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Occupational safety and profit maximization: Friends or foes?

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ABSTRACT

The rise of the Industrial Revolution is often depicted as a cause of hazardous working conditions and is skillfully epitomized in William Blake's tale of a child chimney sweeper. Conventional wisdom puts firm profit in conflict with occupational safety. We reexamine this argument noting that injuries are very costly to firms because they lead to higher wage premiums, worker compensation, and costly work stoppages. We hypothesize that it is precisely for these reasons that firms in the industries with dangerous working conditions have the strongest incentives to innovate and substitute more capital for labor. Using a longitudinal panel of U.S. industries, we test and confirm our hypothesis that higher injury rates lead to higher capital stock per worker, over time. Moreover, our estimates suggest that firms provide more capital and equipment per worker than what would have been there based solely on the compensating wage differential.

1. Introduction

Events such as the January 2006 Sago Mine disaster in West Virginia, in which twelve coal miners died, bring national media attention to the issue of workplace safety. Mass media accounts often reiterated the popularly held belief that the profit-maximizing objective of employers conflicts with the safety of employees. Such views have been widespread ever since the Industrial Revolution, and can be found in many contemporary writings of the time such as in William Blake's tale of a child chimney sweeper subjected to horrible working conditions. At the heart of this populist argument is the claim that a firm's profit is higher when it reduces costs by economizing on the level of safety provided to its employees.

This argument, however, oversimplifies the incentive structure on the part of employers or firms. Standard labor economic theory suggests that jobs with riskier working conditions will pay, when compared with otherwise similar jobs, a higher 'compensating differential' wage rate to offset this higher risk (Moore and Viscusi, 1990). In other words, a competitive labor market compensates workers in dangerous occupations with a wage premium compared to similar but less risky jobs. Schaffner and Kluve (2007) and Hersch (1998) find that a large portion of gender wage gap can be explained by different workplace risk-levels between jobs held by men and women. This wage premium illustrates the first incentive to reduce injuries for a profit-maximizing firm. From the firm's perspective, occupational injuries and more dangerous jobs result in higher wage costs.[1] Thus, firms will provide any known and feasible safety advance that costs less to implement than the change in wages from the improved safety. Because the wage premiums measure workers' voluntary willingness to take on risk for that sum, we can expect firms to provide all the safety advances that workers value more than they cost. Hence, the compensating wage differential ensures that the efficient level of safety is provided without the need for labor safety regulations. For instance, Viscusi (1992) documents that the labor market is able to account for job risk and reduce occupational injuries more effectively than Occupational Safety and Health Administration (OSHA) regulations.[2] Furthermore, Hall and Leeson (2007) contend that stringent labor standards are unlikely to be the reason for safer working environment because highly developed countries have adopted these labor standards relatively late in their development stage when safer working conditions were already the norm.

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[1] Alternatively, rather than increasing money wage rates, firms may offer additional fringe benefits to compensate for additional risk, however this also results in higher total employee compensation costs to the firm.

[2] For an analysis of how drug testing laws impact employment injuries see Kesselring and Pittman (2002).

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On top of the wage premium, workplace injuries may create additional costs that are often overlooked in this debate. These additional costs include work stoppages, workers compensation, insurance costs, labor turnover, and new worker hiring and training expenses.[3] The Sago Mine, for example, was out of operation for 78 days after the accident, costing the parent company the value of the lost production during this period—approximately 21% of the annual production from the mine (105,000 tons of coal worth approximately $4 million). In some continuous production industries, even short work stoppages can result in millions if not billions of dollars once the opportunity cost of forgone production is considered. McAlinden, an economist at the Center for Automotive Research, estimates that each injury-induced workday absence costs automakers at least $17,000. [4] According to this estimate, General Motors could have saved as much as $153 million a year by eliminating about 9000 annual lost workdays since 1993. The same source alludes to the National Safety Council estimates showing that disabling injuries on the job in the U.S. cost all parties involved about $29,000 per incident in 2003 dollars.

The undisclosed legal settlements paid out in the subsequent lawsuits to victims and their families, the bad publicity, high insurance and workers' compensation costs, and the threat of increased government regulatory oversight clearly demonstrate that firms face substantial injury-related costs on top of the wage premium. If the wage premium already induces firms to provide the 'efficient' level of safety from the workers' perspective, the additional costs from work stoppages, for example, should push firms to 'over provide' safety.[5] However, this 'over-provision' of occupational safety can be efficient if viewed through the prism of the efficiency wage argument. The efficiency wage argument claims that firms may find it profitable to pay more than the market clearing wage in order to reduce employee turnover and shirking. [6] A case study by Raff and Summers (1987) finds that Henry Ford's introduction of the five dollar pay day (a doubling of wages) in 1914 is consistent with the evidence of substantial queues for Ford jobs and significant increases in company's productivity and profits. A similar argument can be made about occupational safety: the efficient level of safety is greater than the level suggested by the compensating wage differential alone if wages do not reflect all the injury-related costs.

