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Heterogeneity in Income Tax Incidence

Are the Wages of Dangerous Jobs More Responsive to Tax Changes than the Wages of Safe Jobs?

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Heterogeneity in Income Tax Incidence: Are the Wages of Dangerous Jobs More Responsive to Tax Changes than the Wages of Safe Jobs?*

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Abstract

Income taxes distort the relationship between wages and non-taxable amenities. When the marginal tax rate increases, amenities become more valuable as the compensating differential for low-amenity jobs is taxed away. While there is evidence that the provision of amenities responds to taxes, the literature has ignored the consequences for job characteristics which cannot fully-adjust. This paper compares the wage response of dangerous jobs to the wage response of safe jobs. When tax rates increase, we should see the pre-tax compensating differential for on-the-job risk increase. Empirically, I find large differences in the wage response of jobs based on their riskiness.

Keywords: Income Taxes, Value of a Statistical Life, Tax Incidence, Compensating Differentials
JEL classification: H22, H24, J17, J28, J31

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1 Introduction

The theory of compensating differentials has been well-established since the writings of Adam Smith in 1776. Non-wage amenities should impact workers' wages, and much empirical research has been dedicated to studying the relationship between wages and amenities. However, there is little research studying how compensating differentials interact with income and wage taxes. While non-wage amenities are untaxed, the compensating differential is subject to taxation. Consequently, observed compensating differentials are a function of tax rates. When tax rates change, the pre-tax wages of jobs with different non-wage amenities must shift differentially. Thus, we should observe heterogeneity in the incidence of income taxes based on the amenity-level of the job.

This paper compares the wage response of jobs with different levels of amenities to legislative tax changes. I focus on industries with varying on-the-job hazard rates for three reasons. First, occupational safety is easy to measure. Second, a vast literature has studied the existence and magnitude of compensating differentials with respect to occupational hazards. Individuals working in risky jobs should be compensated for the additional risk with higher wages. This literature has focused on the effect of work-related fatality rates as a means of estimating the value of a statistical life (VSL). Third, amenity levels likely respond to tax changes. However, some amenities are simply fixed characteristics of a job and cannot fully-adjust. Occupational safety is an example where the most dangerous jobs can never become as safe as the safest jobs, regardless of the tax environment. Risk rates may adjust to some extent, but it should still be possible to measure the compensating differential under different tax regimes.

Thus, this paper looks at how the pre-tax wages of dangerous jobs respond to tax changes relative to the pre-tax wages of safe jobs. When tax rates increase, the compensating differential associated with dangerous jobs is taxed away. In response, the pre-tax compensating differential must increase, implying that the wages of the dangerous jobs must increase more than the wages of the safe jobs for a given difference in risk.

It is well-known that individuals and firms respond to tax changes. Taxes distort individual labor supply decisions and occupational choices. Similarly, firms may alter the generosity of their non-taxable amenities in response to taxes. Both of these phenomenon have been studied in the tax literature. However, these effects do not fully encapsulate the magnitude of the distortion resulting from taxes. To some extent, non-taxable amenities cannot completely adjust in response. Jobs have some fixed characteristics which are incapable of responding to tax changes. Instead, wages must adjust. Consequently, taxes may distort the cross-industry relationship between pre-tax wages.

I use the 1983-2002 March CPS with BLS injury data and NIOSH fatality data to estimate the relationship between wages, injury and fatality rates, and marginal net-of-tax rates $(1-\tau)$. Because tax rates are a function of wages, I use an IV strategy similar in spirit to Currie and Gruber [1996a,b] where identification originates solely from legislative federal tax changes and cross-sectional differences in risk. This strategy allows me to control separately for the tax rate and the risk rates and look at the impact of the interaction. Similarly, I am able to control for fixed wage differences through the inclusion of industry-state fixed effects. I find large differences in the wage response of industries to tax changes based on the riskiness of those industries. I show that these estimates are not due to secular wage trends during this time period. Furthermore, the results are robust to the inclusion of individual fixed effects using the PSID.

The next section of this paper briefly summarizes the existing literature. Section 3 presents a basic model illustrating the interaction between wages, risk, and taxes. Section 4 details the data and sample. Section 5 describes the empirical strategy. Section 6 presents the results and Section 7 concludes.

2 Literature Review

2.1 Value of a Statistical Life

A vast literature has studied the empirical relationship between risk and wages for the estimation of the value of a statistical life (Viscusi [1993]). Viscusi and Aldy [2003] provide a thorough review and summarize that the majority of the studies estimate the value of a statistical life between \$5 million and \$12 million, with a median value of \$7 million. The value of a statistical injury has been estimated as between \$20,000 and \$70,000. Adopting similar notation as Viscusi and Aldy [2003], the typical VSL specification is as follows:

$$w_{ij} = \alpha + X_{ij}'\gamma + \beta_1 p_j + \beta_2 q_j + \beta_3 q_j WC_i + \epsilon_{ij} \tag{1}$$

where w_{ij} is the wage of worker i in industry j. X_{ij} is a set of control variables, p_j is the fatality rate, q_j is the injury rate, and WC_i is the worker's compensation replacement rate. While this exact specification is not always employed, the general idea is to estimate the observed relationship between wages and risk rates.

The theory behind compensating differential estimation is also well-explored and difficult to summarize concisely. Many papers, such as Hwang et al. [1992], detail the problems of estimating compensating differentials in the presence of skill heterogeneity.

A large set of papers find a positive correlation between risk and wages. My paper implicitly tests the existence of this relationship. If workers place no value on occupational safety (or related amenities), then there is no compensating differential and wages should not differentially respond to taxes.

2.2 Taxes

It is well-known that wage taxes distort the demand for non-wage amenities. Papers such as Gruber and Lettau [2004] study the provision of these amenities as a response to this tax subsidy. When tax rates change, the relative price between taxable income and non-taxable amenities shifts. Firms respond to workers' demands by providing more or less generous amenities.

In related work, Powell and Shan [2009] study individual-level occupational responses to tax changes, another possible margin of distortion to income taxes. When tax rates decrease, the return to a high wage (low amenity) job decreases. This paper finds that, as expected, individuals move to higher wage occupations when tax rates decrease.

Amenity provision also shifts over time as I will show with my injury and fatality rate data. Hamermesh [1999] discusses the growing inequality of amenities. Shifts in on-the-job risk are important in my context and my empirical strategy accounts for these shifts without any assumptions on the exogeneity or endogeneity of such changes to legislative tax changes. By focusing on the compensating differential (which uses cross-sectional variation in risk), the empirical strategy accounts for changes in the levels of the risk rates over time.

A separate literature studies the incidence of income taxes. Leigh [2010] uses state-level changes in EITC generosity to identify the impact of taxes on wages and finds an economically meaningful effect. Kubik [2004] uses the Tax Reform Act of 1986 to study whether occupations which were disproportionately affected by the tax rate changes experienced large pre-tax wage changes. The paper finds evidence that occupations with the largest tax decreases incurred the largest wage decreases. These results are dependent on the inclusion of occupation-specific linear trends, suggesting that the change in the tax rate is not exogenous. While I am not estimating the same parameters as Kubik [2004], an advantage of my approach is that I am separately controlling for the change in the tax rate and looking at effects "within-tax rate." In other words, I add another "difference," reducing concerns that trends are biasing the results.

Albouy [2009] examines how a non-linear tax schedule differentially affects cities with higher wages. These higher wages can be thought as a compensating differential for working and living in a city with a low quality of life. Taxes disproportionately burden high compensating differential geographic areas in the same way as they impact high compensating differential industries.

In my context, is is plausible that firms respond to higher taxes by increasing safety standards to reduce fatality and injury risks, and I will discuss how my empirical strategy is robust to this possibility later. However, on a basic level, some jobs are simply riskier than others by their inherent nature. Thus, firms must respond on a different margin than the provision of the non-wage amenity. This paper examines how pre-tax wages respond when a non-wage amenity is prohibitively costly to provide. The focus is on heterogeneity in the incidence of income tax changes. Dangerous (low-amenity) jobs should be more responsive to tax changes than safe (high-amenity) jobs.

3 Model

I include a very simple model to illustrate the relationships between wages, taxes, and amenities. The model is similar to the one found in Powell and Shan [2009]. In this model, workers maximize utility which is a function of consumption (c) and on-the-job risk (R). $w(R)$ is the market wage function where $\frac{\partial w(R)}{\partial R} > 0$. $T[z]$ represents the tax burden given total income z where z will simply be the sum of the wage and non-labor income (y).

The marginal worker faces the following maximization problem:

$$\max_{c,R} U(c, R) \quad \text{s.t.} \quad c = w(R) + y - T[w(R) + y]$$

This reduces to

$$\max_R U\left\{w(R) + y - T[w(R) + y], R\right\}$$

The first order condition defines the wage function which keeps the marginal worker indifferent between jobs with different amenity levels:

$$\frac{\partial w}{\partial R} = -\frac{1}{1-T'}\frac{U_R}{U_c} \tag{2}$$

Taking the derivative of equation (2) with respect to $\frac{1}{1-T'}$, we arrive at a testable result

$$\frac{\partial^2 w}{\partial R \partial(\frac{1}{1-T'})} = -\frac{U_R}{U_c} > 0 \tag{3}$$

The inequality follows assuming $U_R < 0, U_c > 0$. This result states that $\frac{\partial w}{\partial R}$ increases when $\frac{1}{1-T'}$ increases (i.e., when T' increases). Stated differently, this equation shows that $\frac{\partial w}{\partial(\frac{1}{1-T'})}$, the incidence of the income tax, is larger for high risk jobs. Thus, the response of wages to taxes is highest for the jobs with the highest risk (i.e., fewest non-wage amenities). The model also shows the marginal net-of-tax rate $(1 - T')$ is the relevant tax parameter since the compensating differential is taxed at the marginal rate.

