); and coefficients greater than one represent predicted increases (e.g. a coefficient of 1.03 represents an approximate 3% rise).

Results from the leading models presented in Table 2, which capture the average or "net" effect of unionization across all mines and time periods, display a striking pattern. On one hand, unionization is associated with a very sizable (more than 25%), robust, and statistically significant *increase* in non-traumatic injuries across all specifications. The results for total injuries are similar but more muted: the disparity is smaller in magnitude, when significant, and is not robust across all specifications. Traumatic injuries, on the other hand, present a very different picture; unionization is now associated with a sizable (more than 20%) and highly significant *decline* in traumatic injuries across all specifications. Similarly, unionization is associated with an even larger (more than 50%) fall in fatal injuries across all six specifications.

In short, the model results are broadly consistent with both of the hypotheses initially posed. First and foremost, unionization is associated with a significant decline in those mine accidents that are least vulnerable to reporting bias. Secondly, the dramatic extent to which unions' measured effect varies by injury type suggests that there are indeed significant discrepancies in reporting practices across union and nonunion mines.[25]

Table 3 probes whether the trends observed vary by mine size. Although the analysis is restricted to the baseline specification, the continuous mine-size term is replaced by discrete size quartile dummies (defined such that a fourth of all mine-quarters fall into each quartile), and the "union" and "union X size" terms are replaced with "union X size quartile" interaction terms. At first glance, the results presented in Table 3 are surprising. Most prior scholarship suggests that larger firms – regardless of union status – have the strongest intrinsic incentives to invest in

[25] The fact that as noted in Table 1, traumatic injuries comprise a much smaller percentage of total injuries in union mines (30.1%) than in nonunion mines (41.9%) might also be construed as "circumstantial evidence" of reporting bias.

workplace safety (Weil 1987:124-28, Genn 1993:220-230, Fenn and Veljanovski 1988:1065; Reilly, Paci, and Holl 1995:280; Ruser 1985:485; Frick and Walters 1998:368). Therefore, one might expect unions' impact on workplace safety to be the strongest among smaller mines. Yet Table 3 reveals precisely the opposite trend: unionization's depressive effect on traumatic and fatal injuries is the greatest and most robust among larger mines. What might explain this seemingly counterintuitive result? Perhaps unions are better equipped to influence workplace safety and injury reporting policies in mines that exceed a certain size threshold. For example, unions in small mines may find it difficult to establish active health and safety committees, conduct independent inspections, and consistently accompany MSHA inspectors on their tours.

Finally, Table 4 probes changes over time by subdividing the analysis into three discrete time periods (1993-1998, 1999-2004, and 2005-2010) using the baseline specification.[26] For both non-traumatic and total injuries, the disparity between union and nonunion mines diminishes over time. Traumatic injuries, however, display a different trend: although there is only a small disparity across groups in the mid 1990s, unionization is associated with a significant and sizable (more than 30%) *decline* in traumatic injuries in subsequent years. Fatal injuries reveal a mixed pattern: although unionization is associated with a large (albeit only at a 10% level of significance) decrease in fatalities around the turn of the century, the disparity shrinks and loses statistical significance in later years. At least if one confines scrutiny to traumatic injuries, then, the data suggest that the union safety effect could be a relatively recent phenomenon.

Although not the focus of this study, the other covariates included as right-hand-side variables reveal several interesting patterns. Appendix Table A2 displays expanded regression coefficients for all of the baseline models. Although many of the estimated effects mirror those of prior studies, some either conflict with previous estimates or illuminate relationships that prior scholarship has not explored. The *Companion Website* discusses these and other ancillary findings.

Interpretation

Taken at face value, my results are broadly consistent with three hypotheses regarding the

[26] The data are broken into three time periods for clarity of presentation. Models with alternative time groupings, presented on the *Companion Website*, do not materially change the results for non-traumatic, total or traumatic injuries. The findings for fatal injuries, although differing somewhat from those presented here, are similarly equivocal.

relationship between unionization and coal mine safety. First, unionization may have improved "real" mine safety levels (reflected in traumatic and fatal injury rates) several decades after the passage of the Coal Act. Second, reporting bias has probably confounded prior studies of unionization's impact, especially when minor and non-traumatic injuries are included in injury counts. Finally, in the latter half of the twentieth century, the union safety effect may not have existed until the turn of the millenium.

Several important questions remain. First, what is the likelihood that omitted variable bias has confounded my identification strategy?

One potentially consequential mine-level characteristic that I cannot observe is the age distribution of the workforce. Epidemiological literature on the frequency of accidents by age is thin and conflicting. Some studies suggest that younger and less experienced miners sustain more injuries on the job (e.g. Laflamme and Blank 1996), but the scholarship is not unanimous on this point. (See, for example, Souza 2009.) Based on a careful review of existing literature, Salminen (2004) reports a bifurcated pattern, in which young workers are more susceptible to non-fatal injuries and older workers are more prone to occupational fatalities. If the distribution of age or experience differs substantially across union and nonunion mines – and if such age differentials independently affect miners' likelihood of sustaining traumatic or fatal injuries – this could bias my results. Unfortunately, demographic variables are unavailable at the mine level, making it difficult to verify the existence, let alone to estimate the magnitude, of such biases.[27] The only source that facilitates any age comparisons is the Current Population Survey (CPS), which includes questions regarding age, occupation, and union membership. Although the small sample size allows for only rough comparisons, the data suggest that the average miner is older today than he was in 1990; that union miners are older than non-union miners; and that the latter discrepancy has grown in recent decades.[28] Yet this age differential seems unlikely to explain

[27] The decennial survey administered by the U.S. Census Bureau – even the "long" form administered to 5% of the population for the Public-Use Microdata Samples (PUMS) – contains no information on union membership. The U.S. Census Bureau's Longitudinal Employer-Household Dynamics Program (LEHD) does contain mine-level demographic data. However, the LEHD dataset excludes Kentucky and Pennsylvania, which contain 43% of all underground, bituminous mines in the U.S., and data for West Virginia and Virginia – which contain an additional 46% of mines in our sample – are available only for 1997 onwards. Additionally, since the Census Bureau and MSHA use different employer identifiers, merging these two datasets would pose significant challenges. (Interview with Angela Andrus, Census Research Data Center, February 9, 2011; Interview with Emily Isenberg at the LEHD Program, U.S. Census, March 3, 2011.)

[28] For example, the typical (median) unionized miner was 41 in 1990; 46 in 2000; and 51 in 2010. In contrast, the median nonunion miner was 38 in 1990, 45 in 2000, and 45.5 in 2010. A t-test comparing the mean ages of union

much of the union safety effect, for two reasons. First, although the union–nonunion gap in the frequency of traumatic injuries expanded markedly during the 1990s, the gap in the proportions of young miners grew, if at all, only marginally during this period.[29] Secondly, although the negative correlation between unionization and mining fatalities intensified during the late 1990s, the union–nonunion gap in the prevalence of older miners, if anything, slightly widened.[30]

Several stakeholders suggested that unionized miners are also more experienced than their nonunionized counterparts (although CPS data reveal no differences in median educational attainment[31]), and that total compensation including fringe benefits is higher at union mines, although both disparities have diminished in recent decades. Unfortunately, there are no data available with which to test the validity of either claim.[32]

In short, I cannot rule out the possibility that omitted variables have biased my analysis.[33] Nevertheless, the scant information available on disparities in miner demographics do not correlate particularly well with the trends observed in the data, suggesting that this particular source of bias, at least, may not be a major concern.

If the observed relationship between unionization and mine safety is indeed causal, this raises a second important question: why do my estimates differ so sharply from prior literature? Perhaps the union safety effect has always existed, but has eluded detection because of the

and nonunion miners reveals that union miners are older at a 10% level of significance. I use CPS Outgoing Rotation Group (ORG) survey data to derive these statistics, restricting the CPS data to observations within the coal mining industry, in the labor force, and not self-employed. Historical CPS data, including the ORG data, is available at http://www.nber.org/cps/.

[29] In 1990 the CPS data indicates that 5% of union miners and 16% of nonunion miners were under the age of 30. In 2000, the percentage of union miners below 30 was 0%, versus 12% of nonunion miners.

[30] In 1990 the CPS data indicates that 16% of union miners and 10% of nonunion miners were over the age of 50. By 2000, 29% of union miners and 21% of nonunion miners were over the age of 50.

[31] The CPS data indicate that the median education level of both union and nonunion miners was a high school diploma or GED in 1990, 2000, and 2010, respectively.

[32] The CPS does not ask any questions regarding the prevalence or magnitude of "fringe" benefits such as pensions or life insurance. Questions regarding job tenure are collected every other year as part of the January supplement, which typically includes about fifteen respondents from the mining industry, of whom only a handful belong to a union. Due to these extremely small sample sizes, one cannot draw any meaningful inferences regarding whether (and to what extent) the average tenure of union and nonunion miners has varied in recent years.

[33] If profitable mines are more (or less) likely to become unionized, profitability could also be an important source of omitted variable bias. Unfortunately, I cannot construct a credible proxy for mine profitability. On the revenue side of the equation, for example, the data provided by the EIA only include revenue from domestic sources, whereas sale of (typically metallurgical) coal abroad can be a critical and highly volatile source of revenue (see, for example, Radenmacher and Braun, 2011). Meanwhile, on the cost side, many factors that affect production – such as capital investments, labor costs per hour, use of subcontracting, receipt of federal subsidies, etc. – cannot be observed in the data; the only relevant information available is total hours worked. In an effort to at least partially mitigate this potential source of bias, I include a productivity measure (thousands of tons produced annually per full-time equivalent worker) in all specifications.

methodological shortcomings of and limited data used in prior work. Since complete data from the 1970s no longer exist, I cannot replicate these early studies. However, when I analyze my own data using a methodology similar to that of Appleton and Baker (1984), the results are qualitatively not unlike those reported here, casting doubt on the possibility that findings reported in early empirical scholarship were entirely spurious.[34] Alternatively, it could be that unions did not, in fact, reduce mining hazards until decades after the Mine Act's passage. Although far from conclusive, the replication exercise suggests that the union safety effect may indeed be a relatively recent phenomenon.

If the latter conclusion is correct – and unions had little impact on mine safety until just before the turn of the millinium – the question is why. There are several possibilities. First, fluctuations over time in the stringency of MSHA's enforcement scrutiny may affect union and nonunion mines differently. For example, Weil (1987), examining data from the early 1980s, finds that union mines were subject to more stringent enforcement scrutiny.[35] Examining data from 1995-2009, Morantz (2012) finds that this disparity has persisted along several dimensions.[36] If MSHA inspects union mines more intensively than nonunion mines – and if this differential has widened over time – it could help explain the observed trends. However, detailed comparison of the results presented here with those reported in Morantz (2012) casts doubt on this hypothesis. Whereas the "union safety effect" described in the Results section is strongest among large mines, the enforcement disparities reported in Morantz (2012) diminish sharply with mine size.

Secondly, unions may have shifted their institutional priorities in the 1990s, deliberately choosing to forfeit potential wage increases in exchange for enhanced workplace safety. CPS data do show some convergence in median (real) wages of union and nonunion miners since the early 2000s. However, there are several reasons to doubt that the UMWA's leadership has

[34] See the *Companion Website* for a detailed description of my attempt to replicate Appleton and Baker's methodology using my own dataset.
[35] Weil (1987) finds that union mines are more likely to designate employee representatives; receive more frequent MSHA inspections of longer average duration; are granted shorter periods in which to abate violations; are granted fewer abatement extensions; receive more citations per inspection; pay higher penalties per violation; and are less successful in reducing penalty amounts through MSHA's internal administrative appeals process than nonunion mines (pp. 120-185).
[36] Morantz (2012) finds that unionization is associated with increases in regular inspection hours per mine quarter, total inspection hours per regular inspection, the proportion of total inspection hours spent onsite, and the proposed fine assessed for significant and substantial violations.

pursued such a strategy.[37]

Finally and most importantly, it may have taken time for the UMWA's leadership to train a cadre of union members capable of effectively exercising their contractual and newfound statutory rights. In the words of one union official, "It can take a generation to institutionalize a robust safety culture and build a corps of experienced miners who can train the newcomers."[38] The labor strife that characterized much of the 1970s (and to a lesser extent the 1980s) likely impeded unions' capacity to enact meaningful changes. Weil (1994:199-200) has identified the election of Rich Trumka in 1982 to the presidency of the UMWA as a critical turning point, after which the union prioritized and funded the training of health and safety committee members. By the late 1980s and early 1990s, under the leadership of Joseph Main, the UMWA's Department of Health and Safety took more systematic measures to train its rank and file, such as the institution of local union training programs.[39] In short, changes in the leadership and institutional focus of the UMWA during the 1970s and '80s that were intended to increase the union's long-term impact on mine safety may not have borne fruit until the 1990s.

Conclusion

Although the United Mine Workers of America has always been a vigorous advocate for miners' safety, prior empirical literature has failed to detect any evidence of a union safety effect on injury or fatality rates. If anything, prior scholarship has reported a puzzling negative relationship between unionization and mine safety during the 1970s, the decade immediately following the Coal Act's passage. This study uses more comprehensive data and updated statistical methods to re-examine the relationship between unionization and mine safety. I focus

[37] First, according to the UMWA leadership, the disparity in benefits between union and nonunion miners has progressively widened even as the gap in hourly wages has narrowed. Therefore, they claimed, the true overall disparity in union–nonunion compensation has changed little in recent years. To the best of my knowledge, this assertion cannot be tested with available data. (Telephone conferences with Brian Sanson, May 21, 2010; and Phil Smith, May 28, 2010.) Second, the UMWA's leadership explained that young miners that began entering the workforce in large numbers in the first decade of the 21st century are much less likely to have family members who are miners, or to have grown up in "mining towns" where explosions and collapses are part of the collective memory. As a result, they show relatively little interest in safety issues. As one official put it, "it has become very difficult to organize on safety issues." (Telephone conference with Phil Smith, May 28, 2010.) Finally, CPS data show no significant convergence in *mean* real wages of union and nonunion miners. The recent convergence in *median* wages could be driven, therefore, by a growing similarity in the prevalence of inexperienced miners rather than enhanced congruence of pay scales. Unfortunately, the extreme paucity of miners surveyed for the CPS sample makes it difficult to conclusively resolve the issue.

[38] Telephone interview with Phil Smith, UMWA, May 28, 2010.

[39] Weil (1987:200); Telephone interview with Michael Buckner, UMWA's Director of Research from 1981-2005, on March 3, 2011.

on the 1993-2010 period, for which reliable mine-level information on union status is available, and use a variety of techniques to mitigate potential biases.

I find that unionization is associated with a sizable and robust decline in both traumatic injuries and fatalities, the two safety outcomes that I argue are the least prone to reporting bias. I construe these results as evidence for a “real” union safety effect in U.S. underground coal mining. At the same time, I find that unionization is associated with higher total and non-traumatic injuries, lending credence to claims that injury reporting practices differ significantly across union and nonunion mines.

Interestingly, the union safety effect on traumatic injuries seems to have escalated just before the turn of the millenium. I propose several possible explanations for this trend, including an overall improvement in labor relations since the 1970s, fluctuations over time in the stringency of MSHA’s enforcement scrutiny, the growing competitive pressures faced by union leaders, and the increasing sophistication and professionalization of UMWA safety programs. The empirical evidence available, although scant, suggests that the latter hypothesis is the most promising. Exploring the historical relationship between UMWA activities and mine safety in greater detail – including a richer, updated institutional account of the precise mechanisms whereby organized labor affects safety outcomes – would be a promising topic for future inquiry.

References

Appleton, William C., and Joe G. Baker. 1984. "The Effect of Unionization on Safety in Bituminous Deep Mines." *Journal of Labor Research*, Vol. 4, No. 2 (Spring), pp. 139-147.

Azaroff, Lenore S., Charles Levenstein, and David H. Wegman. 2002. "Occupational Injury and Illness Surveillance: Conceptual Filters Explain Underreporting." *American Journal of Public Health*, Vol. 92, No. 9, pp. 1421-1429.

Bennett, James D., and David L. Passmore. 1985. "Unions and Coal Mine Safety: Comment [The Effect of Unionization on Safety in Bituminous Deep Mines]." *Journal of Labor Research*, Vol. 6, No. 2 (Spring), pp. 211-216.

Boal, William M. 2009. "The Effect of Unionization on Accidents in U.S. Coal Mining, 1897-1929." *Industrial Relations*, Vol. 48, No. 1, pp. 97-120.

Boden, Leslie Irvin. 1977. "Underground Coal Mining Accidents and Government Enforcement of Safety Regulations." Diss., Massachusetts Institute of Technology.

Brown, Richard. 1995. "Unions, Markets, and Other Regulatory Mechanisms: Theory and Evidence." *University of Toronto Law Journal*, Vol. 44, No. 1, pp. 1–45.

Butler, Richard J., and John D. Worrall. 1983. "Workers' Compensation: Benefit and Injury Claims Rates in the Seventies." *The Review of Economics and Statistics*, Vol. 65, No. 4, pp. 580-589.

Cameron, Adrian Colin, and Pravin K. Trivedi. 1998. *Regression Analysis of Count Data.* New York: Cambridge University Press.

Connerton, Marguerite M. 1978. "Accident Control through Regulation: the 1969 Coal Mine Health and Safety Act Experience." Diss., Harvard University.

Darmstadter, Joel. 1997. "Productivity Change in U.S. Coal Mining." Resources for the Future Discussion Paper No. 97-40. Available online at http://www.rff.org/Documents/RFF-DP-97-40.pdf.

Dedobbeleer, Nicole, François Champagne, and Pearl German. 1990. "Safety Performance among Union and Nonunion Workers in the Construction Industry." *Journal of Occupational and Environmental Medecine*, Vol. 32, Issue 11.

Eaton, A. and T. Nocerino. 2000. "The effectiveness of health and safety committees: Results of a survey of public-sector workplaces." *Industrial Relations*, Vol. 39, No. 2, pp. 265-90.

Fairris, David. 1995. "From Exit to Voice in Shopfloor Governance: The Case of Company Unions." *Business History Review*, Vol. 69, pp. 493-529.

Fenn, Paul and Simon Ashby. 2004. "Workplace Risk, Establishment Size and Union Density." *British Journal of Industrial Relations*, Vol 42, pp. 461-480.

Fishback, Price V. 1986. "Workplace Safety During the Progressive Era: Fatal Accidents in Bituminous Coal Mining, 1912-1923." *Explorations in Economic History*, Vol. 23, No. 3, pp. 269-298.

Fishback, Price V. 1987. "Liability Rules and Accident Prevention in the Workplace: Empirical Evidence from the Early Twentieth Century." *The Journal of Legal Studies*, Vol. 16, No. 2, pp. 305-328.

Fox, Maier B. 1990. *United We Stand: The United Mine Workers of America, 1890-1990.* Washington, D.C: United Mine Workers of America.

Frick, Kaj., and Walters, David R. 1998. "Worker Representation on Health and Safety in Small Enterprises: Lessons from a Swedish Approach." *International Labour Review*, Vol. 137, No. 3, pp. 367–89.

Genn, Hazel. 1993. "Business responses to the regulation of health and safety in England." *Law and Policy*, Vol. 15, pp. 219–33.

Havlovic, Stephen, and McShane, Steven. 1997. "The Effectiveness of Joint Health and Safety Committees and Safety Training in Reducing Fatalities and Injuries in British Columbia Forest Product Mills." Burnaby, BC: Workers Compensation Board of British Columbia.

Hills, Stephen. 1985. "The Attitudes of Union and Nonunion Male Workers Towards Union Representation." *Industrial and Labor Relations Review*, Vol. 38, No. 2, pp. 179–94.

Hirsch, Barry T., and Mark C. Berger. 1984. "Union Membership Determination and Industry Characteristics." *Southern Economic Journal*, Vol. 50, No. 3, pp. 665-679.

Hirsch, Barry T., David A. MacPherson, and J. Michael Dumond. 1997. "Workers' Compensation Recipiency in Union and Nonunion Workplaces." *Industrial and Labor Relations Review*, Vol. 50, No. 2, pp. 213-236.

Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart. 2007. "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference." *Political Analysis*, Vol. 15, No. 3, pp. 199-236.

Laflamme, Lucie, and Vera L. G. Blank. 1996. "Age-Related Accident Risks: Longitudinal Study of Swedish Iron Ore Miners." *American Journal of Industrial Medicine*, Vol. 30, No. 4, pp. 479-87.