We test this hypothesis empirically by examining how the injury rate affects the capital to labor ratio in a longitudinal panel of 353 U.S. industries from 1977 to 1989. While typical economic models focus on equilibriums or steady states, here we consider a dynamic model of labor and capital usage by firms. In particular, we argue that if two industries differ only in injury rates, then the industry with the higher injury rate should be more likely to invest in new innovative technologies that will protect its workers from injuries or simply replace workers in dangerous occupations with machines (i.e. more physical capital). Either way, firms in high-injury industries would find it profitable to innovate or use more machines than workers, leading overtime to higher capital to labor ratios. For example, the ubiquitous chimney sweeps of the Industrial Revolution and the Victorian Age Britain were eventually replaced by a specially designed brush with a telescopic handle. In the logging industry, workers who used to operate chainsaws are increasingly

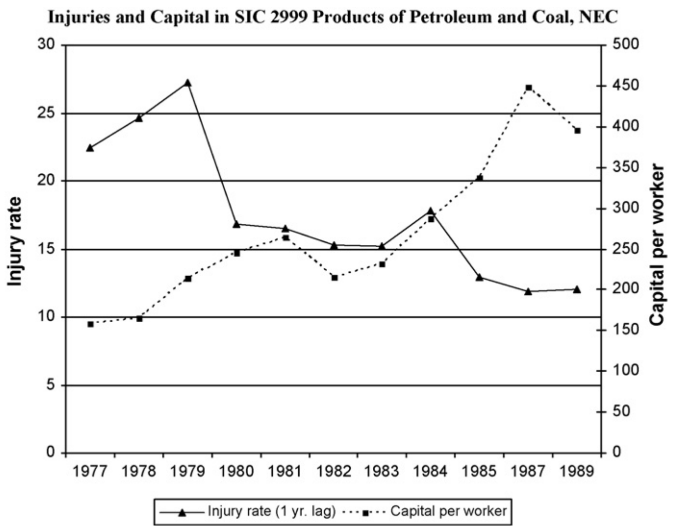

Fig. 1. Injuries and capital in SIC 2999 products of petroleum and coal, NEC.

operating 'feller-bunchers,' a $1 million tractor-type machine with an enclosed and protected cabin for the worker and a remote arm to saw and hold the trees as they are cut. Even in police bomb squads and U.S. military units in Iraq, we see robots and unmanned aerial vehicles increasingly replacing humans in dangerous situations.[7] The aforementioned examples illustrate our argument that profit-maximizing firms have an incentive to utilize more labor-saving technologies in order to minimize their injury-related costs.

This study proceeds as follows. In Section 2, we provide a brief analysis of the injury rate trends. In Section 3, we describe the variables used in this study. In Section 4, we use the profit function to illustrate how injuries may affect the capital to labor ratio, which sets the foundation for our empirical model. Lastly, we present our findings and discuss their robustness.

2. A look at the raw data

Prior to performing a more sophisticated econometric investigation, a quick look at the raw data is worthwhile. The coal industry is, and historically has been, one of the industries with the highest injury rates in the United States. Based on our argument, it should be a prime candidate for being an industry in which heightened pressure exists to invent and invest in new capital and technologies to reduce the use of labor, and to make existing jobs safer. Fig. 1 shows the raw data on worker injury rates and capital investment in this industry for the period of 1977–1989.

As is clearly visible in the figure, during this period, the injury rate fell substantially (in half), from the mid-twenties per 100 employees in the late-1970s to just under 12 per 100 employees by the early-1990s. Simultaneously, we witness large increases in capital per worker during this period, from $150 to just under $400 (almost tripling). The story painted by the data in Fig. 1 seem to confirm our hypothesis that high-injury rates force industries to increase capital investments and innovation in order to reduce injuries.

One reason this industry makes such a good example is because the main factor explaining this trend is indeed capital innovation—the longwall shearer (among others). This massive piece of equipment vastly reduces the demand for labor in the most dangerous part of the mining process. As a result, over the same

[3] Chelius (1991) discusses research showing that there is greater turnover during the first year of employment in dangerous jobs.

[4] Bloomberg.com: U.S. August 13, 2003. "General Motors Reduces Worker Injuries to Lowest for Carmakers."

