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ABSTRACT

Employer Monopsony Power Does Not Reduce the Value of a Statistical Life*

Although wage rates are lower when employers have monopsony power, we find that the value of a statistical life (VSL) is not reduced when labor markets are more concentrated. Because the estimated VSL is the product of the wage and the wage-risk tradeoff rate, a greater tradeoff rate in highly concentrated U.S. labor markets produces a larger VSL. The general relationship we find is robust with respect to different labor market data. Our results provide the first evidence contradicting policy-related concerns that the VSL is lower in monopsonistic labor markets.

JEL Classification: J17, J42

Keywords: value of a statistical life, VSL, monopsony, concentration, HHI

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* Our research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here are those of the authors and do not reflect the views of the BLS. The authors declare no conflicts of interest.

I. Introduction

The role of employer monopsony power in U.S. labor markets has received considerable attention from scholars and policymakers in recent years. In its review of the existing empirical monopsony literature, the U.S. Department of the Treasury (2022) concluded that the “American labor market is characterized by high levels of employer power.” The estimates that the Department of the Treasury (2022) reviewed say that labor market power is responsible for wage losses of at least 15 percent. The reduced wages in monopsonistic markets have potential consequences for the value of a statistical life (VSL), which is the tradeoff rate between money and fatality risks. Examining the relationship between monopsony and the VSL has crucial policy ramifications because the VSL is the economic price used to monetize changes in mortality risks for policies to reduce health, safety, and environmental risks. When noncompetitive forces reduce wages, a related concern is that noncompetitive forces may also reduce the VSL (Kniesner and Viscusi 2023). We present the first evidence concerning the relationship of monopsony to the VSL, which we find is greater in highly concentrated U.S. labor markets. Our focal result reduces concerns that the VSL is distorted and underestimated because of labor market noncompetition.

Labor market estimates of the VSL usually use a semi-logarithmic wage equation specification for which the calculated VSL is based on the product of the wage rate and the regression parameter capturing the marginal price of job safety (Viscusi and Aldy 2003). Employer monopsony power—either through its direct wage effects or through its effects on the marginal price of safety—could be a source of heterogeneity in commonly used VSL estimates. To assess the degree of noncompetitive effects on VSL, we use the restricted access Census of Fatal Occupational Injuries (CFOI) files to construct granular fatality risk measures in

conjunction with a Herfindahl-Hirschman Index (HHI) that measures the local concentration of online job vacancy postings within occupations (Choi and Marinescu 2023).

Prior research evaluates the wage impacts of employer monopsony power using a wide range of empirical strategies, generally finding that increased labor market power reduces wages. Multiple articles exploit cross-sectional variation in wages and local industry- or occupation-based concentration measures (Azar et al. 2020; Azar, Marinescu, and Steinbaum 2022; Rinz 2022; Handwerker and Dey 2023; Qiu and Sojourner 2023; Jarosch, Nimczik, and Sorkin 2024).¹ Our empirical approach is most similar in spirit to their research, as we focus on the effects of monopsony power stemming from market structure and local competition for labor on the hedonic wage-risk equilibrium.²

The substantial and growing body of research has influenced the economic policy priorities of various divisions of the federal government, particularly under the Biden administration. Alongside the U.S. Department of the Treasury’s (2022) assessment, the *2022 Economic Report of the President* identifies monopsony power as a barrier to economic equality: “[p]erfect competition does not describe most labor markets . . . [T]he market power of employers . . . allows for unfair hiring and compensation practices” (Council of Economic

¹ To isolate the plausibly causal effect of labor market concentration on wages, other researchers have exploited changes in concentration induced by merger and acquisition activity (Arnold 2019; Prager and Schmitt 2021; Benmelech, Bergman, and Kim 2022). Structural designs include Yeh et al. (2022), who estimate wage markdowns in U.S. manufacturing industries, and Webber (2022), who estimates firm-level supply elasticities. Other recent work explores the role of labor market power in general equilibrium models (Berger, Herkenhoff, and Mongey 2022; Lamadon, Mogstad, and Setzler 2022; Berger et al. 2024).

² We do not consider the influence of employer monopsony power stemming from search frictions or job differentiation on the VSL (Naidu and Posner 2021).

Advisers 2022). The 2023 Merger Guidelines commit the competition agencies to consider the effects of mergers on labor markets and workers (U.S. Department of Justice and Federal Trade Commission 2023).³ And the now-rescinded 2024 U.S. Office of Management and Budget’s Circular A-4 regulatory analysis guidance notes that “market power may affect . . . benefit and cost estimates” and requires agencies to consider how regulation may strengthen or limit “labor market competition in ways that impact workers” (U.S. Office of Management and Budget 2023).

The most acute policy concern in our context here is whether employer monopsony power is a source of downward bias in the VSL estimates that are prevalent in the administrative state’s benefit-cost analyses. Prior research finds that for some disadvantaged labor groups, such as Black individuals and Mexican immigrants, the VSL is smaller than conventional uniform VSL estimates that reflect the entire population (Viscusi 2003; Hersch and Viscusi 2010). The results just mentioned are consistent with a formulation of the labor market where disadvantaged groups face a distinct, segmented market opportunities locus that is lower and flatter. Consequently, the disadvantaged population receives less compensation for marginal fatality risks. Given that employer monopsony power seems to disadvantage workers in terms of wages and working conditions, the notion that employer monopsony power would decrease the VSL has some intuitive appeal. Our results, however, strongly refute this.

Instead, we find that the implied VSL is larger in highly concentrated, oligopsonistic labor markets. That is, workers in oligopsonistic labor markets receive more compensation for additional risk. A higher compensation for risk is consistent across several different econometric

³ FTC Chairman Andrew N. Ferguson, as of February 18, 2025, stated that the 2023 Merger Guidelines “are in effect and will serve as the framework for the FTC’s merger-review analysis” (Federal Trade Commission 2025).

approaches. A reassuring aspect of the results for the use of labor market estimates of the VSL in policy analyses is that the usual set of controls for industry and occupation in all recent labor market studies using the CFOI data will capture the influence of monopsonistic factors correlated with industry or occupation.

Though workers in more concentrated markets are not shortchanged in terms of compensating differentials for occupational fatality risks, in equilibrium, the increased marginal price of safety and decreased wages associated with monopsony power will lead workers in more concentrated labor markets to be in more dangerous jobs. The focus of our analysis is on the VSL tradeoff rate not on the level of job risks or work quality more generally, which is a separate issue.

Our discussion continues as follows. Section II visualizes how employer monopsony power could impact the VSL and explains our estimating equations. Section III details the CPS MORG and NLSY97 employment samples, the construction of the fatality rate variable from the CFOI files, and the HHI measure. Section IV presents our regression results using the CPS MORG and NLSY97 employment samples using the first differences model advocated in Kniesner et al. (2012). Section V concludes.