Leigh, J. Paul. 1982. "Are Unionized Blue Collar Jobs More Hazardous Than Nonunionized Blue Collar Jobs?" *Journal of Labor Research*, Vol. 3, No. 3, pp. 349–57.

Morantz, Alison. 2009. "The Elusive Union Safety Effect: Towards a New Empirical Research Agenda." *Proceedings of the 61st Annual Meeting of the Labor and Employment Relations Association* (San Francisco, Jan. 3-5, 2009). Champaign, IL: Labor and Employment Relations Association, pp. 130-146.

Morantz, Alison. 2012. "Does Unionization Strengthen Regulatory Enforcement?" *N.Y.U. Journal of Legislation and Public Policy*, Vol. 14, No. 13, pp. 697-727.

Morse, Tim, Laura Punnett, Nicholas Warren, Charles Dillon, and Andrew Warren. 2003. "The Relationship of Unions to Prevalence and Claim Filing for Work-Related Upper-Extremity Musculoskeletal Disorders." *American Journal of Industrial Medicine*, Vol. 44, No. 1, pp. 83-93.

National Research Council. 1982. "Toward Safer Underground Coal Mines." Washington, D.C.: National Academy Press.

Nichols, Theo, David Walters, and Ali C. Tasiran. 2007. "Trade unions, institutional mediation and industrial safety: evidence from the UK." *Journal of Industrial Relations*, Vol. 49, No. 2, pp. 211-25.

Radenmacherm Maggi, and Raphael Braun. 2011. "The Impact of the Financial Crisis on the Global Seaborne Hard Coal Market: Are there Implications for the Future?" *Zeitschrift für Energiewirtschaft*. Vol 35, No. 2, pp. 89-104.

Reardon, Jack. 1996. "The Effect of the United Mine Workers of America on the Probability of Severe Injury in Underground Coal Mines." *Journal of Labor Research*, Vol. 17, No. 2, pp. 239-252.

Reilly, Barry, Pierella Paci, and Peter Holl. 1995. "Unions, Safety Committees and Workplace Injuries." *British Journal of Industrial Relations*, Vol. 33, No. 2, pp. 275–88.

Ruser, John W. 1985. "Workers' Compensation Insurance, Experience-Rating, and Occupational Injuries." *Rand Journal of Economics*, Vol. 16, No. 4, pp. 487–503.

Salminen, Simo. 2004. "Have Young Workers More Injuries than Older Ones? An International

Literature Review." *Journal of Safety Research*, Vol. 35, No. 5, pp. 513-521.

Souza, Kerry. 2009. "Individual and Plant Level Predictors of Acute, Traumatic Occupational Injury in a Manufacturing Cohort." Diss.: Harvard University.

Staats, Elmer B. 1981. "Low Productivity in American Coal Mining: Causes and Cures." Washington, D.C.: General Accounting Office.

Weeks, James L. 1985. "The Effect of Unionization on Safety in Bituminous Deep Mines: Comment." *Journal of Labor Research*, Vol. 6, No. 2 (Spring), pp. 209-210.

Weil, David. 1987. "Government and Labor at the Workplace: The Role of Labor Unions in the Implementation of Federal Health and Safety Policy." Diss.: Harvard University.

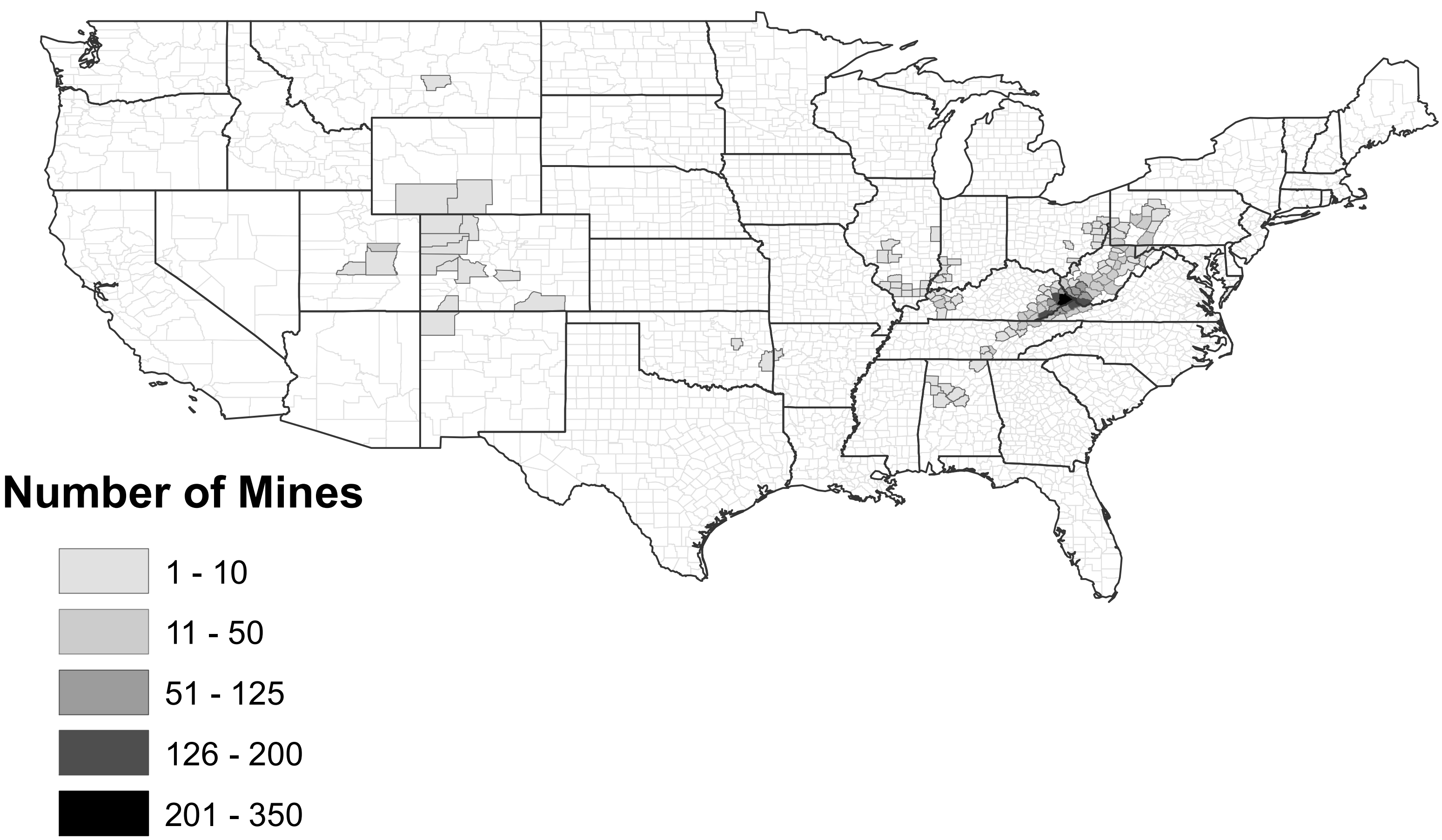
Weil, David. 1991. "Enforcing OSHA: The Role of Labor Unions." *Industrial Relations*, Vol. 30, pp. 20-36.

Weil, David. 1992. "Building Safety: The Role of Construction Unions in the Enforcement of OSHA." *Journal of Labor Research*, Vol. 13, pp. 121-132.

Weil, David. 1994. *Turning the Tide: Strategic Planning for Labor Unions.* New York: Lexington Books.

Figure 1. Underground Bituminous Coal Mines by County

22



County information was provided by MSHA. The county-level mine counts incorporate all 2,662 underground bituminous coal mines that were active for at least one quarter between 1993 and 2010. Note that, due to high rates of entry and exit in the industry, no more than half of the sample was active in any given quarter.

Figure 2. Union Penetration

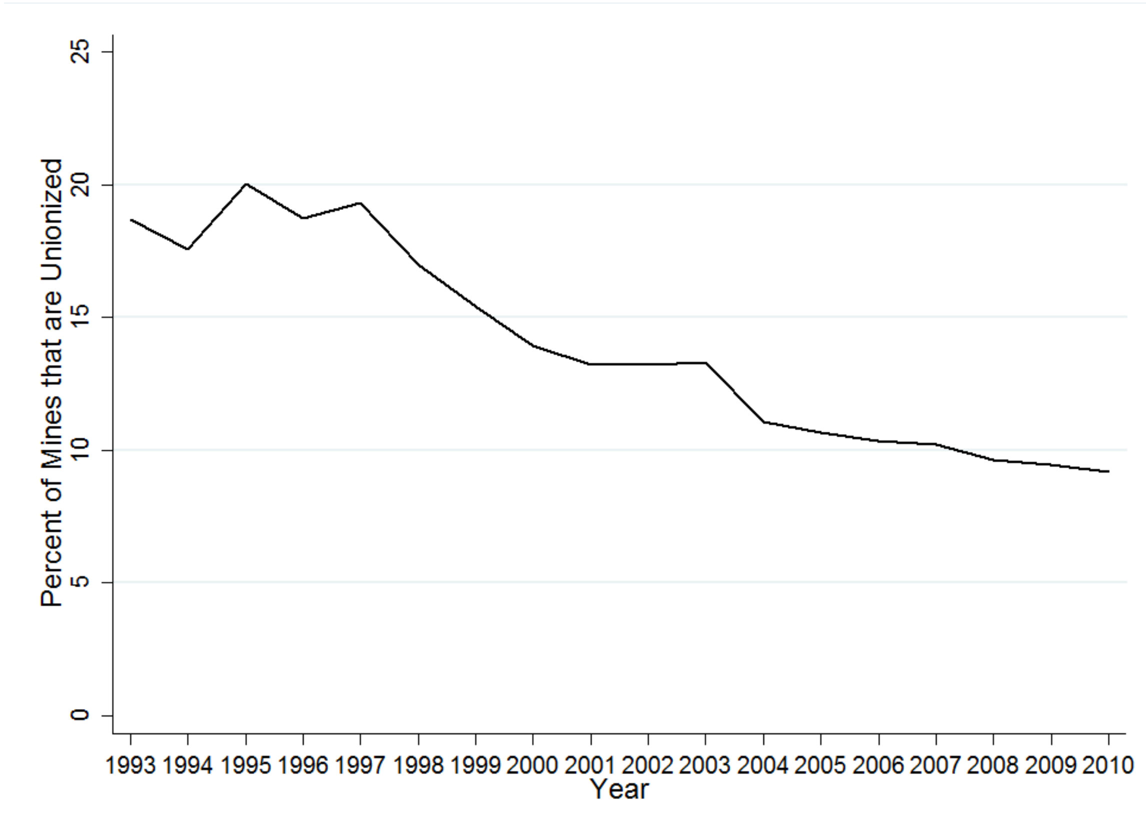


Figure 3. Rates of Total and Traumatic Injuries

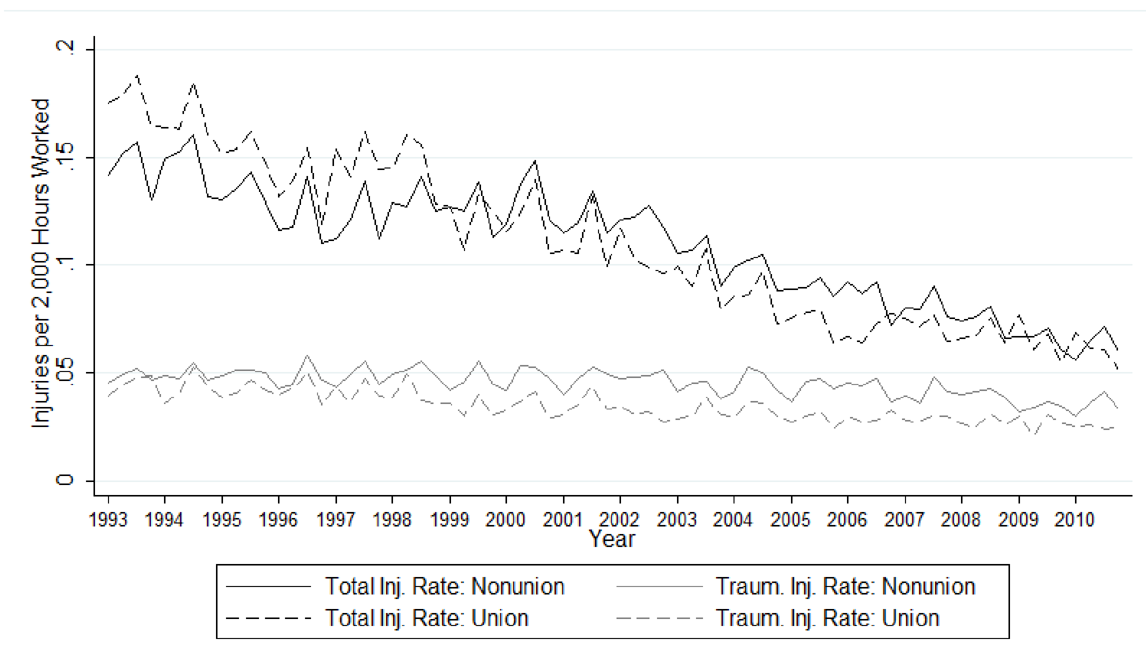


Figure 4. Susceptibility of Injury Type to Reporting Bias

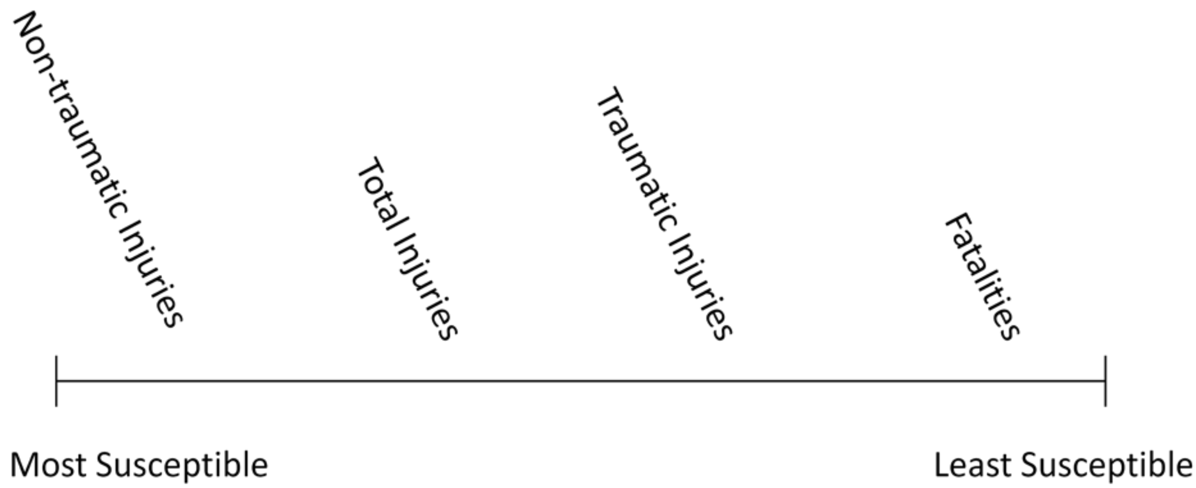


Table 1: Injury Type Breakdown

	All Mines:		Union Mines:		Nonunion Mines:	
Injury Type	**Frequency**	**% of Total**	**Frequency**	**% of Total**	**Frequency**	**% of Total**
Non-Traumatic[a]	47,793	62.5%	20,153	69.9%	27,640	58.1%
Total	76,440	100%	28,847	100%	47,593	100%
Traumatic[b]	28,647	37.5%	8,694	30.1%	19,953	41.9%
Fatality	341	0.4%	75	0.3%	266	0.6%

Notes:

This table reports the frequency of each injury type, as well as the share of total injuries that each category represents. Note that these categories are not mutually exclusive.

a The non-traumatic injury category is comprised of all injuries not classified as traumatic (see below). Note that the non-traumatic and traumatic injury counts sum to the total injury count.

b The traumatic injury category is comprised of the following: amputations; enucleations; fractures; chips; dislocations; foreign bodies in eyes; cuts and lacerations; punctures; burns/scalds; crushings; chemical, electrical, and laser burns; and fatalities. See footnote 13 for more details on this injury category.

Table 2: Effect of Union Status on Injury Frequency: Baseline Models

Specification:	**Baseline (Hours Worked)**		**Employees**		**Tonnage**	
Mine/Controller Size Units:	100 Quarterly FTEs		100 Employees		Millions of Tons	
Version:	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Non-Traumatic Injury Model	1.359***	1.269***	1.381***	1.299***	1.367***	1.290***
	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)	(0.09)
Total Injury Model	1.157***	1.056	1.170***	1.072	1.144***	1.045
	(0.05)	(0.07)	(0.05)	(0.07)	(0.05)	(0.06)
Traumatic Injury Model	0.774***	0.696***	0.774***	0.695***	0.764***	0.683***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
# of Observations	38,890	24,593	38,890	24,593	38,890	24,593
# of Union Mines / # of Total Mines	355 / 2,635	186 / 1,684	355 / 2,635	186 / 1,684	355 / 2,635	186 / 1,684
Fatality Model	0.346***	0.421*	0.358***	0.437*	0.369***	0.424**
	(0.13)	(0.19)	(0.13)	(0.20)	(0.13)	(0.18)
# of Observations	11,045	6,948	11,045	6,948	11,045	6,948
# of Union Mines / # of Total Mines	352 / 2,568	182 / 1,644	352 / 2,568	182 / 1,644	352 / 2,568	182 / 1,644

*Significance levels: *** 1%, ** 5%, * 10%. Standard errors, clustered at the mine level, are shown in parentheses.*
Results Presented: The table reports IRR (incidence rate ratio)[a] coefficients on the union indicator variables in negative binomial regression models. Hours worked is the exposure term.
Definitions: A quarterly FTE is defined as 500 hours worked.
Unit of Observation: The unit of observation is the mine-quarter for the non-traumatic, total, and traumatic injuries regressions. The unit of observation is the mine-year for fatality regressions.
Dependent Variables: The dependent variables are counts of injuries of each type (specified in the far-left column) that occur underground. *Traumatic injuries* are defined to include the following: amputations; enucleations; fractures; chips; dislocations; foreign bodies in eyes; cuts and lacerations; punctures; burns/scalds; crushings; chemical, electrical, and laser burns; and fatalities. (See footnote 13 for more details on the definition on traumatic injuries.) The sum of traumatic and non-traumatic injuries comprises *total injuries*.
Independent Variables: All models include the following regressors: union dummy, mine size (a continuous variable whose units are specified in column header), union X mine size, logged controller size (a continuous variable whose units are specified in column header), mine age, mine productivity, total lost-work injuries (in hundreds) during previous calendar year (for fatality models) or previous four quarters (for non-fatality models), total penalty points (in thousands) during previous calendar year (for fatality models) or previous four quarters (for non-fatality models), dummies indicating presence of each respective mine subunit, quarter/year dummies, district dummies, and a constant term. Public-fields versions also include a longwall indicator. Confidential-fields versions also include the number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production

as a percentage of total production, recoverable coal reserves, and mining method percentages. See Appendix C for complete variable definitions. An expanded version of this table, including a full covariate report, is available at http://amorantz.stanford.edu/papers/union-coal-mine-safety/.

Sample: The sample consists of underground bituminous coal mines with positive coal production and positive hours worked. The public-fields versions contain mine-quarters from 1993–2010, whereas the confidential-fields versions are restricted to 1998–2010. Because the historical variables (lost-work injuries and penalty points) are summed up over the previous four *quarters* in the non-traumatic, total, and traumatic injuries regressions but are summed up over the previous *calendar year* in the fatality regressions, some mines excluded from the fatality models are included in the other models. For example, if a mine is open for all of only one calendar year, it will have no historical data at the *yearly* level, but it will have historical data for three of the four *quarters* it was open. The number of union mines is computed by counting the mines that were unionized for any of the mine-quarters in the sample period. The number of total mines is computed by counting each mine in the sample, regardless of union status.

[a] A coefficient of 1 indicates no change at all in predicted injuries; coefficients between 0 and 1 represent a predicted fall in injuries (e.g. a coefficient of 0.97 represents a 3% decline); and coefficients greater than one represent predicted increases (e.g. a coefficient of 1.03 represents a 3% rise).

