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Birds of a feather: Estimating the value of statistical life from dual-earner families

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Abstract

Economists have long employed hedonic wage analysis to estimate income-fatality risk trade-offs, but some scholars have raised concerns about systematic measurement error and omitted variable bias in the empirical applications of this model. Recent studies have employed panel methods to remove time-invariant individual-specific characteristics that could induce bias in estimation. In an analogous manner, this paper proposes to exploit assortative matching on risk attitudes within married couples to control for worker characteristics that are unobserved to the econometrician. I develop and implement a modified hedonic wage estimator based on a within-couple differenced wage equation for full-time working married couples with the Current Population Survey Merged Outgoing Rotation Group over 1996-2002. The key assumption builds on the findings in the assortative matching literature that individuals often marry those who have common traits across many dimensions, including those that may influence worker wages and are correlated with observed occupational fatality risks. This estimator identifies the compensating differential for occupation fatality risk by using within-couple differencing to remove unobserved determinants of risk attitudes and risk-mitigation ability, on which couples match, from the error term. I find that the value of statistical life (VSL) varies from $9 to $13 million (2016$). The within-couple differenced VSL estimates are stable and more robust to variation in specification of the hedonic wage model than conventional, cross-sectional hedonic wage models. I also find that the value of statistical life takes an inverted-U shape with respect to age.

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1 Introduction

Individuals reveal their preferences over fatality risk and income in an array of market contexts. Economists have long employed empirical tools to estimate the compensating differential for bearing risk in these markets (Viscusi 2018). Specifically, economists investigate the trade-offs between wages and occupational fatality risks in labor markets to estimate the willingness to pay for marginal changes in mortality risk.

The value of statistical life (VSL) derived from these estimates informs evaluations of public policies and proposed regulations intended to reduce the mortality risk associated with air pollution, transportation safety, consumer product safety, food safety, and other risks (Viscusi and Aldy 2003; Robinson 2007). For example, the Environmental Protection Agency uses a VSL of $8.8 million and the Department of Transportation uses a VSL of $9.6 million in their regulatory impact analyses (EPA. 2018; DOT. 2016).[1]

This paper presents a novel empirical strategy for estimating the value of statistical life from labor market data. In particular, I exploit the assortative matching on risk attitudes, experience with risky behaviors, and physical characteristics within married couples to derive a modified hedonic wage estimator. Focusing on dual-earner households in which head of household and spouse each work full time, I take the within-household difference in wages, occupational fatality risk, and all other independent variables common in hedonic wage analysis. I estimate how the differenced wage varies with differenced fatality risk and other differenced controls using the Current Population Survey Merged Outgoing Rotation Group (CPS MORG) data. If a married couple has common unobserved attitudes about and skills in mitigating exposure to occupational fatality risks, then this differencing can remove this unobservable element that could be correlated with the observed occupational fatality risk (and hence bias the coefficient estimate for this variable). This is analogous to panel methods that use individual fixed effects to control for the unobservable, time-invariant characteristics of the individual worker (Kniesner et al. 2012). It is also similar to the approach taken in "twins" analyses that estimate within-twins differences in returns to schooling in order to remove the impacts of genetic endowments (Behrman et al. 1994).

I estimate occupational fatality risk using the Census of Fatal Occupational Injuries (CFOI) and construct a variety of industry, industry-by-age, and industry-by-occupation measures averaged over the preceding three years to address concerns

[1] All dollar values presented in this paper have been converted to 2016 dollars based on the CPI-Urban deflator.

about measurement error. I find that the value of statistical life varies from $9 to $13 million. These estimated VSLs are similar in magnitude from what I would estimate from conventional hedonic wage models (using a log-wage specification with the same sample of heads of households as in the spousal-differences model), but they are much more precise than the log-wage models, most of which produced statistically insignificant coefficient estimates for my suite of risk measures.

I examine the stability of the VSL estimates to variation in the specification of controls in the regression model. I find that the VSL estimates in the within-couple differenced models are robust across the full range of models—from inclusion of a full set of socio-demographics, state and year fixed effects, and industry and occupation fixed effects to the most parsimonious model that simply estimates the differenced wage as a function of the differenced occupational fatality risk and a constant. This contrasts with the conventional hedonic wage models that differ in statistical significance and sign—with several models yielding statistically significant negative VSLs. These comparisons suggest that this differenced estimator purges the model of many of the correlated unobservables that may bias the estimated compensating differential in the conventional empirical framework.

I also find that the value of statistical life appears to take an inverted-U shape with respect to age. In specifications that allow the compensating differential for occupational fatality risk to vary by age group, I find that the VSL increases up to the 45-54 year old age group and then declines. This is generally consistent with many theoretical, revealed preference, and stated preference studies (Aldy and Viscusi 2008; 2007; Krupnick 2007; Shepard and Zeckhauser 1984; Aldy and Smyth 2014).

The next section reviews the literature on assortative matching that serves as the motivation for the empirical strategy. Section three presents the empirical strategy and data. The fourth section presents the results from estimating the modified hedonic wage models. And the fifth section concludes with research and policy implications.