[5] Several studies that matched survey responses to injury data have found that workers generally have a good perception of which occupations are risky and which are not (Viscusi, 1998).

[6] See Shapiro and Stiglitz (1984), Akerlof and Yellen (1986) for some of the earliest efficiency wage models.

[7] A similar argument is made by Yakovlev (2008) who shows that armies with higher capital per soldier ratios suffer fewer battlefield casualties.

Table 1
Changes in employment, capital per worker, and wages in industries with highest injury rates.

SIC	Injury rate (cases per 100 workers)			Employment (thousands of workers)			Capital per worker (thousands of dollars)			Average annual wage (thousands of dollars)		
	1977	1988	% Change	1977	1988	% Change	1977	1988	% Change	1977	1988	% Change
2011	32	30	−4%	117	98	−16%	61	71	16%	14	17	25%
2077	24	22	−10%	9	6	−31%	151	206	36%	12	19	60%
2429	35	30	−13%	6	2	−67%	32	59	82%	8	14	77%
2451	35	29	−19%	42	33	−20%	22	33	50%	9	16	79%
2452	26	28	5%	21	18	−14%	26	37	43%	10	16	61%
3316	27	24	−14%	15	12	−16%	129	145	12%	16	32	96%
3321	25	29	19%	117	73	−38%	76	136	79%	15	28	90%
3325	23	25	8%	44	20	−55%	62	129	108%	13	22	65%
3715	27	26	−4%	23	22	−3%	39	39	0%	10	18	81%
3792	28	24	−14%	22	13	−42%	22	41	89%	9	16	79%

Notes: SIC 2011 Meat Packing Plants, SIC 2077 Animal and Marine Fats and Oils, SIC 2429 Special Product Sawmills, SIC 2451 Mobile Homes, SIC 2452 Prefabricated Wood Buildings and Components, SIC 3316 Cold Finishing of Steel Shapes, SIC 3321 Gray and Ductile Iron Foundries, SIC 3325 Steel Foundries, SIC 3715 Truck Trailers, SIC 3792 Travel Trailers and Campers.

Table 2
Variable summary statistics and sources.[a]

Variable	1977		1989	
	N	Mean (Std. Dev.)	*N*	Mean (Std. Dev.)
Real capital stock per worker in $1000[b]	325	74.97 (82.12)	319	114.68 (128.64)
Real equipment stock per worker in $1000[b]	325	40.46 (47.24)	319	68.83 (80.97)
Real hourly wage of a production worker[b]	325	9.13 (2.26)	319	8.59 (2.31)
Non-lethal injury rate[c]	325	13.97 (6.08)	319	13.26 (5.78)
Federal funds rate[d]	325	5.54 (0)	319	9.21 (0)

[a] The dataset is an unbalanced panel of 353 U.S. industries ranging from SIC 2011 to SIC 3999 and spanning annually from 1977 to 1989. Some industries in this range are omitted due to data limitations.
[b] *Data source*: NBER-CES Manufacturing Industry Database (1958–1996).
[c] *Data source*: Bureau of Labor Statistics. Occupational injuries and illnesses: industry data (pre-1989).
[d] *Data source*: Federal Reserve Board (www.federalreserve.gov).

time period, employment in underground mining in the United States fell from over 130,000 to 70,000 (and it has continued to fall to around 40,000 by 2006). Thus today, because of increased capital investment and innovation, both fewer people work in dangerous mining jobs, and also those who do are now safer. For additional evidence on mine safety and the role of unions, see Reardon (1996) and Appleton and Baker (1984).

In dangerous industries, firms have a strong incentive to find ways to reduce labor in favor of capital, and also to reduce injury rates through capital investment. The patterns shown and discussed above in the raw data are also similarly present in other high-injury rate industries such as SIC 3295 (minerals and earths, ground or otherwise treated), SIC 3274 (lime), SIC 3639 (household appliances, NEC), and SIC 3644 (noncurrent-carrying wiring devices). Through time, these most dangerous industries have indeed seen higher capital to labor ratios, declining employment, and reductions in injury rates.

For example, Table 1 lists top ten industries with the highest injury rates in 1977 and shows how injuries, employment, capital per worker and wages have changed over time. All but two industries had significantly lower injury rates in 1988 than in 1977. Moreover, all industries in Table 1 showed a dramatic decrease in employment and dramatic increase in capital per worker (except for one industry) and wages over the same time period.