3.1 Discussion of Model

3.1.1 Endogeneity of Risk to Taxes

It is certainly possible that risk levels are themselves responsive to taxes, implying that risk is an endogenous variable in the model above. A more comprehensive model could factor in the cost to the firm of improving occupational safety and weigh these costs against the higher wages. In my context, this is unnecessary. This paper does not study how taxes affect risk or wages. Instead, this paper examines how changes in the marginal tax rate impact $\frac{\partial w}{\partial R}$. I will not be using changes - endogenous or exogenous - in risk for identification. A rearrangement of the term in equation (3) gives $\frac{\frac{\partial w}{\partial R}}{\partial(\frac{1}{1-T'})}$. This equation is entirely silent on changes in risk. If a dangerous industry responds to taxes by becoming relatively safer, this action does *not* affect $\frac{\partial w}{\partial R}$. Similarly, risk levels are shifting throughout my sample period. A dangerous industry may become nearly as safe as a safe industry. All else equal, the wage gap between these industries should decrease. However, $\frac{\partial w}{\partial R}$ is unaffected by these shifts in risk. The goal of this paper is to understand how $\frac{\partial w}{\partial R}$ varies with $\frac{1}{1-T'}$.

A problem arises only if risky industries can respond to higher tax rates by becoming exactly as safe as the safest industries. Then, $\frac{\partial w}{\partial R}$ would not be identified in multiple tax regimes and my strategy would not work. The first stage in my empirical strategy implicitly tests for this scenario. My strategy relies on the testable assumption that risk rates are somewhat fixed - dangerous industries tend to have consistently higher risk than safe industries. The risk rates, however, are allowed to change over time.

3.1.2 VSL Estimation

This paper does not provide VSL estimates and it is useful to discuss the reasons behind this decision. The VSL literature discusses many of the pitfalls in using the relationship between wages and risk to derive a VSL estimate. I want to broadly categorize two major issues with the existing literature.

First, as Hwang et al. [1992] discuss, using cross-sectional variation in risk for identification is problematic in a world with skill heterogeneity. High skill workers likely demand a combination of higher wages and lower risk, biasing VSL estimates. This problem extends to more recent work which conditions on individual fixed effects, such as Kniesner et al. [2007]. With panel data, identification can originate from job switching by workers or changes in risk by occupation or industry. Neither of these sources of identification eliminates the problems associated with skill heterogeneity since the changes in risk are likely correlating with changes in skill.

The empirical strategy outlined in this paper likely circumvents the issue of skill heterogeneity since tax changes are orthogonal to workers' skill levels. Workers take changes in their tax rate as given. In this regard, this paper offers a means of eliminating a significant bias in the VSL literature.

Second, the literature rarely discusses that risk is correlated with other job amenities. High risk jobs are different on other dimensions as well. For example, any occupation which requires driving (such as trucking) is high risk, but it is also different from safer jobs because it requires traveling. This may be a disamenity in itself. It is difficult to disentangle risk from these other job amenities and the existing literature is likely biased due to this point. If the goal of this paper were to derive VSL estimates, my empirical strategy would suffer from the same problem. Tax changes differentially impact high risk jobs, not only because on-the-job safety is a non-taxable amenity but also because other non-taxable amenities are correlated with safety. Previous drafts of this paper have included VSL estimates under the assumption that Corr(R, other amenities)=0. However, there is little reason to believe that this is the case. While the empirical strategy does likely circumvent many of the concerns in the literature, I believe that the resulting VSL estimates would still be biased.

Consequently, I focus on measuring the implied tax incidence heterogeneity, using risk as a *proxy* for a job's non-taxable amenities. The assumption is that dangerous jobs are worse than safe jobs when all amenities are considered. Put differently, I assume that dangerous jobs do not have significantly better "other amenities" than safe jobs. In fact, it is more likely that risky jobs have worse non-wage amenities even when on-the-job safety is not considered. This assumption is implicitly tested and verified by my empirical strategy.

3.1.3 Identification Implied by Model

The model shows that the variable of interest is the interaction of risk and the tax rate. Note that identification does not require industry-specific changes in risk over time. Say that industries varied cross-sectionally in on-the-job risk, and this risk remained constant by industry throughout the sample period. The underlying experiment is to compare the difference in wages between the high risk and low risk industries in a low tax environment to the difference in wages between the high risk and low risk industries in a high tax environment. Thus, identification only requires cross-sectional variation in risk and time series variation in taxes.

In practice, these are exactly the sources of variation that I use. While risk levels do change by industry over time and my specification uses risk variables that vary by industry-year, my empirical strategy does not use the changes across years as a source of identification. I do this for three reasons. First, the motivation of this paper is to understand how wages differentially respond to taxes when amenities are, to some extent, fixed. Second, changes in risk may signal changes in the industry. By only using cross-sectional variation in risk and including industry fixed effects, I can reduce concerns that I am simply picking up secular industry-specific trends. Third, the risk measures include year-to-year measurement error.

By only using cross-sectional risk for identification, I eliminate this bias. Practically, using industry-specific changes in risk does not change the results meaningfully and the general conclusions of this paper would remain the same.

4 Data

4.1 Wages and Taxes

I use the 1983-2002 March CPS which provides individual-level data on income, hours worked, industry, and other characteristics. These years were chosen because the Census industrial coding system used by the CPS stays relatively stable over the time period. I calculate tax rates by using NBER's Taxsim program (Feenberg and Coutts [1993]). This program takes information on different forms of income, number of dependents, and filing status. It provides state and federal marginal taxes and the marginal FICA tax rates for each household. The wage income variable in the CPS is pre-tax wage income[1] for the previous year. I divide this quantity by the hours worked[2] in the previous year to get my wage variable. The resulting sample covers 1982-2001.

4.2 Workers' Compensation

The U.S. Chamber of Commerce publishes a series *Workers' Compensation Laws* which provides detailed parameters regarding each state's workers' compensation coverage. I coded the income benefits for temporary total disability - the percent of wages, the minimum benefit, and the maximum benefit. I calculate each observation's average weekly wage and subsequently find the potential benefit level upon injury given that wage. I divide this benefit level by the weekly after-tax wage to get the replacement rate. It is unclear how to define the after-tax wage in this circumstance. I chose to adjust the pre-tax wage by the marginal tax rate (as opposed to the average tax rate). Since my identification strategy focuses on changes

[1] I add "wage and salary income" and "non-farm business income" to get wage income. Non-farm business income is primarily for self-employed workers. While I am excluding the self-employed in my analysis, some workers may earn extra money through this variable. Since the reported hours variable should include this work, I must include both types of income to keep the numerator and denominator consistent.

[2] As customary with CPS and Census data, I define "hours worked" as "weeks worked last year" × "usual hours worked per week (last year)."

in marginal tax rates, the central concern is that these tax changes are also impacting the replacement rate. To remain on the safe side, I use the same variable in the replacement rate.

I also calculate each observation's replacement rate in cases of fatal injury. Both of these rates are important since I look at both injury and fatality rates in this paper. The "death benefit" replacement rate, however, must be treated differently since it is not relevant for workers that are single with no children. In these cases, I simply force the effect of this replacement rate to be 0.

4.3 Fatality Rates

The National Institute for Occupational Safety and Health collected fatality data between 1980 and 2001[3] through the National Traumatic Occupational Fatality Surveillance System (NTOF) (Marsh and Layne [2001]). The NTOF records fatalities listed as work-related on death certificates which are coded as externally-caused for those that were 16 or older. These fatalities are then categorized by industry. The NTOF typically provides these data at the 1-digit SIC level. There are only ten such divisions (including agriculture/forestry/fishing and public administration, both of which are rarely used in this type of analysis), severely limiting the amount of useful variation and reducing any confidence that such a fatality rate accurately describes the true risk experienced by the workers.

By request,[4] I received more detailed fatality data from the NTOF system. It was provided for 49 separate industry categories. To give an example of the importance of this breakdown, the aggregate data set reports one fatality rate for manufacturing. The more detailed data lists fatality rates for 16 different categories within the manufacturing industry. I divide the fatality numbers by the total number of hours worked in that industry-year according to the March CPS to arrive at my fatality rate variable.

Figure 1 shows the trend in fatality rates over the time period studied in this paper. There is a noticeable downward trend throughout my sample. Figure 2 shows the trends in fatality rates by initial risk. While each set of industries is experiencing a decrease in risk, the trend in Figure 1 is driven primarily by the most dangerous industries becoming safer.

[3]The 2001 data exclude fatalities resulting from the September 11 terrorist attacks.
[4]Special thanks to Suzanne Marsh.

To illustrate the magnitudes and variation in these data, I list the fatality rates for the top 10 and bottom 10 industries during 1982-2001 in Table 1.

The NTOF is not without its faults. Using death certificates as the only raw data source leads to an undercount of the number of fatalities. This undercount can be estimated by comparisons to the Census of Fatal Occupational Injuries (CFOI). The Bureau of Labor Statistics currently maintains the CFOI which is a highly-regarded source for the number of fatalities by industry. However, the CFOI did not begin until 1992. Due to the relatively small federal tax schedule changes between 1992 and 2001, this paper requires fatality data for the pre-1992 period.

I compared the CFOI and NTOF rates for 1992-2001 as shown in Figure 3. The NTOF recorded 80.6% as many fatalities as the CFOI. This number was extremely consistent over time. The values ranged from 78.5% to 83.3%, suggesting that the overall average can be assumed for the pre-1992 period. It is also worth noting that the correlation by NTOF industry-year between NTOF and CFOI fatality rates over this time period is 0.95. This correlation suggests that there is no systematic bias by industry and that scaling the resulting estimates by 0.8 should be a valid approach to adjust for the NTOF undercount.

While it is customary in the literature to use fatalities per 100,000 equivalent full-time workers, I - unless otherwise noted - use fatalities per 100 equivalent full-time workers to keep the units the same as the injury rate variable.