II. Conceptual Framework and Estimation Strategy

A. VSL Estimation and Inference

Our principal VSL estimating equation is:

$$\begin{aligned} \log(wage_{it}) = & \beta_1 FatalityRisk_{ojt} + \beta_2 \log(HHI_{cot}) + \beta_3 [FatalityRisk_{ojt} * \log(HHI_{cot})] \\ & + \lambda X_i + \delta_s + \gamma_o + [\gamma_o * \log(HHI_{cot})] + \pi_t + \alpha + \varepsilon_i, \end{aligned} \quad (1)$$

where $\log(wage_{it})$ is the natural logarithm of hourly wages for person i in year t . The fatality risk variable is assigned based on each worker's occupation o and industry j at time t , and

HHI_{cot} is assigned based on the worker's commuting zone c , occupation o , and time t . X_i is a vector of individual-level controls detailed below in the Data section. State, major occupation group, and year fixed effects are represented by δ_s , γ_o , and π_t , respectively. In some regressions we include a set of interaction terms between major occupation group and local concentration, represented by $\gamma_o * \log(HHI_{cot})$, which allows for heterogeneous wage effects of concentration by job type.

Using a 2000-hour work year, the VSL is calculated using the following formula:

$$VSL = \hat{\theta} * \overline{Wage} * 2000 * 100000, \quad (2)$$

where $\hat{\theta}$ is the average marginal effect of $FatalityRisk_{ojt}$ on $\log(wage_{it})$. In conventional VSL estimation, $\hat{\theta}$ is equal to the estimated coefficient of the fatality risk variable. The inclusion of interactions between concentration and risk in our context requires us to instead use average marginal effects. In parts of our analysis, we set $\hat{\theta}$ equal to the marginal effect of fatality risk on wages at various points in the $\log(HHI)$ distribution (30th percentile, median, and 70th percentile). In specifications with an interaction between $FatalityRisk_{ojt}$ and binary variables reflecting concentration levels ($\beta_1 FatalityRisk_{ojt} + \beta_2 HighlyConcentrated_{cot} + \beta_3 [FatalityRisk_{ojt} * HighlyConcentrated_{cot}]$), we set $\hat{\theta} = \beta_1 + \text{mean}(HighlyConcentrated_{cot}) * \beta_3$.

In our main CPS regressions we account for serial correlation in wages by job type and broad geography by clustering standard errors by state, industry, and occupation (Viscusi and Gentry 2015).⁴ Further, VSL standard errors are computed using the following variance formula

⁴ Given the NLSY97's much smaller sample size, we cluster standard errors by only industry and occupation for the NLSY97 robustness checks.

from Kniesner et al. (2012): $Var(VSL) = 100,000^2 * 2,000^2 * (mean(wage))^2 * Var(\beta_1)$, where β_1 is the estimated fatality risk parameter. For models that include interactions between fatality risk and $\log(HHI)$, we replace $Var(\beta_1)$ in the above variance equation with the variance of a nonlinear combination of regression parameters, estimated using the delta method, of the following form: $[\beta_1 + f(\log(HHI)) * \beta_3]$ (Gian et al. 2024). The function $f(\log(HHI))$ takes either the mean, median, 30th percentile, or 70th percentile of the $\log(HHI)$ distribution, as indicated in the tables. If we use a dummy variable reflecting concentration such as *HighlyConcentrated_{cot}*, we replace $f(\log(HHI))$ with $mean(HighlyConcentrated_{cot})$.

B. Possible Effects of Monopsony Power on the VSL

The VSL depends on the wage rate and the estimated slope of the hedonic wage-risk locus. We have clear predictions regarding the effect of employer monopsony power on the wage rate based on prior empirical work. Greater labor market concentration is typically associated with lower wages, which we will also find in our data.⁵

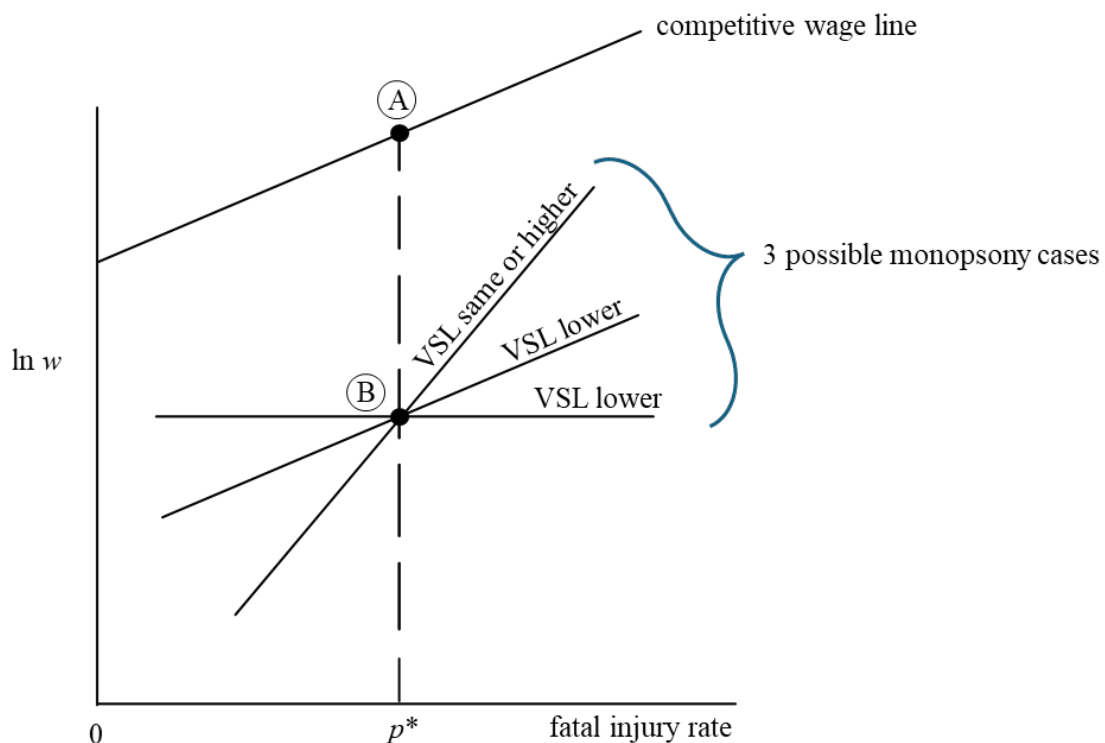
Because the VSL is calculated based on the product of the wage rate and the slope of the wage-fatal injury risk relationship, assessing whether the VSL is higher or lower with monopsony depends on both of these components. Because monopsony reduces worker wages, if there is no statistically significant interactive effect in equation 1, or of this interaction term is

⁵ Monopsony may also affect the fatal injury risk level, as Cramer (2025) finds—using similar labor market concentration data as we use here—that greater concentration is associated with increased occupational injury and illness risk. Although we hypothesize that this result will also hold for occupational fatalities, our focus here is on the implications of monopsony for the VSL at the average market risk level. To the extent that monopsony leads to a higher risk level than competition, accounting for that influence would reduce the adverse wage impact of monopsony but not alter the slope of wage-fatality rate relationship.

negative, then monopsony definitely reduces the VSL. If, however, monopsony boosts the wage-fatal injury risk tradeoff, then the effect of monopsony on the VSL is ambiguous.