3. Data

Our dataset is a longitudinal panel of 353 U.S. industries arranged by the Standard Industrial Classification (SIC) code. The industries in our dataset range from SIC 2011 to SIC 3999 and span annually from 1977 to 1989. Our measure of K is real capital stock that includes equipment and plant (structures). We also employ an alternative measure of capital stock that excludes structures because only equipment is likely to be the relevant variable. Our measure of L is the number or production workers, and measure of w is the average hourly worker real wage rate. Thus, our capital to labor ratio is simply K divided by L. All of the above variables are obtained from the NBER-CES Manufacturing Industry Database.[8] The real capital stock K in the NBER-CES is imputed from investment flows using a perpetual inventory model with stochastic service lives and beta decay (see Mohr, 1995 for details). The cost or rental rate of capital r is measured by the effective federal funds rate (annualized bank interest) adjusted for inflation. We assume that the cost of capital in the United States is the same across all industries in a given year and can be approximated by the interest rate at which private banks lend funds to other depository institutions.

The injury rate data is from the Bureau of Labor Statistics and represents the number of non-lethal injuries or illnesses per 100 equivalent full-time workers. We decided against using the injury rate with fatalities because changes in the BLS definition of the injury rate after 1988 and changes in the industry classification codes from SIC to NAICS severely limit the number of useable observations. In order to maximize the number of observations for a consistently measured injury variable, we have to rely on the non-lethal injury rate over from 1977 to 1988. Nevertheless, the non-lethal injury rate is a good proxy for the injury rate with fatalities because we find the two measures to be highly correlated (with correlation coefficient of 0.9850 and statistical significance at the

[8] The NBER-CES database is a joint effort between the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center for Economic Studies (CES). It contains annual industry-level data on output, employment, payroll, investment, capital stock, TFP, and various industry-specific price indexes. The database covers all 4-digit manufacturing industries spanning from 1958 to 1996. For more information visit: http://www.nber.org/nberces/.

Table 3
Pair-wise correlations.

	Capital per worker	Equipment per worker	Wage rate	Interest rate	Injury rate
Capital per worker	1.0000				
Equipment per worker	0.9878*	1.0000			
Wage rate	0.7307*	0.7348*	1.0000		
Interest rate	−0.1192*	−0.1273*	−0.0292	1.0000	
Injury rate	0.0441*	0.0705*	0.0385*	0.0386*	1.0000

All variables are in logarithms.
* Statistically significant at the 5% level.

1% level). Our summary statistics and data sources are shown in Table 2.

The pair-wise correlations for the variables used in this study are shown in Table 3. These correlations reveal that capital stock per worker and equipment stock per worker are strongly correlated with each other and the wage rate.

The injury rate is significantly correlated with both capital and equipment stock per worker, but not as strongly as the wage rate. However, the injury rate has a stronger correlation with equipment rather than capital stock per worker, as suspected. Although the injury rate is also significantly correlated with the wage and interest rates, these correlation are very weak in magnitude and do not create a multicollinearity problem as confirmed by our variance inflation tests.

4. The empirical model and estimates

Since the basic question we attempt to answer is whether firms face a tradeoff between occupational safety and profit, the ubiquitous profit function is the natural starting point for our analysis. Let there be a hypothetical firm that maximizes profit in a perfectly competitive market with exogenously determined output and input prices:

$$Max\ \pi = pF(K, L) - rK - wL, \tag{1}$$

where profit π equals the market price of firm's output p times the amount of output $Q = F(K, L)$ produced from the combination of capital K and labor L employed by the firm minus the cost of capital and labor at rates r and w per unit. Maximizing the profit function for a perfectly competitive firm with respect to capital and labor, yields the conventional first-order conditions showing that the ratio of marginal products of capital and labor is a function of capital and labor hired in proportion to their respective costs r and w:

$$\frac{\partial F(K, L)/\partial L}{\partial F(K, L)/\partial K} = \frac{F_L}{F_K} = \frac{w}{r}. \tag{2}$$

The above equation is interpreted as follows. A firm will maximize profit as long as it hires capital and labor in proportion to their respective costs r and w, which are also equal to the marginal products of capital F_K and labor F_L. Allow us to illustrate the implications of this conclusion more concretely with a specific functional form:

$$Max\ \pi = p(K^{1/2}L^{1/2}) - rK - wL, \tag{3}$$

where $Q = K^{1/2}L^{1/2}$ is a convenient constant returns to scale (CRS) production function with diminishing marginal products of capital and labor. It can be shown that solving the first-order profit-maximizing conditions for Eq. (3) yields a very insightful result:

$$\frac{K}{L} = \frac{w}{r}. \tag{4}$$

The above equation shows that the capital to labor ratio is directly related to the wage rate w and inversely related to the capital rental rate r. Holding everything else equal, an industry with a higher wage rate, perhaps as a result of injuries, should utilize a higher level of capital relative to labor. Expressing the variables as logarithms converts regression coefficients into elasticities, which is very convenient for comparing coefficient estimates across differently measured variables. Taking advantage of this property, we transform Eq. (4) and obtain:

$$\ln\left(\frac{K}{L}\right) = \ln(w) - \ln(r). \tag{5}$$

Since CRS production functions such as the Cobb-Douglas type provide a reasonably good approximation of the overall production processes in the economy, Eq. (5) serves as the basic foundation for our empirical model. If our logic is correct, the industries with high-injury rates should eventually increase their capital to labor ratios in order to lower their injury-related costs and maximize profits. Injuries could influence the capital to labor ratio directly (on top of wages) and indirectly (through wages due to compensating differential). We test this hypothesis using different model specifications and empirical techniques in order to confirm the robustness of our findings. We start with the simplest empirical model that is based on Eq. (5) and augment it with the injury rate to test its direct impact on the capital to labor ratio. The following model is estimated via pooled OLS using observations for over 350 industries (i) that span across a dozen of years (t):[9]

$$\ln\left(\frac{K_{it}}{L_{it}}\right) = \alpha + \beta_1\ \ln(w_{it}) - \beta_2 \ln(r_{it}) + \beta_3 \ln(\eta_{i,t-1}) + \varepsilon_{it}, \tag{6}$$

where $\eta_{i,t-1}$ is a one-year lag of the work-related injury rate and ε_{it} is the error term. We lag the injury rate in order to avoid capturing the reverse causality effect in the coefficient estimate. The reverse causality issue may arise if the capital to labor ratio also determines the amount of injuries in the same year. This is less likely to occur if we use the injury rate from a prior year.[10] The estimates shown in Table 4 support our basic hypothesis that higher injury and wage rates increase the capital to labor ratio, while higher rental rates decrease it. All coefficient estimates in this regression are both economically and statistically significant (at the 1% level), although the coefficients for the injury rate and the rental rate are significantly smaller in magnitude than the wage rate coefficient. Since all variables are in logarithms, their coefficient estimates can be interpreted as elasticity estimates. Thus the economic interpretation of the coefficient for our main variable of interest, the injury rate, implies that a doubling of the injury rate results in a 6% increase in the firm's capital to labor ratio.

However, this model specification and the OLS estimator may suffer from several shortcomings that could lead to biased and inconsistent estimates. For instance, the model specification test indicates that our first regression suffers from a significant model specification error probably because it ought to be specified as a dynamic (autoregressive) model since we are dealing with panel

[9] Depending on the regression or model specification, the number of observations could be as large as 3924.

[10] Lagging the variable to avoid the reverse causality problem may not work well in the presence of autocorrelation, which is the case in our dataset. We control for autocorrelation in the other regressions.

Table 4
The effect of injury rate on capital per worker.

Regression	1	2	3	4	5	6
Estimator	Pooled OLS	Industry FE	Pooled OLS	Robust Regression	PCSE	2SLS-IV
First-differenced	No	No	Yes	Yes	Yes	Yes
Dependent variable						
1-year lag	–	0.67*** (0.01)	0.06*** (0.02)	0.07*** (0.02)	−0.03 (0.03)	0.06*** (0.02)
Injury rate						
1-Year lag	0.06*** (0.02)	–	–	–	–	–
2-Year lag	–	0.05*** (0.01)	0.03* (0.02)	0.02** (0.01)	0.04*** (0.01)	0.03** (0.01)
Real wage rate	2.40*** (0.04)	0.43*** (0.03)	0.13* (0.08)	0.15*** (0.03)	0.14*** (0.05)	0.98*** (0.20)
Real interest rate	−0.27*** (0.03)	−0.02*** (0.01)	−0.08*** (0.01)	−0.07*** (0.01)	−0.10*** (0.01)	−0.01 (0.02)
Constant	−0.50*** (0.10)	0.41*** (0.05)	0.03*** (0.002)	0.03*** (0.002)	0.03*** (0.002)	0.04*** (0.003)
R-square	0.56	0.98	0.03	0.03	0.05	0.69
F-statistic	1511***	1517***	21***	34***	–	27***
F-statistic, test that all $u_i = 0$	–	2.38***	–	–	–	–
Baltagi–Wu LBI	–	1.93				
Wald chi-squared	–	–	–	–	123***	–
Sargan over-identification IV test, *P*-value	–	–	–	–	–	0.70
Anderson under-identification IV test, *P*-value	–	–	–	–	–	0.00
Observations	3924	3153	3108	3108	3153	3108

All variables are in logarithms.
*** Significance level at 1%.
** Significance level at 5%.
* Significance level at 10%.