Table 3: Effect of Union Status on Injury Frequency: Discrete Size Groups

	Non-Traumatic Injuries	Total Injuries	Traumatic Injuries	Fatalities
Union X Size Quartile 1	1.222	1.227*	1.223	0.000***
	(0.16)	(0.14)	(0.19)	(0.00)
Union X Size Quartile 2	1.237***	1.171**	0.988	0.321
	(0.10)	(0.08)	(0.09)	(0.32)
Union X Size Quartile 3	1.424***	1.196***	0.815***	0.824
	(0.12)	(0.08)	(0.05)	(0.51)
Union X Size Quartile 4	1.250***	0.999	0.695***	0.307***
	(0.07)	(0.05)	(0.04)	(0.09)
Observations	38,890	38,890	38,890	11,045
# of Union Mines / # of Total Mines	355 / 2,635	355 / 2,635	355 / 2,635	352 / 2,568

*Significance levels: *** 1%, ** 5%, * 10%. Standard errors, clustered at the mine level, are shown in parentheses.*
Results Presented: The table reports IRR (incidence rate ratio)[a] coefficients on the union indicator variables in negative binomial regression models. Hours worked is the exposure term.
Definitions: A quarterly FTE is defined as 500 hours worked.
Unit of Observation: The unit of observation is the mine-quarter for the non-traumatic, total, and traumatic injuries regressions. The unit of observation is the mine-year for fatality regressions.
Dependent Variables: The dependent variables are counts of injuries of each type (specified in the top row) that occur underground. *Traumatic injuries* are defined to include the following: amputations; enucleations; fractures; chips; dislocations; foreign bodies in eyes; cuts and lacerations; punctures; burns/scalds; crushings; chemical, electrical, and laser burns; and fatalities. (See footnote 13 for more details on the definition on traumatic injuries.) The sum of traumatic and non-traumatic injuries comprises *total injuries*.
Independent Variables: All specifications presented above rely exclusively on regressors that are publicly available. In addition to discrete union-size interaction terms, all models include the following regressors: size quartiles (as determined by total FTEs), logged controller size (a continuous variable reflecting the controller's total number of FTEs), mine age, mine productivity, total lost-work injuries (in hundreds) during previous calendar year (for the fatality model) or previous four quarters (for non-fatality models), total penalty points (in thousands) during previous calendar year (for the fatality model) or previous four quarters (for non-fatality models), dummies indicating presence of each respective mine subunit, quarter/year dummies, district dummies, longwall indictor, and a constant term. See Appendix C for complete variable definitions. An expanded version of this table, including a full covariate report, is available at http://amorantz.stanford.edu/papers/union-coal-mine-safety/.
Sample: The sample consists of underground bituminous coal mines with positive coal production and positive hours worked from 1993–2010. Because the historical variables (lost-work injuries and penalty points) are summed up over the previous four *quarters* in the non-traumatic, total, and traumatic injuries regressions but are summed up over the previous *calendar year* in the fatality regressions, some mines excluded from the fatality models are included in the other models. For example, if a mine is open for all of only one calendar year, it will have no historical data at the *yearly* level, but it will have historical data for three of the four *quarters* it was open. The number of union mines is computed by counting the mines that were unionized for any of the mine-quarters in the sample period. The total number of mines is computed by counting each mine in the sample, regardless of union status.
[a] A coefficient of 1 indicates no change at all in predicted injuries; coefficients between 0 and 1 represent a predicted fall in injuries (e.g. a coefficient of 0.97 represents a 3% decline); and coefficients greater than one represent predicted increases (e.g. a coefficient of 1.03 represents a 3% rise).

Table 4: Effect of Union Status on Injury Frequency: Time Trend

Model	FTE Public (Baseline)	1993-1998	1999-2004	2005-2010
Non-Traumatic Injury Model	1.359*** (0.07)	1.504*** (0.09)	1.243** (0.12)	1.283** (0.16)
Total Injury Model	1.157*** (0.05)	1.320*** (0.07)	1.052 (0.09)	1.003 (0.10)
Traumatic Injury Model	0.774*** (0.04)	0.919 (0.06)	0.673*** (0.06)	0.698*** (0.08)
Observations	38,890	16,629	11,460	10,801
# of Union Mines / # of Total Mines	355 / 2,635	294 / 1,765	129 / 1,141	65 / 928
Fatality Model	0.346*** (0.13)	0.378* (0.19)	0.331* (0.20)	0.555 (0.38)
Observations	11,045	4,763	3,308	2,974
# of Union Mines / # of Total Mines	352 / 2,568	290 / 1,690	128 / 1,093	65 / 903

*Significance levels: *** 1%, ** 5%, * 10%. Standard errors, clustered at the mine level, are shown in parentheses.*
Results Presented: The table reports IRR (incidence rate ratio)[a] coefficients on the union indicator variables in negative binomial regression models. Hours worked is the exposure term. The “FTE Public (Baseline)” column contains coefficient estimates from the principal baseline models (using 100 quarterly FTEs as the size measure and relying exclusively on public data) presented in Table 2. The results presented in the other three columns correspond, respectively, to coefficient estimates from identical models run on six-year subsamples.
Definitions: A quarterly FTE is defined as 500 hours worked.
Unit of Observation: The unit of observation is the mine-quarter for the non-traumatic, total, and traumatic injuries regressions. The unit of observation is the mine-year for fatality regressions.
Dependent Variables: The dependent variables are counts of injuries of each type (specified in the far-left column) that occur underground. *Traumatic injuries* are defined to include the following: amputations; enucleations; fractures; chips; dislocations; foreign bodies in eyes; cuts and lacerations; punctures; burns/scalds; crushings; chemical, electrical, and laser burns; and fatalities. (See footnote 13 for more details on the definition on traumatic injuries.) The sum of traumatic and non-traumatic injuries comprises *total injuries*.
Independent Variables: All specifications presented above rely exclusively on regressors that are publicly available. All models include the following regressors: union dummy, mine size (a continuous variable reflecting the mine’s total number of FTEs) , union X mine size, logged controller size (a continuous variable reflecting the controller’s total number of FTEs), mine age, mine productivity, total lost-work injuries (in hundreds) during previous calendar year (for fatality models) or previous four quarters (for non-fatality models), total penalty points (in thousands) during previous calendar year (for fatality models) or previous four quarters (for non-fatality models), dummies indicating presence of each respective mine subunit, quarter/year dummies, district dummies, a longwall indicator, and a constant term. See Appendix C for complete variable definitions. An expanded version of this table, including a full covariate report, is available at http://amorantz.stanford.edu/papers/union-coal-mine-safety/.
Sample: The sample consists of underground bituminous coal mines with positive coal production and positive hours worked from 1993–2010. Because the historical variables (lost-work injuries and penalty points) are summed up over the previous four *quarters* in the non-traumatic, total, and traumatic injuries regressions but are summed up over the previous *calendar year* in the fatality regressions, some mines excluded from the fatality models are included in the other models. For example, if a mine is open for all of only one calendar year, it will have no

historical data at the *yearly* level, but it will have historical data for three of the four *quarters* it was open. The number of union mines is computed by counting the mines that were unionized for any of the mine-quarters in the sample period. The total number of mines is computed by counting each mine in the sample, regardless of union status.

[a] A coefficient of 1 indicates no change at all in predicted injuries; coefficients between 0 and 1 represent a predicted fall in injuries (e.g. a coefficient of 0.97 represents a 3% decline); and coefficients greater than one represent predicted increases (e.g. a coefficient of 1.03 represents a 3% rise).

Appendix Table A1: Characteristics of Underground, Bituminous Coal Mines: Sample Means

Variable	*Union Mean*	*Nonunion Mean*	**Variable**	*Union Mean*	*Nonunion Mean*
Total sample size[a]			**Mine characteristics**		
Mine-quarters	5,689	33,201	Mine age (in years)	17.15	6.89
Mines[b]	355	2,444		(16.44)	(7.72)
Injury Rates (per			Productivity	7.41	6.93
annual FTE)				(4.05)	(4.59)
Total injuries	0.1295	0.1076			
	(0.1714)	(0.2676)	Percent Captive	0.0798	0.0738
Traumatic injuries	0.0357	0.0397	Production	(0.2582)	(0.2563)
	(0.0357)	(0.0397)			
Non-traumatic injuries	0.0937	0.0679	Subsidiary indicator	0.3529	0.2062
	(0.1413)	(0.1743)		(0.4779)	(0.4046)
Fatalities	0.0003	0.0010			
	(0.0062)	(0.0537)	Longwall indicator	0.3146	0.0408
				(0.4644)	(0.1978)
Mine and Controller					
Size Measures			Subunits contained[c]		
Mine FTEs	194.68	58.76	*Surface*	0.8613	0.8272
	(207.44)	(87.40)		(0.3457)	(0.3781)
Size Quartile 1	9.77	9.87	*Mill or prep plant*	0.2781	0.0439
	(4.12)	(4.44)		(0.4481)	(0.2048)
Size Quartile 2	26.36	25.39			
	(5.28)	(5.32)	Mining method		
Size Quartile 3	51.53	49.33	percentages		
	(10.57)	(10.12)	*Conventional*	0.0755	0.1625
Size Quartile 4	320.67	179.18		(0.2641)	(0.3675)
	(200.23)	(135.64)	*Continuous*	0.6552	0.7763
				(0.4262)	(0.4088)
Mine Employees	176.65	51.91	*Longwall*	0.664	0.0341
	(181.42)	(73.47)		(0.3895)	(0.1644)
			Shortwall	0.0019	0.0001
Mine Tonnage	368,828	123,184		(0.0379)	(0.0110)
	(459,803)	(267,355)			
			Geological features		
Controller FTEs	1,451.81	632.69	Number of Coal beds	1.0197	0.9999
	(1,910.59)	(1,146.56)		(0.1537)	(0.1811)
Controller employees	1,292.98	542.75	Mean coal bed	0.9227	0.8483
	(1,673.56)	(980.04)	thickness (in yards)	(0.8580)	(0.713)
Controller tonnage	3,125,170	1,296,810	Recoverable reserves	19,593	6,857
	(4,624,872)	(2,556,860)	(in millions of tons)	(31,958)	(27,711)

Results Presented: Table contains mean values for all mine quarters in each group; standard deviations are in parentheses. See Appendix C for complete variable definitions.

[a] Total sample sizes represent counts (of mine-quarters and of mines, respectively) as opposed to mean values.

[b] Because a mine that was unionized for part of the sample period and nonunionized for part of the sample period is counted here as both a union mine and a nonunion mine, some mines are double counted for a total of 2,799

mines. The total number of mines used in the baseline regressions is 2,635. The difference between these two numbers, 164 mines, is the number of mines that switched union status at some point during the sample period. These are the mines that are included in the fixed effects models in Appendix Table A3.

[c] Only descriptive statistics for the surface and the mill or prep plant subunits are shown here. Other subunits include auger subunit; culm-refuse subunit; dredge subunit; independent shops or yard subunit; strip, quarry, or pit subunit; underground subunit; and other subunits. Descriptive statistics for all ten subunits are available on the *Companion Website* (http://amorantz.stanford.edu/papers/union-coal-mine-safety/).

Appendix Table A2: Effect of Union Status on Injury Frequency: Expanded Covariate Report for Baseline, Public-Fields Specifications

	Non-Traumatic Injury Model	Total Injury Model	Traumatic Injury Model	Fatality Model
Union	1.335***	1.143***	0.780***	0.346***
	(0.07)	(0.05)	(0.04)	(0.13)
Union X Size	0.975	0.962**	0.982	1.019
	(0.02)	(0.02)	(0.02)	(0.03)
Mine Size	0.869***	0.890***	0.925***	0.899***
	(0.02)	(0.02)	(0.02)	(0.03)
Log of Controller Size	0.943***	0.985**	1.047***	1.021
	(0.01)	(0.01)	(0.01)	(0.06)
Mine Age	0.999	0.999	0.999	1.007
	(0.00)	(0.00)	(0.00)	(0.01)
Productivity	0.994	0.997	0.997	0.942***
	(0.00)	(0.00)	(0.00)	(0.02)
Lost-Day Injuries in Prev. Year	1.000***	1.000***	1.000***	1.000
	(0.00)	(0.00)	(0.00)	(0.00)
Penalty Points in Prev. Year	1.000***	1.000***	1.000***	1.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Longwall Indicator	0.914	0.898*	0.919	1.569
	(0.05)	(0.05)	(0.07)	(0.54)
Mining Subunit Dummies[a]	Y	Y	Y	Y
District Fixed Effects[a]	Y	Y	Y	Y
Quarter/Year Fixed Effects[a]	Y	Y	Y	Y
Observations	38,905	38,905	38,905	11,045
# of Union Mines / # of Total Mines	355 / 2,639	355 / 2,639	355 / 2,639	352 / 2,568

*Significance levels: *** 1%, ** 5%, * 10%. Standard errors, clustered at the mine level, are shown in parentheses.*
Results Presented: The information presented in this table is identical to that presented in the Baseline/Public-Fields column of Table 2, but includes additional coefficient estimates. Each value represents the IRR (incidence rate ratio)[a] coefficient on an independent variable in a negative binomial regression model. Hours worked is the exposure term.
Definitions: A quarterly FTE is defined as 500 hours worked.
Unit of Observation: The unit of observation is the mine-quarter for the non-traumatic, total, and traumatic injuries regressions. The unit of observation is the mine-year for fatality regressions.
Dependent Variables: The dependent variables are counts of injuries of each type (specified in the top row) that occur underground. *Traumatic injuries* are defined to include the following: amputations; enucleations; fractures; chips; dislocations; foreign bodies in eyes; cuts and lacerations; punctures; burns/scalds; crushings; chemical, electrical, and laser burns; and fatalities. (See footnote 13 for more details on the definition on traumatic injuries.) The sum of traumatic and non-traumatic injuries comprises *total injuries*.
Independent Variables: All models include the following regressors: union dummy, mine size (a continuous variable reflecting the mine's total number of FTEs), union X mine size, logged controller size (a continuous variable reflecting the controller's total number of FTEs), mine age, mine productivity, total lost-work injuries (in hundreds)

during previous calendar year (for fatality models) or previous four quarters (for non-fatality models), total penalty points (in thousands) during previous calendar year (for fatality models) or previous four quarters (for non-fatality models), dummies indicating presence of each respective mine subunit, quarter/year dummies, district dummies, longwall indicator, and a constant term. See Appendix C for complete variable definitions. An expanded version of this table, including a complete covariate report, is available at http://amorantz.stanford.edu/papers/union-coal-mine-safety/.
Sample: The sample consists of underground bituminous coal mines with positive coal production and positive hours worked, including all mine-quarters from 1993–2010. Because the historical variables (lost-work injuries and penalty points) are summed up over the previous four *quarters* in the non-traumatic, total, and traumatic injuries regressions but are summed up over the previous *calendar year* in the fatality regressions, some mines excluded from the fatality models are included in the other models. For example, if a mine is open for all of only one calendar year, it will have no historical data at the *yearly* level, but it will have historical data for three of the four *quarters* it was open. The number of union mines is computed by counting the mines that were unionized for any of the mine-quarters in the sample period. The total number of mines is computed by counting each mine in the sample, regardless of union status.
[a] A coefficient of 1 indicates no change at all in predicted injuries; coefficients between 0 and 1 represent a predicted fall in injuries (e.g. a coefficient of 0.97 represents a 3% decline); and coefficients greater than one represent predicted increases (e.g. a coefficient of 1.03 represents a 3% rise).

APPENDIX TABLE A3: FIXED EFFECTS MODELS

Specification:	**Baseline (Hours Worked)**		**Employees**		**Tonnage**	
Mine/Controller Size Units:	100 Quarterly FTEs		100 Employees		Millions of Tons	
Version:	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Non-Traumatic Injury Model	1.374***	1.091	1.385***	1.101	1.440***	1.103
	(0.14)	(0.15)	(0.14)	(0.15)	(0.13)	(0.12)
Total Injury Model	1.208**	1.056	1.205**	1.066	1.258***	1.063
	(0.09)	(0.11)	(0.09)	(0.12)	(0.09)	(0.09)
Traumatic Injury Model	0.896	1.037	0.882	1.058	0.971	1.032
	(0.09)	(0.12)	(0.09)	(0.14)	(0.08)	(0.10)
# of Observations	4,075	1,558	4,075	1,558	4,075	1,558
# of Union Mines / # of Total Mines	164 / 164	79 / 79	164 / 164	79 / 79	164 / 164	79 / 79
Fatality Model	0.381**	5.067	0.386**	2.607	0.423**	. [a]
	(0.17)	(9.08)	(0.17)	(3.88)	(0.18)	.
# of Observations	1,082	412	1,082	412	1,082	412
# of Union Mines / # of Total Mines	151 / 151	71 / 71	151 / 151	71 / 71	151 / 151	71 / 71

*Significance levels: *** 1%, ** 5%, * 10%. Standard errors, clustered at the mine level, are shown in parentheses.*

Limitations of Fixed Effects Model: Only a small proportion of underground coal mines (6.2%) changed union status during the period examined (1993-2010). Those that did change union status seem to be highly unrepresentative of the population as a whole: at least 19% of coal mines that de-unionized and 78% of mines that became unionized during the sample period experienced major disruptions (defined as production, employment, or hours worked dropping by over 50%; a year or more of inactivity; or change of the mine operator or mine controller) during the year when the transition took place. Any analysis predicated upon this idiosyncratic subgroup is likely to yield biased estimates of unionization's true effect, which is why I place this table in an appendix.

Results Presented: The table reports IRR (incidence rate ratio)[b] coefficients on the union indicator variables in negative binomial regression models. Hours worked is the exposure term.

Definitions: A quarterly FTE is defined as 500 hours worked.

Unit of Observation: The unit of observation is the mine-quarter for the non-traumatic, total, and traumatic injuries regressions. The unit of observation is the mine-year for fatality regressions.

Dependent Variables: The dependent variables are counts of injuries of each type (specified in the top row) that occur underground. *Traumatic injuries* are defined to include the following: amputations; enucleations; fractures; chips; dislocations; foreign bodies in eyes; cuts and lacerations; punctures; burns/scalds; crushings; chemical, electrical, and laser burns; and fatalities. (See footnote 13 for more details on the definition on traumatic injuries.) The sum of traumatic and non-traumatic injuries comprises *total injuries*.

Independent Variables: All models include the following regressors: union dummy, mine size (a continuous variable whose units are specified in column header), union X mine size, logged controller size (a continuous

variable whose units are specified in column header), mine age, mine productivity, total lost-work injuries (in hundreds) during previous calendar year (for fatality models) or previous four quarters (for non-fatality models), total penalty points (in thousands) during previous calendar year (for fatality models) or previous four quarters (for non-fatality models), dummies indicating presence of each respective mine subunit, quarter/year dummies, district dummies, and a constant term. Public-fields versions also include a longwall indicator. Confidential-fields versions also include the number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See Appendix C for complete variable definitions. An expanded version of this table, including a full covariate report, is available at http://amorantz.stanford.edu/papers/union-coal-mine-safety/.
Sample: The sample consists of underground bituminous coal mines with positive coal production and positive hours worked that switched union status at some point during the sample period. The public-fields versions contain mine-quarters from 1993–2010, whereas the confidential-fields versions are restricted to 1998–2010. Because the historical variables (lost-work injuries and penalty points) are summed up over the previous four *quarters* in the non-traumatic, total, and traumatic injuries regressions but are summed up over the previous *calendar year* in the fatality regressions, some mines excluded from the fatality models are included in the other models. For example, if a mine is open for all of only one calendar year, it will have no historical data at the *yearly* level, but it will have historical data for three of the four *quarters* it was open.
[a] Of the 412 mine-years in our sample for the confidential-fields version of the tonnage specification (rightmost column above), there were only 10 fatalities, which occurred in 5 unionized mine-years and 5 nonunionized mine-years. Because of the small sample size and lack of significant variation, the negative binomial regression did not converge for this model.
[b] A coefficient of 1 indicates no change at all in predicted injuries; coefficients between 0 and 1 represent a predicted fall in injuries (e.g. a coefficient of 0.97 represents a 3% decline); and coefficients greater than one represent predicted increases (e.g. a coefficient of 1.03 represents a 3% rise).

APPENDIX B: DESCRIPTION OF MODEL SPECIFICATIONS

The list below describes the three specifications and two versions that are included in Table 2.

Hours Worked (Baseline) Specification: Mine **s**ize is measured in units of 100 quarterly FTEs. Controller size is measured by the log of hours worked across all mines controlled by that controller, in units of 100 quarterly FTEs.