4.4 Injury Rates

The Bureau of Labor Statistics has recorded injury rates by detailed industry since 1976 as part of their series *Occupational Injuries and Illnesses in the United States by Industry.* They survey about 250,000 firms every year. Over 1982-2001, two variables are consistently recorded - the total injury (and illness) rate and the rate of injuries (and illnesses) resulting in 1+ days away from work. I focus on this latter variable because it is more commonly used in the literature. Before 1992, these numbers included fatalities. Since fatalities make up an extremely small percentage of all injuries, it should be acceptable to merge the pre-1992 and 1992-2001 data together. Injury rates are reported to one decimal point. Even the injury rates of the highest fatality rate industries would be unaffected by excluding fatality rates at this level. I also show results for an early sub-sample which does not cross this 1992 data change and the estimates appear to be unaffected. The BLS simultaneously collects hours data from the surveyed firms and constructs injuries per 200,000 hours (or 100 full-time equivalent workers).

Injury rates are provided at a combination of 2-, 3-, and 4-digit industries, depending on the industry. Overall, over 800 industries are listed, classified by the Standard Industrial Classification (SIC) system. However, since the CPS uses the Census coding system, I had to merge the two data sets with a crosswalk which required aggregating many of these industries. In the end, I am left with about 180 separate industries. The aggregate injury rate is charted by year in Figure 4. Table 2 shows the 10 most dangerous industries and the 10 least dangerous industries ranked by the overall injury rate. The correlation between the injury and fatality rates in my data is 0.39.

4.5 Sample

My sample includes all workers in the private labor force ages 25-55 that are not self-employed. I exclude all agricultural industries. This leaves me with 757,647 observations. I drop 45,365 observations with allocated wage income, hours worked, or weeks worked. I drop 6,622 observations because they have wages below \$2 or above \$200 in 2001 dollars. I exclude 19,813 observations because I attribute a workers' compensation replacement rate (injury or fatality) over 200%[5] to them. Finally, I only use workers who are listed as the head of the household or the spouse of the head of the household, which excludes 81,490 observations. I am more confident about the tax rates of household heads and their spouses because it is otherwise difficult to determine the tax filing situation. I am left with 604,352 observations.

Table 3 presents summary statistics for the entire sample and sub-samples based on overall risk for the entire 1982-2001 period. Comparing across sub-samples, we can see that the safest jobs have the highest wages. They also tend to have the highest percentage of college educated workers.

I report full-sample estimates, but I also split the sample into two smaller time periods. The Census industrial coding system changes in 1992, corresponding to 1991 wages. The classification changes were minor, but "crossing" this 1991 threshold requires aggregating a few industries together (Tristao [2005]). Therefore, I decided to concentrate on the time periods 1982-1990 and 1991-2001.

[5]These workers tend to report very low hours worked per week.

5 Empirical Strategy

5.1 Derivation of Specification

Let $\tilde{w}$ be the log of the pre-tax wage net of covariates and fixed effects. My model suggest that the true specification is

$$\frac{\partial \tilde{w}}{\partial R} = \rho + \beta_2 \ln(1-\tau) + \beta_3 \ln(WC) + \nu \tag{4}$$

The model states that the pre-tax compensating differential is a function of the tax rate. The workers' compensation replacement rate should also impact the relationship between wages and risk since workers in high risk jobs benefit more from a high replacement rate. Because the tax rate directly affects the replacement rate, these variables are not orthogonal and it is important to separately account for the replacement rate.

Translating equation (4) into an estimable equation, we have

$$\tilde{w} = \rho R + \beta_2[R \times \ln(1-\tau)] + \beta_3[R \times \ln(WC)] + \epsilon \tag{5}$$

Substituting in for $\tilde{w}$, the specification is

$$\ln w = \gamma_t + \alpha_{sj} + X'\delta_t + \rho R + \beta_0 \ln(1-\tau) + \beta_1 \ln(WC) + \beta_2[R \times \ln(1-\tau)] + \beta_3[R \times \ln(WC)] + \epsilon \tag{6}$$

5.2 Specification

This final specification fits perfectly with the model and basic premise of this paper. The tax rate should have a differential effect on wages based on the risk level. Therefore, the variables of interest for this paper are $R' \times \ln(1-\tau)$. I can non-parametrically account for differences between industries through the inclusion of industry-state fixed effects.

Because of nonlinearities in the tax schedule, different industries experience different tax changes. Consequently, I must separately account for $\ln(1-\tau)$ to ensure that all comparisons of industries with different risk levels occurs *for a given tax change.* I treat the coefficient on $\ln(1-\tau)$ as a nuisance parameter and do not interpret it as the incidence of the income tax. Similarly, I include $\ln(WC)$ independently. This strategy can be interpreted as a differences-in-differences framework. I control for $\ln(1-\tau)$ and R and then look at the interaction of the two variables.

The final specification is:

$$\ln w_{ijkst} = \gamma_t + \alpha_{sj} + X_i'\delta_t + R_{kt}'\rho + \beta_0 \ln(1-\tau_{ijkst}) + \ln(WC_{ijkst})'\beta_1 \\ + \left[R_{kt}' \ln(1-\tau_{ijkst})\right]' \beta_2 + \left[R_{kt}' \ln(WC_{ijkst})\right]' \beta_3 + \epsilon_{ijkst} \quad (7)$$

where i indexes individual, j lowest industry, k industry aggregate, s state, t year. w_{ijkst} represents the wage, τ_{ijkst} is the marginal tax rate (.5 * FICA + federal + state),[6] WC_{ijkst} refers to the workers' compensation after-tax replacement rate (for injuries, deaths, or both), and X_i is a vector of individual-level covariates. R_{kt} refers to the injury rate, the fatality rate, or both for industry aggregate k at year t.

Even though my identification strategy relies solely on changes in federal tax rates, I include state-industry interactions. These are necessary for proper identification of β_3. There are no national-level workers' compensation changes so identification relies on state-level changes over time. Consequently, it is important to account for fixed state-industry differences.

"Industry aggregate" refers to the level of variation of the risk variable. This is different depending on whether the injury rate is included or the fatality rate is included. The "lowest industry" refers to the level that the industry fixed effects control for and the level of variation for the tax instrument. There are 204 of these industries. To clarify, the value of the risk variables can be the same for several of these industries within a year. The exogenous tax variation, however, will vary for each lowest industry.[7]

As discussed earlier, it is important to control for the workers' compensation replacement rate and the form it takes above is the same as the specifications in the VSL literature. As suggested in Viscusi and Aldy [2003], the replacement rate should be interacted with the risk variables because workers in high risk industries are more likely to benefit from higher replacement rates. I "attach" the injury rate to the temporary total disability replacement rate and the fatality rate to the death benefit replacement rate. I control for the replacement

[6] I only use the portion of the FICA tax rate paid by the worker and exclude the employer portion. I do this because the pre-tax wage variable implicitly includes the portion of the FICA taxes that s/he must pay, but it does not include the part paid by the employer

[7] The results in this paper are not meaningfully different if the tax instruments are only allowed to vary at the industry aggregate level.

rate(s) related to the risk measures included. As mentioned above, I force the coefficient on the death benefit replacement rate to be equal to 0 for single workers with no children. Practically, I accomplish this by setting $\ln(WC^F_{ijkst}) = 0$.

The covariates are allowed to have different coefficients for each year. The returns to individual characteristics, especially education, are changing over this time period and it is important to account for these changes. I include the following covariates: 5 year age group dummies, gender dummies, education dummies, and race dummies.

In practice, I de-mean the risk variables within each year because identification originates from cross-sectional variation in risk. I de-mean the tax and replacement rates by industry because identification originates from industry-specific changes in taxes and replacement rates. De-meaning the input variables is customary with interaction terms and does not meaningfully impact the final results here.

β_2 is the coefficient of interest and we expect it to be negative. We should expect β_3 to be negative as well.[8] In my instruments, only cross-sectional risk variation is used. Industry-state fixed effects account for the cross-sectional correlation between risk and unobserved factors in a completely flexible manner. All standard errors are adjusted for clustering at the industry aggregate level.

[8] Variation in the workers' compensation replacement rate could also potentially be thought of as a change in price which has differential incidence. There are two reasons that I do not attempt to interpret these coefficients in such a way. First, the implicit experiment here is not very clean for the replacement rate. The replacement rate requires state-level changes for identification, but the industry risk rates are only provided at a national level. Attaching a state replacement rate measure with a national risk measure may be inappropriate if risk levels respond to the replacement rate. For my purposes, this problem should not meaningfully bias the estimate of β_2 and the results of this paper are robust to the exclusion of the replacement rate variables. Second, I specified the replacement rate in such way to make sure that the coefficient on the risk-tax interaction was not being driven by workers' compensation. I did not want identification of the replacement rate to result from choice in functional form so I made sure that the replacement rate variable implicitly had the same term as the risk-tax interaction variable. When $R \times \ln(WC)$ is expanded, we get $R \times [\ln(\text{potential benefit}) - \ln(\text{weekly wage}) - \ln(1-\tau)]$. This choice ensures that the replacement rate and tax variables are not identified separately by functional form. However, the form of the replacement rate variable is not ideal for interpretation of the coefficient.

5.3 Heterogeneity in Tax Incidence

The incidence of the tax rate is $\frac{\partial \ln w}{\partial \ln(\frac{1}{1-\tau})}$. Evaluating equation (7), we get

$$\frac{\partial \ln w}{\partial \ln(\frac{1}{1-\tau})}|_{R=\hat{R}} = -(\beta_0 + \hat{R}'\beta_2) \tag{8}$$

Tax incidence focuses on the wage response to tax changes. Identification of β_0 is unclear and I have cautioned against interpreting this coefficient as the mean incidence of income taxes. The estimates are likely biased due to wage trends during this time period. I include it in the main specification because it is important to measure the effect of the interaction of taxes and risk for a given tax rate. Since this paper looks at heterogeneity in the tax incidence, it should not be surprising that this term is differenced out below.