Figure 1 illustrates the possibilities. The top line in Figure 1 reflects the competitive market reference point for which there is a higher base wage rate. Point A on this curve indicates the competitive market wage rate for the fatality rate p^* in the sample. The three lower lines in Figure 1 indicate the different possibilities for the interactive effect of monopsony and fatality risks, where point B indicates the market fatality rate and sample wage rate for monopsonistic firms at the intersection of possible monopsony tradeoff rate curves. The lowest monopsony tradeoff rate line is flatter than that for competition, in which case the VSL under monopsony will definitely be lower. The middle monopsony tradeoff rate line has the same slope as the competitive market line. Coupling the same slope with a lower wage rate under monopsony will generate a lower VSL for monopsony than for the competitive market. The top monopsony tradeoff rate is steeper than that in the competitive case, which will reduce or potentially reverse the adverse effect of monopsony on the VSL. The empirical results below are consistent with the top line in Figure 1, which has a steeper tradeoff rate.

Figure 1. The Effect of Monopsony = Wage x Slope



III. Data

A. CPS MORG Employment Sample

Our primary employment sample is the 2011–2021 Current Population Survey Merged Outgoing Rotation Group (CPS MORG) extracts provided by IPUMS (Flood et al. 2024). The sample consists of respondents ages 16 to 70 who work at least 35 hours a week. We drop self-employed, agricultural, and military workers. Our dependent variable is hourly wages in 2022 dollars.⁶ If hourly wage data are not provided for a certain respondent, we impute weekly

⁶ We adjust for inflation using average annual CPI-U.

earnings divided by usual weekly hours.⁷ As is standard in VSL estimation studies, we exclude persons with an hourly wage below \$2 or above \$100 to mitigate the influence of outliers.⁸

Our empirical analysis controls for a wide range of demographic variables, including sex, race, education, marital status, metropolitan status, potential work experience and its square,⁹ and whether the respondent is paid hourly, covered by a union, or works for the government. The education variable is a slight recode of the IPUMS educational attainment variable to approximate years of education.¹⁰ We also control for annual two-digit NAICS industry nonfatal injury and illness rates using public data on the lost workday injury and illness rate for cases involving a lost workday from the U.S. Bureau of Labor Statistics (BLS).¹¹ The final sample, which is summarized in Table 1, consists of 1,329,085 observations not missing any of the key variables.

⁷ Usual weekly hours are equal to the IPUMS variable UHRSWORKORG if available, and UHRSWORK1 if not.

⁸ IPUMS documentation reports that the earnings top-code for non-ASEC samples of the CPS is \$2884.61 per week. We opted to use the standard \$2 to \$100 hourly wage screen to have one consistent sample screen that could apply to both the CPS and NLSY97. To check the robustness of our approach, we also examined two alternatives. First, we tried dropping all individuals with a weekly unadjusted wage at or above \$2884.61. Second, we tried inflating the wages of all individuals with a weekly wage unadjusted at or above \$2884.61 by 1.4. VSL estimates using the two alternative strategies are comparable to and well within the confidence interval of, our baseline VSL estimates.

⁹ Potential work experience is defined as age – education – 5.

¹⁰ The recoding is as follows: no schooling = 0; 1st through 4th grade = 2.5; 5th through 8th grade = 6.5; 9th grade = 9; 10th grade = 10; 11th grade = 11; 12th grade, no diploma, high school graduate, or GED = 12; some college with no degree = 13; associate's degree of any kind = 14; bachelor's degree = 16; master's degree = 17; professional degree = 18; and doctorate degree = 19.

¹¹ To merge in the injury and illness rates to the CPS MORG data, we use crosswalks provided by the U.S. Census Bureau to match census industries to NAICS industry classifications.

B. NLSY97 Employment Sample

To complement the main CPS MORG employment sample, we also use Rounds 18, 19, and 20 of the National Longitudinal Survey of Youth 1997 (NLSY97). Though the NLSY97 is much smaller than the CPS MORG, the advantage of the NLSY97 is that it includes information on the county of every respondent in each survey year using the restricted access geocode file, making it possible to match measures of labor market concentration to the worker's local labor market. (In the CPS MORG, county information is suppressed for respondents in smaller population counties.) Summary statistics for the NLSY97 are presented in Appendix Table A1.¹²

¹² For each individual in the NLSY97, we keep only data on his or her main job in each interview round. We then apply the same sample screens to the data and control for the substantially the same demographic information. One difference in our estimation strategy compared to when we use the CPS MORG is that in the NLSY97 we observe job tenure directly, so we use tenure and its square rather than potential work experience and its square as covariates. Another difference with the CPS MORG is that the NLSY97 does not have an identifier for if a respondent is paid hourly, so we do not include that as a covariate. The final NLSY97 sample consists of 9,318 observations not missing any of our key variables.

Table 1: CPS Summary Statistics

VARIABLES	(1) Mean	(2) SD
Hourly Wage in 2022 Dollars	29.35	17.62
HHI	1,958	2,054
Highly Concentrated (HHI > 2,500) (0/1)	0.290	0.454
Male (0/1)	0.551	0.497
White (0/1)	0.779	0.415
Black (0/1)	0.127	0.333
Native American (0/1)	0.00975	0.0983
Asian (0/1)	0.0627	0.242
Multiracial (0/1)	0.0174	0.131
Hispanic Ethnicity (0/1)	0.168	0.374
Potential Experience	22.77	12.86
Years of Education	13.95	2.514
Married (0/1)	0.585	0.493
Paid Hourly (0/1)	0.536	0.499
Union (0/1)	0.135	0.342
Government Worker (0/1)	0.165	0.371
Metropolitan Status (0/1)	0.880	0.325
Injury and Illness Rate per 100,000	1,003	541.2
Missing Injury and Illness Rate (0/1)	0.00389	0.0622

Notes: N=1,329,085 for all variables. Summary statistics from the CPS Merged Outgoing Rotation Group extracts provided by IPUMS (2011–2021). Results reflect CPS earnings weights. For the small number of observations missing injury and illness rate data, we set the injury and illness rate equal to zero and include a separate dummy variable.

C. Fatality Rate Variable Construction

We construct hours-based fatality rates using restricted access data from the BLS’s CFOI files, which provide a comprehensive count of all work-related fatalities that has been corroborated using multiple data sources. For reference, the public CFI national fatal work injury rate was 3.5 fatalities per 100,000 full-time workers in 2023 (U.S. Bureau of Labor

Statistics 2024).¹³ Disclosure restrictions prevent the release of the fatality rate in the sample used in our study, but our sample was broadly representative of the U.S. workforce. Our constructed fatality rate variable varies by both industry and occupation. In total, we have 1,030 potential annual industry-occupation cells, based on 103 industries and 10 major occupation groups. The 103 industries include 97 three-digit NAICS industry classifications and six select two-digit NAICS industries.¹⁴ The 10 major occupation groups correspond to the census major occupation group aggregations,¹⁵ omitting the Armed Forces category.