data here.[11] To confirm this suspicion, we perform the same test for the model in Eq. (6) now augmented with the lagged capital to labor ratio and the second-year lag of the injury rate as additional regressors. This new, dynamic model passes our model specification test. In addition, our panel data is also characterized by autocorrelation, heteroskedasticity, and time-invariant fixed effects, which could make our pooled OLS estimates biased and inconsistent. Therefore, we estimate this dynamic model with industry fixed effects and standard errors robust to autocorrelation and heteroskedasticity. The fixed-effects estimator yields more consistent estimates compared to the conventional (pooled) OLS and random effects estimators in the presence of time-invariant unobserved characteristics that are correlated with omitted variables.[12] We estimate the following specification with the time-invariant, industry-specific fixed effects z_i:

$$\ln\left(\frac{K_{it}}{L_{it}}\right) = \alpha + \gamma \ln\left(\frac{K_{i,t-1}}{L_{i,t-1}}\right) + \beta_1 \ln(w_{it}) - \beta_2 \ln(r_{it}) + \beta_3 \ln(\eta_{i,t-2}) + z_i + \varepsilon_{it}. \quad (7)$$

The estimates for this model are shown in Table 4 and are again both economically and statistically significant (at the 1% level). These estimates are similar to those in the previous regression except that the wage rate and interest rate coefficients have smaller magnitudes (0.43 and −0.02, respectively). From an economic standpoint, the coefficient on our variable of interest, the injury rate, implies that doubling the injury rate would result in 5% increase in a firm's capital to labor ratio. This is only slightly lower than it was in the prior specification where the similar impact was estimated to be 6%.

In order for the above fixed effects estimates to be consistent, the regressors must be strictly exogenous (Wooldridge, 2002). In other words, current period regressors must not be correlated with the previous period's disturbance. This condition is unlikely to hold in a dynamic model with the fixed effects (i.e. unobserved heterogeneity) even if there is no autocorrelation. To address this issue we estimate the following first-differenced autoregressive model:

$$\Delta \ln\left(\frac{K_{it}}{L_{it}}\right) = \alpha + \gamma\Delta \ln\left(\frac{K_{i,t-1}}{L_{i,t-1}}\right) + \beta_1\Delta \ln(w_{it}) - \beta_2\Delta \ln(r_{it}) + \beta_3\Delta \ln(\eta_{i,t-2}) + \varepsilon_{it}. \quad (8)$$

First-differencing converts the logarithms into growth rates and removes the time-invariant, industry-specific fixed effects as well as the first-order autocorrelation. We estimate this model via pooled OLS with heteroskedasticity-robust standard errors. The estimates for this second regression shown in Table 4 also indicate that higher injury and wage rates increase the capital to labor ratio, while higher interest or rental rates decrease it (all variables are statistically significant at the 10% level). Our variable of interest is again economically significant as well, with a doubling of the (growth rate of the) injury rate leading to a 3% increase in the (growth rate of the) capital to labor ratio, a similar value to what was obtained in the other specifications.

Next, we estimate the model in Eq. (8) via robust regression (a form of weighted least squares), which performs well in the presence of outliers, heteroskedasticity, and other anomalies that might violate some of the OLS assumptions. The robust regression results shown in Table 4 are consistent with previous OLS estimates and offer higher levels of statistical significance. The robust estimates indicate that the growth in the capital to labor ratio is responsive to the growth in the wage rate (0.15), the interest rate (−0.07), and the injury rate (0.02). Economically, these estimates are similar to our other models with a doubling of the (growth rate of the) injury rate leading to a 2% increase in the (growth rate of the) capital to labor ratio.

As an additional robustness check, we estimate Eq. (8) using feasible generalized least squares (FGLS) and Prais-Winsten panel corrected standard errors (PCSE) regressions that are recommended for panel data characterized by autocorrelation and heteroskedasticity (Yaffee, 2003). FGLS and PCSE estimators often yield similar results, but their estimates may diverge for small samples. Some econometricians prefer to use the PCSE estimator because the asymptotically efficient FGLS estimator may perform poorly in finite samples (Beck and Katz, 1995). We try a wide vari-

[11] We use the model specification test where the dependent variable is regressed on its own predicted value as well as the square of the predicted value. The predicted value should be significantly correlated with the dependent variable if the model has good explanatory power, but the squared term should not be significantly related to the dependent variable if the model has no omitted variable bias.

[12] The Breusch-Pagan, Hausman, and *F* tests have all rejected the random-effects estimator in favor of the fixed-effects estimator.

Table 5
The effect of injury rate on equipment per worker.