Employees Specification: Mine size is measured in hundreds of employees. Controller size is measured by the log of employees across all mines controlled by that controller, in hundreds of employees.

Tonnage Specification: Mine size is measured in millions of tons. Controller size is measured by the log of tonnage across all mines controlled by that controller, in millions of tons.

Public-Fields Version: All models include the following regressors: union dummy, union-size interaction term, mine size measure (defined as specified in column headers or the table note), logged controller size measure (defined as specified in column headers or the table note), mine age, mine productivity, number of lost-work injuries (in hundreds) in the previous calendar year (for fatality models) or previous four quarters (for non-fatality models), total penalty points (in thousands in the previous calendar year (for fatality models) or previous four quarters (for non-fatality models), a constant term, dummies indicating presence of each type of mine subunit, quarter/year dummies, district dummies, and a longwall indicator.

Confidential-Fields Version: All models include the following regressors: union dummy, union-size interaction term, mine size measure (defined as specified in column headers or the table note), logged controller size measure (defined as specified in column headers or the table note), mine age, mine productivity, number of lost-work injuries (in hundreds) in the previous calendar year (for fatality models) or previous four quarters (for non-fatality models), total penalty points (in thousands) in the previous calendar year (for fatality models) or previous four quarters (for non-fatality models), a constant term, dummies indicating presence of each type of mine subunit, quarter/year dummies, district dummies, number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and the mining method percentages.

Appendix C: Variable Dictionary

Variable Name	Variable Definition	Source
Non-traumatic injuries	Total number of injuries not classified as traumatic	MSHA
Total injuries	Total number of injuries and fatalities reported	MSHA
Traumatic injuries	A subset of injuries that are least prone to reporting bias (see footnote 13)	MSHA
Fatalities	Total number of fatalities reported	MSHA
District dummies	1 if mine is located in a given MSHA district, 0 otherwise	MSHA
Ln (Controller Size)	Log of controller size measure. Controller size measure is either 100 FTEs, 100 employees, or one million tons	MSHA
Lost-workday injuries	Lost-workday injuries are those that result in time lost from work. When included as a regressor, it is the number of such injuries in the previous calendar year (for fatality models) or previous four quarters (for non-fatality models), in hundreds.	MSHA
Mine age	Age of mine in years since the first operator began work at the mine (top censored at 1970)	MSHA
Penalty Points	Thousands of penalty points in the previous calendar year (for fatality models) or previous four quarters (for non-fatality models)	MSHA
Productivity	Thousands of tons of coal produced per annual FTE (2,000 hours)	MSHA
Quarter/year indicators	1 if observation is for a given year or quarter, 0 otherwise	MSHA
Size Measure	Size measure is either 100 FTEs, 100 employees, or one million tons	MSHA
Subunit indicator	1 if mine contains a given subunit, 0 otherwise Subunit types include e.g. “surface” and “mill or prep plant”	MSHA
Mean coal bed thickness	The mean thickness of all coal beds at the mine, in yards	EIA[a]

Mining method percentages	Proportion of underground operation that uses a given mining method, expressed as fraction between 0 and 1; types include conventional, continuous, longwall, shortwall, and other	EIA
Number of coal beds	Number of coal beds at the mine site	EIA[a]
Percent captive production	Percent of production for mine or parent company's own use	EIA[a,b]
Recoverable reserves	Estimated tonnage of remaining coal reserves	EIA[a,b]
Subsidiary indicator	1 if mine is a subsidiary of a larger firm, 0 otherwise	EIA[a]
Union indicator	1 if mine is unionized, 0 otherwise	EIA
Longwall Indicator	1 if mine is a longwall mine, 0 otherwise	NIOSH

Source: MSHA inspection records, 1993–2010; EIA coal mine data 1993–2010; NIOSH coal mine data 1993–2010.

[a] These data fields were obtained on a confidential basis, and are considered trade secrets by the companies that provided them.

[b] These data fields are unavailable prior to 1998.

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DOES UNIONIZATION STRENGTHEN REGULATORY ENFORCEMENT? AN EMPIRICAL STUDY OF THE MINE SAFETY AND HEALTH ADMINISTRATION

*Alison Morantz**

Introduction

Often described as "the day the New Deal began,"[1] the catastrophic blaze at the Triangle Shirtwaist Factory helped usher in a new era of state and federal regulation. The next century witnessed the pas-

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1. *See, e.g.*, *The Birth of the New Deal*, Economist, Mar. 17, 2011, at 39 (attributing quote to Secretary of Labor Frances Perkins, who designed many of the social welfare programs that became hallmarks of the New Deal); Jodie T. Allen, *A Century After Triangle, Unions Face Uncertain Future,* Pew Res. Center (Mar. 23, 2011), http://pewresearch.org/databank/dailynumber/?NumberID=1217 (attributing quote to Frances Perkins); Bjorn Claeson, *Century After Historic Fire, Focus is On Worker Safety*, Hous. Chron., (Mar. 25, 2011) http://www.chron.com/opinion/outlook/article/Century-after-historic-fire-focus-is-on-worker-1684355.php (attributing quote to Frances Perkins).

sage of the Coal Mine Health and Safety Act of 1969,[2] the Occupational Safety and Health Act of 1970 (OSH Act),[3] the Federal Mine Safety and Health Act of 1977 (Mine Act),[4] the proliferation of state workers' compensation laws,[5] and a panoply of other legal reforms designed to mitigate the occupational hazards that an unfettered labor market posed to American workers.[6] Somewhat surprisingly, given their prominence in the federal regulatory firmament, the Occupational Safety and Health Administration (OSHA) and the Mine Safety and Health Administration (MSHA) have received relatively little empirical scrutiny. Numerous scholars have catalogued the shortcomings of administrative standards setting and rulemaking[7] or proposed legal reforms that might enhance the agencies' effectiveness.[8] However, only a handful of studies have scrutinized granular enforcement data in an effort to understand how inspectors "on the ground" carry out day-to-day tasks such as monitoring workplaces, citing violations, and assessing penalties.[9] This article contributes to the scant empirical

2. Pub. L. No. 91-173, 83 Stat. 792 (1969) (codified as amended at 30 U.S.C. §§ 901–45 (2006)).

3. Pub. L. No. 91-596, 84 Stat. 1590 (1970) (codified as amended at 29 U.S.C. §§ 651–78 (2006)).

4. Pub. L. No. 95-164, 91 Stat. 1290 (1977) (amended by Mine Improvement and New Emergency Response Act of 2006, Pub. L. No. 109-236).

5. *See* Price V. Fishback & Shawn Everett Kantor, *The Adoption of Workers' Compensation in the United States, 1900–1930*, 41 J.L. & ECON. 305, 320 (1998) (detailing the adoption of workers compensation laws in the United States).

6. For a description of the legislation passed in New York in the wake of the fire, see RICHARD A. GREENWALD, THE TRIANGLE FIRE, THE PROTOCOLS OF PEACE, AND INDUSTRIAL DEMOCRACY IN PROGRESSIVE ERA NEW YORK 161 (2005).

7. *See, e.g.*, John Howard, *OSHA Standards-Setting: Past Glory, Present Reality and Future Hope*, 14 EMPLOYEE RTS. & EMPL. POL'Y J. 237, 240–51 (2010); Thomas O. McGarity, *Some Thoughts on 'Deossifying' the Rulemaking Process*, 41 DUKE L.J. 1385, 1387–96 (1992); Stuart Shapiro, *The Role of Procedural Controls in OSHA's Ergonomic Rulemaking*, 67 PUB. ADMIN. REV. 688, 690 (2007).

8. *See, e.g.*, Jarod S. Gonzalez, *A Pot of Gold at the End of the Rainbow: An Economic Incentives-Based Approach to OSHA Whistleblowing*, 14 EMPLOYEE RTS. & EMPL. POL'Y J. 325, 326 (2010); César Cuauhtémoc García Hernández, *Feeble, Circular and Unpredictable: OSHA's Failure to Protect Temporary Workers*, 27 B.C. THIRD WORLD L.J. 193, 214–17 (2007); Adam J. Hiller & Leah E. Saxtein, *Falling Through the Cracks: The Plight of Domestic Workers and Their Continued Search for Legislative Protection*, 27 HOFSTRA LAB. & EMP. L.J. 233, 260–64 (2009); Jay Lapat & James P. Notter, *Inspecting the Mine Inspector: Why the Discretionary Function Exception Does Not Bar Government Liability for Negligent Mine Inspections*, 23 HOFSTRA LAB. & EMP. L.J. 413, 434–39 (2006); Brooke Lierman, *To Assure Safe and Healthful Working Conditions: Taking Lessons from Labor Unions to Fulfill OSHA's Promises*, 12 LOY. J. PUB. INT. L. 1, 32–36 (2010).

9. *See* Mary E. Deily & Wayne B. Gray, *Agency Structure and Firm Culture: OSHA, EPA, and the Steel Industry*, 23 J.L. ECON. & ORG. 685, 686–88 (2007); Wayne B. Gray & John Mendeloff, *The Declining Effects of OSHA Inspections on Manufacturing Injuries, 1979 to 1998*, 58 IND. LAB. REL. REV. 571, 575 (2005); Ali-

literature on the enforcement of occupational safety and health laws by examining whether the intensity, scope and stringency of MSHA's enforcement activities vary significantly across unionized and non-unionized underground coal mines.

Coal mine safety is an especially timely and fertile area of empirical inquiry. For much of the twentieth century, coal mining was one of the most dangerous occupations in the United States, and several recent, well-publicized mine explosions have highlighted the roles that federal regulatory enforcement and unionization can play in preventing catastrophic loss of life.[10] Yet the only prior study to examine whether a union's presence at a mine enhances the stringency of MSHA's regulatory enforcement relies upon data that is decades out of date.[11] Moreover, recent empirical scholarship on the "union safety effect"—linking mine unionization to lower rates of fatal and traumatic injuries[12]—raises the question of whether organized labor could affect the intensity of MSHA's enforcement scrutiny.

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son Morantz, *Has Regulatory Devolution Injured American Workers? State and Federal Enforcement of Construction Safety*, 25 J.L. Econ. & Org. 183, 190–94 (2009); David Weil, *Are Mandated Health and Safety Committees Substitutes For or Supplements To Labor Unions?*, 52 Indus. Lab. Rel. Rev. 339, 346 (1999) [hereinafter Weil, *Mandated Health and Safety Committees*]; David Weil, *Assessing OSHA Performance: New Evidence From the Construction Industry,* 20 Pol'y Analysis & Mgmt. 651, 654 (2001) [hereinafter Weil, *Assessing OSHA Performance*]; David Weil, *Building Safety: The Role of Construction Unions in the Enforcement of OSHA,* 12 J. Lab. Res. 121, 123–24 (1992) [hereinafter Weil, *Building Safety*]; David Weil, *Enforcing OSHA, The Role of Labor Unions*, 30 Indus. Rel. 20, 25–28 (1991) [hereinafter Weil, *Enforcing OSHA*].

10. *See, e.g.*, Carrie Coolidge, *The Most Dangerous Jobs in America: Recent West Virginia Mining Tragedy a Reminder of Unsafe Occupations*, Forbes, Jan. 5, 2006, http://www.msnbc.msn.com/id/10725454/ns/business-forbes_com/t/most-dangerous-jobs-america/ (noting that according to data from the Bureau of Labor Statistics, the mining industry has the second-highest fatality rate per 100,000 employees); John Holusha, *Sago Mine Hearing Opens with Questions*, N.Y. Times, May 2, 2006, http://www.nytimes.com/2006/05/02/us/02cnd-mine.html (describing emotional testimony by relatives of twelve miners killed by the explosion of Sago Mine on January 2, 2006); Ian Urbina, *Call for Criminal Inquiry Into Deadly Mine Collapse*, N.Y. Times, May 9, 2008, at A25 (describing the results of an independent investigation into the death of nine miners as a result of the collapse of Crandall Canyon mine in August 2007); Ian Urbina, *No Survivors Found After West Virginia Mine Disaster*, N.Y. Times, Apr. 9, 2010, at A1 (describing an explosion at Upper Big Branch mine in West Virginia, which killed twenty-nine miners) [hereinafter Urbina, *No Survivors Found*].

11. David Weil, Government and Labor at the Workplace: The Role of Labor Unions in the Implementation of Federal Health and Safety Policy 23–43, 120–34 (May 13, 1987) (unpublished Ph.D dissertation, Harvard University) (on file with author) [hereinafter Weil, Government and Labor at the Workplace].

12. Alison Morantz, *Coal Mine Safety: Do Unions Make a Difference?* (Stanford Law Sch. Law & Econ. Olin Paper Series, Paper No. 413, 2011), *available at* http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1846700 (finding that unionized mines

This article probes three closely intertwined questions. First, do the frequency, distribution, intensity, and/or scope of MSHA inspections differ significantly across union and non-union mines? Second, do conventional metrics of regulatory enforcement stringency and compliance—such as the frequency of violations and the magnitude of penalties—vary by union status? Finally, do such disparities (if any) seem likely to explain the "union safety effect" reported in recent empirical scholarship?

The analysis reveals, first, that unionization predicts significantly greater frequency, duration, and intensity of MSHA inspections. Second, unionization correlates with a significant rise in the average fine assessed for non-trivial violations. However, both of these disparities diminish sharply with mine size, whereas the union, non-union differential in traumatic and fatal injuries is most robust and pronounced among large mines. Therefore, the disparities in enforcement behavior reported here do not seem to fully explain the "union safety effect" identified in prior scholarship.

The remainder of the article is organized as follows. Part I summarizes existing literature on the relationship between regulatory enforcement, mine safety, and unionization. Part II provides a brief overview of how MSHA inspectors implement their statutory duties. Part III describes the data and empirical methodology upon which the analysis relies, and Part IV presents the results. The concluding section, Part V, highlights the study's key findings, discusses its implications, and identifies several promising areas for future research.

I.
Summary of Prior Scholarship on the Impact of Unionization on Regulatory Enforcement

Scholars have identified a variety of mechanisms whereby unions can increase the quantity and intensity of regulatory enforcement.[13]

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report fewer fatalities and traumatic injuries per hour than non-unionized mines) [hereinafter Morantz, *Coal Mine Safety*].

13. *See, e.g.*, Thomas Kochan et al., The Effectiveness of Union-Management Safety and Health Committees 85 (1977); Richard Brown, *Unions, Markets and Other Regulatory Mechanisms: Theory and Evidence,* 44 U. Toronto L.J. 1, 38–39 (1995) (suggesting means through which unionization may increase regulatory implementation); Neil Gunningham, *Occupational Health and Safety, Worker Participation, and the Mining Industry in a Changing World of Work*, 29 Econ. & Indus. Democracy 336, 338–39 (2008) (suggesting that unionized workers are more likely to voice concerns and call for inspections); Robert Stewart Smith, *Greasing the Squeaky Wheel: The Relative Productivity of OSHA Complaint Inspections*, 40 Indus. & Lab. Rel. Rev. 35, 44 (1986) (arguing that regulatory complaints are more likely to come from unionized entities); Weil, *Assessing OSHA Performance*, *supra* note 9,

For example, unions may increase the likelihood that inspections will take place by filing complaints with pertinent regulatory agencies.[14] Unions can also ensure that workers exercise their statutory rights by accompanying an inspector on his or her tour of the workplace and pointing out subtle hazards that might otherwise evade detection.[15] A number of empirical studies focusing on the manufacturing and construction industries support the hypothesis that unionization increases the quantity and intensity of regulatory enforcement.[16] Several other studies of U.S., Australian, and Canadian workplaces also indirectly lend credence to this claim.[17]

Only one prior empirical study has probed whether MSHA enforcement and compliance patterns differ across union and non-union coal mines.[18] The study reported that, in the early 1980s, union mines were more likely to designate employee representatives, received more frequent MSHA inspections of longer average duration, received more citations per inspection, were granted shorter periods in which to abate violations, were granted fewer abatement extensions, paid higher penalties per violation, and were less successful, as compared to non-union mines, in reducing penalty amounts through MSHA's

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at 656–57; Weil, *Mandated Health and Safety Committees*, *supra* note 9 (arguing that mandated health and safety committees increase OSHA enforcement to a greater extent in unionized workplaces than in non-unionized workplaces); Weil, *Building Safety*, *supra* note 9 (arguing that OSHA regulations are more stringently and effectively enforced on unionized construction sites than on non-unionized construction sites); Weil, *Enforcing OSHA*, *supra* note 9 (arguing that the rate of OSHA enforcement is much higher in large unionized workplaces than in comparable non-unionized workplaces in the manufacturing sector); Weil, Government and Labor at the Workplace, *supra* note 11 (arguing that unionization increases the quality of regulatory scrutiny under both OSHA and MSHA); Heather L. Grob, Self Regulation and Safety Programs in Construction 114, 131, 193 (July 1998) (unpublished Ph.D. dissertation, University of Notre Dame) (on file with Hesburgh Library, University of Notre Dame) (finding that OSHA enforcement is less important for workplaces with union safety programs because those programs are more successful than non-union safety programs).

14. *See* Alison Morantz, *The Elusive Union Safety Effect: Toward a New Empirical Research Agenda*, 61 LAB. & EMP. REL. ASS'N PROC. 130, 133–34 (2009) [hereinafter Morantz, *Elusive Union Safety Effect*].

15. *Id.* at 134.

16. *See, e.g.*, Weil, *Assessing OSHA Performance*, *supra* note 9, at 656–57; Weil, *Mandated Health and Safety Committees*, *supra* note 9, at 352–54; Weil, *Building Safety*, *supra* note 9, at 127–28; Weil, *Enforcing OSHA*, *supra* note 9, at 28–31.

17. Morantz, *Elusive Union Safety Effect*, *supra* note 14, at 135 (noting that several prior studies suggested that unionization increases the strictness and quality of regulatory scrutiny); Brown, *supra* note 13, at 38–39 (discussing Canada); Gunningham, *supra* note 13, at 338–39 (discussing Australia).

18. Weil, Government and Labor at the Workplace, *supra* note 11, at 107–85.

internal administrative appeals process.[19] These disparities were typically most pronounced among smaller mines.[20] On the basis of these findings, the study concludes that MSHA regulations were more stringently and effectively enforced at unionized mines.[21]

Although not focusing on MSHA's enforcement behavior, two recent studies find that unionization predicts a robust, sizable decline in the frequency of serious mining accidents. The first study, focusing on the early twentieth century, concludes that unionism significantly lowered the frequency of mining fatalities by at least twenty percent during this period.[22] Analyzing data from 1993–2009, the second study similarly finds that unionization predicts a sizable and statistically significant drop in traumatic injuries and fatalities, and that the magnitude of this "union safety effect" has—at least by some measures—grown since the turn of the millennium.[23] Neither study pinpoints the causal mechanisms driving these disparities, but the latter speculates that differences in MSHA's enforcement scrutiny could play a role.[24]

This article builds upon earlier scholarship by probing whether the disparities in enforcement behavior documented in the 1980s also characterize the more recent period (1995–2009). After comparing various indicia of regulatory oversight and compliance across the two settings, the article considers whether the findings could provide at least a partial explanation for the "union safety effect" reported in prior scholarship.

II.
Federal Enforcement of Safety Regulations in the Mining Industry

Although the first federal statute governing coal mine safety passed in 1891, Congress did not grant mine inspectors enforcement authority until 1952.[25] A series of statutory reforms in the latter half of the twentieth century gradually enlarged the scope of federal author-

19. *Id.* Although most of Weil's analysis relies on data from a single year (1982), several comparisons also include data from 1978, 1981, 1983, and 1985. *Id.*

20. *Id.* at 183.

21. *Id.* at 179.

22. William M. Boal, *The Effect of Unionism on Accidents in U.S. Coal Mining, 1897-1929*, 48 Ind. Rel. 97, 117 (2009).

23. Morantz, *Coal Mine Safety*, *supra* note 12, at 12.

24. *Id.* at 15.