We calculate a moving three-year average fatality rate to provide a more precise measure of the low-probability risks and to reduce the number of empty cells without any fatalities. The fatality rate variable otherwise accords with BLS documentation (Northwood 2010) and uses the following equation:

$$Fatality\ Rate = \left(\frac{N}{EH} \right) * 200,000,000.$$

For any given year the numerator N equals the sum all fatalities in the CFOI of non-volunteer, non-military individuals over age 16 in the relevant industry-occupation cell occurring in that year and the prior two years. The denominator of the fatality risk variable, EH , is the estimated

¹³ We are not permitted to share summary statistics regarding our constructed fatality rate variable due to confidentiality concerns by the BLS.

¹⁴ This six two-digit industries are included because some census industries, such as construction, can only be matched to a two-digit NAICS industry. We further collapsed the following pairs of three-digit NAICS industries because the Census to NAICS industry crosswalk makes it difficult to disentangle the pairs: (523, 525), (924, 925), and (926, 927). Additionally, the small number of persons working in the not-specified manufacturing industries and not-specified retail trade are dropped because their codes cannot be mapped to even a single 2-digit NAICS code.

¹⁵ Available at: <https://www2.census.gov/programs-surveys/cps/methodology/Occupation%20Codes.pdf>.

total hours of work performed by all employees in an industry and occupation category in the same three years.¹⁶

Though there are 1,030 possible industry-occupation cells in any year the actual number of calculated fatality rate cells each year is smaller. The smaller number of calculated fatality rate cells happens because there must be at least one individual in the CPS within that industry and occupation to generate the denominator. From 2011–2021 there are 9,180 total fatality rate cells (an annual average of around 835 annual cells).

D. Local Labor Market Concentration Data

We generally define labor markets as a six-digit SOC occupation and commuting zone, which is a commonly used approach throughout the monopsony literature (Azar et al. 2020; Azar, Marinescu, and Steinbaum 2022; Azar et al. 2023; Handwerker and Dey 2023).¹⁷ Commuting zones are collections of adjacent counties that approximate local economies. Occupational mobility within six-digit SOC occupations is relatively low; 76 percent of job

¹⁶ The annual total hours estimate is calculated from CPS MORG samples provided by IPUMS (Flood et al. 2024). Among the sample of employees at work each year (dropping the unemployed or those absent from work), we use the earnings weight variable to estimate the population within each industry-occupation cell. We then multiply the estimated population by 50 (representing 50 weeks) and the average weekly hours within the industry-occupation pair. Following Viscusi and Gentry (2015), if no employees in an industry and occupation category report usual weekly hours, we impute the average hours across all industry-occupation cells. Finally, we multiply the resulting ratio by 200,000,000, reflecting the base fatality rate for 100,000 full-time employees working 40 hours per week for 50 weeks annually.

¹⁷ Handwerker and Dey (2023) aggregate some occupations into broader categories depending on the requisite educational qualifications.

changers remain in the same six-digit SOC occupation (Schubert, Stansbury, and Taska 2024). This suggests six-digit SOC occupations are a reasonable way of defining labor markets.

Our source of labor market concentration data is Choi and Marinescu (2023). The same data have been used in multiple prior labor monopsony papers (Azar et al. 2020; 2023). To calculate the labor market Herfindahl-Hirschman Index for each market, Choi and Marinescu measure each firm's share of online job vacancy postings. The online job vacancy posting data is from Lightcast (formerly Burning Glass Technologies). The HHI is the sum of the square of each firm's share of online job vacancy postings. Azar et al. (2020) believe that a vacancy-based concentration measure is more appropriate than employment-based measures because "workers remain in jobs for longer," so "concentration of employment may be a less relevant gauge of available work and employer market power than is the concentration of vacancies among the relatively few firms who are likely to be hiring." We use Choi and Marinescu's "lower-bound" HHI estimates, which assumes each online job vacancy with a missing employer name is distinct from every other missing employer and all identified employers (Choi and Marinescu 2023). Because the Choi and Marinescu data are quarterly, we take the unweighted average across all quarters to generate an annual HHI estimate for each labor market.¹⁸

¹⁸ For the NLSY97, we average across the last two quarters of the survey year and the first two quarters of the following year because that is roughly the NLSY97 fielding period (<https://www.nlsinfo.org/content/cohorts/nlsy97/intro-to-the-sample/interview-methods>). For example, for respondents in Round 18 (named survey year 2017), we average across Q3 and Q4 of 2017 and Q1 and Q2 of 2018. For Round 20, we only average across Q1 and Q2 of 2021 because the Choi and Marinescu HHI data does not go past that date.

Further details on the procedures used to prepare the Choi and Marinescu (2023) data for the CPS MORG and NLSY97 analysis are available in Technical Appendix 1. There we also explain our strategy for assigning HHI data to the large proportion of respondents in the CPS MORG that lack county identifiers.

IV. Results

A. CPS MORG Results

Table 2 presents results from a series of hedonic wage regressions that include fatal risk measures, nonfatal risk measures, and various labor market concentration measures. The coefficient on each concentration measure is negative and statistically significant at the one percent level, suggesting that increased concentration is associated with lower wages. The association is consistent with the findings of most of the existing empirical literature. The fatal and nonfatal risk measures are positive and statistically significant at the one and five percent level, respectively, corroborating the existence of meaningful compensating differentials for broad categories of occupational hazards. The implied VSL ranges from \$13.3 million to \$13.7 million and appears stable regardless of which variant of the concentration measure is employed.

We next examine how the implied VSL differs when allowing the fatality rate to vary by concentration levels. Column 1 of Table 3, which includes neither concentration measures nor fatality risk interaction terms and serves as a reference point for conventional estimation, provides our benchmark VSL of \$13.43 million.

Table 2: Log wage regressions on concentration and risk measures

VARIABLES	(1)	(2)	(3)	(4)
Log(HHI)	-1.27e-02*** (9.65e-04)			
Highly Concentrated (HHI > 2500)		-1.85e-02*** (2.88e-03)		
Above Median HHI			-2.01e-02*** (3.09e-03)	
Above Median HHI w/n Major Occ				-2.24e-02*** (2.55e-03)
Fatality Rate per 100,000	2.33e-03*** (3.84e-04)	2.28e-03*** (3.85e-04)	2.27e-03*** (3.84e-04)	2.28e-03*** (3.85e-04)
Injury and Illness Rate per 100,000	1.26e-05** (5.14e-06)	1.25e-05** (5.18e-06)	1.23e-05** (5.14e-06)	1.23e-05** (5.16e-06)
R ²	4.47e-01	4.47e-01	4.47e-01	4.47e-01
VSL in Millions	13.70	13.39	13.30	13.36
Lower Bound 95% CI VSL	9.279	8.957	8.875	8.935
Upper Bound 95% CI VSL	18.12	17.82	17.72	17.79

Notes: N=1,329,085. Results reflect CPS earnings weights except for calculating the various median HHI levels. Standard errors clustered by state, major occupation group, and 3-digit NAICS industry in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each regression also includes controls for sex, race, reporting Hispanic ethnicity, education, marital status, metropolitan status, potential work experience, potential work experience squared, and whether the respondent is paid hourly, covered by a union, or works for the government. We also include a dummy variable if missing 2-digit NAICS industry nonfatal injury and illness rate and state, year, and major occupation group fixed effects. The sample mean wage is used to calculate the VSL.