2 Marital matching

The idiom “birds of a feather flock together” is illustrated by evidence in a wide array of social contexts, including marital matching. Becker (1973, 1974) developed a theory of marriage markets that can help explain the empirical evidence on assortative matching. In particular, he notes that positive assortative matching is optimal along many characteristics each member of a couple may have (with some exceptions associated with opportunities for substitution in household production). Such matching occurs across many dimensions—such as “physical capital” and “IQ, education, height, attractiveness, skin color, ethnic origin, and other characteristics” (Becker 1973).

A long literature has identified assortative matching on a vast array of physical characteristics, including height, weight, body shape, finger length as well as quantitative measures of health—such as blood pressure, kidney function, and cholesterol—as well as self-reported measures of healthiness (Robinson et al. 2017; Stulp et al. 2017; Silventoinen et al. 2003; Luo 2017). These physical characteristics can influence occupational injury risk and the individual’s ability to mitigate exposure to such risks. Rawlik et al. (2019) find evidence of assortative mating on disease and longevity, suggesting common life expectancies (a key determinant of the willingness to pay to reduce mortality risk in the value of statistical life literature). There is also some evidence that strongly left-handed individuals disproportionately marry other left-handed individuals and they are more likely to suffer an injury than right-handed individuals (Perelle and Ehrman 1983; Coren 1989). Left-handed individuals also realize lower labor earnings than right-handed individuals (Goodman 2014).

While Becker does not explore the question of risk attitudes and matching, a number of the individual characteristics over which couples match have been associated with specific risk-taking behaviors in the empirical literature. Broman (1993) finds positive associations in smoking, drinking, and other risky behaviors among spouses (and in other social relationships). Clark and Etile (2006) study smoking in married couples and they find that smoking reflects assortative matching, instead of social learning or bargaining within a marriage. Likewise, Chiappori et al. (2010) find assortative matching on smoking and how accounting for common smoking behavior permits a clearer assessment of assortative matching on educational attainment.

While this evidence does not necessarily concern occupational injury risk, individuals undertaking risky behavior in one domain often do so in other domains. For example, Hersch (1996) finds positive correlations among an array of behaviors with specific risk or safety characteristics, including smoking, seat belt use, exercise, preventative dental care, and blood pressure checks. Hakes and Viscusi (2007) also show that smokers are more likely to avoid using automobile seat belts. Santmyire et al. (2001) provide evidence that people undertaking protective behavior with respect to ultraviolet radiation exposure in order to reduce the likelihood of contracting skin cancer are also less likely to smoke and more likely to wear seat belts. Black and Kniesner (2003) show that workers' occupational fatality risk is positively correlated with illegal drug use.

Some survey instruments have explicitly elicited respondents' attitudes toward risk as well as those of their spouses. Barsky et al. (1997) evaluated responses to the Health and Retirement Survey, including to a battery of hypothetical financial gambles. The measures of risk attitudes constructed from these questions are positively correlated with reported behaviors, including smoking, drinking, insurance take-up, and financial investment strategies. They also find that the risk attitudes measures are positively correlated within couples. Kimball et al. (2009) explore risk preferences within the Panel Study of Income Dynamics, which employed a similar set of financial gambles as in the HRS instrument. They also find positive correlation in risk attitudes within families (both among couples and among couples and their children). Dohmen et al. (2012) show assortative matching on risk attitudes within couples in two waves of a socio-economic survey in Germany. Bacon et al. (2014) build on these results to illustrate both assortative matching and positive spousal socialization on risk attitudes over time. Two individuals with similar risk attitudes and similar wealth (or identical wealth when considering household wealth as common to the head of household and the spouse) are likely to have similar preferences over income and risk (Eeckhoudt and Hammitt 2004).

The literature suggests that individuals match through marriage in part based on attitudes towards risk and that individuals tend to have correlated risk attitudes across a variety of risk or safety contexts. In the data described below and used in this empirical analysis, I also find that within married couples in which each partner works at least 30 hours per week, their occupational fatality risk is positively correlated across an array of occupational fatality risk measures. The match on risk attitudes and physical traits that may be associated with risk-mitigation and self-preservation skills (or that may be correlated with occupational fatality risk and labor compensation) motivates the empirical strategy described in the next section.

3 Empirical strategy and data

3.1 Empirical strategy

The general empirical approach employs variants of the standard hedonic wage regression common in the value of statistical life literature (Viscusi and Aldy 2003). As a starting point, consider the worker's wage, w_i, as a function of occupational fatality risk, p_i, a vector of worker socio-demographics, X_i, industry and occupation fixed effects, η_j and θ_k, respectively, representing unobserved industrial and occupational characteristics, state-year fixed effects, ψ_{st}, to represent unobservable state-specific policies and market conditions that may vary over time, and a random error, ε_i reflecting unmeasured factors influencing worker i's wage:

$$w_i = \beta p_i + X_i' \gamma + \eta_j + \theta_k + \psi_{st} + \varepsilon_i \tag{1}$$

The typical empirical strategy estimates (1) or a minor modification of (1), such as by transforming the dependent variable to the natural logarithm of the wage and estimating the equation (Viscusi and Aldy 2003; Viscusi 2004).