25. *See* The Federal Coal Mine Safety Act of 1952, Pub. L. No. 82-552, 66 Stat. 692 (1952); *History of Mine Safety and Health Legislation*, Mine Safety & Health Admin., http://www.msha.gov/mshainfo/mshainf2.htm (last visited Sept. 7, 2011).

ity.[26] Most importantly, the Mine Act created MSHA to regulate and inspect coal, metal, and non-metal mines.[27]

MSHA is subdivided into two sections: one that oversees coal mines and another that oversees metal and non-metal mines.[28] The Coal Mine Safety and Health section is, in turn, divided into twelve districts encompassing approximately forty-five field offices located throughout the nation's coal-producing regions.[29] Inspectors at MSHA's field offices conduct several different types of inspections. The most frequent are "regular" inspections that must, under the Mine Act, be conducted four times per year at every underground coal mine.[30] Other inspection types include spot inspections (that focus on location(s) warranting special scrutiny), technical inspections of particular operational systems (such as ventilation or roof control), respirable dust monitoring inspections, post-accident investigations, and inspections triggered by employee complaints.[31]

Although the Mine Act's regulations specify that every violation of a mandatory health or safety standard "shall" trigger the assessment of a civil penalty,[32] the process whereby such penalties are calculated depends upon the type of assessment. Regular assessments—which are capped at $70,000[33] and averaged about $623 during the period analyzed[34]—are calculated using tables that assign penalty points

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26. *See, e.g.*, *History of Mine Safety and Health Legislation*, *supra* note 25.

27. MSHA describes its core statutory functions as follows:

> The Mine Act provides that MSHA inspectors shall inspect each surface mine at least 2 times a year and each underground mine at least 4 times a year (seasonal or intermittent operations are inspected less frequently) to determine whether there is compliance with health and safety standards or with any citation, order, or decision issued under the Mine Act, and whether an imminent danger exists. If violations of safety or health standards are found, inspectors will issue citations to the mine operators . . . [O]ther important mandatory activities [include] assessing and collecting civil monetary penalties for violations of mine safety and health standards . . . .

MSHA's Statutory Functions, Mine Safety & Health Admin., http://www.msha.gov/mshainfo/mshainf1.htm (last visited Sept. 7, 2011).

28. *See Organizational Chart*, Mine Safety & Health Admin., http://www.msha.gov/aboutmsha.htm (last visited Oct. 25, 2011).

29. *See Coal Mine Safety and Health*, Mine Safety & Health Admin., http://www.msha.gov/programs/coal.htm (last visited Sept. 7, 2011).

30. Federal Mine Safety and Health Act of 1977, Pub. L. No. 91-173, § 103, 83 Stat. 742, 749–50 (1969).

31. *Id.*

32. 30 C.F.R. § 100.3(a)(1) (2010).

33. § 100.3(a)(1).

34. Mine Safety & Health Admin., (Oct. 25, 2011) (unpublished electronic database, Stanford University) (on file with author) [hereinafter MSHA Data].

based on several statutorily mandated criteria.[35] Among these criteria are the size of the mine, the operator's history of prior violations and corresponding degree of negligence, the gravity of the violation and severity of any resulting injury, and whether the operator has made a good-faith effort to abate the hazard.[36] After calculating the total penalty points for a given violation, MSHA officials use a conversion table to determine the corresponding fine.[37]

The other two assessment types, "single" assessments and "special" assessments, are less common and permit MSHA officials considerably greater discretion when setting penalties. Single assessments, which ceased to exist in 2007,[38] are relatively nominal fines (averaging $60) levied for minor violations.[39] Special assessments are used in extraordinary circumstances that warrant a deviation from the usual formulaic approach—for example, to penalize egregiously deceptive conduct by a mine operator.[40] Unlike regular assessments, special assessments can, and frequently do, exceed $70,000.[41] Their mean value during the sample period was $7,024.[42]

Three other aspects of the penalty-assessment process merit detailed explanation. First, the negligence component of the penalty-point formula consists of a scale ranging from zero (no negligence) to fifty ("reckless disregard").[43] Only 1.8% of regular violations in the dataset receive a negligence rating of thirty-five or higher.[44] These are described henceforth as "high-negligence" violations, while those receiving a rating of ten or lower are described as "low-negligence" violations. A second important facet of the penalty-point calculation is whether a given violation caused, or was adjudged highly likely to cause, an injury. Slightly over 1% of regular violations in the dataset meet this criterion, a subset referred to as "likely-injury-causing" violations.[45] Finally, MSHA categorizes some violations as "significant

35. *See* § 100.3(a)(2).

36. § 100.3.

37. *Id.*

38. Criteria and Procedures for Proposed Assessment of Civil Penalties, 72 Fed. Reg. 13,592, 13,621 (Mar. 22, 2007) (deleting the single penalty assessment provision).

39. MSHA Data, *supra* note 34.

40. § 100.5 (2011).

41. *Id. See also* MSHA Data, *supra* note 34.

42. MSHA Data, *supra* note 34.

43. § 100.3.

44. MSHA Data, *supra* note 34.

45. MSHA Data, *supra* note 34.

and substantial" (S&S).[46] S&S violations are those for which, "based upon the particular facts surrounding the violation[,] there exists a reasonable likelihood that the hazard contributed to, or will result in, an injury or illness of a reasonably serious nature."[47] Approximately 38% of all violations and 66% of regular violations in the dataset are classified as S&S.[48] Although a violation's categorization as S&S does not affect its penalty points or its monetary assessment,[49] the designation can, under certain conditions, enable MSHA to take the extraordinary step of ordering all miners to vacate the mine section affected by the violation.[50]

III.
Explanation of Empirical Methodology and Description of Data Used

The dataset used here, which matches MSHA's inspection records to mine-level data obtained from the Department of Energy's Energy Information Administration (EIA) and the National Institute for Occupational Safety and Health (NIOSH), is nearly identical to that used in a previous study.[51] The MSHA portion of the dataset contains detailed inspection records—including cited violations and assessed penalties—for the years 1995–2009.[52] The EIA dataset, encompassing every coal mine in the U.S., includes information on union status, geological characteristics (such as mine age, number of coal beds, and coal bed thickness), the share of production attributable to various extraction techniques (such as conventional, continuous, longwall, shortwall, and other mining methods), and economic vari-

46. *See* Mine Safety and Health Admin., U.S. Dep't of Labor, Handbook No. PH08-I-1, Citation and Order Writing Handbook for Coal Mines and Metal and Nonmetal Mines 18 (2008), *available at* http://www.msha.gov/readroom/handbook/ph08-i-1.pdf.

47. *Id.*

48. MSHA Data, *supra* note 34.

49. *See* Mine Safety and Health Admin., U.S. Dep't of Labor, *Sago Mine Information Citation and Order Explanations*, http://www.msha.gov/sagomine/citationsandorders.asp (last visited Sept. 7, 2011) (describing the procedure for finding and recording S&S violations, which does not include an alteration of penalty points or monetary assessments).

50. *See* 30 U.S.C. §§ 814(d)(1), e(1) (2006).

51. *See* Morantz, *Coal Mine Safety*, *supra* note 12, at 5–8.

52. Although some records were available for years prior to 1995, MSHA officials indicated that the assessments file is incomplete for years prior to 1995. Therefore, in contrast to Morantz, *Coal Mine Safety*, *supra* note 12, all of the empirical analysis in this article commences in 2005. E-mail from Chad Hancher, Management and Program Analyst, Mine Safety and Health Admin., to Alison Morantz, Professor of Law, Stanford Law School (June 10, 2011) (on file with author).

ables (such as productive capacity and recoverable reserves) for the years 1995–2009.[53] The NIOSH dataset, available for the same time period, specifies whether each mine uses the longwall mining method and the MSHA district to which the mine belongs.[54] To ensure relative comparability across the mines examined, the analysis is restricted to underground, bituminous coal mines.

Importantly, the analysis presented here does not account for the potentially consequential role of independent contractors, whom mine operators may employ to perform specific functions within the mine. A report released by the West Virginia Governor's Independent Investigation Panel in May 2011, in the wake of the Upper Big Branch mining disaster,[55] suggests that the increase in contract mining significantly complicates regulators' task of identifying and correcting mine hazards.[56] Unfortunately, available data are insufficiently detailed to permit any empirical analysis of how many contractors a given mine utilizes, how intensively those contractors are inspected, or how much work they perform. Therefore, violations committed by independent contractors are excluded from the empirical analysis.[57]

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53. For more information on EIA and its reports, see U.S. ENERGY INFO. ADMIN., *Coal: All Reports*, http://www.eia.gov/coal/reports.cfm?t=9999&f=d (last visited Oct. 9, 2011).

54. For more information on NIOSH and its reports, see NAT'L INST. FOR OCCUPATIONAL SAFETY AND HEALTH, *NIOSH Office of Safety and Mine Research: Publications*, http://www.cdc.gov/niosh/mining/pubs/ (last visited Oct. 9, 2011).

55. *See* Urbina, *No Survivors Found*, *supra* note 10.

56. J. DAVITT MCATEER ET AL., UPPER BIG BRANCH, THE APRIL 5, 2010 EXPLOSION: A FAILURE OF BASIC COAL MINE SAFETY PRACTICES 18 (2011), *available at* http://www.nttc.edu/programs&projects/minesafety/disasterinvestigations/upperbigbranch/UpperBigBranchReport.pdf (observing that the increased use of contract workers "has made it more difficult for federal and state governments to accurate[ly] assess and characterize a company's safety performance.").

57. The omission of contractor violations could, in theory, bias the results. For example, if contract mining is more prevalent among unionized mines, MSHA officials might spend more time inspecting union mines for this reason alone (i.e., because there are more persons working onsite). As a robustness check, alternative specifications were estimated in which violations committed by mine operators *and* onsite contractors (if any) were included. These results, presented on this article's companion website, do not vary materially from the findings presented here. *See* Alison Morantz, COMPANION WEBSITE FOR DOES UNIONIZATION STRENGTHEN REGULATORY ENFORCEMENT?, http://amorantz.stanford.edu/mining_unionization_and_regulation.html (last visited Nov. 6, 2011).

TABLE 1. DESCRIPTIVE STATISTICS[58]

Variable	Union Mines	Nonunion Mines	All Mines
Number of Mines	269	1,954	2,100
Number of Mine-Quarters	4,460	26,428	30,888
Mean Hours Worked per Qtr.	102,336 (105,574)	30,488 (44,303)	40,863 (62,659)
Mean Employees[59] per Qtr.	184.23 (184.04)	53.67 (74.47)	75.52 (108.36)
Mean Coal Tonnage[60] per Qtr.	403,320 (483,518)	132,198 (280,797)	171,346 (332,106)

As is shown in Table 1, union mines constitute a relatively small fraction—approximately 13%—of the sample, and only a slightly higher fraction—approximately 14%—of mine-quarters. Table 1 also reveals that union mines are, on average, much larger than non-union mines. The mean hours worked, the mean number of employees, and the mean coal tonnage per mine-quarter[61] are all more than three times as large at union mines as at non-union mines.

The empirical analysis unfolds in two stages. The first stage uses ordinary least squares (OLS) regression models,[62] with standard errors clustered on mine, to isolate differences in the frequency, intensity, and scope of MSHA inspections across union and non-union mines. In particular, the analysis compares regular inspection hours per mine-quarter, total inspection hours per regular inspection, and the proportion of all inspection hours spent onsite per regular inspection.

The second stage of the empirical analysis uses OLS regression models, with standard errors clustered on mine, to explore the frequency and distribution of violations, the magnitude of penalties and the speed of abatement across the two environments. Initially, the inquiry focuses on disparities in total violations per mine-quarter and per 1000 onsite inspection hours, respectively. Scrutiny then shifts to disparities in fines and penalty points, including the log of total proposed penalties per mine-quarter and several alternative measures of

58. Standard deviations, where applicable, are reported in parentheses. Mines that were unionized for some but not all of the quarters in which they were active are included in both the union and non-union mine counts; therefore, the sum of union and non-union mines is greater than the value of all mines.

59. *See* MINE SAFETY & HEALTH ADMIN., U.S. DEP'T OF LABOR, REPORT ON 30 C.F.R. PART 50, at 14 (1986), *available at* http://www.msha.gov/stats/part50/rptonpart50.pdf (defining employees as the average number of persons working during a given quarter, rounded to the nearest whole number).

60. Tonnage is the total coal production of all sections (including surface operations) at an underground mine.

61. The mine-quarter is the unit of observation that represents the activity of a given mine in a given quarter.

62. For an explanation of OLS regression models, see *Ordinary Least Squares for Simple Regression*, XYCOON, http://www.xycoon.com/ols.htm (last visited Oct. 17, 2011).

penalty points. The analysis concludes by comparing total abatement periods for the most frequent subset of S&S violations.

This article presents and discusses results from several leading specifications.[63] Each table contains two alternative versions of three models, for a total of six specifications. The two versions of each model differ in that the "public-fields" version relies exclusively on public data, whereas the "confidential-fields" version incorporates confidential data fields obtained from the EIA. The first model uses full-time equivalents (FTEs)[64] as the defining measure of mine size. Because it is conventional in epidemiology,[65] industrial medicine,[66] and economics[67] to use FTEs as a size metric when comparing the

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63. Results from the full analysis cannot be presented due to space constraints.

64. Yearly FTEs are defined as 2,000 man-hours, and quarterly FTEs are defined as 500 man-hours.

65. *See, e.g.*, Hasanat Alamgir et al., *Epidemiology of Work-Related Injuries Requiring Hospitalization Among Sawmill Workers in British Columbia, 1989-1997*, 22 EUR. J. EPIDEMIOLOGY 273, 273 (2007) (using FTEs as the denominator for the injury rate at sawmills); Peng Bi et al., *Occupational Blood and Body Fluid Exposure in an Australian Teaching Hospital*, 134 EPIDEMIOLOGY & INFECTION 465, 466 (2006) (using FTEs as the denominator for the rate of hospital staff injuries); Sean P. Clarke et al., *Sharp-Device Injuries to Hospital Staff Nurses in 4 Countries*, 28 INFECTION CONTROL & HOSP. EPIDEMIOLOGY 473, 473 (2007) (using FTEs as the denominator for the rate of hospital staff injuries); SeJean Sohn et al., *Effect of Implementing Safety-Engineered Devices on Percutaneous Injury Epidemiology*, 25 INFECTION CONTROL & HOSP. EPIDEMIOLOGY 536, 538 (2004) (using FTEs as the denominator for annual instance of injuries).

66. *See, e.g.*, Michelle Kaminski, *Unintended Consequences: Organizational Practices and Their Impact on Workplace Safety and Productivity*, 6 J. OCCUPATIONAL HEALTH PSYCHOL. 127 (2001) (using FTEs as the denominator for the rate of lost-time injuries); Lina Lander et al., *Near-Miss Reporting System as an Occupational Injury Preventive Intervention in Manufacturing*, 54 AM. J. INDUS. MED. 40, 45 (2011) (using FTEs as the denominator for the rate of nonfatal occupational injuries); Richard Letz et al., *A Cross Sectional Epidemiological Survey of Shipyard Workers Exposed to Hand-Arm Vibration*, 49 BRIT. J. INDUS. MED. 53, 58 (1992) (using FTEs to measure the time until the onset of symptoms resulting from the use of vibratory tools); Timothy K. Thomas et al., *Is It Safe On Deck? Fatal and Non-Fatal Workplace Injuries Among Alaskan Commercial Fishermen*, 40 AM. J. INDUS. MED. 693, 693 (2001) (using FTEs as the denominator to calculate the fatality rate for Alaskan fishermen).

67. *See, e.g.*, Robert C. Bird & John D. Knopf, *Do Wrongful-Discharge Laws Impair Firm Performance?*, 52 J.L. & ECON. 197, 207 (2009) (using FTEs to measure bank firm employment); Carl-Ardy Dubois & Martin McKee, *Cross-National Comparisons of Human Resources for Health — What Can We Learn?*, 1 HEALTH ECON. POL'Y. & L. 59, 70 (2006) (discussing the impact of using FTEs for cross-national labor comparisons); John W. Ruser, *The Changing Composition of Lost-Workday Injuries*, 122 MONTHLY LAB. REV. 11 (1999) (using FTEs as the denominator in calculating the injury rate of workers); Nicolas R. Ziebarth & Martin Karlsson, *A Natural Experiment on Sick Pay Cuts, Sickness Absence, and Labor Costs* (HEDG Working Paper No. 09/34 2009), *available at* http://www.york.ac.uk/res/herc/documents/wp/09_34.pdf (using FTEs to measure the number of doctors working for the German Medical Service).

frequency—or prevalence—of workplace-related events, this is described as the "baseline" model. To test the robustness of these results, the second and third models utilize employees[68] and coal tonnage,[69] respectively, as alternative measures of mine size. Appendix A describes the covariates included in the public-fields and confidential-fields versions of each model, and Appendix B lists the definition and source of each independent variable.[70] Additional model specifications, robustness checks, and the (non-confidential) data used in the analysis are available on this article's companion website.[71]

IV.
Results of Empirical Analysis

Tables 2 through 4, encompassing the first stage of the empirical analysis, present results from OLS models comparing the inspection intensity of MSHA inspections across union and non-union mines.[72] Table 2, which focuses on regular inspection hours per mine-quarter, suggests that union mines are subjected to more intensive scrutiny.[73] Unionization predicts a statistically significant rise of at least eighteen regular inspection hours across all specifications.[74] However, Table 2 also indicates that the disparity diminishes sharply with mine size.[75] Table 3, probing total inspection hours per regular inspection, displays a very similar pattern.[76] Although union status predicts a steep and robust spike in total inspection hours per regular inspection, the effect again diminishes sharply with mine size.[77] Rounding out the first phase of the analysis, Table 4 analyzes the proportion of all inspection hours spent on-site per regular inspection and reveals that this proportion is significantly higher at unionized mines. This time, the disparity varies little by mine size.[78]

Tables 5 through 11, presenting results from the second stage of the empirical analysis, focus on violations, assessments, and abate-

68. *See supra* note 59.

69. *See supra* note 60.

70. *See infra* Appendices A, B.

71. *See* Alison Morantz, Companion Website for Does Unionization Strengthen Regulatory Enforcement?, *supra* note 57.

72. *See infra* Tables 2–4.

73. *See infra* Table 2.

74. *Id*.

75. *Id.* This inference follows from Table 2's negative and highly significant coefficient on the interaction term.

76. *See infra* Table 3.

77. *Id.*

78. *See infra* Table 4.

ment periods.[79] Table 5 reveals that total violations per mine-quarter do *not* vary significantly by union status.[80] Although not robust across all specifications, Table 6 indicates that MSHA inspectors tend to cite fewer violations per inspection hour at union mines.[81] As is shown in Table 7, union mines also receive higher penalties per mine quarter.[82] Table 8, which limits the analysis to the ten most prevalent violations that are classified as S&S, confirms that union mines receive more penalty points per violation.[83] Tables 9 and 10 seek to pinpoint the source of the latter disparity by comparing, respectively, the assignment of penalty points for mine size[84] and for the number of persons affected.[85] Table 9 suggests that unionization predicts a significant increase in number-of-persons-affected penalty points.[86] Similarly, Table 10 reveals that even when one controls for mine size in a continuous fashion, unionization predicts a significant increase in mine-size penalty points.[87] Yet as shown in Table 11, total abatement periods are statistically indistinguishable across union and non-union mines.[88]

At first glance, one might infer from Tables 8 through 10 that MSHA inspectors—whether consciously or not—treat union mines differently than their otherwise similar, yet non-unionized, counterparts when assigning penalty points. The remainder of this part considers alternative hypotheses that might explain the disparities in

79. *See infra* Tables 5–11.

80. *See infra* Table 5. Robustness checks respectively comparing the frequency of S&S violations, non-S&S violations, high-negligence violations, and low-negligence violations, also fail to find any significant disparities by union status. *See* COMPANION WEBSITE FOR DOES UNIONIZATION STRENGTHEN REGULATORY ENFORCEMENT?, *supra* note 57.

81. *See infra* Table 6. Since union mines are inspected more intensely yet receive similar violations per mine-quarter, a negative correlation between union status and violations cited (per inspection hour) is to be expected.

82. *See infra* Table 7.

83. *See infra* Table 8.

84. MSHA calculates mine size based on the annual tonnage produced in a previous calendar year. *See* 30 C.F.R. § 100.3(b) (2010).

85. "Persons affected" is defined as the number of persons potentially affected if the event has occurred or were to occur. Federal Coal Mine Health and Safety Act of 1969, Pub. L. No. 91-173, § 103(e), 83 Stat. 742, 750 (1969) (amended by Mine Improvement and New Emergency Response Act of 2006, Pub. L. No. 109-236).

86. *See infra* Table 9.

87. *See infra* Table 10.