For context, a recent meta-analysis of CFOI-based VSL studies calculates a mean “best-set” VSL of \$12.74 million and mean “all-set” VSL of \$14.15 million (Kniesner, Sullivan, and Viscusi 2024; Viscusi 2018).¹⁹ Our baseline VSL is also in line with estimates used by government

¹⁹ Values updated to 2022 dollars using average annual CPI-U. Best-set estimates refer to “those preferred by the authors,” whereas all-set estimates include “all of the estimates presented by the authors in the original articles” (Kniesner, Sullivan, and Viscusi 2024).

agencies for valuing the benefits of mortality reductions in regulatory analyses. The U.S. Department of Transportation, for instance, employed a VSL of \$12.5 million in 2022 dollars (U.S. Department of Transportation 2024).

Column 2 adds a continuous concentration measure and an interaction term between fatal risk and concentration. The VSL, which is calculated by setting $\hat{\theta}$ in Equation (2) equal to the average marginal effect of fatality risk from the regression equation, is \$10.47 million. In column 3 we further augment the estimating equation with a set of interaction terms between each major occupation group and log(HHI), allowing for heterogeneous wage impacts of labor market concentration by broad occupational classification. The estimated VSL in column 3 is \$11.05 million and quite close to the estimate in column 2. Allowing for the fatality risk variable to vary by concentration levels and evaluating the VSL using the average marginal effect of fatality risk on wages yields a modestly smaller VSL than values from conventional estimating equations. All the implied VSLs in Table 3, however, fall well within each other's 95 percent confidence intervals.

While Table 3 compares the VSL with and without concentration controls, Table 4 examines how the VSL changes at different focal values in the distribution of labor market concentration scores. Here, we calculate the VSL by setting $\hat{\theta}$ equal to the marginal wage effect of fatality risk at different representative values of the log(HHI) distribution—namely, the 30th, 50th, 70th percentiles. Additionally, to directly account for the independent effects of monopsony

Table 3: Log wage regressions on fatality rate, with and without concentration interactions

VARIABLES	(1)	(2)	(3)
Fatality Rate per 100,000	0.0023*** (0.0004)	-0.0178*** (0.0012)	-0.0086*** (0.0013)
Log(HHI)		-0.0200*** (0.0011)	-0.0166*** (0.0016)
Fatality Rate * Log(HHI)		0.0029*** (0.0002)	0.0015*** (0.0002)
R ²	0.4464	0.4481	0.4505
Major Occ * Log(HHI) Terms	NO	NO	YES
Avg. Marginal Effect of Fatality Rate	0.00229	0.00178	0.00188
VSL in Millions	13.43	10.47	11.05
Lower Bound 95% CI VSL	9.050	6.262	7.095
Upper Bound 95% CI VSL	17.80	14.68	15

Notes: N=1,329,085. Results reflect CPS earnings weights. Standard errors clustered by state, major occupation group, and 3-digit NAICS industry in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each regression also includes controls for sex, race, reporting Hispanic ethnicity, education, marital status, metropolitan status, potential work experience, potential work experience squared, and whether the respondent is paid hourly, covered by a union, or works for the government. We also include 2-digit NAICS industry nonfatal injury and illness rates (with a dummy if missing in any year) and state, year, and major occupation group fixed effects. In column 3, we include an additional set of interaction terms between each major occupation group and log(HHI) (omitting the management, business, and financial occupation group interaction). VSL confidence intervals are computed following Kniesner et al. (2012), where the variance of the fatality risk parameter for the interaction models is estimated using the delta method. The sample mean wage is used to calculate the VSL.

power on wages in the VSL calculation, in Table 4 we replace $\overline{Wage}$ in Equation (2) (the overall sample mean wage) with the mean wage across observations the second, third, and fourth log(HHI) quintiles, respectively, for columns 1, 2, and 3. Note that the 30th percentile of the log(HHI) distribution is the midpoint of the second log(HHI) quintile, the median is the midpoint of the third quintile, and the 70th percentile is the midpoint of the fourth quintile.

Table 4: Log wage regressions on fatality rate with concentration interaction, evaluating VSL at different concentration levels

VARIABLES	(1) VSL At 30th Percentile Log(HHI)	(2) VSL At Median Log(HHI)	(3) VSL At 70th Percentile Log(HHI)
Fatality Rate per 100,000	-0.0086*** (0.0013)	-0.0086*** (0.0013)	-0.0086*** (0.0013)
Fatality Rate * Log(HHI)	0.0015*** (0.0002)	0.0015*** (0.0002)	0.0015*** (0.0002)
R ²	0.4505	0.4505	0.4505
Major Occ * Log(HHI) Terms	YES	YES	YES
Marginal Effect of Fatality Rate	0.000975	0.00227	0.00329
VSL in Millions	5.566	12.88	19.03
Lower Bound 95% CI VSL	1.591	8.996	14.53
Upper Bound 95% CI VSL	9.541	16.76	23.54

Notes: N=1,329,085. Results reflect CPS earnings weights. Standard errors clustered by state, major occupation group, and 3-digit NAICS industry in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each regression also includes controls for sex, race, reporting Hispanic ethnicity, education, marital status, metropolitan status, potential work experience, potential work experience squared, and whether the respondent is paid hourly, covered by a union, or works for the government. We also include 2-digit NAICS industry nonfatal injury and illness rates (with a dummy if missing in any year), state, year, and major occupation group fixed effects, a standalone log(HHI) term, and a set of interaction terms between each major occupation group and log(HHI) (omitting the management, business, and financial occupation group interaction). VSL confidence intervals are computed following Kniesner et al. (2012), where the variance of the fatality risk parameter for the interaction models is estimated using the delta method. Columns 1, 2, and 3 use the mean wage across observations in the second, third, and fourth log(HHI) quintiles, respectively, to calculate the VSL.

The regression equation in Table 4 further includes the major occupation group and concentration interaction terms, so the specification is identical to column 3 of Table 3.

Table 4 shows that the VSL is larger in more concentrated labor markets. The VSL at the 30th percentile of the log(HHI) distribution is \$5.57 million. This is close to the 10th percentile of the distribution of CFOI-based, all-set VSL estimates from the meta-analyses mentioned

earlier (Kniesner, Sullivan, and Viscusi 2024; Viscusi 2018). The VSL at median log(HHI) is \$12.88 million, roughly a half million dollars smaller than our benchmark VSL that does not account for labor market concentration. Notably, the 30th percentile and median log(HHI) VSL estimates fall outside one another's 95 percent confidence intervals, exhibiting a statistically meaningful difference. The VSL at the 70th percentile log(HHI) distribution—\$19.03 million—is just below the 75th percentile of the distribution of CFOI-based, all-set VSL estimates (Kniesner, Sullivan, and Viscusi 2024; Viscusi 2018). The 70th percentile and median estimates similarly fall outside of one another's 95 percent confidence intervals. Though wages are lower under monopsony, the positive effect of monopsony on the slope of the hedonic wage-risk locus appears much more consequential for VSL estimation.