To parameterize heterogeneity in the incidence of the tax rate, I compare a risky industry (defined as the 75th percentile most dangerous industry) to a safe industry (defined as the 25th percentile). For example, when I use injuries only, I can calculate

$$P(\text{Injury} \leq \text{Injury}_l) = 0.25, \quad P(\text{Injury} \leq \text{Injury}_h) = 0.75$$

The tax incidence heterogeneity metric is

$$\begin{aligned} & \frac{\partial \ln w}{\partial \ln(\frac{1}{1-\tau})}|\text{Injury}_h - \frac{\partial \ln w}{\partial \ln(\frac{1}{1-\tau})}|\text{Injury}_l \\ = & -[\beta_0 + \beta_2(\text{Injury}_h)] + [\beta_0 + \beta_2(\text{Injury}_l)] \\ = & \beta_2(\text{Injury}_l - \text{Injury}_h) \end{aligned} \tag{9}$$

As expected, the β_0 terms drops out. I've treated this term as a nuisance parameter because I am not convinced that it can be interpreted solely as the incidence of the marginal tax rate. β_2 is the only relevant estimate to derive the heterogeneity measure. The calculation using only fatality rates is similar. When both risk rates are used, the following equations are used

$$P(\beta_0 + R'\beta_2 \leq \Psi_l) = 0.25, \quad P(\beta_0 + R'\beta_2 \leq \Psi_h) = 0.75$$

The tax incidence heterogeneity metric is

$$\text{Tax Incidence Heterogeneity} = \Psi_h - \Psi_l \tag{10}$$

When both risk rates are used, the percentiles of "riskiness" are implicitly a weighted average of the injury and fatality rates using the regression coefficients as weights. I also present tax heterogeneity metrics which compare the 90^{th} percentile to the 10^{th} percentile. The percentiles defining the dangerous and safe jobs will use the last year of the sample that is used to estimate the coefficients. Because the variation in occupational riskiness is decreasing over time, the early sample coefficients are multiplied by a larger number. It is important to note that there is little reason to think that the tax heterogeneity metric magnitudes will be similar when injury rates or fatality rates are used. These rates may signal certain types of jobs and correlate with different amenities.

5.4 Description of Instruments

A central point of this paper is to understand the consequences of tax changes when amenities do not fully-adjust. For this reason, I control separately for the risk level. I also hold risk constant in the instrument when interacting with the tax rate. Holding risk constant has several benefits. First, it ensures that identification only originates from tax schedule changes and not shifts in risk over time. By holding risk constant for each industry and controlling for industry-state fixed effects, each risk level has a fixed effect associated with it, non-parametrically accounting for omitted variables correlating with risk.

Second, it eliminates biases due to year-to-year measurement error in the risk variables. While risk levels may change exogenously and endogenously to taxes, these changes only impact the strength of the first stage and do not affect the validity of the final results.

Since the marginal tax rate is a function of an individual's wage, I must instrument the tax variables. In the spirit of Currie and Gruber [1996a,b], I use a "simulated instrument" by holding a baseline sample constant and allowing the instrument to vary due to tax schedule changes only.

To implement this strategy, I create a baseline sample for each industry and then let tax rates change based on tax schedule changes only. To illustrate this approach, I will detail how I calculate predicted tax rates for each industry in 1985 using federal tax variation only.

1. Create baseline sample (1982 CPS).
2. Inflate incomes to 1985 values.
3. Find tax rate for each person using 1985's federal tax schedule (and FICA).
4. Average marginal tax rates by industry to get predicted tax rate ($\hat{\tau}_{jkt}$).

When I focus on my later (1991-2001) sample, my baseline sample is the 1991 CPS. The resulting instrument is $\ln(1-\hat{\tau}_{jkt})$. The variation comes solely from federal tax schedule changes. Industry*State interactions account for fixed wage level differences.

The workers' compensation replacement rate must also be instrumented since the replacement rate is a function of the wage. The predicted replacement rate is formed in the exact same way that the predicted tax rates are created, except that the baseline sample also depends on state. The baseline sample is adjusted for inflation for each year and that state-year's workers' compensation parameters are applied to each observation. The replacement rates are calculated and averaged by industry and state to get $\ln(\widehat{WC}_{jkst})$.

While the risk rates change differentially across industries over time in equation (7), I have outlined why it is desirable for exogenous variation in $R'_{kt}\ln(1-\tau_{ijkst})$ to originate *only* from changes in the tax schedule. The corresponding instrument interacts the log of the predicted net-of-tax rate (as described above) with a risk proxy that does not allow for industry-specific changes over time. An obvious candidate for this risk proxy is the average risk for an industry over the sample period.

The final instruments are:

1. $\ln(1-\hat{\tau}_{jkt})$
2. $\ln(\widehat{WC}_{jkst})$
3. $\overline{R}'_{k.} \times \ln(1-\hat{\tau}_{jkt})$
4. $\overline{R}'_{k.} \times \ln(\widehat{WC}_{jkst})$

Because of the inclusion of industry-state fixed effects, the tax and workers' compensation variables are all implicitly de-meaned in the instrument.

5.5 Sources of Variation

This paper relies on legislative federal tax changes for identification. The Economic Recovery Tax Act of 1981 (ERTA1981) changed marginal tax rates from 1982 to 1984. The Tax Reform Act of 1986 (TRA1986) is the major tax change during the sample period. TRA86 drastically reduced the number of income tax brackets and the top federal income tax rate was cut to 28 percent. The Omnibus Budget Reconciliation Act of 1990 and 1993 subsequently increased the number of income tax brackets and the top federal income tax rate. In addition, the Earned Income Tax Credit (EITC) was significantly expanded during my sample. Figure 5 shows the progression of the average marginal tax rate during the time period 1982-2001.

Cross-sectional risk variation is also necessary and was discussed in the Data section. There is a time-series correlation between risk and tax rates. This paper does not study this relationship. As discussed above, industry-specific changes in risk over time - exogenous or endogenous to tax rates - do not cause problems for the empirical strategy of this paper since I am studying the relationship between $\frac{\partial w}{\partial R}$ and $\ln(1-\tau)$ as illustrated by equation (4). It would be problematic to classify some industries as "dangerous" and some as "safe" in a base period and then compare their wages as tax rates change, fixing this designation over time. If the dangerous industries become much safer (as seen in Figure 2), then wages should converge regardless of the tax rate. However, I allow the risk rates to change, using the actual injury and fatality rates in specification (7). Changes in risk over time pose a problem only by hurting the strength of the first stage. I argued that there are several advantages to fixing the risk rate in the instrument. Thus, my instruments assume that there is some correlation in risk across year within an industry. If risk rates were randomly-assigned each year, then this would not be true and there would not be a first stage. My first stage tests this assumption implicitly.

5.6 Interpretation of Estimates

Rosen [1986] explains that empirical compensating differentials must be interpreted as the valuation of the marginal worker. This holds true with the above empirical strategy as well and, in general, it is the "same" marginal worker as the traditional VSL literature since I am comparing workers in dangerous industries to workers in safe industries (my risk variation is cross-sectional in the instrument). There is one caveat to this description, however.

Since I am using tax changes as variation, it is possible the marginal worker changes over time. When tax rates increase, workers in risky jobs are disproportionately harmed. Pre-tax wages must increase (relative to safe jobs), but there is also the potential that workers might re-sort based on risk preferences. This change in the marginal worker is part of the impact of interest and works against finding an effect. I also include regression results using individual-level panel data and find similar effects. The individual fixed effects can be thought of as controlling for individual preferences concerning risk/amenities. Thus, re-sorting does not appear to have much of an impact on the results. These findings suggest that wages are fully-adjusting, keeping the marginal worker relatively constant.

6 Results

6.1 Traditional VSL Specification

For the sake of comparison with the VSL literature, I estimate the "traditional" VSL specification. I perform cross-sectional analysis for each year, estimating

$$\ln w_{ik} = \gamma + X_i'\delta + R_k'\beta + \nu_{ik} \tag{11}$$

A summary of these results is presented in Table 4. Identification depends solely on cross-sectional variation in risk. The implied value of a statistical life is very unstable and is actually estimated to be negative more often than positive. This set of results is generally consistent with the findings of Black and Kniesner [2003]. The value of a statistical injury is consistently negative, which is surprising given previous findings in the literature.

6.2 Main Results

Turning to the estimation of this paper's specification, the OLS results shown in Table 5 are extremely hard to interpret given that tax rates and replacement rates are endogenous. The results suggest some evidence of heterogeneity.

Table 6 presents the first stage for the entire sample when both risk rates are included. With up to 7 endogenous variables and instruments, it can be difficult to determine if a specification is identified. For example, if one instrument were highly-correlated with all the endogenous variables, simple F-statistics might suggest that the equation is identified when it is clearly not. I report Shea's Partial R^2 statistics (Shea [1997]), which measures the explanatory power of the instruments for each endogenous variable independent of the other variables. The first stage is relatively strong for all the variables.

Since most of the tax changes occur in the early part of the sample, the first stage should be much stronger for the 1982-1990 sample than the 1991-2001 one. Table 7 shows that this is the case. The Shea's R^2 statistics decrease substantially for the later sample. Consequently, we should expect the estimates from the early sample to be much more precise than those from the later one.

The tax incidence heterogeneity numbers compare the elasticity of the wage with respect to the marginal net-of-tax-rate for the 75th (90th) percentile most dangerous industry to the 25th (10th) percentile for the last year of the relevant sample (1990 or 2001) using equation (10). Table 8 shows the industries and their risk rates which are used in these calculations. These are the industries that are implicitly being compared. For example, the full sample uses the 2001 risk distribution. The 25^{th} percentile of the injury rate variable is the Scientific and Controlling Instrument Industry with an injury rate of 0.9 injuries per 100 employees. The 75^{th} percentile is the Engine and Turbines Industry with an injury rate of 2.3. The fatality rates are also included. Table 9 presents the same information for the 90^{th} and 10^{th} percentile.