For the coefficient estimate $\hat{\beta}$ to represent the unbiased, causal impact of occupational fatality risk on workers' wages, the covariance of the occupational fatality risk measure and the error must be zero. If the econometrician does not observe some worker characteristics that are both correlated with observed occupational fatality risk and observed labor compensation, then $\hat{\beta}$ would suffer from omitted variable bias. If the error in measuring occupational fatality risk is systematic—suppose that taller-than-average workers in a given industry and occupation are less likely to die in an occupational accident than is reflected in the average fatality rate for that industry and occupation but more likely to receive greater-than-average wages—then this may also introduce bias in the estimated compensating differential for occupational fatality risk.

These unobservables could be represented by a modification of the error term: $\varepsilon_i = \tau_i + \xi_i$, where the former term represents factors correlated with occupational fatality risk and the latter term represents other components of the error term that are exogenous to occupational fatality risk. These correlated factors could be risk attitudes or inherent physical traits that introduce either omitted variable bias or measurement error. For example, the risk attitudes could reflect how a worker may select among occupational options that differ in compensation and occupational fatality risk. These attitudes may also play a role in how a worker manages and mitigates exposure to such risk in the workplace. These factors could also include physical characteristics—height, strength, dexterity, etc.—that may play a role in risk mitigation as well. The bottom line result is that attitudes and physical endowments could each cause the subjective probability a worker assigns to a risk to deviate from the objective probability of occupational fatality risk the econometrician observes in data of fatal occupational injuries. This endogeneity of p_i and τ_i can result in biased coefficient estimates (Ashenfelter 2006; Black and Kniesner 2003; Kniesner et al. 2012).

To address this problem, I exploit the "birds of a feather" phenomenon in marital matching described above. If couples match on these unobserved (to the econometrician but not to the couple) characteristics, then taking the within-couple difference would eliminate these unobservables from the error term in the regression model. More formally, the key assumption in this strategy is that $\tau_i^H = \tau_i^S$, for the head of household, H, and spouse, S, respectively. This does not require them to have identical occupational fatality risks—indeed, across the various occupational fatality risk measures I've constructed (and described below), heads of household (primarily men as identified in the CPS MORG dataset) have higher fatality risks than their spouses. Across my measures of occupational fatality risk, the head of household and spouse fatality risks are positively correlated.

Let us assume that $\tau_i^H = \tau_i^S = \tau_i^F$ where F corresponds to a family-specific measure that accounts for risk attitudes and risk-relevant physical capital. Implicit in this assumption is that male and female workers within the same household have common preferences over fatality risk and income. This could reflect the matching—individuals with similar preferences over risk appear to marry based on the review of the literature in the previous section—as well as a model of household decision-making that makes no distinction between the head of household and spouse in terms of their value within the household. This could result if the members of the household approach decisions involving risk as a function of household wealth.

Taking the difference of (1) for heads of household and their spouses, yields the following equation:

$$w_i^H - w_i^S = \left[\beta^H p_i^H - \beta^S p_i^S\right] + \left[X_i^{H\prime}\gamma^H - X_i^{S\prime}\gamma^S\right] + \left[\eta_j^H - \eta_j^S\right] + \left[\theta_k^H - \theta_k^S\right] + \left[\tau_i^F + \xi_i^H - \tau_i^F - \xi_i^S\right]$$

which yields

$$\Delta w_i = \tilde{\beta}\Delta p_i + \Delta X_i'\tilde{\gamma} + \eta_j^{HS} + \theta_k^{HS} + \tilde{\varepsilon}_i \tag{2}$$

where the Δ operator corresponds to the head of household-spouse difference for head of household i (within-couple differences), the tilde coefficients represent the coefficients to be estimated on these differences, the HS-superscripted fixed effects represent the differences in the industry and occupation fixed effects within the couple for head of household i, and $\tilde{\varepsilon}_i = \xi_i^H$ - ξ_i^S. Assuming heads of households and their spouses match on the unobserved characteristics that may be correlated with their wage-occupational fatality risk choices, then the component of the error term correlated with the occupational fatality risk measure is removed through this differencing, i.e., cov(Δp, $\tilde{\varepsilon}$)=0. Technically, year and state fixed effects fall out of such a differencing, but I include these to account for potential market-specific (state) and time-specific (year) changes in the level of differences in male-female wages.

Abstracting from the rest of the estimated hedonic wage equation, rearranging the wage difference and risk difference variables yields a measure for the compensating differential:

$$\Delta wage/\Delta p = \hat{\hat{\beta}} \tag{3}$$

Scaling (3) by the unit of the risk measure (fatalities per 100,000 per year) and converting an hourly compensation measure to an annual full-time equivalent (assumed as 2,000 hours per full-time equivalent), yields the measure for the value of a statistical life:

$$VSL \approx \hat{\hat{\beta}} \times 100{,}000 \times 2{,}000 \tag{4}$$

The approximation reflects the fact that we are estimating the income-risk trade-off among within-household differences, as opposed to differentiating the traditional wage-risk locus to produce the marginal effect of fatality risk on labor compensation. Given the small differences in wages and risks described below, this would appear to be a reasonable approximation.