Table 5 presents the VSL yielded by an estimating equation that includes interactions between the fatality risk variable and dichotomous labor market concentration measures. Using the highly concentrated labor market variable in column 1,²⁰ the VSL is \$14.05 million. In column 2, with the above median HHI measure, the VSL is \$13.47 million, which is statistically indistinguishable from our baseline VSL. More interestingly, the coefficients on the interaction between fatality rate and the concentration dummy variable are positive, relatively large in magnitude, and statistically significant at the one percent level. This indicates that there is a substantially greater rate of compensation for marginal fatality risks for individuals in more concentrated labor markets.

²⁰ We opt to use the older 2,500 HHI threshold for highly concentrated markets for ease of comparability with prior work.

Table 5: Log wage regressions on fatality rate with concentration dummy variable interactions

VARIABLES	(1)	(2)
Fatality Rate per 100,000	0.0011*** (0.0004)	0.0008** (0.0004)
Fatality Rate * Highly Con. (HHI > 2500)	0.0044*** (0.0005)	
Fatality Rate * Above Median HHI		0.0033*** (0.0005)
R ²	0.4490	0.4492
Major Occ * Concentration Dummy Terms	YES	YES
VSL in Millions	14.05	13.47
Lower Bound 95% CI VSL	9.947	9.350
Upper Bound 95% CI VSL	18.16	17.59

Notes: N=1,329,085. Results reflect CPS earnings weights except for calculating the median HHI level. Standard errors clustered by state, major occupation group, and 3-digit NAICS industry in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each regression also includes controls for sex, race, reporting Hispanic ethnicity, education, marital status, metropolitan status, potential work experience, potential work experience squared, and whether the respondent is paid hourly, covered by a union, or works for the government. We also include 2-digit NAICS industry nonfatal injury and illness rates (with a dummy if missing in any year), state, year, and major occupation group fixed effects, a standalone concentration dummy term, and a set of interaction terms between each major occupation group and the concentration dummy (omitting the management, business, and financial occupation group interaction). To calculate the VSL, we take the sum of the coefficient on the standalone fatality rate variable and the coefficient of the interaction term multiplied by the proportion of the sample for which the concentration dummy variable equals one. The VSL standard error is estimated using the delta method on the same combination of parameters. The sample mean wage is used to calculate the VSL.

So far, we have assessed the effect of monopsony power on the VSL by allowing the fatality risk and labor market concentration variables to interact in a single estimating equation.

An alternative approach is to split the main employment sample into subsamples, based on whether individuals are in “high” or “low” concentration labor markets, and then estimate separate equations for each subsample. This simplifies the VSL calculation because $\hat{\theta}$ is equal to the estimated coefficient of the fatality risk parameter. Moreover, it is straightforward here to

control for the independent wage effects of monopsony by setting $\overline{Wage}$ equal to the mean wage within the high- or low-monopsony subsample. This also allows our other covariates to vary depending on whether workers are in concentrated or competitive markets.

Table 6 presents results from a deeper dive into concentration's consequences. Column 1 splits the sample according to whether the respondent works in a highly concentrated (HHI > 2500) labor market or not. The difference in the VSL estimates is marked: \$28.12 million in highly concentrated labor markets compared to \$8.29 million in all other labor markets. In column 2, which splits the sample based on whether respondents are in a labor market with an HHI score above or below the sample median, displays similar results although the disparity is less dramatic. The VSL for the above-median HHI group is \$20.59 million, which is smaller than the VSL for the highly concentrated subsample in column 1. The below-median HHI group VSL of \$8.01 million, however, is statistically indistinguishable from the VSL for the below 2,500 HHI group.

It is possible the differences in the VSL in columns 1 and 2 could partially reflect differences in the occupational composition of the high- and low-concentration subsamples. Column 3 consequently allows the relevant median HHI value used to partition the sample to vary by major occupation group. Results in column 3, where workers were only be assigned to the high- or low-concentration group based on comparisons to workers in similar jobs, show that there remain sizeable and significant differences in the implied VSLs: \$17.43 million for the above-median group compared to \$10.64 million for the below-median group.

Table 6: Split sample log wage regressions on fatality rate

	(1)	(2)	(3)
	HHI	HHI	HHI Above
	Above	Above	Median
	2500	Median	Within
VARIABLES			Major
			Occupation
Fatality Rate per 100,000	0.0049*** (0.0005)	0.0036*** (0.0005)	0.0030*** (0.0004)
Observations	446,824	664,528	664,451
R-squared	0.4103	0.4249	0.4319
VSL in Millions	28.12	20.59	17.34
Lower Bound 95% CI VSL	22.26	15.42	12.29
Upper Bound 95% CI VSL	33.97	25.76	22.40
	(1)	(2)	(3)
	HHI	HHI	HHI Below
	Below	Below	Median
	2500	Median	Within
VARIABLES			Major
			Occupation
Fatality Rate per 100,000	0.0014*** (0.0004)	0.0013*** (0.0004)	0.0018*** (0.0004)
Observations	882,261	664,557	664,634
R ²	0.4643	0.4691	0.4633
VSL in Millions	8.292	8.007	10.64
Lower Bound 95% CI VSL	4.040	3.404	6.073
Upper Bound 95% CI VSL	12.54	12.61	15.21

Notes: Results reflect CPS earnings weights except for calculating the various median HHI levels. Standard errors clustered by state, major occupation group, and 3-digit NAICS industry in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each regression also includes controls for sex, race, reporting Hispanic ethnicity, education, marital status, metropolitan status, potential work experience, potential work experience squared, and whether the respondent is paid hourly, covered by a union, or works for the government. We also include 2-digit NAICS industry nonfatal injury and illness rates (with a dummy if missing in any year) and state, year, and major occupation group fixed effects. VSL confidence intervals are computed following Kniesner et al. (2012). Each column uses the mean wage within the split sample group to calculate the VSL. The below group is inclusive of values equal to the cutoff.

Across the board, the top row of Table 6 displays VSLs that are significantly larger than the estimates in the bottom row. The results at the top of Table 6 are consistent with the existence of a steeper hedonic locus under an oligopsonistic market structure.

B. Hedonic Wage Equilibrium Under Monopsony

Visually, monopsony power's impact corresponds to a steeper yet lower hedonic wage locus. In the context of Figure 1, this would correspond to Panel B. Following Viscusi and Hersch (2001), there is likely labor market segmentation whereby workers in more concentrated occupational groups face a different market opportunities locus. The most concentrated markets have a lower wage rate, but also a different, steeper slope. The effect of employer monopsony power on the slope of the hedonic wage-risk locus appears to dominate any independent negative wage effects of reduced labor market competition in terms of its impact on the VSL.