The main results of this paper are shown in Tables 10-12. The reader is encouraged to focus on the tax heterogeneity estimates at the bottom, but the coefficients are also presented. Each table has 3 columns where each column represents a separate regression based on which risk rate is included - injury (column 1), fatality (column 2), and both (column 3). The IV results imply tax incidence heterogeneity of 0.1 to 0.3. This suggests that when the marginal net-of-tax rate decreases 10% that the 75^{th} percentile most dangerous job experiences a pre-tax wage increase 1-3% larger than the 25^{th} percentile most dangerous job. Comparing the 90^{th} to 10^{th} percentile, the implied heterogeneity is 0.5-0.7. Thus, a 10% decrease in the marginal net-of-tax rate causes the wages of the most dangerous jobs to increase by 5-7% more than the wages of the safest jobs. As expected, the estimates for β_3 are also negative. These results suggest that wages differentially respond to changes in the workers' compensation replacement rate.

The coefficients of interest are very similar when I focus on the 1982-1990 time period as show in Table 11. These results suggest that a marginal net-of-tax rate decrease of 10% increases the wages of dangerous jobs by 1-5% more than the wages of safe jobs. When comparing the 90^{th} to the 10^{th} percentile jobs, the implied heterogeneity is 0.6 to 1.0.

As mentioned previously, there are large tax schedule changes during this time period. The first stage strength is much weaker after 1990. Table 12 reports results from 1991-2001. The first stages now are very weak. However, the tax incidence heterogeneity estimates are consistent with those of the earlier time period.

6.3 Robustness Checks

6.3.1 Wage Trends

A large literature details the growth of wage inequality during the time period of my sample. A major concern of the analysis in this paper is that wage trends are driving the results. The specific story that I am concerned about assumes that risky jobs are relatively unskilled jobs. Then, due to wage trends, the wages of the risky jobs dropped relative to the wages of the safe jobs. Taxes decrease in the middle of the sample and my specification attributes the relative drop of the wages of the risky jobs to this tax decrease.

My results should be robust to this critique for three reasons. First, I let the return to individual covariates change over time. Goldin and Katz [2007] state, "The majority of the increase in wage inequality since 1980 can be accounted for by rising educational wage differentials..." Second, I use all tax changes as sources of exogenous variation. While TRA86 did decrease taxes, there are also periods where taxes increased during my sample. The 1991-2001 estimates are more imprecisely measured than the earlier period estimates, but they still suggest very large effects during a period where tax rates increased on average.

Third, to drive the results of this paper, these wage trends must occur *within a given tax rate*. My specification separately controls for the after-tax rate and, therefore, implicitly compares industries with similar initial wages. I am not suggesting that the after-tax rate is an adequate proxy for wage trends if one wanted to study wage trends specifically. Instead, because identification originates from tax changes, any spurious correlation due to wage trends must occur within a given tax change. The fact that I am implicitly comparing industries with similar initial wages is consistent with the robustness of my estimates when initial wages are more explicitly accounted for.

In Table 13, I summarize a series of regressions which controls for initial wages. Each block represents the same regressions seen in the previous tables, but I only report the resulting tax heterogeneity incidence estimates for the sake of simplicity. I compare industries within wage deciles by interacting the year fixed effects with fixed effects based on 1982 wage deciles. The estimates are consistent with the earlier findings.

6.3.2 Individual-Level Heterogeneity

Finally, it could be argued that simply accounting for industry-state heterogeneity is inadequate. Instead, we might be concerned that when taxes change, the skill composition of industries change based on risk. This story suggests that when tax rates change, workers re-sort themselves across industries. To consider this possibility, I use individual-level panel data to account for individual heterogeneity.

The Panel Survey of Income Dynamics (PSID) records wage and income information for families for multiple years. I estimate the following specification for the years 1981-1996:[9]

$$\begin{aligned}\ln w_{ijkst} = \gamma_t + \alpha_s + \lambda_i + X_{it}'\delta_t + \beta_0 \ln(1-\tau_{ijkst}) + \ln(WC_{ijkst})'\beta_1 \\ + \left[R_{kt}' \times \ln(1-\tau_{ijkst})\right]'\beta_2 + \left[R_{kt}' \times \ln(WC_{ijkst})\right]'\beta_3 + \epsilon_{ijkst} \quad (12)\end{aligned}$$

The strategy is similar. I use tax rates predicted at the industry-level in the instruments. Risk rates are held constant in the instrument and *assume that the individual does not change industries*. Similarly, predicted tax rates are assigned assuming that the individual does not change industries. Thus, as before, all variation originates from tax schedule changes.

Most people are included in the sample for a significant length of time. It could be argued that an individual fixed effect spanning 16 years is inadequate. Instead, I treat each 5-year span for an individual as a separate "person"/fixed effect. In other words, a person in my sample for 1981-1990 is treated as two separate people - one for 1981-1985 and one for 1986-1990.[10] The standard errors must be appropriately adjusted and I use the multi-dimensional clustering algorithm suggested by Cameron et al. [2006] to account for

[9] More recent PSID data have not been finalized yet.

[10] The results are robust to other permutations of this breakdown.

clustering at the individual level and the levels of the risk measures.[11]

The PSID sample is much smaller than the CPS so we would expect the estimates to be less precise. There is some evidence of this, but the results in Table 14 are consistent with the CPS results, suggesting that skill and taste heterogeneity are not biasing the results presented in this paper.

7 Conclusion

The income tax literature has provided evidence that income taxes distort individuals' decisions concerning the optimal combination of wages and amenities. Individuals may change occupations to consume different levels of amenities or firms may respond in the provision of their amenities. However, the literature has generally ignored the possibility that some amenities may be, to some extent, defining features of a job and prohibitively costly to change. In these cases, pre-tax wages must adjust. These wage shifts alter the compensating differentials between different types of jobs.

I look at the interaction of tax rates and on-the-job safety, finding significantly different wage responses between safe and dangerous jobs. When the marginal net-of-tax rate decreases by 10%, the pre-tax wages of the 75^{th} percentile most dangerous job increase by 1-5% more than the pre-tax wages of the 25^{th} percentile. When comparing the 90^{th} to the 10^{th} percentile, the wages of the dangerous job increase by 6-10% more. These results suggest that tax changes differentially hurt some industries more than others. Because of the NTOF undercount, these numbers are likely an underestimate of the true distortion. These results suggest that heterogeneity in the wage response to taxes is economically meaningful and an important component of the total distortion of income taxation.

[11] Since the injury and fatality rates are provided at different levels, this method implies that I adjust for 2-way clustering when one risk rate is included and 3-way clustering when both are included.

A Data Appendix

A.1 Injuries

Injury data were found in the *Survey of Occupational Injuries and Illnesses* series and online at the Bureau of Labor Statistics website (www.bls.gov). I used the variable titled "Cases involving days away from work." The 1982-1988 data are categorized by the 1977 Standard Industrial Classification system while the 1989-2001 data use the 1987 Standard Industrial Classification system. The data are published at the 2-, 3-, or 4-digit level based on industry. The Census Industrial Classification system used by the CPS, however, is most related to the 3-digit SIC level. The 4-digit level (reported for manufacturing industries) is too detailed and never used while a few 2-digit industries correspond directly to the CIC system.

If no injury rate is reported for a given 3-digit industry,[12] I impute the value using the injury rate given for its 2-digit industry and the other 3-digit industries in that 2-digit category. The SOII also reports employment data, so I can calculate the injury rate of the "missing industries" within a 2-digit category.

I use a crosswalk to assign each industry to a CIC category. When one CIC industry corresponds to multiple SIC industries, I average the injury rates, weighted by employment, to the CIC level.

A.2 NTOF Fatality Rates

5.7% of fatalities are listed as "Not Classified" in the NTOF data. I calculate the percentage of classified fatalities that occur in each industry and make the assumption that the unclassified fatalities occurred randomly. Thus, an industry with 2% of all classified fatalities in 1985 will be assigned 2% of the unclassified fatalities in that year as well.

Fatality rates were merged to CIC coding system using the crosswalk provided in Appendix II of *Fatal Injuries to Civilian Workers in the United States, 1980-1995*.

[12] There are several reasons that an injury rate might be missing but, in general, these tend to be very small industries.