3.2 Identification

Two of the primary threats to statistical identification in this literature have been the endogeneity of workers occupational fatality risk and the measurement error in the risk variable. The within-couple differencing employed in this study has a statistical analog in panel-based hedonic models. In those approaches, the compensating differential model is estimated with the time-invariant characteristics of worker i controlled for explicitly (Kniesner et al. 2012). As a result, the compensating differential reflects the within-worker differences for a given worker's wage and fatality risk. This can purge presumably time-invariant characteristics—such as attitudes toward risk. In a similar fashion, the twins-based empirical models of education and labor market outcomes purge genetic endowment—that is common within monozygotic twins—to identify the returns to education (Behrman et al. 1994). Likewise, the within-couple differencing in this paper is intended to purge physical characteristics, observable (to the spouse) endowments, and risk attitudes and behaviors that could be correlated with occupational fatality risk on the assumption that marital matching pairs couples who are similar across these attributes. Thus, this within-couple differencing provides an alternative identification strategy that is similar in approach—but differs in the source of exogenous variation—to panel-based estimation in the VSL literature.

Second, this paper has employed a variety of fatality risk measures—by categorization of the relevant worker cell and through various time lags—to mitigate the risk that measurement error could induce attenuation bias. Specifying risk as a slower-moving lagged average and by accounting for how risk could vary by age or occupation—as well as industrial affiliation—reduces the extent to which measurement error could affect the empirical estimation. Finally, as has been noted in many previous papers (Viscusi 2004; Viscusi and Aldy 2003), the use of the Bureau of Labor Statistics Census of Fatal Occupational Injuries also addresses concerns about systematic bias in other measures of on-the-job fatality risk.

3.3 Data

3.3.1 Occupational fatality rates

I have constructed a set of measures of occupational fatality rates for the U.S. workforce. There are three sets of measures based on the level of aggregation: industry, industry by age group, and industry by occupation. In all three sets, industry is defined as (approximately) 2-digit SIC industry for the 1993-2002 period.[2] Age groups correspond to one of the following ranges as defined in the Bureau of Labor Statistics Census of Fatal Occupational Injuries database: <16, 16-17, 18-25, 26-35, 36-45, 46-54, 55-64, >65. Occupation corresponds to one of seven major categories: management, professional, and related occupations; service occupations; sales and office occupations; natural resources, construction, and maintenance occupations; production, transportation, and material moving occupations; and military-specific occupations.

To construct occupational fatality rates, I aggregate all fatalities within an industry, an industry-age group, and an industry-occupation for a given year and scale this count by the full-time equivalent workforce for that category produced from the NBER Current Population Survey Merged Outgoing Rotation Group (MORG) datasets.[3] The fatality rates are produced annually over 1993-2002. I have estimated the contemporaneous one-year fatality rate, as well as one-year, two-year, and three-year lagged average rates for each cell. All measures are reported in terms of occupational fatalities per 100,000 full-time equivalents. To address concerns about measurement error (Black and Kniesner 2003; Kniesner et al. 2012), I focus on the three-year lagged measures in the analyses below.

The mean three-year lagged occupational fatality rates in my regression samples for heads of household is 4.33 per 100,000 for the industry measure, 4.38 for the industry-age measure, and 4.21 for the industry-occupation measure (Table 1). The average within-household difference in occupational fatality rates used in the regression analyses range from about 1.3 to 1.5 per 100,000 across the three measures.

Using multiple-year averages of fatality rates can smooth out the effects of infrequent shocks that may result in greater fluctuations on a year-to-year basis. A one-year spike or collapse in the observed fatality rate may not match well to the worker's subjective fatality rate, which may be better informed by the worker's consideration of longer-term trends in workplace safety. While many past studies have employed a measure of occupational fatality risk based on the worker's self-identified industry (Viscusi and Aldy 2003), some more recent studies have constructed fatality rates based on industry and occupation (Viscusi 2004; Kniesner et al. 2012) and

[2]The exceptions to this include the following. First, the three SIC 2-digit construction industry classifications (15, 16, and 17) are grouped together. Second, there are two pairs of finance, insurance, and real estate industries that are paired together: security and commodity brokers (SIC 62) is paired with holding and other investment offices (SIC 67), and insurance carriers (SIC 63) is paired with insurance agents, brokers, and service (SIC 64). These reflect aggregations in the Current Population Survey.

[3]These can be accessed at: http://www.nber.org/morg/annual/.