Regression	1	2	3	4	5	6
Estimator	Pooled OLS	Industry FE	Pooled OLS	Robust Regression	PCSE	2SLS-IV
First-differenced	No	No	Yes	Yes	Yes	Yes
Dependent variable						
1-Year lag	–	0.69*** (0.01)	0.09*** (0.02)	0.10*** (0.02)	-0.01 (0.03)	0.09*** (0.02)
Injury rate						
1-Year lag	0.12*** (0.02)	–	–	–	–	–
2-Year lag	–	0.05*** (0.01)	0.03* (0.02)	0.03** (0.01)	0.04*** (0.01)	0.03** (0.01)
Real wage rate	2.63*** (0.04)	0.35*** (0.03)	0.13* (0.08)	0.16*** (0.04)	0.13** (0.05)	0.91*** (0.21)
Real interest rate	−0.32*** (0.03)	−0.03*** (0.01)	−0.07*** (0.01)	−0.06*** (0.01)	−0.09*** (0.01)	−0.01 (0.02)
Constant	−1.62*** (0.11)	0.38*** (0.06)	0.03*** (0.002)	0.03*** (0.002)	0.04*** (0.002)	0.04*** (0.003)
R-square	0.57	0.98	0.03	0.03	0.05	0.75
F-statistic	1667***	1483***	19***	35***	–	26***
F-statistic, test that all $u_i = 0$	–	2.37***	–	–	–	–
Baltagi–Wu LBI	–	1.94	–	–	–	–
Wald chi-squared	–	–	–	–	102***	–
Sargan over-identification IV test, *P*-value	–	–	–	–	–	0.79
Anderson under-identification IV test, *P*-value	–	–	–	–	–	0.00
Observations	3924	3153	3108	3108	3108	3108

All variables are in logarithms.
*** Significance level at 1%.
** Significance level at 5%.
* Significance level at 10%.

ety of autocorrelation corrections in both FGLS and PCSE estimators in order to control for any autocorrelation that may remain after first-differencing, but all of them produce very similar results. Due to space constraints in Table 4, we only show the results from a fairly representative PCSE regression. The PCSE estimates are statistically significant at the 1% level and confirm the previous finding that wages and injuries increase the capital to labor ratio. Again the results are economically significant, with the doubling of the injury rate leading to a 4% increase in a firm's capital to labor ratio.

Although all of our estimates so far have shown that the injury rate has a direct impact on the capital to labor ratio, one remaining issue could make our results biased and inconsistent. This issue is the endogeneity bias that might be present in the wage rate coefficient estimates. The first-differenced model in Eq. (8) might produce biased and inconsistent estimates if the wage rate is endogenous or is significantly correlated with the disturbance, lagged dependent variable, or the injury rate. For example, the wage rate coefficient might be biased because it embodies the compensating wage differential (risk premium) in proportion to the injury rate in a particular industry. In other words, injuries can influence the capital to labor ratios in two separate but non-mutually exclusive ways: (1) indirectly, through higher wage premiums or differentials that compensate workers for more dangerous working conditions and (2) directly, through work stoppages, insurance costs, lawsuit settlements, worker compensation, and so on. So far, our estimates have focused only on the direct or explicit effect of the injury rate on the capital to labor ratio because the indirect effect is not explicitly separable from the observed wage rate, but ought to be correlated with it. In fact, the pair-wise correlations in Table 3 reveal that the injury rate is positively and significantly, albeit weakly, correlated with the wage rate suggesting that the wage rate embodies the injury-related risk premium. To account for this indirect effect, we estimate the following first-differenced model via two-stage least squares (2SLS-IV) with autocorrelation and heteroskedasticity-robust standard errors.

First-stage regression:

$$\Delta\ \ln(w_{it}) = \alpha_1 + \gamma_1 \Delta \ln\left(\frac{K_{i,t-1}}{L_{i,t-1}}\right) + \beta_1 \Delta\ \ln(w_{i,t-1}) + \beta_2 \Delta \ln(\eta_{i,t-1}) + \beta_3 \Delta \ln(\eta_{i,t-2}) + \beta_4 \Delta \ln(r_{it}) + \nu_{it} \quad (9)$$

Second-stage regression:

$$\Delta\ \ln\left(\frac{K_{it}}{L_{it}}\right) = \alpha_2 + \gamma_2 \Delta \ln\left(\frac{K_{i,t-1}}{L_{i,t-1}}\right) + \beta_5 \Delta\ \ln(\hat{w}_{it}) - \beta_6 \Delta \ln(r_{it}) + \beta_7 \Delta \ln(\eta_{i,t-2}) + \omega_{it}. \quad (10)$$