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B Figures

Figure 1: Fatality Rates, 1982-2001

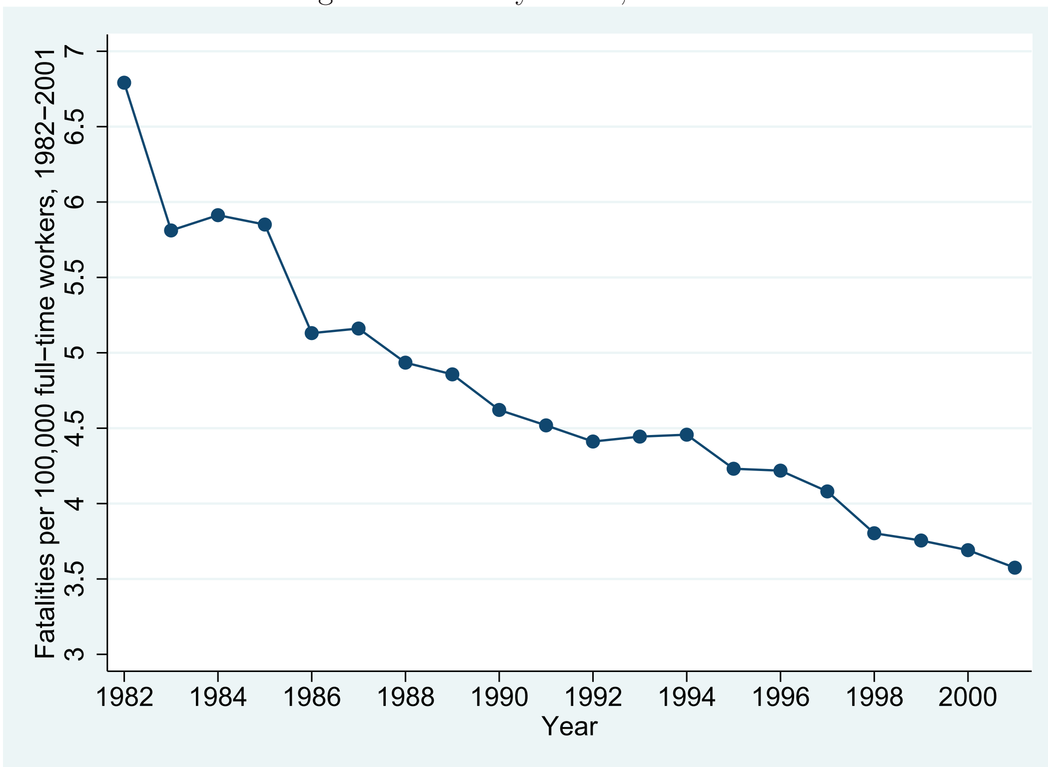


Figure 2: Fatality Rates by Initial (1982) Risk

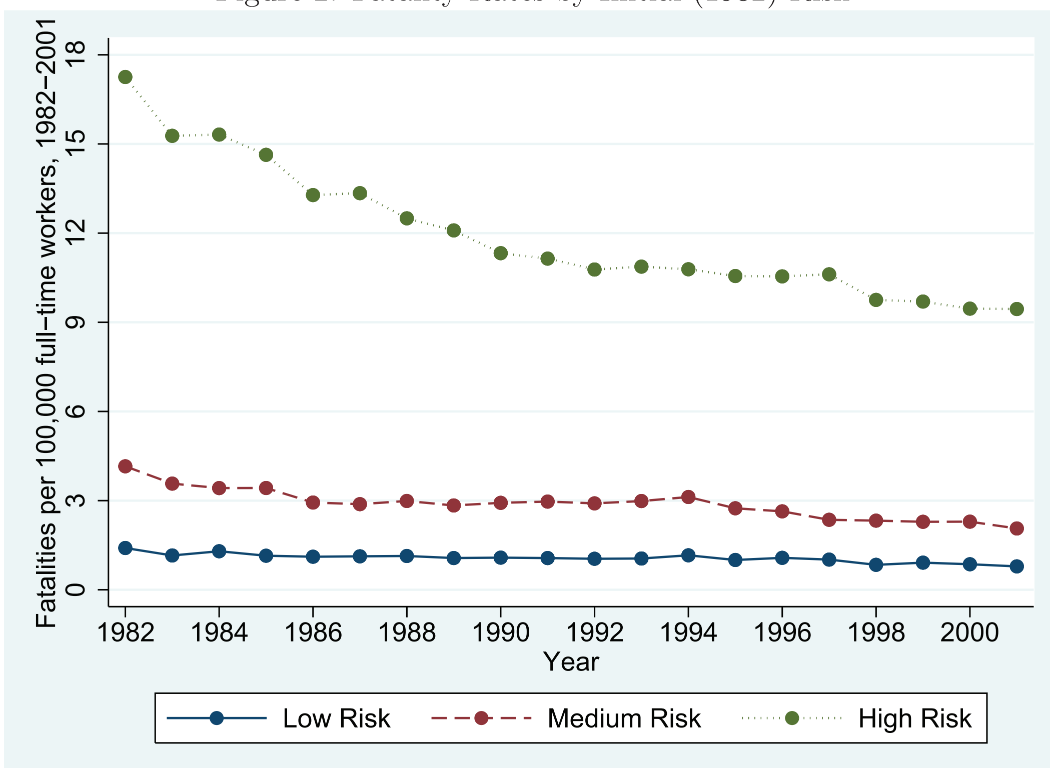


Figure 3: NTOF vs. CFOI Fatality Rates, 1992-2001

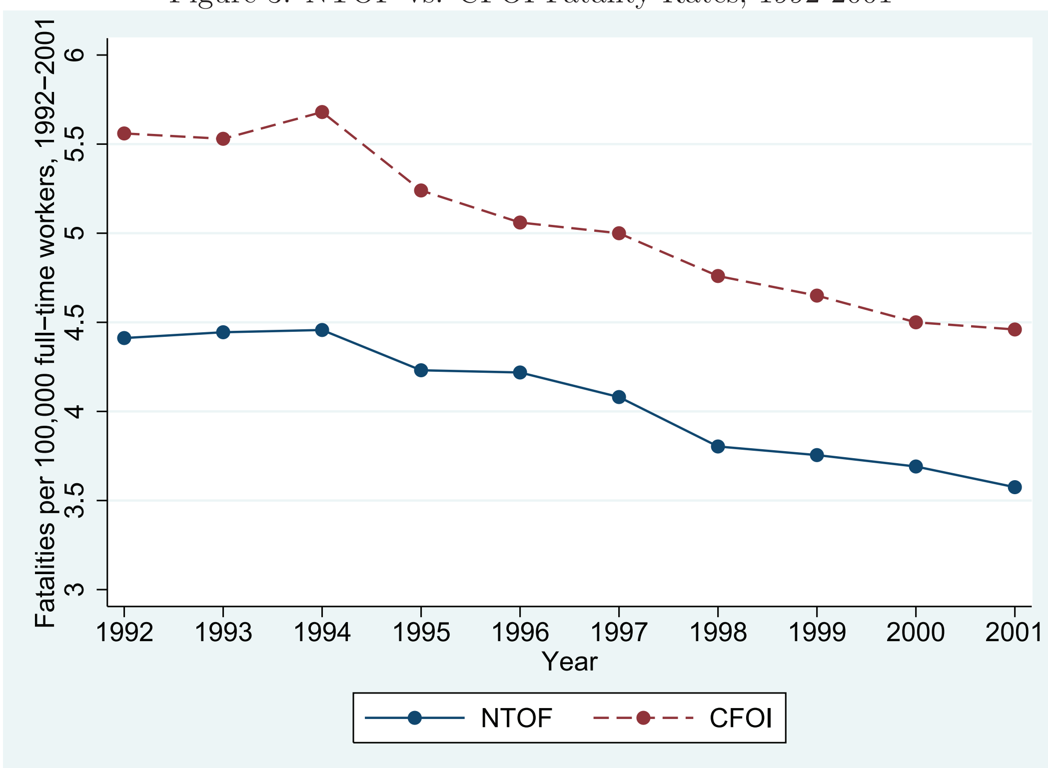


Figure 4: Injury Rates, 1982-2001

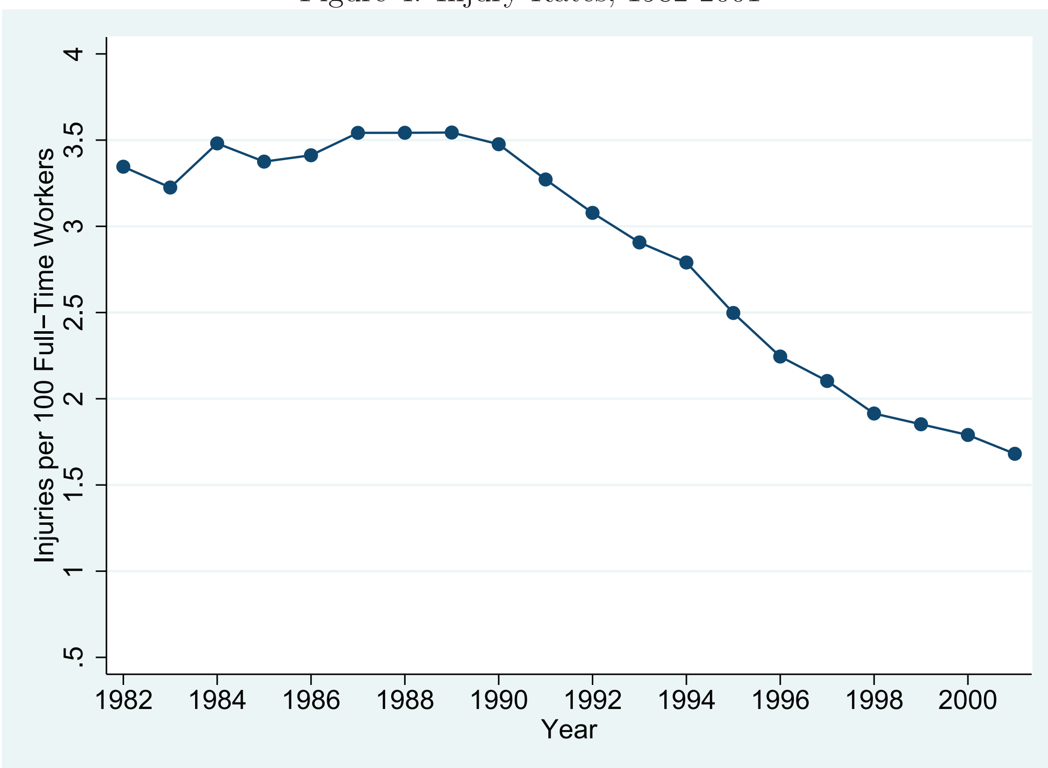
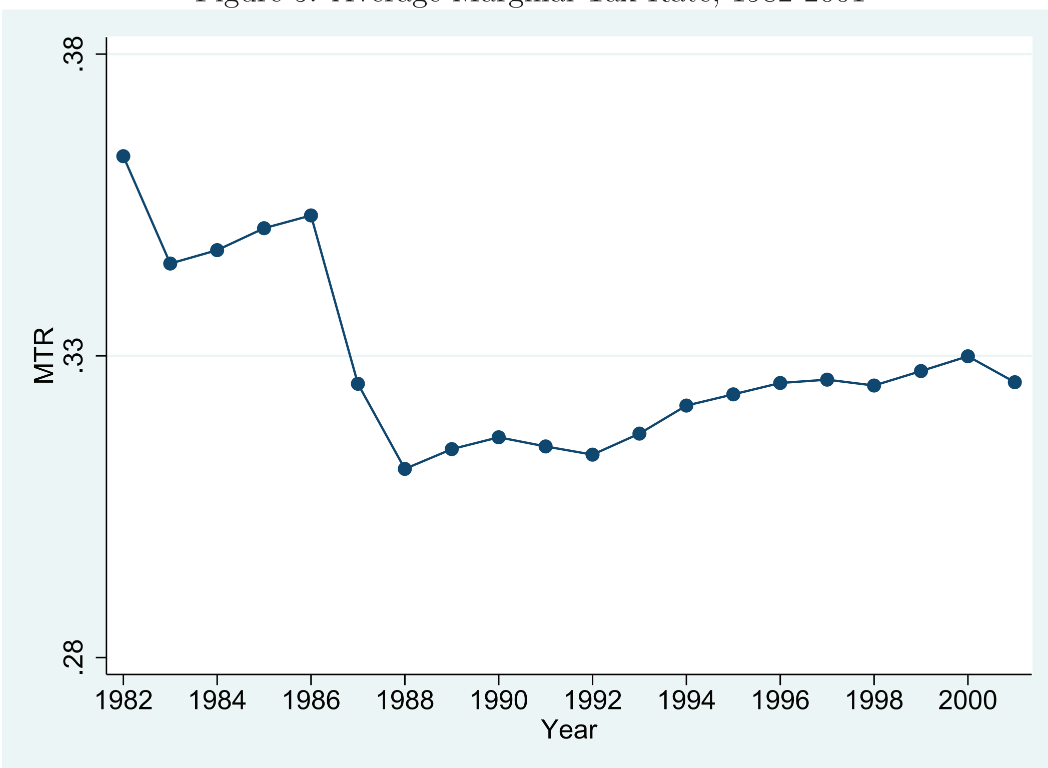