Table 1 Summary statistics

Variable name	Mean	Standard deviation
Within-couple differences		
Fatality rate (per 100,000): 1-year average, industry	1.29	6.74
Fatality rate (per 100,000): 2-year average, industry	1.29	6.70
Fatality rate (per 100,000): 3-year average, industry	1.29	6.67
Fatality rate (per 100,000): 1-year average, industry-age	1.32	7.58
Fatality rate (per 100,000): 2-year average, industry-age	1.33	7.29
Fatality rate (per 100,000): 3-year average, industry-age	1.33	7.20
Fatality rate (per 100,000): 1-year average, industry-occupation	1.56	9.17
Fatality rate (per 100,000): 2-year average, industry-occupation	1.54	8.57
Fatality rate (per 100,000): 3-year average, industry-occupation	1.53	8.36
Wage	3.22	15.01
Black	0.0010	0.095
Asian	−0.0034	0.12
Native American	−0.000013	0.096
High School Degree	−0.019	0.53
Bachelor's Degree	0.0025	0.048
Graduate Degree	0.0090	0.34
Union Member	0.034	0.47
Age	1.12	4.85
Head of Household		
Fatality rate (per 100,000): 1-year average, industry	4.27	5.41
Fatality rate (per 100,000): 2-year average, industry	4.31	5.34
Fatality rate (per 100,000): 3-year average, industry	4.33	5.32
Fatality rate (per 100,000): 1-year average, industry-age	4.29	6.08
Fatality rate (per 100,000): 2-year average, industry-age	4.34	5.85
Fatality rate (per 100,000): 3-year average, industry-age	4.38	5.78
Fatality rate (per 100,000): 1-year average, industry-occupation	4.21	7.33
Fatality rate (per 100,000): 2-year average, industry-occupation	4.22	6.88
Fatality rate (per 100,000): 3-year average, industry-occupation	4.21	6.76
Wage	24.85	13.48
Black	0.080	0.27
Asian	0.040	0.20
Native American	0.0094	0.096
High School Degree	0.61	0.49
Bachelor's Degree	0.21	0.40
Graduate Degree	0.11	0.31
Union Member	0.19	0.39
Age	42.0	9.97

N=151,087

industry and age (Aldy and Viscusi 2008; Viscusi and Aldy 2007). The expanded classification of categories for the risk variable can account for the fact that there is considerable within-industry fatality risk as a function of occupation—e.g., compare a coal miner to an accountant working in the administrative office of a coal mining company—and as a function of age—e.g., older workers are less likely to be injured on the job, but conditional on an injury are much more likely to die. Using multiple-year measures aggregated over industry-occupation and industry-age categories can address some of the measurement error concerns raised in the literature (for a discussion of these, see Ashenfelter 2006; Kniesner et al. 2012).

3.3.2 Worker wages and characteristics

I produced a 1996-2002 dataset with repeated cross-sections drawn from the CPS MORG datasets. This includes hourly wage or hourly equivalent of salary, usual hours worked per week, and various socio-demographic data such as age, race, educational attainment, union status, residency in an urban area, state, industry, and occupation for both heads of households and their spouses.

The fatality rate measures were mapped to heads of households and spouses based on their industry and, depending on the rate measure, age or occupation. For the regression analyses, I limit the samples to heads of households working at least 30 hours per week with spouses who also work at least 30 hours per week. I also limit the sample to those reporting hourly wages (or hourly equivalent of labor compensation) equal to or greater than the lowest federal minimum wage during this period. Table 1 presents the summary statistics for the fatality risk measures and these worker wage and characteristics data both in terms of within-couple differences and for heads of household.

The Current Population Survey MORG datasets have frequently been employed to estimate compensating differentials for occupational fatality risk in the literature. About one-third of the U.S. hedonic wage studies reviewed in Viscusi and Aldy (2003) employed CPS data (with about one-third using Panel Study of Income Dynamics data and about one-third using a variety of other data sources), and several papers have used CPS data in conjunction with the CFOI data, including Black and Kniesner (2003), Kniesner et al. (2012), Viscusi (2004), Viscusi and Aldy (2007), and Aldy and Viscusi (2008). The CPS MORG provides a large sample—typically with more than 100,000 full-time workers per year—that can facilitate more precise estimation of coefficients of interest, especially in this context in which I have limited the sample to dual-earner households.

4 Results

4.1 Base case results

Table 2 presents the regression results for the within-couple differences model, with each column corresponding to an alternative measure of occupational fatality risk. In all models, the three-year lagged measure of risks is used in estimation. Across all

Table 2 Within-couple differenced regression results, 1996-2002

Risk measure	Industry	Industry-age	Industry-occupation
Δ Fatality rate	0.087**	0.044*	0.064**
	(0.031)	(0.021)	(0.016)
Δ Black	−1.63**	−1.63**	−1.61**
	(0.42)	(0.42)	(0.42)
Δ Native American	0.35	0.34	0.32
	(0.39)	(0.39)	(0.40)
Δ Asian	−1.52**	−1.53**	−1.54**
	(0.32)	(0.32)	(0.32)
Δ High School	1.65**	1.65**	1.64**
	(0.10)	(0.10)	(0.10)
Δ Bachelor's Degree	6.32**	6.30**	6.30**
	(0.19)	(0.19)	(0.19)
Δ Graduate Degree	9.79**	9.78**	9.77**
	(0.31)	(0.31)	(0.31)
Δ Union Member	1.13*	1.10*	1.09*
	(0.44)	(0.44)	(0.44)
ΔAge	0.30**	0.30**	0.31**
	(0.025)	(0.025)	(0.25)
VSL	17.4**	8.8*	12.8**
R^2	0.135	0.135	0.135

*/** represents significant at the 5/1 percent level. Standard errors clustered by SIC-2 industry. All regressions include state-by-year fixed effects, industry fixed effects, and occupation fixed effects. VSLs are reported in millions of 2016$. N = 151,087

risk measures, the coefficient estimates are positive and statistically significant at the 1 percent level (industry and industry-occupation risk measures) or the 5 percent level (industry-age risk measure). The bottom of each table presents the value of statistical life. The industry risk measures yield the highest VSL of $17.4 million VSL. In contrast, the industry-age lagged three-year average risk measure model produces a VSL of about half that amount at $8.8 million. The industry-occupation risk measure VSL is about $12.8 million. Given some of the concerns raised previously in the literature about measurement error with an industry-only measure of occupational fatality risks (Viscusi 2004; Viscusi and Aldy 2007; Aldy and Viscusi 2008; Kniesner et al. 2012), the industry-occupation and industry-age fatality risk models may be preferred to the industry risk measure model estimates.