88. *See infra* Table 11. Robustness checks similarly show that there are no significant disparities in assigned or actual abatement periods for the top ten regular (or top ten S&S) violations. *See* COMPANION WEBSITE FOR DOES UNIONIZATION STRENGTHEN REGULATORY ENFORCEMENT?, *supra* note 57.

persons-affected and "mine-size" penalty points revealed in Tables 9 and 10.[89]

With regard to the assignment of persons-affected penalty points, other characteristics of mining operations that correlate with union status—but are not caused by unionization—could be driving the disparity. For example, if miners in unionized mines work in closer geographic proximity to one another than their counterparts in non-unionized mines (for example, because of minimum-staffing provisions in collective bargaining agreements), then more unionized miners could be endangered by a given hazard even if inspectors apply the statutory criteria in an evenhanded manner. Unfortunately, available data are not granular enough to permit one to probe the validity of this conjecture.

With regard to the assignment of mine-size penalty points, further analysis suggests that the disparity is *not* driven by differences in the behavior of individual inspectors, but rather by the formula itself. Instead of using an algebraic formula in which penalty points bear a consistent, linear relationship to mine size, mines are grouped into several discrete, uneven size categories based on annual tonnage. All mines within a given category receive the identical number of penalty points.[90] As Figures 1a, 1b, and 1c (and Table 1) demonstrate, union mines tend to be larger than non-union mines regardless of how size is defined. Moreover, although the distribution of non-union mines is unimodal, the distribution of union mines is bimodal.[91] Therefore, the disparity arises from the fact that the penalty-point formula treats mine size in a highly discontinuous fashion, whereas the models used to generate the results presented here treat size as a continuous variable. In other words, the disparity in "mine-size" penalty points apparently stems not from any systematic bias in the way inspectors apply the formula, but from the highly discontinuous—and uneven—nature of MSHA's penalty-point formula, combined with the fact that union mines tend to be much larger (and have a differently-shaped size distribution) than their non-unionized counterparts.

The disparities identified here substantially mirror those reported in prior work using data from the early 1980s.[92] Unionization once again correlates with greater frequency, duration and intensity of MSHA's regulatory enforcement, and these disparities are usually most pronounced among smaller mines. Moreover, union mines gen-

89. *See infra* Tables 9 and 10.
90. *See* 30 C.F.R. § 100.3(b) (2010).
91. *See infra* Figures 1a, 1b, and 1c.
92. *See* Weil, Government and Labor in the Workplace, *supra* note 11, at 179.

erally receive higher penalty points and fines for non-trivial violations. Unlike prior scholarship, however, the analysis presented here reveals no statistically significant disparities in the duration of abatement periods, the ratio of proposed to current penalties, or total citations issued per inspection.[93]

V.
Summary and Discussion of Main Findings

During the year preceding the Triangle Shirtwaist Factory fire, shirtwaist makers across New York City went on strike, demanding higher pay and safer working conditions under the leadership of the International Ladies Garment Workers Union.[94] The Triangle Waist Company was one of the companies that refused to settle.[95] Until it shut its doors in 1918, the company refused to recognize the Union or accede to its demands.[96] The catastrophe helped galvanize public support for two cornerstones of a progressive policy agenda: the protection of workers' right to bargain collectively with their employers through elected labor unions, and the direct government regulation of hazardous working conditions. The New Deal helped pave the way for both of these reforms. However, the complex interaction between labor unions and the federal regulatory apparatus designed to protect workers' safety and health has only recently become a topic of empirical scrutiny.

Focusing on the coal mining industry and relying upon data from 1995–2009, this article contributes to this scant scholarship by probing whether inspection intensity and regulatory compliance differ between union and non-union mines.

The findings suggest that MSHA's regulatory enforcement behavior varies significantly by union status. In particular, unionization predicts statistically significant and robust increases in regular inspection hours per mine-quarter, total inspection hours per regular inspection, and the proportion of total inspection hours spent onsite. These enforcement disparities are mostly confined to smaller mines. Although unionization has no apparent effect on total violations per

93. Unfortunately, due to data constraints, not all of Weil's findings can be verified for the more recent time period. *See id.* at 122, 157 (discussing the greater use of employee representatives and less frequent abatement extensions at unionized mines).

94. Peter Dreier & Donald Cohen, *The Fire Last Time: Labor, Big Business, and the Forgotten Lessons of a Disaster That Happened 100 Years Ago This Month*, New Republic, Mar. 12, 2011, http://www.tnr.com/article/politics/85134/wisconsin-unions-walker-triangle-shirtwaist-fire.

95. *Id.*

96. *Id.*

mine-quarter or on total abatement periods, it does correlate with large increases in the proposed fine (and penalty points) assessed for significant and substantial violations. Although sizable and robust, these findings seem unlikely to fully explain the lower incidence of traumatic and fatal injuries at union mines reported in prior scholarship. While most of the differentials shown here decline sharply with mine size, the "union safety effect" reported in earlier work is most pronounced among large mines.[97]

Several important questions remain unanswered. First, are the observed differences in enforcement behavior confined to the mining industry, or do they apply to other regulatory agencies? Secondly, what are the causal mechanisms driving these disparities? For example, might specific characteristics of union workplaces—such as the higher prevalence of complaint inspections and/or greater likelihood that an experienced miner will accompany an MSHA inspector on his/her tour—induce greater enforcement intensity? Third, why are most of the disparities confined to smaller mines? Finally and most importantly, could federal regulators bring about further improvements in U.S. mine safety by channeling a larger share of inspection resources towards smaller, non-unionized mines? All of these questions represent promising topics for future inquiry.

97. *Morantz*, *supra* note 12.

Table 2. Effect of Union Status on Regular Inspection Hours per Mine-Quarter

Specification	Baseline (Hours Worked)		Employees		Tonnage	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	24.089*** (7.00)	28.335*** (8.64)	19.284** (7.68)	22.794** (9.37)	18.346*** (6.04)	18.893** (7.56)
Union X Mine Size	-20.991*** (7.39)	-27.578*** (7.02)	-24.827*** (9.26)	-32.700*** (8.93)	-39.289* (21.30)	-46.851** (23.40)
Mine Size	95.021*** (7.86)	104.234*** (7.82)	105.830*** (9.84)	120.333*** (10.32)	179.759*** (23.65)	173.459*** (24.81)
Log of Controller Size	3.341*** (1.08)	2.656** (1.08)	4.968*** (1.32)	3.998*** (1.42)	8.887*** (0.88)	8.461*** (1.12)
Observations	23,751	17,017	23,044	16,526	23,044	16,526
# of Union Mines / # of Total Mines	228 / 1,531	152 / 1,124	228 / 1,524	152 / 1,118	228 / 1,524	152 / 1,118
R^2	0.73	0.75	0.73	0.74	0.71	0.72

Source: MSHA, EIA and NIOSH, 1995–2009.
Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.
Dependent Variable: Number of regular inspection hours per mine-quarter.
Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, and district dummies. Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.
Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the mine level. The unit of analysis for all models is the mine-quarter.
Sample: The sample consists of underground bituminous coal mines with positive coal production and positive hours worked. The public-fields version models contain mine quarters from 1995–2009, whereas the confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

Table 3. Effect of Union Status on Total Inspection Hours per Regular Inspection

Specification	Baseline (Hours Worked)		Employees		Tonnage	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	26.118*** (6.96)	30.248*** (8.88)	22.138*** (7.56)	25.686*** (9.73)	15.809*** (6.06)	16.070** (7.80)
Union X Mine Size	-22.007*** (6.39)	-28.176*** (6.19)	-26.452*** (7.95)	-33.743*** (8.12)	-30.000* (16.81)	-33.625* (19.59)
Mine Size	93.538*** (7.10)	102.464*** (7.27)	106.040*** (9.03)	119.382*** (10.03)	180.862*** (18.47)	171.963*** (19.74)
Log of Controller Size	3.267*** (1.10)	2.415** (1.22)	4.600*** (1.33)	3.686** (1.63)	8.894*** (0.92)	8.861*** (1.16)
Observations	21,789	14,926	21,153	14,489	21,153	14,489
# of Union Mines / # of Total Mines	222 / 1,363	147 / 950	222 / 1,360	147 / 948	222 / 1,360	147 / 948
R^2	0.80	0.81	0.79	0.81	0.77	0.78

Source: MSHA, EIA and NIOSH, 1995–2009.
Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.
Dependent Variable: Total number of inspection hours per regular inspection.
Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, and district dummies. Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.
Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the mine level. The unit of analysis for all models is the regular inspection.
Sample: The sample consists of regular inspections that occurred at underground bituminous coal mines with positive coal production and positive hours worked. The public-fields version models contain mine quarters from 1995–2009, whereas the confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

Table 4. Effect of Union Status on Proportion of All Inspection Hours Spent Onsite per Regular Inspection

Specification	**Baseline (Hours Worked)**		**Employees**		**Tonnage**	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	0.020*** (0.01)	0.024*** (0.01)	0.018*** (0.01)	0.021*** (0.01)	0.013** (0.01)	0.017** (0.01)
Union X Mine Size	-0.005 (0.00)	-0.005* (0.00)	-0.005 (0.00)	-0.005 (0.00)	-0.001 (0.01)	-0.004 (0.01)
Mine Size	0.012*** (0.00)	0.013*** (0.00)	0.012*** (0.00)	0.013*** (0.00)	0.006 (0.01)	0.011 (0.01)
Log of Controller Size	0.003*** (0.00)	0.004*** (0.00)	0.004*** (0.00)	0.005*** (0.00)	0.005*** (0.00)	0.006*** (0.00)
Observations	21,789	14,926	21,153	14,489	21,153	14,489
# of Union Mines / # of Total Mines	222 / 1,363	147 / 950	222 / 1,360	147 / 948	222 / 1,360	147 / 948
R^2	0.13	0.12	0.13	0.13	0.13	0.13

Source: MSHA, EIA and NIOSH, 1995–2009.
Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.
Dependent Variable: Proportion of all inspection hours that are spent onsite per regular inspection.
Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, and district dummies. Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.
Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the mine level. The unit of analysis for all models is the regular inspection.
Sample: The sample consists of regular inspections that occurred at underground bituminous coal mines with positive coal production and positive hours worked. The public-fields version models contain mine quarters from 1995–2009, whereas the confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

Table 5. Effect of Union Status on Total Violations per Mine-Quarter

Specification	Baseline (Hours Worked)		Employees		Tonnage	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	1.310 (1.50)	1.996 (2.08)	0.805 (1.57)	1.400 (2.18)	-0.373 (1.45)	-0.663 (1.91)
Union X Mine Size	-1.094 (1.35)	-1.638 (1.65)	-1.366 (1.55)	-2.066 (1.92)	3.120 (5.57)	3.655 (6.40)
Mine Size	8.261*** (1.20)	9.664*** (1.46)	9.597*** (1.34)	11.303*** (1.80)	11.029*** (2.90)	12.190*** (3.25)
Log of Controller Size	0.497*** (0.19)	0.670** (0.29)	0.572** (0.23)	0.771** (0.36)	0.882*** (0.19)	0.978*** (0.29)
Observations	23,380	16,790	22,704	16,324	22,704	16,324
# of Union Mines / # of Total Mines	227 / 1,519	151 / 1,114	227 / 1,514	151 / 1,109	227 / 1,514	151 / 1,109
R^2	0.62	0.64	0.62	0.64	0.61	0.63

Source: MSHA, EIA and NIOSH, 1995–2009.
Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.
Dependent Variable: Total violations per mine-quarter.
Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, and district dummies. Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.
Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the mine level. The unit of analysis for all models is the mine-quarter.
Sample: The sample consists of underground bituminous coal mines with positive coal production and positive hours worked. The public-fields version models contain mine quarters from 1995–2009, whereas the confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

Table 6. Effect of Union Status on Total Violations per 1000 Onsite Inspection Hours per Mine-Quarter

Specification	Baseline (Hours Worked)		Employees		Tonnage	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	-31.363*** (10.40)	-26.716** (11.28)	-21.789** (8.49)	-23.297** (10.93)	-17.609** (8.76)	-17.683 (11.33)
Union X Mine Size	9.307** (4.63)	7.315 (5.24)	7.081 (5.67)	6.324 (7.42)	19.759 (26.08)	16.175 (31.75)
Mine Size	-12.422** (5.62)	-5.180 (6.15)	-4.407 (6.46)	1.526 (8.60)	13.967 (22.66)	27.636 (27.66)
Log of Controller Size	-1.915 (2.21)	-2.581 (2.44)	-6.278*** (1.81)	-6.789** (2.70)	-6.843*** (1.61)	-6.885*** (2.33)
Observations	23,273	16,694	22,601	16,230	22,601	16,230
# of Union Mines / # of Total Mines	227 / 1,519	151 / 1,114	227 / 1,514	151 / 1,109	227 / 1,514	151 / 1,109
R^2	0.023	0.028	0.029	0.030	0.030	0.031

Source: MSHA, EIA and NIOSH, 1995–2009.
Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.
Dependent Variable: Total Violations per 1000 Onsite Inspection Hours per mine-quarter.
Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, and district dummies. Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.
Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the level. The unit of analysis for all models is the mine-quarter.
Sample: The sample consists of underground bituminous coal mines with positive coal production and positive hours worked. The public-fields version models contain mine quarters from 1995–2009, whereas the confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

Table 7. Effect of Union Status on Log of Total Proposed Penalties per Mine-Quarter

Specification	Baseline (Hours Worked)		Employees		Tonnage	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	0.228*** (0.08)	0.240** (0.10)	0.184** (0.09)	0.207** (0.10)	0.135* (0.07)	0.090 (0.09)
Union X Mine Size	-0.113* (0.07)	-0.170*** (0.05)	-0.119 (0.08)	-0.196*** (0.06)	-0.180 (0.15)	-0.242* (0.13)
Mine Size	0.301*** (0.05)	0.378*** (0.06)	0.326*** (0.07)	0.435*** (0.07)	0.495*** (0.12)	0.624*** (0.16)
Log of Controller Size	0.111*** (0.01)	0.102*** (0.02)	0.134*** (0.02)	0.123*** (0.02)	0.123*** (0.01)	0.112*** (0.02)
Observations	23,349	16,767	22,679	16,305	22,679	16,305
# of Union Mines / # of Total Mines	227 / 1,517	151 / 1,113	227 / 1,512	151 / 1,108	227 / 1,512	151 / 1,108
R^2	0.53	0.56	0.54	0.56	0.53	0.55

Source: MSHA, EIA and NIOSH, 1995–2009.
Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.
Dependent Variable: Log of total proposed penalties per mine-quarter.
Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, and district dummies. Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.
Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the mine level. The unit of analysis for all models is the mine-quarter.
Sample: The sample consists of underground bituminous coal mines with positive coal production and positive hours worked. The Public-fields version models contain mine quarters from 1995–2009, whereas the confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

Table 8. Effect of Union Status on Total Penalty Points per S&S Violation—Ten Most Common Violation Types

Specification	Baseline (Hours Worked)		Employees		Tonnage	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	2.112*** (0.73)	2.014*** (0.75)	1.991*** (0.75)	2.012** (0.79)	1.121 (0.70)	1.112 (0.74)
Union X Mine Size	-0.385 (0.25)	-0.396* (0.22)	-0.427 (0.28)	-0.433 (0.28)	-0.315 (0.66)	-0.339 (0.61)
Mine Size	0.173 (0.29)	0.297 (0.35)	-0.144 (0.33)	0.076 (0.43)	0.495 (0.63)	0.462 (0.73)
Log of Controller Size	1.140*** (0.13)	0.881*** (0.13)	1.341*** (0.14)	1.061*** (0.15)	1.120*** (0.11)	0.939*** (0.11)
Observations	106,483	83,968	104,030	82,081	104,030	82,081
# of Union Mines / # of Total Mines	226 / 1,547	150 / 1,134	225 / 1,540	150 / 1,129	225 / 1,540	150 / 1,129
R^2	0.81	0.84	0.81	0.84	0.81	0.84

Source: MSHA, EIA and NIOSH, 1995–2009.

Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.

Dependent Variable: Total number of penalty points per S&S violation (limited to the ten most common violation types).

Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, district dummies, and dummies for each violation type (i.e., section of CFR deemed to have been violated). Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.

Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the mine level. The unit of analysis for all models is the S&S violation—ten most common violation types.

Sample: The sample consists of S&S violations received by underground bituminous coal mines with positive coal production and positive hours worked, but is restricted to the ten most common violation types. The public-fields version models contain mine quarters from 1995–2009, whereas the confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

Table 9. Effect of Union Status on Persons Potentially Affected Penalty Points per S&S Violation—Ten Most Common Violation Types

Specification	**Baseline (Hours Worked)**		**Employees**		**Tonnage**	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	0.182** (0.09)	0.274** (0.11)	0.240** (0.10)	0.360*** (0.12)	0.114 (0.09)	0.219** (0.11)
Union X Mine Size	-0.028 (0.02)	-0.030 (0.02)	-0.056* (0.03)	-0.065** (0.03)	-0.007 (0.07)	-0.044 (0.08)
Mine Size	0.010 (0.03)	-0.016 (0.03)	0.018 (0.03)	-0.003 (0.04)	-0.036 (0.07)	-0.126 (0.08)
Log of Controller Size	-0.038*** (0.01)	-0.045*** (0.02)	-0.040*** (0.01)	-0.051*** (0.02)	-0.028** (0.01)	-0.035** (0.01)
Observations	106,483	83,968	104,030	82,081	104,030	82,081
# of Union Mines / # of Total Mines	226 / 1,547	150 / 1,134	225 / 1,540	150 / 1,129	225 / 1,540	150 / 1,129
R^2	0.12	0.12	0.12	0.12	0.12	0.12

Source: MSHA, EIA and NIOSH, 1995–2009.

Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.

Dependent Variable: Number of penalty points assigned due to the number of persons that could be affected per S&S violation (limited to the ten most common violation types).

Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, district dummies, and dummies for each violation type (i.e., section of CFR deemed to have been violated). Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.

Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the mine level. The unit of analysis for all models is the S&S violation—ten most common violation types.