Although workers receive lower wages in concentrated markets, they are not shortchanged in terms of compensating differentials for occupational fatality risks. A steeper hedonic locus does not imply that workers in monopsonistic markets necessarily fare better than workers in competitive markets, however. The VSL represents both the rate of compensation for additional risk and the marginal price of reduced risk. Workers in monopsonistic markets are thus (1) paid less overall and (2) pay a greater price to move into a safer job. Moreover, in equilibrium, workers in more concentrated labor markets are in more dangerous jobs.²¹

²¹ The qualitative effects of employer monopsony power on the hedonic labor market equilibrium are the inverse of the effects of OSHA regulations and enforcement activities. In simulation analyses, Kniesner and Leeth (1988; 1989) find that OSHA raises and flattens the hedonic locus, which consequently pushes workers into safer jobs (Kniesner and Leeth 2014).

An analysis of the how job quality varies by labor market concentration levels is consistent with workers in more concentrated markets facing a greater worker fatality rate. Table 7 provides the results from a series of regressions using CFI and CPS MORG data, where the dependent variable is the natural logarithm of (one plus) the fatality rate. The explanatory variable of interest is the natural logarithm of our HHI measure. In each specification, concentration has a statistically significant and positive association with fatal job risk. A one percent increase in labor market concentration corresponds to roughly a 0.01 to 0.06 percent increase in fatality risk, depending on which covariates are included. The greater elasticity estimates of 0.05 and 0.06 are more informative since the lower estimates account for regional differences that are correlated with labor market concentration measures. Consistent with our interpretation of the equilibrium impacts of our VSL findings, workers in more concentrated labor markets face greater risks.

C. Robustness Tests with the NLSY97

We next replicate our main results from Table 3 and Table 4 using the NLSY97. An advantage of the NLSY97 is that we directly observe the county of every respondent each survey year. Additionally, we can exploit the panel data structure to control for latent individual heterogeneity in time-invariant unobservable differences such as productivity and risk preferences. We opt for a first-differences model over a fixed effects model for reasons discussed in Kniesner et al. (2012).

In Table 8, which is the NLSY97 analog of Table 3, we observe a similar pattern as in the CPS MORG. The baseline implied VSL without any concentration controls is \$20.05 million. The 95 percent confidence interval of that estimate is large, ranging from -\$1.7 to \$41.80 million. The imprecision of the estimate is somewhat expected given the NLSY97's considerably smaller

Table 7: Log fatality rate regressions on concentration

VARIABLES	(1)	(2)	(3)	(4)
Log(HHI)	0.0638*** (0.0069)	0.0474*** (0.0040)	0.0112*** (0.0025)	0.0119*** (0.0024)
R ²	0.0115	0.2786	0.6712	0.6838
Demographic Controls	NO	YES	YES	YES
Fixed Effects	NO	NO	YES	YES
Nonfatal Controls	NO	NO	NO	YES

Notes: N=1,329,085. Results reflect CPS earnings weights. The dependent variable is the natural logarithm of one plus the fatality rate. Standard errors clustered by state, major occupation group, and 3-digit NAICS industry in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Demographic controls include sex, race, reporting Hispanic ethnicity, education, marital status, metropolitan status, potential work experience, potential work experience squared, and whether the respondent is paid hourly, covered by a union, or works for the government. Fixed effects refer to state, year, and major occupation group fixed effects. Nonfatal controls refer to 2-digit NAICS industry nonfatal injury and illness rate (with a dummy if missing in any year).

sample size. Including both a continuous concentration measure and an interaction between concentration and fatality risk results—and evaluating the VSL at $\hat{\theta}$ equal to the average marginal effect of fatality risk—results in an implied VSL that is several million dollars smaller. The implied VSL that accounts for concentration ranges from \$17.31 to \$15.30, depending on whether the set of major occupation and concentration interaction terms is included.

Table 9 presents the implied VSLs at different points in the log(HHI) distribution using the NLSY97 data. Like the results shown in Table 4 with the CPS MORG, moving to more concentrated labor markets increases the VSL appreciably. Unlike with CPS results, however, the estimates are not statistically distinguishable from one another given the wide-ranging 95 percent confidence intervals.

Table 8: First differences log wage regressions on fatality rate, with and without concentration interactions

VARIABLES	(1)	(2)	(3)
Δ Fatality Rate per 100,000	0.0032* (0.0017)	-0.0015 (0.0028)	-0.0057 (0.0040)
Δ Log(HHI)		0.0022 (0.0030)	0.0082* (0.0044)
Δ (Fatality Rate * Log(HHI))		0.0006* (0.0003)	0.0012** (0.0005)
R ²	0.0326	0.0336	0.0361
Δ (Major Occ * Log(HHI)) Terms	NO	NO	YES
Avg. Marginal Effect of Fatality Rate	0.00315	0.00272	0.00241
VSL in Millions	20.05	17.31	15.30
Lower Bound 95% CI VSL	-1.700	-3.890	-6.394
Upper Bound 95% CI VSL	41.80	38.52	36.99

Notes: N=4,572. Results reflect NLSY sample weights. Standard errors clustered by major occupation group and 3-digit NAICS industry in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each regression also includes controls for job tenure, job tenure squared, government employee status, union status, marital status, and whether the respondent lives in a rural area. Sex, race, ethnicity, and education have insufficient intertemporal variation to be estimated with the first differences model. We also include 2-digit NAICS industry nonfatal injury and illness rates (with a dummy if missing in any year) and region, year, and major occupation group fixed effects. In column 3, we include an additional set of interaction terms between each major occupation group and log(HHI) (omitting the management, business, and financial occupation group interaction). VSL confidence intervals are computed following Kniesner et al. (2012), where the variance of the fatality risk parameter for the interaction models is estimated using the delta method. The sample mean wage is used to calculate the VSL.

Still, the observation that the NLSY97 data produce similar trends in implied VSL point estimates provides some assurance regarding our CPS estimation strategy—namely, with respect to the influence of unobserved individual heterogeneity and our inability to observe the county of every respondent in the CPS.

Table 9: First differences log wage regressions on fatality rate with concentration interaction, evaluating VSL at different concentration levels

VARIABLES	(1) VSL At 30th Percentile Log(HHI)	(2) VSL At Median Log(HHI)	(3) VSL At 70th Percentile Log(HHI)
Δ Fatality Rate per 100,000	-0.0057 (0.0040)	-0.0057 (0.0040)	-0.0057 (0.0040)
Δ (Fatality Rate * Log(HHI))	0.0012** (0.0005)	0.0012** (0.0005)	0.0012** (0.0005)
R ²	0.0361	0.0361	0.0361
Δ (Major Occ * Log(HHI)) Terms	YES	YES	YES
Marginal Effect of Fatality Rate	0.00145	0.00265	0.00365
VSL in Millions	9.543	16.59	21.82
Lower Bound 95% CI VSL	-32.76	-21.75	-18.61
Upper Bound 95% CI VSL	51.84	54.93	62.26

Notes: N=4,572. Results reflect NLSY sample weights. Standard errors clustered by major occupation group and 3-digit NAICS industry in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each regression also includes controls for job tenure, job tenure squared, government employee status, union status, marital status, and whether the respondent lives in a rural area. Sex, race, ethnicity, and education have insufficient intertemporal variation to be estimated with the first differences model. We also include 2-digit NAICS industry nonfatal injury and illness rates (with a dummy if missing in any year), region, year, and major occupation group fixed effects, a standalone log(HHI) term, and a set of interaction terms between each major occupation group and log(HHI) (omitting the management, business, and financial occupation group interaction). VSL confidence intervals are computed following Kniesner et al. (2012), where the variance of the fatality risk parameter for the interaction models is estimated using the delta method. Columns 1, 2, and 3 use the mean wage across observations in the second, third, and fourth log(HHI) quintiles, respectively, to calculate the VSL.