The coefficient estimates on the differences in socio-demographics are consistent with the labor market literature. Labor compensation for minorities is less than for white workers (the omitted category). Labor compensation increases with greater levels of educational attainment (relative to the omitted category of educational attainment less than a high school degree). Everything else equal, union members earn more than non-members. With the exception of the within-couple differenced measure for the Native American identifier, the coefficient estimates representing these socio-demographics are statistically significant at the 1 percent level.

These models pool seven years of cross-sectional labor market observations to estimate the average effect of each differenced variable on the wage difference. While not shown here, I have also estimated variants of these pooled models with year-specific compensating differentials for occupational fatality risk. The year-specific VSLs are—for most years across the three risk measures on an averaged three-year lag basis—statistically significant and similar in magnitude as the pooled results. The year-2002 industry risk measure model is not statistically significant. Across the three risk measures, there is also a general upward trend in the VSLs, although the magnitudes cannot be statistically distinguished over time.

4.2 Comparison with conventional log-wage models

To enable a comparison with the standard hedonic wage model long used in this literature, I have estimated log-wage models using the same sample of heads of household (Table 3). I have specified a set of control variables in levels that correspond to the within-household differences of these variables in Table 2. Across all three risk variable specifications, the non-risk measures—identifiers for race, educational attainment, union membership, and urban residency as well as worker age—are each statistically significant and have signs consistent with prior hedonic wage literature.

While the log-wage models produce VSLs comparable in magnitude to their differences model counterparts, only the industry-occupation model yields a statistically significant coefficient estimate for the risk measure. In this last case, the log-wage model produces an estimated VSL of \$13.9 million, slightly larger than the \$12.8 million estimate in the within-couple differenced models. With the set of variables drawn from the CPS MORG dataset typically employed in a log-wage model, only the risk measures in the first two regression models are statistically insignificant.

As noted above, several papers have criticized the hedonic wage VSL literature regarding the non-classical measurement error and potential for omitted variable bias in estimating the conventional log-wage hedonic model. Black et al. (2003) find that the coefficient estimate on the occupational fatality risk variable varies considerably and can be positive and statistically significant or negative and statistically significant depending on the choice of control variables in the log-wage estimating equation. To assess the robustness of the VSL estimates using this within-couple differenced estimator, I employed a varying set of control variables in six alternative specifications (Fig. 1). Model 1 employs the same set of controls as in Tables 2 and 3, and the subsequent models remove the state-year fixed effects, industry-differenced fixed effects, occupation-differenced fixed effects, and differenced social-demographic controls, until model 6, which is simply the regression of differenced wages on differenced occupational fatality risk and a constant.

As a benchmark, I use the same sample of heads of household to estimate a log-wage regression with the counterparts to the differenced regression (e.g., worker's

Table 3 Head of household log-wage regression results, 1996-2002

Risk measure	Industry	Industry-Age	Industry-Occupation
Fatality rate	0.0028	0.0014	0.0028**
	(0.0181)	(0.0014)	(0.0010)
1[Black]	−0.12**	−0.12**	−0.12**
	(0.011)	(0.011)	(0.011)
1[Native American]	−0.042**	−0.043**	−0.043**
	(0.014)	(0.014)	(0.014)
1[Asian]	−0.068**	−0.068**	−0.068**
	(0.015)	(0.015)	(0.015)
1[High School]	0.26**	0.26**	0.26**
	(0.013)	(0.013)	(0.012)
1[Bachelor's Degree]	0.49**	0.49**	0.49**
	(0.022)	(0.022)	(0.022)
1[Graduate Degree]	0.62**	0.62**	0.61**
	(0.020)	(0.020)	(0.020)
1[Union Member]	0.087**	0.086**	0.086**
	(0.028)	(0.028)	(0.028)
1[Urban]	0.10**	0.10**	0.10**
	(0.059)	(0.059)	(0.057)
Age	0.042**	0.042**	0.042**
	(0.0019)	(0.0019)	(0.0019)
Age^2	−0.00041**	−0.00042**	−0.00041**
	(0.000025)	(0.000025)	(0.000025)
VSL	14.1	7.2	13.9**
R^2	0.34	0.34	0.34

*/** represents significant at the 5/1 percent level. Standard errors clustered by SIC-2 industry. All regressions include state-by-year fixed effects, industry fixed effects, and occupation fixed effects. VSLs are reported in millions of 2016$. N = 151,026

age instead of the within-couple difference in ages). I likewise remove various sets of controls and estimate various combinations of controls.