Sample: The sample consists of S&S violations received by underground bituminous coal mines with positive coal production and positive hours worked, but is restricted to the ten most common violation types. The public-fields version models contain mine quarters from 1995–2009, whereas the confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

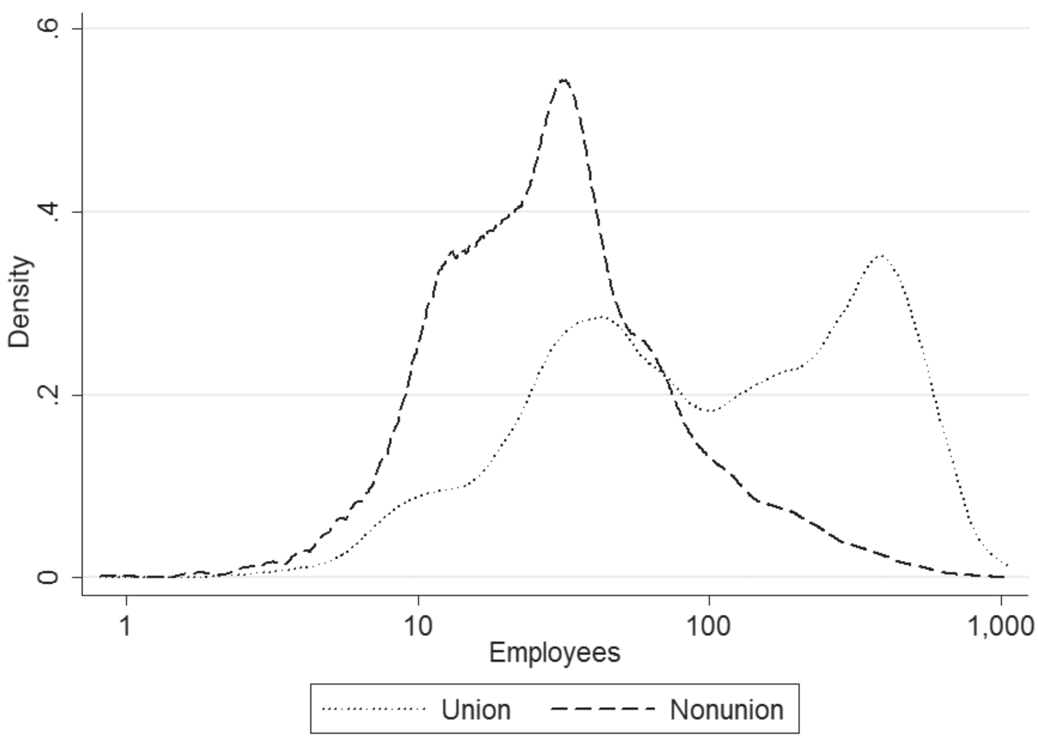
Table 10. Effect of Union Status on Mine Size Penalty Points per S&S Violation—Ten Most Common Violation Types

Specification	**Baseline (Hours Worked)**		**Employees**		**Tonnage**	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	1.263*** (0.26)	1.287*** (0.29)	1.155*** (0.27)	1.202*** (0.28)	0.844*** (0.22)	0.753*** (0.25)
Union X Mine Size	-0.327** (0.14)	-0.380*** (0.11)	-0.361** (0.16)	-0.432*** (0.12)	-0.901*** (0.35)	-0.878*** (0.30)
Mine Size	0.516*** (0.13)	0.602*** (0.13)	0.505*** (0.16)	0.658*** (0.15)	0.863*** (0.33)	0.771** (0.34)
Log of Controller Size	0.503*** (0.04)	0.381*** (0.04)	0.563*** (0.05)	0.424*** (0.05)	0.516*** (0.04)	0.416*** (0.04)
Observations	106,483	83,968	104,030	82,081	104,030	82,081
# of Union Mines / # of Total Mines	226 / 1,547	150 / 1,134	225 / 1,540	150 / 1,129	225 / 1,540	150 / 1,129
R^2	0.70	0.73	0.70	0.72	0.70	0.72

Source: MSHA, EIA and NIOSH, 1995–2009.
Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.
Dependent Variable: Number of penalty points assigned due to mine size per S&S violation (limited to the ten most common violation types).
Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, district dummies, and dummies for each violation type (i.e., section of CFR deemed to have been violated). Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.
Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the mine level. The unit of analysis for all models is the S&S violation—ten most common violation types.
Sample: The sample consists of S&S violations received by underground bituminous coal mines with positive coal production and positive hours worked, but is restricted to the ten most common violation types. The public-fields version models contain mine quarters from 1995–2009, whereas the confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

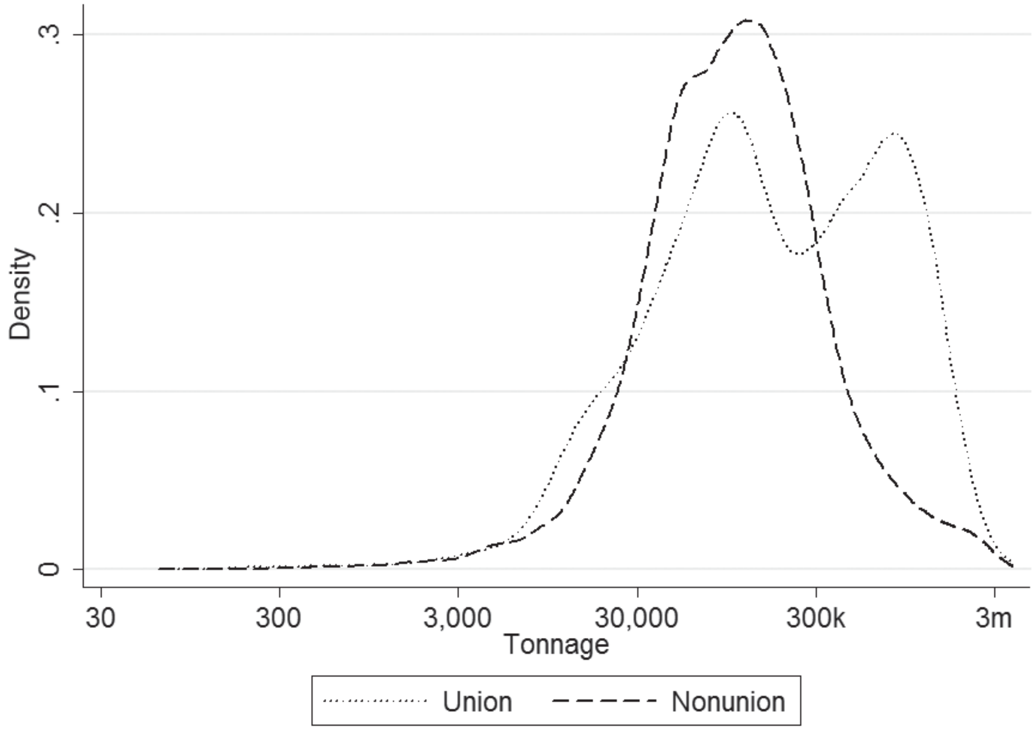
FIGURE 1A: TOTAL HOURS WORKED[a]

FIGURE 1B: EMPLOYEES[a]



[a] The horizontal axis represents the log of the size measure. Therefore the density plots are in fact density plots of the log of the size measure.

FIGURE 1C: TONNAGE[a]



[a] The horizontal axis represents the log of the size measure. Therefore the density plots are in fact density plots of the log of the size measure.

Table 11. Effect of Union Status on Total Abatement Period per S&S Violation—Ten Most Common Violation Types

Specification	**Baseline (Hours Worked)**		**Employees**		**Tonnage**	
Model	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version	Public-Fields Version	Confid.-Fields Version
Mine/Controller Size Units:	100 Quarterly FTEs	100 Quarterly FTEs	100 Employees	100 Employees	Millions of Tons	Millions of Tons
Union	0.333 (0.67)	-0.044 (0.47)	0.407 (0.69)	-0.030 (0.48)	-0.024 (0.58)	-0.407 (0.41)
Union X Mine Size	-0.201 (0.14)	-0.084 (0.12)	-0.251 (0.17)	-0.109 (0.15)	-0.326 (0.43)	0.053 (0.29)
Mine Size	-0.132 (0.13)	-0.173 (0.13)	-0.078 (0.16)	-0.109 (0.17)	-0.405 (0.44)	-0.945** (0.42)
Log of Controller Size	-0.101 (0.08)	-0.131 (0.10)	-0.140* (0.08)	-0.239*** (0.08)	-0.118* (0.07)	-0.183*** (0.07)
Observations	110,128	86,745	107,424	84,706	107,424	84,706
# of Union Mines / # of Total Mines	226 / 1,548	150 / 1,134	225 / 1,540	150 / 1,129	225 / 1,540	150 / 1,129
R^2	0.020	0.027	0.021	0.030	0.021	0.030

Source: MSHA, EIA and NIOSH, 1995–2009.

Definitions: Significance levels: *** 1%, ** 5%, * 10%. FTE is defined as 2,000 man-hours.

Dependent Variable: Total abatement period per S&S violation (limited to the ten most common violation types), defined as the termination date minus the issue date.

Independent Variables: All models include the following regressors: union dummy, union X size, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, total lost-work injuries (in hundreds) in previous four quarters, total penalty points (in thousands) in previous four quarters, constant term, dummies indicating presence of each type of mine subunit, quarter dummies, district dummies, and dummies for each violation type (i.e., section of CFR deemed to have been violated). Public-fields version models include a longwall indicator. Confidential-fields version models include number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and mining method percentages. See *infra* Appendix B for full definitions of all variables.

Models: All models are ordinary least squares regressions; standard errors (shown in parentheses) are clustered at the mine level. The unit of analysis for all models is the S&S violation—ten most common violation types.

Sample: The sample consists of S&S violations received by underground bituminous coal mines with positive coal production and positive hours worked, but is restricted to the ten most common violation types. The public-fields version models contain mine quarters from 1995–2009, whereas the Confidential-fields version models are restricted to 1998–2009. All specifications exclude mine-quarters in which a mine began production for the first time or resumed production after a year or more of inactivity.

Appendix A: Description of Model Specifications

The list below describes the three specifications and two models that are included in each set of regressions. In addition, in violation-level models that are restricted to the ten most common (top ten) violations—Tables 8, 9, 10, and 11—all specifications include dummies for these ten violation types.

Baseline Model (Hours Worked): Mine size is measured in 100 quarterly FTEs. Controller size is measured by the log of hours worked across all mines controlled by that controller, in 100 FTEs.

Employees Model: Mine size is measured in 100 employees. Controller size is measured by the log of employees across all mines controlled by that controller, in 100 employees.

Tonnage Model: Mine size is measured in one million tons. Controller size is measured by the log of tonnage across all mines controlled by that controller, in millions of tons.

Public-Fields Specification: All models include the following regressors: union dummy, union-size interaction term, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, number of lost-work injuries (in hundreds) in the previous four quarters, total penalty points (in thousands) in the previous four quarters, a constant term, dummies indicating presence of each type of mine subunit, quarter dummies, district dummies, and a longwall indicator. In addition, for regressions labeled S&S Violation—Ten Most Common Types, dummies for each violation type (i.e., section of CFR deemed to have been violated) are included.

Confidential-Fields Specification: All models include the following regressors: union dummy, union-size interaction term, mine size measure (defined as specified in column headers), logged controller size measure (defined as specified in column headers), mine age, productivity, number of lost-work injuries (in hundreds) in the previous four quarters, total penalty points (in thousands) in the previous four quarters, a constant term, dummies indicating presence of each type of mine subunit, quarter dummies, district dummies, number of coal beds, mean coal bed thickness (in yards), subsidiary indicator, captive production as a percentage of total production, recoverable coal reserves, and the mining method percentages. In addition, for violation-level regressions, dummies for each violation type (i.e., section of CFR deemed to have been violated) are included.

Appendix B: Variable Dictionary

Variable Name	Variable Definition	Source
District dummies	1 if mine is located in a given MSHA district, 0 otherwise	MSHA
Ln (Controller Size)	Log of controller size measure. Controller size measure is either 100 FTEs, 100 employees, or one million tons	MSHA
Lost-workday injuries	The subset of injuries that result in some loss of work	MSHA
Mine age	Age of mine in years since the first operator began work at the mine (top censored at 1950)	MSHA
Penalty Points	Thousands of penalty points in the previous year	MSHA
Productivity	Thousands of tons of coal produced per man-year	MSHA
Quarter/year indicators	1 if observation is for a given year or quarter, 0 otherwise	MSHA
Size Measure	Size measure is either 100 FTEs, 100 employees, or one million tons	MSHA
Subunit indicator	1 if mine contains a given subunit, 0 otherwise Subunit types include "surface" and "mill or prep plant"	MSHA
Mean coal bed thickness	The mean thickness of all coal beds at the mine, in yards	EIA[a]
Mining type	Proportion of underground operation that is of a given type, expressed as fraction between 0 and 1; types include conventional, continuous, longwall, shortwall, and other	EIA
Number of coal beds	Number of coal beds at the mine site	EIA[a]
Percent captive production	Percent of production for mine or parent company's own use	EIA[a,b]
Recoverable reserves	Estimated tonnage of remaining coal reserves	EIA[a,b]
Subsidiary indicator	1 if mine is a subsidiary of a larger firm, 0 otherwise	EIA[a]
Union indicator	1 if mine is unionized, 0 otherwise	EIA
District dummies	1 if a mine is in a given district, 0 otherwise	NIOSH
Longwall Indicator	1 if mine is a longwall mine, 0 otherwise	NIOSH

Source: MSHA inspection records, 1995–2009; EIA coal mine data 1995–2009; NIOSH coal mine data 1995–2009.

[a] These data fields were obtained on a confidential basis, and are considered trade secrets by the companies that provided them.

[b] These data fields are unavailable prior to 1998.

Appendix E Illustrative Excerpts from Program Code

Because the programs used to convert the data from its original format, estimate all of the models, and perform all of the diagnostic testing encompass dozens of files and thousands of lines of code, it would be impractical to include all of them in this report. Instead, we include illustrative excerpts of program code from two core parts of our analysis: the CART procedure used to winnow down our list of possible covariates, and the Bayesian forecasting model using to generate our targeting algorithms.

