EE
7/24/07
2:00 PM

Roy Model Sorting and Non-Random Selection in the Valuation of a Statistical Life

Thomas DeLeire

and

Christopher Timmins

July 2007

Abstract

The value of a statistical life (VSL) is a key component in many regulatory analyses. Along with stated preference and human capital procedures, revealed preference techniques based on markets for labor or safety-related products are commonplace in determining its magnitude. Wage-hedonics uses the fact that workers who select riskier occupations will be compensated with a higher wage rate. However, according to occupational sorting theory (Roy 1951), observed wage distributions are distorted by individuals selecting jobs according to both common and idiosyncratic returns. We show that this type of sorting will typically lead to a bias in wage-hedonic VSL estimates, and we demonstrate two simple approaches to estimation that correct for it. Implementing these strategies with data from the Current Population Survey, we recover VSL estimates that are two to three times larger than those based on the traditional wage-hedonic model, statistically significant, and robust to a wide array of specifications.

Keywords: value of statistical life, Roy model, wage-hedonics

JEL Classification: J17, J31

The authors would like to thank Joe Aldy, Laura Taylor, and all the participants in the Duke Applied Microeconomics Lunch for their helpful comments. *Contacts*: Thomas DeLeire, University of Wisconsin-Madison, 1180 Observatory Drive, Madison, WI. tdeleire@gmail.edu. Christopher Timmins, Department of Economics, Duke University, PO Box 90097, Durham, NC 27708. christopher.timmins@duke.edu.

1. INTRODUCTION

Cost-benefit analyses of environmental, workplace, and product safety regulations frequently require estimates of the monetary value of fatality risk reductions. This value typically comes in the form of the value of a statistical life (or, alternatively, the value of a statistical death averted) and is often estimated with wage-hedonic methods.[1] Workers are compensated for choosing to work in risky jobs. However, workers vary in their idiosyncratic skills, and the return to these skills may vary greatly across occupations. In this paper we show that worker sorting based on idiosyncratic returns can bias value of statistical life (VSL) estimates derived with the wage-hedonic technique, and we demonstrate a new empirical strategy to correct for this source of bias. In particular, we employ two techniques introduced by Bayer, Khan, and Timmins (2007) to control for polychotomous selection when individuals care about more than just pecuniary returns. These techniques extend the idea originally posited in the Roy model (1951), which explains occupational sorting as a function of only wages. The extension is appropriate for wage-hedonics since, in those models, workers sort across occupations based on non-pecuniary job attributes like fatality risk in addition to their wages.[2]

Correcting for this bias is both empirically important and has significant policy implications. Estimated VSL's for males aged 18-60 rise by as much as a factor of three and become statistically significant, compared with VSL's based on the same data but derived with traditional techniques. We find this bias, moreover, in age-specific VSL's that exhibit patterns similar to those found by previous researchers. Estimated VSL's for women are reasonable in magnitude and statistically significant, unlike their counterparts based on traditional wage-hedonic techniques. These larger estimates of the VSL (which are also less sensitive to specification) suggest a greater willingness among Americans to

[1] The value of a statistical life (VSL) is constructed from individuals' revealed or stated willingness to trade-off other consumption for a marginal reduction in fatality risk (e.g., risk of on-the-job fatality in the context of wage-hedonics). Suppose, for example, that an individual is willing to pay $40 for a policy that results in a 1-in-100,000 reduction in the chance of dying. If we were to take 100,000 individuals confronted with this choice, the policy would lead to one fewer death among them. Although none of those individuals know which of them will be saved by the policy, their aggregate willingness to pay is 40 x $100,000 = $4 million. This number is taken as the VSL. If asked for a willingness to pay to avoid his or her own particular death, any one individual would not be able to give a credible answer to the willingness-to-pay question.

[2] The estimation strategy described below also has applications in other empirical contexts – for example, individuals migrating across cities, where utility is determined by both the wages and local amenities.

pay for reductions in fatality risk through environmental, workplace, and product safety regulations than previously believed.

This paper proceeds as follows. Section 2 describes the Roy model and explains why we should expect sorting based on idiosyncratic returns to yield biased estimates of the VSL calculated with traditional wage-hedonic techniques. Section 3 discusses how our estimator deals with (or fails to address) some other well-known problems with the wage-hedonic approach. Section 4 outlines our first estimation strategy, which semi-parametrically identifies workers' risk preferences in the presence of Roy sorting. Section 5 describes the data we use to implement this approach, including information about individual workers from the CPS, data describing occupational fatalities from the Bureau of Labor Statistics, and data on other occupational attributes from the Department of Labor's Dictionary of Occupational Titles. Section 6 reports the results of our first estimator alongside results derived from a traditional wage-hedonic procedure, and discusses the results of a number of alternative model specifications. Section 7 describes and implements our alternative estimation technique, which makes use of stronger independence and distributional assumptions but requires less of the data. Section 8 discusses policy implications and concludes.

2. ROY SORTING BIAS IN THE WAGE-HEDONIC ESTIMATE OF THE VSL

Rosen (1986) refers to the theory of equalizing differences as the "fundamental (long-run) market equilibrium construct in labor economics." It explains how the difference in wages between risky and safe jobs is determined – if some jobs are less safe than others, the market equalizing difference (or "compensating differential") is set so that enough workers sort into the risky occupation to clear the market. This was the idea behind Thaler and Rosen's (1975) seminal research on using labor market outcomes to value life – i.e., wage-hedonics.