Figure 1 reveals quite a stark divergence in the stability of VSL estimates across the two estimators. In the left panel, the differenced VSLs are all positive and statistically significant, with the modest exception of model (4), in which the VSL is statistically different from zero at the 10 percent level. The VSL magnitudes are sensitive to the inclusion of industry fixed effects, perhaps reflecting the role of inter-industry wage differentials (Gibbons and Katz 1992), with the VSL in the most parsimonious specification (6) about twice the VSL in the base model specification

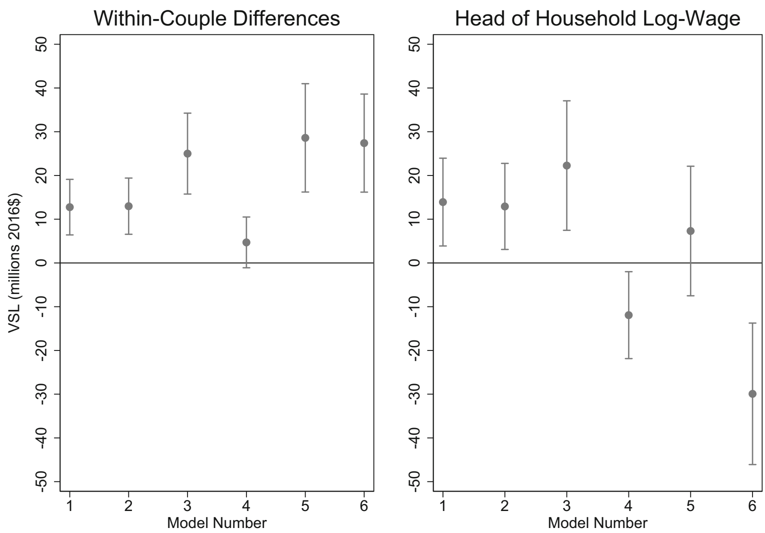

Fig. 1 Variation in VSLs across estimators. Notes: The left panel presents VSLs for within-couple differenced models and the right panel presents VSLs for log-wage models. All models are estimated with the lagged three-year average industry-occupation measure of fatality risk (either within-couple differenced or head of household value). 95 percent confidence intervals are based on standard errors estimated with clustering on SIC-2 industry. The six specifications include the following controls as within-couple differences (left panel) or head of household values (right panel): Model 1: age, race, educational attainment, union status, industry fixed effects, occupation fixed effects, state-by-year fixed effects. Model 2: age, race, educational attainment, union status, industry fixed effects, occupation fixed effects. Model 3: age, race, educational attainment, union status, occupation fixed effects. Model 4: age, race, educational attainment, union status, industry fixed effects. Model 5: age, race, educational attainment, union status. Model 6: no controls

(1). It is important to recognize that none of the variations yield VSL estimates whose 95 percent confidence intervals fall outside the range of the base estimate (model 1).

In contrast, the right panel shows considerable heterogeneity in the VSL estimates. While the base case yields a similar magnitude (and only slightly less precise) VSL than its within-couple differenced analog, removing select control variables dramatically changes the statistical significance and/or the sign of the coefficient estimate for occupational fatality risk. Indeed, in two models (4 and 6), the log-wage model produces large in magnitude, negative, and statistically different from zero VSL estimates, consistent with Black et al. (2003).

The stability of the VSL estimate in the differenced estimator suggests that the differencing removes some of the unobservable determinants of the wage that are correlated with occupational fatality risk as revealed in the conventional log-wage models. To be fair, the differencing also removes potentially confounding factors that the econometrician typically observes and controls for in a standard hedonic wage regression, such as educational attainment. The convergence of both approaches on a similar VSL in their respective base cases (model 1) may also suggest that a log-wage model with a rich set of controls may mitigate much of the confounding from omitted variables.

4.3 VSLs over the life cycle

An individual giving up current income to reduce her exposure to the risk of dying increases the likelihood of enjoying the benefits of current and future consumption and leisure. How much current income an individual may forego for a reduction in risk exposure depends on expectations over future consumption, which will reflect life expectancy, income, and the individual's preferences over the timing of consumption. Shepard and Zeckhauser (1984) illustrated this through a deterministic life-cycle utility model that shows how the willingness to pay to reduce mortality risk declines with age under perfect borrowing and annuity markets, but takes an inverted-U shape over the life-cycle without such markets. Johansson (1996, 2002), and Aldy and Smyth (2014) employed numerical simulations calibrated to U.S. data to show how the income-risk trade-off follows an inverted-U shape over the life cycle. The empirical literature—both revealed preference and stated preference—typically reveals either an inverted-U or an age-declining value of statistical life (Aldy and Viscusi 2007; Krupnick 2007; Viscusi and Aldy 2003).

To examine the question of whether workers' revealed preferences over labor compensation and occupational fatality risk vary with their age, I estimate models that interact indicators of age groups (for the head of household) with the occupational fatality risk measures. As in Aldy and Viscusi (2008), I use the following age groups: 18-24, 25-34, 35-44, 45-54, and 55-62. These categories reflect the constraints in the reporting of occupational fatalities and aggregation to ensure a reasonable subsample size for estimating the coefficients of interest. Given the potential for a worker to retire and claim social security after his or her 62nd birthday and to avoid modeling the labor market retirement decision, I limit the estimation to workers between the ages of 18 and 62. Limiting the age range in these analyses only reduces the estimation sample by 1 percent relative to the samples used in estimating the models presented in Tables 2 and 3.