V. Conclusion

The research presented here examines a novel source of heterogeneity in VSL estimation: labor market power of employers. Equilibrium impacts of employer concentration are certainly of concern, and we confirm empirically that workers under oligopsony conditions are paid less, as is well documented. Moreover, we also find that the marginal price of safety, as reflected in the VSL, is greater in concentrated markets.

Our focus here has been on an issue that is also of great importance to regulatory policies for the valuation of health, safety, and environmental regulations—the effect of employer monopsony power on the estimated value of a statistical life (VSL). Regulatory benefits monetized using the VSL comprise the majority of the benefits of new government regulations (Viscusi 2018). The concern motivating our research was whether monopsony power in US labor markets distorts health-enhancing regulatory decisions by leading to an underestimate of the VSL. Although workers in more concentrated markets receive lower wages and face greater fatality risks, the compensating wage differential for workplace health hazards are greater in monopsonistic markets. Policy concerns about noncompetitive forces possibly biasing VSL estimates downward, and in turn distorting policy decisions on health and safety regulations based on the VSL, are not supported by the evidence we have presented here.

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Table A1: NLSY97 Summary Statistics

VARIABLES	(1) Mean	(2) SD
Hourly Wage in 2022 Dollars	31.78	16.97
HHI	1,678	2,168
Highly Concentrated (HHI > 2,500) (0/1)	0.209	0.407
Male (0/1)	0.549	0.498
White (0/1)	0.736	0.441
Black (0/1)	0.152	0.359
Native American (0/1)	0.00713	0.0841
Asian (0/1)	0.0239	0.153
Multiracial (0/1)	0.0762	0.265
Hispanic Ethnicity (0/1)	0.128	0.335
Tenure	6.171	4.981
Highest Grade Completed	14.74	3.028
Married (0/1)	0.555	0.497
Rural (0/1)	0.199	0.399
Government Worker (0/1)	0.187	0.390
Union (0/1)	0.166	0.372
Injury and Illness Rate per 100,000	954.6	534.3
Missing Injury and Illness Rate (0/1)	0.0121	0.109
NCA	0.157	0.363

Notes: N=9,318. NLSY97 summary statistics from Rounds 18, 19, and 20. Results reflect NLSY sample weights. For the small number of observations missing injury and illness rate data, we set the injury and illness rate equal to zero and include a separate dummy variable.

Technical Appendix I

We use SOC occupation to census occupation crosswalks from the U.S. Census Bureau to merge the Choi and Marinescu HHI data to the CPS MORG and NLSY97, which respectively use the 2010²² and 2002 vintages of the census occupation coding scheme. A complication is that the crosswalks are not perfectly one-to-one. Some census occupation codes match to multiple SOC codes.²³ To handle multiple matches, we first attempted to match all census occupation codes to a six-digit SOC occupation and directly impute the Choi and Marinescu (2023) HHI score for each commuting zone. If there was no six-digit match for a census occupation code, we remove the last digit and take a weighted average of all matching five-digit SOC occupations. The weights correspond to national occupational employment estimates from the U.S. Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS) program.²⁴ We then repeat the process at the four-digit level for all census occupation codes still missing HHI data.

Our process results in HHI scores for each 2010 census occupation (for the CPS MORG) or 2002 census occupation (for the NLSY97) and each commuting zone. We identify the

²² The CPS MORG switched to the 2018 vintage of the census occupation codes starting in 2020, but we use the IPUMS harmonized “occ2010” variable to largely circumvent this issue.

²³ For example, in the 2010 census occupation to 2010 SOC crosswalk, “Janitors and building cleaners” corresponds to 37-201X.

²⁴ If a certain six-digit SOC occupation is missing from the OEWS data, we impute a weight of $1/n$, where n is equal to the number of matching SOC codes. In the CPS MORG, for each year from 2012 to 2018, we use that year's national occupational employment estimates. The coding scheme for the OEWS changed outside of the years 2014-2018. Because of this, we use the 2012 OEWS estimates for CPS MORG data from 2011, and the 2018 OEWS estimates for CPS MORG data from 2019, 2020, and 2021. For the NLSY97, we use the 2018 OEWS estimates for all rounds.

commuting zone based on county information using a crosswalk also provided by Choi and Marinescu (2023). For the NLSY97, using the restricted access geocode file from the BLS, we observe the county of every respondent in each survey round. Because counties with smaller populations are not permitted to be identified in public use data, for the CPS MORG we only observe the county of residence for approximately 42 percent of respondents.

For the remaining CPS MORG observations with unidentified counties, we generate an aggregated state-level HHI measure for each occupation. To construct the state level measures, we start with a dataset of all counties and their annual population estimates from the U.S. Census Bureau. We then remove from that list all counties that are observed in the CPS. This is because, by definition, individuals with missing HHI data do not reside in the counties that are large enough to meet disclosure requirements. Then, we aggregate the remaining county populations into commuting zone populations because it is at that level where the Choi and Marinescu (2023) HHI data are available. If a commuting zone spans multiple states, we calculate the population within that commuting zone separately by each state. We then have a population estimate for each commuting zone in every state among the universe of unidentified counties. We also have an HHI score for each commuting zone and occupation pair. We then take a weighted average across each occupation's HHI scores for every commuting zone in the state, where the weights equal the commuting zone's share of the state population among the universe of unidentified counties.²⁵ It is worth highlighting that we do not have to use state-level aggregate HHI measures

²⁵ We use the annual census county population estimates for each year from 2011–2020. In 2021, the U.S. Census Bureau switched its geographical unit for population estimates in Connecticut from counties to county-equivalent planning regions. To avoid complications related to this change, we use the county population estimates from 2020 to generate 2021 state-level aggregated HHI measures.

for the NLSY97 data, and so the NLSY97 analysis serves as a robustness check on the approach for the CPS MORG.

Lastly, we merge the HHI these data to the CPS MORG first using the IPUMS harmonized “occ2010” variable, and, if unsuccessful, we then attempt to use the unharmonized occupation variable. This is because there are a small number of deviations from the IPUMS harmonized “occ2010” variable and the 2010 census occupation list. To merge the HHI data to the NLSY97 we only use the census occupation code.