E.1 R Code for CART

The following code is used to fit the CART to the coal quarterly data (for the coal total and coal traumatic models). It lists all the variables to be used in the `rpart()` function, then fits the models and outputs most predictive variables and the fitted trees.

```
# This file runs coal CART for quarterly data

# Load rpart package
library(rpart)

# Set infile and out-directory
# The infile should be a CSV that is saved in coal_to_csv.do
infile <- "X:/Projects/Mining/Targeting_Pilot/data/5_prepped/csvs
                                            /coal_L4_sample.csv"
outdir <- "X:/Projects/Mining/Targeting_Pilot/CART_results/coal"

# Set working directory
setwd(outdir)

# Load in common CART functions
source("X:/Projects/Mining/Targeting_Pilot/programs/6_CART/CART_functions.R")

# Load in the data
x <- read.csv(infile)

# Change total_hours_worked into units of 100,000
x$total_hours_worked = x$total_hours_worked / 100000

# DEFINE FUNCTIONS

# Create fit function
# Note that this CREATES the function; the function doesn't actually get
#       CALLED or RUN until later.
# This is where we set the default control parameter ("control")
# This function takes three arguments:
```

```
#   var = the (count) variable to be predicted (LHS)
#   data = the object containing all the data
#   control = the control parameter (we use a default but it can also be
#       specified)
# Using these arguments, the function builds the actual call to the CART
#       ("rpart") function
fit.var <- function(var, data, control=0.000075) {
    data.fit <- rpart(cbind(data[["total_hours_worked"]], data[[var]]) ~
        # PREDICTOR VARIABLES:
        highwall_indicator + portable_operator_indicator + room_pillar_indicator +
            safety_committee_indicator +
        east_dum + central_appalachia + cent_app_plus_IL + district +
        mine_type +
        primary_canvas_code + primary_sic_code + primary_sic_code_group +
        subsidiary +
        mine_age_first_op + mine_age_current_op + mine_age_active +
            mine_age_contig +
        ever_103i +
        season +
        any_union_A4 + any_union_T4 +
        order_A4 + order_T4 + order_103k_A4 + order_103k_T4 + order_104b_A4 +
            order_104b_T4 +
        order_104d1_A4 + order_104d1_T4 + order_104d2_A4 + order_104d2_T4 +
            order_104g1_A4 + order_104g1_T4 +
        order_107a_A4 + order_107a_T4 + order_days_A4 + order_days_T4+
        ee_order_days_A4 + ee_order_days_T4 + total_ee_order_days_A4 +
            total_ee_order_days_T4 +
        total_order_days_A4 + total_order_days_T4 + pct_order_A4 +
            pct_order_T4 +
        hours_per_EE_A4 + hours_per_EE_T4 +
        union_X_traum_qt_A4 +
        union_X_traum_qt_T4 +
        union_X_revnu_A4 +
        union_X_revnu_T4 +
        union_X_hrs_per_ee_A4 +
        union_X_hrs_per_ee_T4 +
        union_X_tot_inj_rt_A4 +
        union_X_tot_inj_rt_T4 +
        union_X_traum_inj_rt_A4 +
        union_X_traum_inj_rt_T4 +
        union_X_nontraum_inj_rt_A4 +
        union_X_nontraum_inj_rt_T4 +
        union_X_fatal_rt_A4 +
        union_X_fatal_rt_T4 +
        union_X_risky_acc_rt_A4 +
```

```
union_X_risky_acc_rt_T4 +
union_X_pen_pts_rt_A4 +
union_X_pen_pts_rt_T4 +
union_X_hours_A4 +
union_X_hours_T4 +
union_X_ees_A4 +
union_X_ees_T4 +
union_X_prod_A4 +
union_X_prod_T4 +
union_X_tot_ord_days_A4 +
union_X_tot_ord_days_T4 +
subsid_X_traum_qt_A4 +
subsid_X_traum_qt_T4 +
subsid_X_revnu_A4 +
subsid_X_revnu_T4 +
subsid_X_hrs_per_ee_A4 +
subsid_X_hrs_per_ee_T4 +
subsid_X_tot_inj_rt_A4 +
subsid_X_tot_inj_rt_T4 +
subsid_X_traum_inj_rt_A4 +
subsid_X_traum_inj_rt_T4 +
subsid_X_nontraum_inj_rt_A4 +
subsid_X_nontraum_inj_rt_T4 +
subsid_X_fatal_rt_A4 +
subsid_X_fatal_rt_T4 +
subsid_X_risky_acc_rt_A4 +
subsid_X_risky_acc_rt_T4 +
subsid_X_pen_pts_rt_A4 +
subsid_X_pen_pts_rt_T4 +
subsid_X_hours_A4 +
subsid_X_hours_T4 +
subsid_X_ees_A4 +
subsid_X_ees_T4 +
subsid_X_prod_A4 +
subsid_X_prod_T4 +
subsid_X_tot_ord_days_A4 +
subsid_X_tot_ord_days_T4 +
cent_ap_X_traum_qt_A4 +
cent_ap_X_traum_qt_T4 +
cent_ap_X_revnu_A4 +
cent_ap_X_revnu_T4 +
cent_ap_X_hrs_per_ee_A4 +
cent_ap_X_hrs_per_ee_T4 +
cent_ap_X_tot_inj_rt_A4 +
cent_ap_X_tot_inj_rt_T4 +
```

```
cent_ap_X_traum_inj_rt_A4 +
cent_ap_X_traum_inj_rt_T4 +
cent_ap_X_nontraum_inj_rt_A4 +
cent_ap_X_nontraum_inj_rt_T4 +
cent_ap_X_fatal_rt_A4 +
cent_ap_X_fatal_rt_T4 +
cent_ap_X_risky_acc_rt_A4 +
cent_ap_X_risky_acc_rt_T4 +
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cent_ap_X_pen_pts_rt_T4 +
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cent_ap_X_hours_T4 +
cent_ap_X_ees_A4 +
cent_ap_X_ees_T4 +
cent_ap_X_prod_A4 +
cent_ap_X_prod_T4 +
cent_ap_X_tot_ord_days_A4 +
cent_ap_X_tot_ord_days_T4 +
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cent_ap_IL_X_traum_qt_T4 +
cent_ap_IL_X_revnu_A4 +
cent_ap_IL_X_revnu_T4 +
cent_ap_IL_X_hrs_per_ee_A4 +
cent_ap_IL_X_hrs_per_ee_T4 +
cent_ap_IL_X_tot_inj_rt_A4 +
cent_ap_IL_X_tot_inj_rt_T4 +
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cent_ap_IL_X_traum_inj_rt_T4 +
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cent_ap_IL_X_risky_acc_rt_T4 +
cent_ap_IL_X_pen_pts_rt_A4 +
cent_ap_IL_X_pen_pts_rt_T4 +
cent_ap_IL_X_hours_A4 +
cent_ap_IL_X_hours_T4 +
cent_ap_IL_X_ees_A4 +
cent_ap_IL_X_ees_T4 +
cent_ap_IL_X_prod_A4 +
cent_ap_IL_X_prod_T4 +
cent_ap_IL_X_tot_ord_days_A4 +
cent_ap_IL_X_tot_ord_days_T4 +
east_X_traum_qt_A4 +
```

```
east_X_traum_qt_T4 +
east_X_revnu_A4 +
east_X_revnu_T4 +
east_X_hrs_per_ee_A4 +
east_X_hrs_per_ee_T4 +
east_X_tot_inj_rt_A4 +
east_X_tot_inj_rt_T4 +
east_X_traum_inj_rt_A4 +
east_X_traum_inj_rt_T4 +
east_X_nontraum_inj_rt_A4 +
east_X_nontraum_inj_rt_T4 +
east_X_fatal_rt_A4 +
east_X_fatal_rt_T4 +
east_X_risky_acc_rt_A4 +
east_X_risky_acc_rt_T4 +
east_X_pen_pts_rt_A4 +
east_X_pen_pts_rt_T4 +
east_X_hours_A4 +
east_X_hours_T4 +
east_X_ees_A4 +
east_X_ees_T4 +
east_X_prod_A4 +
east_X_prod_T4 +
east_X_tot_ord_days_A4 +
east_X_tot_ord_days_T4 +
rate_acc_class_code_1_A4 + rate_acc_class_code_1_T4 +
rate_acc_class_code_2_A4 + rate_acc_class_code_2_T4 +
rate_acc_class_code_3_A4 + rate_acc_class_code_3_T4 +
rate_acc_class_code_4_A4 + rate_acc_class_code_4_T4 +
rate_acc_class_code_5_A4 + rate_acc_class_code_5_T4 +
rate_acc_class_code_6_A4 + rate_acc_class_code_6_T4 +
rate_acc_class_code_7_A4 + rate_acc_class_code_7_T4 +
rate_acc_class_code_8_A4 + rate_acc_class_code_8_T4 +
rate_acc_class_code_9_A4 + rate_acc_class_code_9_T4 +
rate_acc_class_code_10_A4 + rate_acc_class_code_10_T4 +
rate_acc_class_code_11_A4 + rate_acc_class_code_11_T4 +
rate_acc_class_code_12_A4 + rate_acc_class_code_12_T4 +
rate_acc_class_code_13_A4 + rate_acc_class_code_13_T4 +
rate_acc_class_code_14_A4 + rate_acc_class_code_14_T4 +
rate_acc_class_code_15_A4 + rate_acc_class_code_15_T4 +
rate_acc_class_code_16_A4 + rate_acc_class_code_16_T4 +
rate_acc_class_code_17_A4 + rate_acc_class_code_17_T4 +
rate_acc_class_code_18_A4 + rate_acc_class_code_18_T4 +
rate_acc_class_code_19_A4 + rate_acc_class_code_19_T4 +
rate_acc_class_code_20_A4 + rate_acc_class_code_20_T4 +
```

```
rate_acc_class_code_21_A4 + rate_acc_class_code_21_T4 +
rate_acc_class_code_26_A4 + rate_acc_class_code_26_T4 +
rate_acc_class_code_27_A4 + rate_acc_class_code_27_T4 +
rate_acc_class_code_28_A4 + rate_acc_class_code_28_T4 +
rate_acc_class_code_29_A4 + rate_acc_class_code_29_T4 +
rate_acc_class_code_30_A4 + rate_acc_class_code_30_T4 +
rate_acc_class_code_31_A4 + rate_acc_class_code_31_T4 +
rate_acc_class_code_32_A4 + rate_acc_class_code_32_T4 +
rate_high_risk_acc_A4 + rate_high_risk_acc_T4 +
auger_subunit_dummy_A4 + auger_subunit_dummy_T4 +
continuous_mmp_A4 + continuous_mmp_T4 +
conventional_mmp_A4 + conventional_mmp_T4 +
culm_refuse_subunit_dummy_A4 + culm_refuse_subunit_dummy_T4 +
dredge_subunit_dummy_A4 + dredge_subunit_dummy_T4 +
ind_shop_yard_subunit_dummy_A4 + ind_shop_yard_subunit_dummy_T4 +
rate_injury_high_likely_A4 + rate_injury_high_likely_T4 +
rate_injury_not_likely_A4 + rate_injury_not_likely_T4 +
rate_injury_occured_A4 + rate_injury_occured_T4 +
rate_injury_reas_likely_A4 + rate_injury_reas_likely_T4 +
rate_injury_unlikely_A4 + rate_injury_unlikely_T4 +
longwall_mmp_A4 + longwall_mmp_T4 +
mean_likelihood_A4 + mean_likelihood_T4 +
mean_negligence_A4 + mean_negligence_T4 +
mill_prep_subunit_dummy_A4 + mill_prep_subunit_dummy_T4 +
onsite_hours_A4 + onsite_hours_T4 +
other_mining_subunit_dummy_A4 + other_mining_subunit_dummy_T4 +
other_pct_A4 + other_pct_T4 +
recoverable_reserves_A4 + recoverable_reserves_T4 +
recovery_pct_A4 + recovery_pct_T4 +
reg_insp_hours_A4 + reg_insp_hours_T4 +
reg_onsite_insp_hours_A4 + reg_onsite_insp_hours_T4 +
shortwall_mmp_A4 + shortwall_mmp_T4 +
strip_quar_subunit_dummy_A4 + strip_quar_subunit_dummy_T4 +
surface_pct_A4 + surface_pct_T4 +
surface_ug_subunit_dummy_A4 + surface_ug_subunit_dummy_T4 +
total_coal_prod_A4 + total_coal_prod_T4 +
total_employees_A4 + total_employees_T4 +
total_inspection_hours_A4 + total_inspection_hours_T4 +
total_hours_worked_A4 + total_hours_worked_T4 +
ug_subunit_dummy_A4 + ug_subunit_dummy_T4 +
underground_pct_A4 + underground_pct_T4 +
active_prod_A4 + active_prod_T4 +
controller_ees_A4 + controller_ees_T4 +
controller_fte_A4 + controller_fte_T4 +
ctrl_intermed_injuries_rate_A4 + ctrl_intermed_injuries_rate_T4 +
```

```
ctrl_light_injuries_rate_A4 + ctrl_light_injuries_rate_T4 +
ctrl_lost_day_injuries_rate_A4 + ctrl_lost_day_injuries_rate_T4 +
ctrl_non_traum_injuries_rate_A4 + ctrl_non_traum_injuries_rate_T4 +
ctrl_num_injuries_rate_A4 + ctrl_num_injuries_rate_T4 +
ctrl_total_injuries_rate_A4 + ctrl_total_injuries_rate_T4 +
ctrl_traum_injuries_rate_A4 + ctrl_traum_injuries_rate_T4 +
ctrl_accidents_rate_A4 + ctrl_accidents_rate_T4 +
ctrl_fatalities_rate_A4 + ctrl_fatalities_rate_T4 +
ctrl_reg_insp_hours_A4 + ctrl_reg_insp_hours_T4 +
ctrl_penalty_points_rate_A4 + ctrl_penalty_points_rate_T4 +
controller_mines_A4 + controller_mines_T4 +
regular_assess_rate_A4 + regular_assess_rate_T4 +
single_assess_rate_A4 + single_assess_rate_T4 +
special_assess_rate_A4 + special_assess_rate_T4 +
higher_neg_viol_rate_A4 + higher_neg_viol_rate_T4 +
lower_neg_viol_rate_A4 + lower_neg_viol_rate_T4 +
sig_or_sub_viol_rate_A4 + sig_or_sub_viol_rate_T4 +
non_sig_or_sub_viol_rate_A4 + non_sig_or_sub_viol_rate_T4 +
rate_injury_likely_viol_rate_A4 + rate_injury_likely_viol_rate_T4 +
sig_or_sub_proportion_A4 + sig_or_sub_proportion_T4 +
higher_neg_prop_A4 + higher_neg_prop_T4 +
rate_injury_likely_prop_A4 + rate_injury_likely_prop_T4 +
prop_pen_rate_A4 + prop_pen_rate_T4 +
prop_pen_rate_reg_insp_A4 + prop_pen_rate_reg_insp_T4 +
viol_onsite_hrs_rate_A4 + viol_onsite_hrs_rate_T4 +
ss_viol_onsite_hrs_rate_A4 + ss_viol_onsite_hrs_rate_T4 +
viol_reg_insp_rate_A4 + viol_reg_insp_rate_T4 +
ss_viol_reg_insp_rate_A4 + ss_viol_reg_insp_rate_T4 +
viol_insp_rate_A4 + viol_insp_rate_T4 +
ss_viol_insp_rate_A4 + ss_viol_insp_rate_T4 +
viol_onsite_reg_rate_A4 + viol_onsite_reg_rate_T4 +
ss_viol_onsite_reg_rate_A4 + ss_viol_onsite_reg_rate_T4 +
num_affected_viol_rate_A4 + num_affected_viol_rate_T4 +
num_affected_size_rate_A4 + num_affected_size_rate_T4 +
contested_prop_A4 + contested_prop_T4 +
dust_samples_rate_A4 + dust_samples_rate_T4 +
sections_insp_rate_A4 + sections_insp_rate_T4 +
non_traum_quot_A4 + non_traum_quot_T4 +
light_quot_A4 + light_quot_T4 +
rate_contractor_size_pts_A4 + rate_contractor_size_pts_T4 +
rate_controller_size_pts_A4 + rate_controller_size_pts_T4 +
rate_good_faith_pts_A4 + rate_good_faith_pts_T4 +
rate_grav_injury_pts_A4 + rate_grav_injury_pts_T4 +
rate_grav_likelihood_pts_A4 + rate_grav_likelihood_pts_T4 +
rate_grav_persons_pts_A4 + rate_grav_persons_pts_T4 +
```

```
        rate_mine_size_pts_A4 + rate_mine_size_pts_T4 +
        rate_negligence_pts_A4 + rate_negligence_pts_T4 +
        rate_rep_viol_pts_A4 + rate_rep_viol_pts_T4 +
        rate_viol_per_day_pts_A4 + rate_viol_per_day_pts_T4 +
        rate_penalty_points_A4 + rate_penalty_points_T4 +
        rate_violator_agent_A4 + rate_violator_agent_T4 +
        rate_violator_contractor_A4 + rate_violator_contractor_T4 +
        rate_violator_miner_A4 + rate_violator_miner_T4 +
        rate_violator_operator_A4 + rate_violator_operator_T4 +
        rate_active_sections_A4 + rate_active_sections_T4 +
        rate_idle_sections_A4 + rate_idle_sections_T4 +
        rate_total_sections_insp_A4 + rate_total_sections_insp_T4 +
        inspection_rate_A4 + inspection_rate_T4 +
        reg_inspection_rate_A4 + reg_inspection_rate_T4 +
        intermed_injuries_rate_A4 + intermed_injuries_rate_T4 +
        lost_day_injuries_rate_A4 + lost_day_injuries_rate_T4 +
        non_traum_injuries_rate_A4 + non_traum_injuries_rate_T4 +
        num_injuries_rate_A4 + num_injuries_rate_T4 +
        total_injuries_rate_A4 + total_injuries_rate_T4 +
        traum_injuries_rate_A4 + traum_injuries_rate_T4 +
        light_injuries_rate_A4 + light_injuries_rate_T4 +
        accidents_rate_A4 + accidents_rate_T4 +
        fatalities_rate_A4 + fatalities_rate_T4 +
        mean_bed_thickness_A4 + mean_bed_thickness_T4 +
        number_coal_beds_A4 + number_coal_beds_T4 +
        controller_prod_A4 + controller_prod_T4 +
        revenue_A4 + revenue_T4 +
        stock_val_A4 + stock_val_T4 +
        total_productivity_A4 + total_productivity_T4 +
        revenue_rate_A4 + revenue_rate_T4 +
        stock_val_rate_A4 + stock_val_rate_T4,
# END LIST OF PREDICTOR VARIABLES
method = "poisson",
    control=rpart.control(cp=control),
   data=data)
data.fit
}

# CREATE THE FITS
# Now that we've defined all the functions we're gonna use, we need to
#       actually run the fits

# TRAUMATIC INJURIES
# Fit model
traum.fit <- fit.var("traum_injuries", data=x, control=0.00005)
```

```
# Prune model
# Get the cp and varlist for the pruned model
prune.list <- prune.vars(traum.fit)

# now we actually prune the model
pruned.traum.fit <- prune(traum.fit, cp=prune.list$cp)

# shorter list to account for interaction terms
prune22.list <- prune.vars(traum.fit, vcount=22)
pruned22.traum.fit <- prune(traum.fit, cp=prune22.list$cp)

out.tree("traumatic",traum.fit, "coal_traum", onefile=T,width=66,
    height=25.5,paper="special")
out.tree("traumatic",pruned.traum.fit, "coal_traum_streamline30",
    onefile=T,width=66,height=25.5,paper="special")
out.tree("traumatic",pruned22.traum.fit, "coal_traum_streamline22",
    onefile=T,width=66,height=25.5,paper="special")

# Top section of tree
# Try to get 10 or so nodes
top.prune.list <- prune.vars(traum.fit, vcount=5)
top.traum.fit <- prune(traum.fit, cp=top.prune.list$cp)
out.tree("traumatic",top.traum.fit, "coal_traup_top",onefile=T,width=11,
    height=8.5,paper="USr")
```

E.2 JAGS and R Code for Bayesian Forecasting

The following code is used by the JAGS program to define the Bayesian coal total injury model, and is contained in the `coal-total.bug` file.

```
model{
    for(i in 1:N){
        total_injuries[i] ~ dpois(mu[i])
        log(mu[i]) <- log_total_hours_worked[i] +
            intercept +
            beta[1,qtr[i]] * cent_app_plus_IL[i] +
            beta[2,qtr[i]] * east_dum[i] +
            beta[3,qtr[i]] * recovery_pct_A4[i] +
            beta[4,qtr[i]] * ctrl_light_injuries_rate_A4_0[i] +
            beta[5,qtr[i]] * lg_ctrl_light_injuries_rate_A4[i] +
            beta[6,qtr[i]] * ctrl_total_injuries_rate_A4_0[i] +
            beta[7,qtr[i]] * lg_ctrl_total_injuries_rate_A4[i] +
            beta[8,qtr[i]] * inspection_rate_A4_0[i] +
            beta[9,qtr[i]] * lg_inspection_rate_A4[i] +
```

```
            beta[10,qtr[i]] * onsite_hours_A4_0[i] +
            beta[11,qtr[i]] * lg_onsite_hours_A4[i] +
            beta[12,qtr[i]] * rate_acc_class_code_31_A4_0[i] +
            beta[13,qtr[i]] * lg_rate_acc_class_code_31_A4[i] +
            beta[14,qtr[i]] * total_injuries_rate_A4_0[i] +
            beta[15,qtr[i]] * lg_total_injuries_rate_A4[i] +
            beta[16,qtr[i]] * lg_controller_ees_A4[i] +
            beta[17,qtr[i]] * strip_quar_subunit_dummy_A4_dum[i] +
            beta[18,qtr[i]] * ug_subunit_dummy_A4_dum[i] +
            beta[19,qtr[i]] * east_X_lg_tot_inj_rt_A4[i] +
            beta[20,qtr[i]] * east_X_tot_inj_rt_A4_0[i] +
            beta[21,qtr[i]] * recovery_pct_A4_CART[i] +
            districtseason_eff[districtseason[i]]
    }
    # structure on the linear parameters
    for(k in 1:J){
        beta[k,1] ~ dnorm(0, 0.0001)T(-50,50)
        for(t in 2:Q){
            beta[k,t] ~ dnorm(beta[k,t-1],tau[k])T(-50,50)
        }
    tau[k] ~ dunif(0.5,10000)
    sig[k] <- 1.0/sqrt(tau[k])
    #  last beta
    betalast[k] <- beta[k,Q]
    #  new beta at time Q+1
    betanew[k] ~ dnorm(beta[k,Q],tau[k])
    }
    # districtseason_eff
    for(k in 2:ndistrictseason){
        districtseason_eff[k] ~ dnorm(0, 0.0001)T(-10,10)
    }
    districtseason_eff[1] <- 0.0
    intercept ~ dnorm(-11, 0.0001)T(-40,20)
}
```

To process the above `coal-total.bug` file, `R` requires a script, replicated below, contained in the file `coal-total.R`. This script loads the required data, sets the prior means for the coefficients, calls the `JAGS` program to run the MCMC and fit the model, and saves the results.

```
.libPaths(c("/mnt/glusterfs/software/free/R-2.15.0/lib/R/library",
                                                "/usr/lib/R/library"))

# Load libraries
library(rjags)
```

```
library(R2jags)

args <- commandArgs(T)
setwd(args[1])
# Set working directory
x <- read.csv("coal_total_final.csv")

# Cut down the data to a sample of 50k obs.
ss <- sample(nrow(x),50000)
x <- x[ss,]
N <- nrow(x)

qtr <- x$qtr
Q <- max(qtr)

districtseason <- x$districtseason
ndistrictseason <- max(districtseason)

total_injuries <- x$total_injuries
log_total_hours_worked <- log(x$total_hours_worked)

# MAIN COVARIATES:

cent_app_plus_IL <- x$cent_app_plus_IL
east_dum <- x$east_dum
recovery_pct_A4 <- x$recovery_pct_A4
ctrl_light_injuries_rate_A4_0 <- x$ctrl_light_injuries_rate_A4_0
lg_ctrl_light_injuries_rate_A4 <- x$lg_ctrl_light_injuries_rate_A4
ctrl_total_injuries_rate_A4_0 <- x$ctrl_total_injuries_rate_A4_0
lg_ctrl_total_injuries_rate_A4 <- x$lg_ctrl_total_injuries_rate_A4
inspection_rate_A4_0 <- x$inspection_rate_A4_0
lg_inspection_rate_A4 <- x$lg_inspection_rate_A4
onsite_hours_A4_0 <- x$onsite_hours_A4_0
lg_onsite_hours_A4 <- x$lg_onsite_hours_A4
rate_acc_class_code_31_A4_0 <- x$rate_acc_class_code_31_A4_0
lg_rate_acc_class_code_31_A4 <- x$lg_rate_acc_class_code_31_A4
total_injuries_rate_A4_0 <- x$total_injuries_rate_A4_0
lg_total_injuries_rate_A4 <- x$lg_total_injuries_rate_A4
lg_controller_ees_A4 <- x$lg_controller_ees_A4
strip_quar_subunit_dummy_A4_dum <- x$strip_quar_subunit_dummy_A4_dum
ug_subunit_dummy_A4_dum <- x$ug_subunit_dummy_A4_dum
east_X_lg_tot_inj_rt_A4 <- x$east_X_lg_tot_inj_rt_A4
east_X_tot_inj_rt_A4_0 <- x$east_X_tot_inj_rt_A4_0
recovery_pct_A4_CART <- x$recovery_pct_A4_CART
```

```
J <- 21

rm(x)

coal.data <- list("N","total_injuries","log_total_hours_worked",
                  "J","Q","qtr",
                  "districtseason", "ndistrictseason",
                  "cent_app_plus_IL",
                  "east_dum",
                  "recovery_pct_A4",
                  "ctrl_light_injuries_rate_A4_0",
                  "lg_ctrl_light_injuries_rate_A4",
                  "ctrl_total_injuries_rate_A4_0",
                  "lg_ctrl_total_injuries_rate_A4",
                  "inspection_rate_A4_0",
                  "lg_inspection_rate_A4",
                  "onsite_hours_A4_0",
                  "lg_onsite_hours_A4",
                  "rate_acc_class_code_31_A4_0",
                  "lg_rate_acc_class_code_31_A4",
                  "total_injuries_rate_A4_0",
                  "lg_total_injuries_rate_A4",
                  "lg_controller_ees_A4",
                  "strip_quar_subunit_dummy_A4_dum",
                  "ug_subunit_dummy_A4_dum",
                  "east_X_lg_tot_inj_rt_A4",
                  "east_X_tot_inj_rt_A4_0",
                  "recovery_pct_A4_CART")

# Number of iterations
Niter <- 40000

district.prior.mean <- c(
    -.1026644,
    -.1778535,
    -.3332436,
    -.2874044,
    -.3139769,
    -.2282602,
    -.3781201,
    -.4459323,
    -.4385682,
    -.3680194,
    -.5082364,
```

```
    -.2830556,
    -.2619277,
    -.2040192,
    -.3262996,
    -.3469341,
    -.325913,
    -.2717553,
    -.3974491,
    -.3645436,
    -.3624417,
    -.2738319,
    -.4784765,
    -.3395878,
    -.2958221,
    -.2399992,
    -.4845954,
    -.3728827,
    -.3380147,
    -.2296787,
    -.3704442,
    -.4758215,
    -.4678529,
    -.442632,
    -.5363921,
    -.4041793,
    -.3184453,
    -.2585521,
    -.4355256,
    -.4049131,
    -.382045,
    -.3002594,
    -.4644271,
    -.2698829,
    -.3182011,
    -.2257892,
    -.3878841)
beta.prior.mean <- c(
    .0005061,
    -.076746,
    .0001254,
    .0195732,
    -.001721,
    -.0740387,
    .6599684,
    .9444069,
```

```
    -.0580908,
    -.811498,
    .0420256,
    -.0698022,
    .0957753,
    .2826213,
    1.152119,
    -.0105272,
    -.115882,
    .2476359,
    -.0382617,
    -.1357543,
    -.0317947)

# Inits
coal.inits <- function(){
    list(
        beta = matrix(rep(beta.prior.mean,Q)+rnorm(J*Q,0,0.1),J,Q),
        districtseason_eff = c(NA, district.prior.mean +
            rnorm(ndistrictseason-1,0,0.1)),
        intercept = rnorm(1,-11.00,0.1),
        # betanew = rnorm(J,0,1),
        # tau = rgamma(J,3)/30
        tau = runif(J,100,1000)
    )
}

# Parameters to save
coal.params <- c("betanew","betalast","sig","districtseason_eff","intercept")

# run MCMC
coal_total.sim <- jags(data=coal.data, inits=coal.inits,
                      parameters.to.save=coal.params,
                      n.thin = 10,
                      model.file="coal-total.bug",
                      #n.chains=3,
                      n.chains=1,
                      n.iter=Niter)

coal_total_out <- as.data.frame(coal_total.sim$BUGSoutput$sims.matrix)
#  6000 rows, ??? columns
write.csv(coal_total_out,"coal_total_out.csv",quote=F,row.names=F)
```