I find evidence that the VSL follows an inverted-U shape with respect to age, peaking with the 45-54 age group. Table 4 shows the results for each of the three risk measures, based on the lagged three-year average of the fatality rate. The youngest age group has statistically insignificant and small in magnitude (and varying sign) VSL estimates. For each of the next three age groups—25-34, 35-44, and 45-54—the models produce statistically significant VSLs that increase with age, reaching \$14 to \$16 million for the industry-age and industry-occupation measures in the oldest of these three age groups. For the 55-62 age group, the VSL declines significantly from the 45-54 age group measures. For example, the industry-occupation measure yields a VSL of \$6 million, statistically significant only at the 10 percent level, for the 55-62 age group. These patterns follow those in the revealed preference analyses in Aldy and Viscusi (2008) and the numerical simulations in Aldy and Smyth (2014), as well as the life-cycle pattern of consumption.

I also estimated models that simply interact the within-couple age difference with the occupational fatality risk measure. The coefficient estimates on these interactions are negative and statistically significant. For example, the coefficient (standard error) estimates for the differenced fatality risk variable and differenced fatality risk variable interacted with the differenced age variable are 0.069 (0.017) and -0.007 (0.002)

Table 4 Within-couple differenced regression results by age group, 1996-2002

Risk measure	Industry	Industry-Age	Industry-Occupation
Δ Fatality rate*1[18-24 Age Group]	−0.011	−0.0039	0.015
	(0.042)	(0.022)	(0.023)
Δ Fatality rate*1[25-34 Age Group]	0.049	0.027	0.054**
	(0.034)	(0.026)	(0.021)
Δ Fatality rate*1[35-44 Age Group]	0.084**	0.062*	0.064**
	(0.029)	(0.025)	(0.016)
Δ Fatality rate*1[45-54 Age Group]	0.12**	0.070*	0.083**
	(0.036)	(0.032)	(0.020)
Δ Fatality rate*1[55-62 Age Group]	0.090*	0.039	0.030
	(0.037)	(0.24)	(0.020)
VSL, 18-24 Age group	−2.3	−0.8	3.0
VSL, 25-34 Age group	9.8	5.5	10.8**
VSL, 35-44 Age group	16.7**	12.4*	12.8**
VSL, 45-54 Age group	23.6**	14.0*	16.5**
VSL, 55-62 Age group	18.0*	7.8	6.0
R^2	0.136	0.136	0.136

*/** represents significant at the 5/1 percent level. Standard errors clustered by SIC-2 industry. All regressions include state-by-year fixed effects, industry fixed effects, and occupation fixed effects. VSLs are reported in millions of 2016$. N = 149,625

for the industry-occupation risk measure. When evaluated at the mean age difference of 1.1 years in the regression sample, the net effect of the risk measure and risk measure interacted with age difference coefficients are nearly identical VSLs: $12.2 million at the sample average for this model with interactions versus $12.8 million for the model without interactions employing the industry-occupation risk measure. The magnitude of the interaction coefficients, however, suggests quickly declining VSLs as the age difference between the head of household and spouse increases. At about two standard deviations in the age difference, the willingness to pay to reduce fatality risk would approach zero. This suggests that a simple interaction with the age difference variable may be imposing an inappropriate linear relationship. Such a result is consistent with the Viscusi and Aldy (2003) finding in their review of hedonic wage studies that simply interacted the risk variable with age as well as what Aldy and Viscusi (2008) found in terms of an inverted-U shape of the value of statistical life over the life cycle from hedonic wage models.

5 Conclusions

This paper builds on an extensive hedonic wage literature to illustrate a new source of variation to use in estimating income-risk trade-offs in labor markets. By drawing from the theoretical and empirical literature on assortative matching in marriage markets, I motivate a new hedonic wage estimator based on the within-marriage differences in wages and the factors associated with wages, including occupational fatality risk. In particular, the extensive evidence of assortative matching on physical attributes, risk-taking behavior, and risk attitudes provides the basis for the assumption that the within-marriage difference can remove elements of the error term representing risk attitudes and skills at risk mitigation that could otherwise bias the estimated compensating differential for bearing occupational fatality risk in labor markets.

The VSLs estimated through this new estimator exploit a different source of variation than the existing revealed preference papers in the VSL literature. The within-couple differenced regression models produce precisely-estimated coefficient estimates that are more robust to model specification than conventional, cross-sectional hedonic wage regressions. The VSLs of $9 to $13 million are consistent with the high end of revealed preference estimates reported in Viscusi and Aldy (2003) and estimated through panel-based approaches in Kniesner et al. (2012). In line with past research, the value of statistical life appears to vary with respect to age, taking an inverted-U shape with respect to worker's age and peaking in the mid-40s to mid-50s.

This paper provides additional evidence that individuals reveal in labor markets their preferences over income and fatality risk. Understanding such trade-offs can illustrate the consequences of public policies intended to reduce the public's exposure to small changes in fatality risk. The results from the within-couple differenced estimator provide support for the VSLs currently employed by government agencies, such as the EPA and Department of Transportation.

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