Figure 5: Average Marginal Tax Rate, 1982-2001



C Tables

Table 1: Top and Bottom 10 Fatality Rates by Industry, 1982-2001 NTOF Data

Industry	Fatalities per 100,000 FTE Workers	Injuries per 100 FTE Workers
Forestry & Fisheries	44.15	3.59
Metal/Coal/Nonmetal Mining	28.14	4.54
Lumber & Wood	26.54	6.32
Oil & Gas Extraction	21.98	3.33
Trucking/Warehousing/Storage	20.55	6.13
Agricultural Production	18.88	3.54
Construction	14.08	4.87
Agricultural Services	11.56	3.72
Other Transportation	9.81	4.97
Electric Light & Power	9.57	1.38
Mean	4.43	2.73
Printing/Publishing/Allied	1.41	2.27
Insurance & Real Estate	1.27	1.08
Apparel & Accessory Stores	1.24	1.16
Electrical Machinery	1.20	2.08
Other Professional Services	1.10	1.03
Educational Services	0.76	1.22
Health Services, Except Hospitals	0.74	2.69
Hospitals	0.69	3.29
Apparel & Other Textile	0.65	2.35
Banking and Other Finance	0.64	0.48

Table 2: Top and Bottom 10 Injury Rates by Industry, 1982-2001 BLS

Industry	Injuries per 100 FTE Workers	Fatalities per 100,000 FTE Workers
Logging	8.66	27.03
Ship and boat building and repairing	8.02	2.99
Leather: tanned, curried, and finished	7.27	5.87
Wood building and mobile homes	7.27	25.07
Air transportation	7.15	9.69
Coal mining	6.58	28.20
Beverage industries	6.44	4.13
Other primary iron and steel industries	6.32	8.97
Trucking service	6.22	20.38
Nursing and personal care facilities	6.18	0.74
Mean	2.73	4.52
Beauty shops	0.62	2.27
Offices and clinics of dentists	0.57	0.74
Insurance	0.55	1.26
Banking	0.54	0.64
Offices and clinics of physicians	0.52	0.74
Credit Agencies	0.34	0.62
Brokerage and investments	0.34	0.63
Computer and data programming service	0.34	2.33
Legal services	0.31	1.10
Accounting, auditing, bookkeeping services	0.29	1.11

Table 3: Summary Statistics

Summary Statistics by Fatality Rate Group

Entire Sample			Lowest Fatality Rate Industries		
	Mean	Std Dev		Mean	Std Dev
wage	17.76	13.24	wage	18.73	14.54
τ	0.33	0.11	τ	0.34	0.10
Injury Rate	2.81	1.96	Injury Rate	1.93	1.55
Fatality Rate	4.36	5.77	Fatality Rate	1.05	0.48
Age	39.23	8.34	Age	39.43	8.31
%College	50.02	50.00	%College	62.18	48.50
%Female	45.65	49.81	%Female	61.57	48.64
%White	87.70	32.90	%White	87.20	33.41

Middle Fatality Rate Industries			Highest Fatality Rate Industries		
	Mean	Std Dev		Mean	Std Dev
wage	16.59	12.54	wage	17.92	11.83
τ	0.32	0.12	τ	0.32	0.11
Injury Rate	2.62	1.53	Injury Rate	4.45	2.07
Fatality Rate	2.85	0.87	Fatality Rate	11.80	7.51
Age	39.03	8.40	Age	39.21	8.30
%College	45.87	49.83	%College	36.58	48.17
%Female	43.13	49.53	%Female	23.83	42.61
%White	87.00	33.63	%White	89.32	30.89

Summary Statistics by Injury Rate Group

Entire Sample			Lowest Injury Rate Industries		
	Mean	Std Dev		Mean	Std Dev
wage	17.76	13.24	wage	19.83	15.36
τ	0.33	0.11	τ	0.35	0.10
Injury Rate	2.81	1.96	Injury Rate	1.07	0.61
Fatality Rate	4.36	5.77	Fatality Rate	2.07	2.03
Age	39.23	8.34	Age	39.24	8.31
%College	50.02	50.00	%College	65.08	47.67
%Female	45.65	49.81	%Female	55.67	49.68
%White	87.70	32.90	%White	88.18	32.28

Middle Injury Rate Industries			Highest Injury Rate Industries		
	Mean	Std Dev		Mean	Std Dev
wage	16.30	12.20	wage	16.94	11.17
τ	0.32	0.12	τ	0.32	0.11
Injury Rate	2.67	0.87	Injury Rate	4.97	1.75
Fatality Rate	3.19	4.56	Fatality Rate	8.36	7.60
Age	39.05	8.36	Age	39.42	8.36
%College	47.01	49.91	%College	35.59	47.88
%Female	48.91	49.99	%Female	30.24	45.93
%White	86.61	34.05	%White	88.18	32.29

Table 4: Summary of VSL regressions year-by-year

	Value of Statistical Injury ($)	Value of Statistical Life ($ millions)
Mean Estimate	-182,566	0.1
Std Dev of Estimates	64,436	7.1
Minimum	-374,704	-11.3
Maximum	-96,712	12.4
# Pos&Sig	0	0
# Pos&NS	0	8
# Neg&NS	0	12
# Neg&Sig	20	0

A separate cross-sectional regression was estimated for each year. Standard errors clustered by industry aggregate. Covariates include state dummy variables, age dummies, gender dummy, race dummies, education dummies.

Table 5: OLS Results, 1982-2001

Dependent Variable: log(wage)			
	(1)	(2)	(3)
Injury Rate	0.003		0.003
	(0.002)		(0.002)
Fatality Rate		1.686	0.507
		(0.690)	(0.987)
$\ln(1-\tau)$	-1.791***	-1.697***	-1.780***
	(0.015)	(0.021)	(0.017)
Injury Rate x $\ln(1-\tau)$	-0.018**		-0.031***
	(0.007)		(0.008)
Fatality Rate x $\ln(1-\tau)$		1.085	8.195***
		(2.286)	(2.468)
$\ln(WC^I)$	-0.953***		-0.753***
	(0.012)		(0.013)
$\ln(WC^F)$		-0.779***	-0.239***
		(0.011)	(0.011)
Injury Rate x $\ln(WC^I)$	-0.016***		-0.016**
	(0.006)		(0.006)
Fatality Rate x $\ln(WC^F)$		-1.222	0.479
		(2.464)	(2.438)
N	594119	598438	591920
Fixed Effects	Industry*State	Industry*State	Industry*State
Implied Heterogeneity:			
$75^{th} - 25^{th}$	0.025**	-0.002	0.039***
	(0.010)	(0.004)	(0.011)
$90^{th} - 10^{th}$	0.047**	-0.012	0.066***
	(0.019)	(0.025)	(0.022)

Significance levels: * 10%, ** 5%, *** 1%. Standard errors in parentheses are clustered by industry aggregate. The "Implied Heterogeneity" results use equation (10). Covariates include the following individual characteristics interacted with year dummies: age dummies, gender dummy, race dummies, education dummies.

Table 6: First Stage, 1982-2001

	$\ln(1-\tau)$	Injury $\times \ln(1-\tau)$	Fatality $\times \ln(1-\tau)$	$\ln(WC^I)$	$\ln(WC^F)$	Injury $\times \ln(WC)$	Fatality $\times \ln(WC)$
$\ln(1-\hat{\tau})$	0.565***	-0.126	0.000	-0.188***	-0.180**	0.420**	0.001
	(0.055)	(0.154)	(0.000)	(0.070)	(0.069)	(0.198)	(0.001)
$\overline{\text{Injury}} \times \ln(1-\hat{\tau})$	-0.001	0.939***	0.000	0.095***	0.087***	-0.927***	0.000
	(0.016)	(0.049)	(0.000)	(0.023)	(0.021)	(0.075)	(0.000)
$\overline{\text{Fatality}} \times \ln(1-\hat{\tau})$	6.731	17.694	0.971***	-10.616	-12.961	39.497	-0.470*
	(4.391)	(14.021)	(0.100)	(7.306)	(11.152)	(25.487)	(0.271)
$\ln(1-\widehat{WC}^I)$	-0.000	-0.021*	-0.000	0.610***	0.182***	0.081**	-0.000
	(0.005)	(0.012)	(0.000)	(0.024)	(0.024)	(0.039)	(0.000)
$\ln(1-\widehat{WC}^F)$	0.007*	0.012	0.000	0.027***	0.350***	-0.009	0.000**
	(0.003)	(0.009)	(0.000)	(0.009)	(0.041)	(0.019)	(0.000)
$\overline{\text{Injury}} \times \ln(1-\widehat{WC}^I)$	-0.006**	-0.029***	-0.000	0.027***	0.012**	0.654***	0.000*
	(0.003)	(0.007)	(0.000)	(0.010)	(0.006)	(0.039)	(0.000)
$\overline{\text{Fatality}} \times \ln(1-\widehat{WC}^F)$	0.998***	2.892***	0.005	0.622	9.064***	6.001	0.571***
	(0.334)	(1.044)	(0.006)	(2.132)	(3.089)	(5.503)	(0.044)
N	591920	591920	591920	591920	591920	591920	591920
Fixed Effects	Industry*State	Industry*State	Industry*State	Industry*State	Industry*State	Industry*State	Industry*State
Shea's R^2	0.0014	0.0229	0.0228	0.0214	0.0152	0.289	0.0388

Significance levels: * 10%, ** 5%, *** 1%. Standard errors in parentheses are clustered by industry aggregate. Covariates include the following individual characteristics interacted with year dummies: age dummies, gender dummy, race dummies, education dummies.