In the first-stage regression, the market wage rate w_{it} is instrumented by its own one-year lag and one-year lag of the injury rate $\eta_{i,t-1}$. Then, the predicted value of the wage rate from the first-stage regression enters the second-stage regression in Eq. (10). If proper instruments are chosen, the coefficient estimates for w_{it} and $\eta_{i,t-2}$ in the second-stage regression should be unbiased. The Sargan over-identification test confirms that our instruments are valid, while the Durbin–Wu–Hausman chi-square test confirms that the wage rate is endogenous. If there was significant bias in our previous estimates, we should observe significantly different coefficients for the wage rate and injury rate in the 2SLS-IV regression. The last estimates in Table 4 show that the wage and injury variables have the expected signs and are statistically significant (except for the interest rate). In addition, the coefficient for the wage rate is now 0.98, which is about six times higher compared to our previous first-differenced regressions. Since this large increase in the wage rate coefficient is matched by a large reduction in the lagged dependent variable's coefficient, we hypothesize that most of the bias comes not from the injury rate's influence on the wage rate (supported by the weak pair-wise correlation between the two variables), but rather from the lagged capital to labor ratio in our dynamic model. Again, our main variable of interest, the injury rate, has an economically significant impact estimated to be almost identical to what we found in our other specifications. Here a doubling of the injury rate results in a 3% increase in the capital to labor ratio.

As an additional robustness check, we re-estimate the regressions in Table 4 using equipment stock per worker as the dependent variable instead of capital stock per worker. Our capital stock per worker variable includes equipment as well as structures and because of that may not be a very accurate or relevant measure for our hypothesis testing. It is more likely that firms change their equipment rather than structures in response to higher injuries. Hence, we re-estimate the same regressions in Table 4 using equipment stock per worker as the dependent variable.

The new estimates in Table 5 are very similar to those in Table 4 and provide additional support for our hypothesis. As an additional robustness check, we re-estimate the FGLS regressions using a balanced-panel of industries in order to correct for contemporaneous correlation and group-wise heteroskedasticity. This procedure shrinks our dataset by several hundred observations, but yields no significant changes in the estimates. The economic significance of the injury rate is almost identical to what we found in Table 4. In one specification it is higher than before, with a doubling of the injury rate leading to a 12% increase in the equipment to labor ratio, but for the remaining specifications the impact ranges from 3 to 5%, in line with our estimates in Table 4.

All of our regressions show that both the wage rate and the injury rate have significant positive effects on the capital to labor ratio. Since the injury rate is statistically significant along with the wage rate in all of our regressions, it suggests that firms may provide safety beyond the efficient level that is based solely on the compensating wage differential. This over-provision of safety is not inefficient if viewed through the prism of the efficiency wage argument. In other words, the significance of the injury rate in our estimates suggests that firms internalize at least some of the costs associated with work stoppages, workers compensation, insurance costs, labor turnover, and new worker hiring and training. These estimates are consistent with our hypothesis that the injury-induced wage premiums and the additional costs associated with workplace injuries force profit-maximizing firms to create a safer working environment by shielding their workers with more or better equipment. Thus, the desire to create a safer working environment is consistent with the firm's profit-maximizing objective.

5. Conclusion

Contrary to popular opinion, we find that profit-maximizing firms have a very strong incentive to provide safer working conditions by substituting more capital for labor in more dangerous occupations. The overlooked yet critical link behind this claim is that firms face higher wages and injury-related costs (insurance, worker compensation, work stoppages, etc.) when workplace safety is low. All else constant, this means that labor is relatively more costly than capital in these industries once the cost of injuries is factored in. This gives firms an incentive to find and adopt new capital and technologies that reduce worker exposure to danger and lead to lower injury rates over time. Using a longitudinal panel of U.S. industries, we have documented empirically that industries with higher injury rates have higher future capital to labor ratios.

Individual examples, such as the longwall shearer machine used in coal mining, provide the context within which these aggregate impacts can be understood. Major reductions in employment levels and injury rates accompanied the technological advancements during the period we examine, notably the invention and widespread adoption of the longwall shearer. A study by Conway and Svenson (1998) concurs with this hypothesis by noting that a decrease in occupational injuries in the early to mid-1990s coincides with a significant shift of employment away from the injury-prone industries.

Our empirical findings suggest that in a dynamic and competitive market economy, market forces will encourage more rapid rates of injury-reducing technological innovations in industries with high-injury rates. Thus, market-based economies with a well-functioning legal system can be expected to move, over time, towards less intensive labor usage in dangerous occupations (as machines replace workers) and increasing occupational safety for the few workers remaining in dangerous occupations (as better machines make for a safer workplace).

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