Table 7: Shea's R^2 Statistics by Sample

	1982-2001	1982-1990	1991-2001
$\ln(1-\tau)$	0.0014	0.0019	0.0000
Injury x $\ln(1-\tau)$	0.0229	0.0230	0.0009
Fatal x $\ln(1-\tau)$	0.0228	0.0251	0.0004
$\ln(WC^I)$	0.0214	0.0191	0.0113
$\ln(WC^F)$	0.0152	0.0309	0.0117
Injury x $\ln(WC^I)$	0.0289	0.0138	0.0038
Fatal x $\ln(WC^F)$	0.0388	0.0275	0.0126
N	591920	249242	310579

Each column reports the Shea's R^2 statistics for each variable for that sample. Covariates include Industry*State dummy variables and the following individual characteristics interacted with year dummies: age dummies, gender dummy, race dummies, education dummies.

Table 8: Injury and Fatality Rates for Tax Incidence Heterogeneity Calculation ($75^{th} - 25^{th}$)

	Injury Rates	
	75th Percentile	25th Percentile
2001	Engines and Turbines	Scientific and Controlling Instrument
	2.3 per 100	0.9 per 100
1990	Crude Petroleum & Natural Gas Extraction	Colleges and Universities
	5.0 per 100	1.7 per 100
	Fatality Rates	
	75th Percentile	25th Percentile
2001	Motor Vehicles/Auto Supply Dealer	Other Professional
	2.7 per 100,000	0.8 per 100,000
1990	Motor Vehicles/Auto Supply Dealer	Insurance and Real Estate
	3.9 per 100,000	1.2 per 100,000

Table 9: Injury and Fatality Rates for Tax Incidence Heterogeneity Calculation ($90^{th} - 10^{th}$)

	Injury Rates	
	90th Percentile	10th Percentile
2001	Construction	Banking
	3.0 per 100	0.4 per 100
1990	Construction	Other Health Services
	6.2 per 100	0.8 per 100
	Fatality Rates	
	90th Percentile	10th Percentile
2001	Construction	Apparel & Accessory Store
	11.5 per 100,000	0.5 per 100,000
1990	Construction	Banking
	14.5 per 100,000	0.7 per 100,000

Table 10: IV Results, 1982-2001

Dependent Variable: log(wage)			
	(1)	(2)	(3)
Injury Rate	0.008***		0.008***
	(0.003)		(0.003)
Fatality Rate		0.660	-0.460
		(0.869)	(0.880)
$\ln(1-\tau)$	-1.093***	-0.658***	-1.060***
	(0.237)	(0.236)	(0.258)
Injury Rate x $\ln(1-\tau)$	-0.219***		-0.194***
	(0.034)		(0.045)
Fatality Rate x $\ln(1-\tau)$		-48.015***	-15.099
		(8.331)	(10.285)
$\ln(WC^I)$	-0.034		0.003
	(0.022)		(0.041)
$\ln(WC^F)$		-0.049**	-0.048
		(0.024)	(0.038)
Injury Rate x $\ln(WC^I)$	-0.033***		-0.029**
	(0.010)		(0.012)
Fatality Rate x $\ln(WC^F)$		-5.523**	-1.201
		(2.798)	(3.095)
N	594119	598438	591920
Fixed Effects	Industry*State	Industry*State	Industry*State
Implied Heterogeneity:			
$75^{th}-25^{th}$	0.307***	0.090***	0.274***
	(0.048)	(0.016)	(0.066)
$90^{th}-10^{th}$	0.577***	0.526***	0.674***
	(0.091)	(0.091)	(0.103)

Significance levels: * 10%, ** 5%, *** 1%. Standard errors in parentheses are clustered by industry aggregate. The "Implied Heterogeneity" results use equation (10). Covariates include the following individual characteristics interacted with year dummies: age dummies, gender dummy, race dummies, education dummies.

Table 11: IV Results, 1982-1990

Dependent Variable: log(wage)			
	(1)	(2)	(3)
Injury Rate	-0.002		-0.004
	(0.003)		(0.003)
Fatality Rate		-1.463*	1.242*
		(0.809)	(0.743)
$\ln(1-\tau)$	-0.824***	-0.345	-0.725***
	(0.224)	(0.242)	(0.243)
Injury Rate x $\ln(1-\tau)$	-0.158***		-0.115***
	(0.026)		(0.036)
Fatality Rate x $\ln(1-\tau)$		-47.006***	-25.423***
		(7.642)	(8.264)
$\ln(WC^I)$	0.014		-0.025
	(0.035)		(0.046)
$\ln(WC^F)$		0.066**	0.071**
		(0.032)	(0.036)
Injury Rate x $\ln(WC^I)$	-0.014		-0.006
	(0.012)		(0.014)
Fatality Rate x $\ln(WC^F)$		-4.455	-3.779
		(3.543)	(3.758)
N	249806	254371	249242
Fixed Effects	Industry*State	Industry*State	Industry*State
Implied Heterogeneity:			
$75^{th}-25^{th}$	0.520***	0.126***	0.427***
	(0.084)	(0.020)	(0.120)
$90^{th}-10^{th}$	0.857***	0.648***	0.962***
	(0.139)	(0.105)	(0.171)

Significance levels: * 10%, ** 5%, *** 1%. Standard errors in parentheses are clustered by industry aggregate. The "Implied Heterogeneity" results use equation (10). Covariates include the following individual characteristics interacted with year dummies: age dummies, gender dummy, race dummies, education dummies.

Table 12: IV Results, 1991-2001

Dependent Variable: log(wage)			
	(1)	(2)	(3)
Injury Rate	0.017**		0.016**
	(0.007)		(0.007)
Fatality Rate		1.579	0.773
		(2.764)	(2.612)
$\ln(1-\tau)$	-0.094	0.201	-0.099
	(1.740)	(1.946)	(1.804)
Injury Rate x $\ln(1-\tau)$	-0.343*		-0.228
	(0.178)		(0.210)
Fatality Rate x $\ln(1-\tau)$		-96.650	-84.672
		(69.870)	(85.497)
$\ln(WC^I)$	-0.046		-0.070
	(0.060)		(0.068)
$\ln(WC^F)$		0.011	0.029
		(0.060)	(0.066)
Injury Rate x $\ln(WC^I)$	-0.140***		-0.142**
	(0.050)		(0.061)
Fatality Rate x $\ln(WC^F)$		-16.095*	-9.451
		(8.245)	(9.028)
N	311502	311634	310579
Fixed Effects	Industry*State	Industry*State	Industry*State
Implied Heterogeneity:			
$75^{th}-25^{th}$	0.479**	0.182	0.461**
	(0.249)	(0.132)	(0.216)
$90^{th}-10^{th}$	0.902**	1.058	1.482*
	(0.468)	(0.765)	(0.784)

Significance levels: * 10%, ** 5%, *** 1%. Standard errors in parentheses are clustered by industry aggregate. The "Implied Heterogeneity" results use equation (10). Covariates include the following individual characteristics interacted with year dummies: age dummies, gender dummy, race dummies, education dummies.

Table 13: IV Results Controlling for Wage Decile x Year Interactions

Implied Heterogeneity				
		Injury	Fatality	Both
$75^{th} - 25^{th}$	1982-2001	0.319***	0.092***	0.304***
		(0.052)	(0.016)	(0.074)
	1982-1990	0.538***	0.121***	0.478***
		(0.085)	(0.023)	(0.125)
$90^{th} - 10^{th}$	1982-2001	0.601***	0.536***	0.673***
		(0.097)	(0.093)	(0.133)
	1982-1990	0.887***	0.624***	1.005***
		(0.140)	(0.118)	(0.200)

Significance levels: * 10%, ** 5%, *** 1%. Standard errors in parentheses are clustered by industry aggregate. The "Implied Heterogeneity" results use equation (10). Regressions control for wage deciles (based on 1982 wage levels) interacted with year fixed effects. Covariates include the following individual characteristics interacted with year dummies: age dummies, gender dummy, race dummies, education dummies.

Table 14: Individual-Level Data, 1981-1996

Implied Heterogeneity			
	Injury	Fatality	Both
$75^{th} - 25^{th}$	0.409***	0.070	0.358**
	(0.153)	(0.047)	(0.160)
$90^{th} - 10^{th}$	0.721***	0.328	0.672**
	(0.270)	(0.220)	(0.329)
N	40556	43194	40556
Fixed Effects	Individual	Individual	Individual

Significance levels: * 10%, ** 5%, *** 1%. Standard errors in parentheses are clustered by industry aggregate and individual. The "Implied Heterogeneity" results use equation (10). Covariates include the following individual characteristics interacted with year dummies: age dummies, gender dummy, race dummies, education dummies, tenure at current job, tenure-squared.