A second literature in labor economics has examined the implications of idiosyncratic differences in returns to workers' abilities for their choice of occupation. These implications were first demonstrated by Roy (1951), whose name has since been associated with this class of sorting models. The idea behind the Roy model is simple. In an example with just two occupations, workers who choose occupation #1 over occupation #2 receive greater pecuniary returns from this choice than those workers who chose occupation #2 would have received had they chosen occupation #1, *ceteris paribus*. The difference between the wages received by workers in occupation #1 and occupation #2 will not, therefore, reflect the difference between the wages that the *average* worker would have received in each sector. In the simplest possible case, this type of sorting does not create a problem for measuring compensating wage differentials. However, with only minor complications, it can have important implications for the ability of wage-hedonics to recover the value of any job attributes (including fatality risk). We demonstrate why with a series of numerical examples.[3]

Suppose that the returns individual *i* would receive from working in each of two occupations are determined by the following wage equation:

(1) $$w_{i,j} = \beta R_j + \varepsilon_{i,j} \qquad j = 1, 2$$

where the idiosyncratic component of wages is drawn from a bivariate normal distribution.

(2) $$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim i.i.d.\ N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right)$$

R_j measures the fatality risk in occupation *j*. Occupation #1 is assumed to be "safe" ($R_1 = 0$), whereas occupation #2 is "risky" ($R_2 = 1$). For the sake of simplicity, we set the coefficient on risk in the wage equation (β) to be 1. Figure 1 illustrates the unconditional distribution of wages in each occupation. The compensating wage differential ($1) is apparent in the difference between the means of these two distributions.

The distributions portrayed in Figure 1 are not, however, the distributions observed by the researcher. Individuals sort across occupations to maximize utility, which is determined in this simple example by wages in combination with fatality risk. Individual *i* receives the following utility from choosing to work in occupation *j*:

[3] For a formal description of these features of the Roy model, see Heckman and Honore (1990).

(3) $U_{i,j} = w_{i,j} - \beta R_j$

In the case described in equations (1) and (2), the average wage in occupation #2 will still be higher than that in occupation #1 by $1 to compensate for its added risk, even after individuals have optimally sorted. Figure 2 demonstrates this result. We construct Figure 2 by simulating a pair of wages for each of one million individuals and assigning that individual to the occupation with the highest utility. We then plot the *conditional* wage distribution for each occupation (i.e., conditional upon workers having optimally sorted into that sector). Note that, consistent with the predictions of the Roy model, the means of both distributions increase while their variances decrease. Importantly, the difference in the means of the two conditional distributions (1.57-0.57 = 1.00) still reflects the true compensating wage differential from which we could derive an unbiased measure of the value of a statistical life. This is because that difference is deducted from utility before Roy sorting occurs and is therefore not distorted by the sorting process.

Now consider a minor modification of the sorting model in equations (1) and (2). In particular, suppose the variance of the unconditional wage distribution in occupation #1 (i.e., the "safe" occupation) is greater than that in occupation #2.

(4) $\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim i.i.d.\ N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix} \right)$

Figure 3 shows that the difference in the means of the *unconditional* wage distributions still reveals the true compensating wage differential. However, when individuals sort, occupation #1 offers greater opportunities for very high wage draws (large idiosyncratic returns). The result is a bigger upward shift in the mean of the occupation #1 conditional wage distribution. Comparing the means of the two conditional distributions in Figure 4 reveals a downward bias in the estimate of the compensating differential (1.46-0.92 = 0.54), implying an understated VSL.

This sorting-induced bias is compounded if individuals' wage draws are positively correlated across occupations. Consider an extreme case:

$$(5) \qquad \begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim i.i.d.\ N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 2 & 0.9 \\ 0.9 & 1 \end{pmatrix} \right)$$

Now, the individuals receiving the highest draws in occupation #1 are the same individuals who would have received a draw from the upper tail of the occupation #2 distribution. Those left in occupation #2 tend to be those individuals who receive low draws in both occupations. Figure 5 illustrates that this further compresses the difference in the means of the conditional wage distributions (i.e., down to 1.07-0.80 = 0.27), making the sorting-induced downward bias in the implied VSL even more severe. The opposite is true if wage draws are negatively correlated across occupations:

$$(6) \qquad \begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim i.i.d.\ N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 2 & -0.9 \\ -0.9 & 1 \end{pmatrix} \right)$$

although in this example, the negative correlation is not strong enough to offset the initial sorting bias. Figure 6 illustrates this case, in which the compensating differential only falls to 1.69-1.06 = 0.63.

In these numerical examples, the direction and size of the bias induced by Roy sorting depends upon the relative sizes of the variances of the unconditional wage distributions in combination with the correlation of individuals' wage draws across occupations.[4] Heckman and Honore (1990), however, prove that these unconditional distributions cannot be recovered without first assuming a value for the correlation in individuals' wage draws across occupations (e.g., independence). This leaves the researcher in a difficult position with respect to the bias in the wage-hedonic estimate of the VSL induced by Roy sorting – one would need to first assume a degree of correlation in wage draws in order to recover the unconditional wage distributions, but the degree of correlation itself affects the size of the bias induced by Roy sorting. In Section 4, we demonstrate how one can avoid this problem and correct the sorting bias in the VSL (i)

[4] In particular, by making the variance in occupation #2 larger than that in occupation #1, we could have made the bias in the VSL go in the opposite direction.

without knowing the unconditional wage distributions and (ii) without assuming anything about the correlation in individuals' wage draws across occupations.

3. OTHER PROBLEMS WITH THE WAGE-HEDONIC ESTIMATE OF THE VSL

The wage-hedonic technique has been used extensively (and rigorously scrutinized) for decades. We present only a brief overview of the resulting large literature. Viscusi and Aldy (2003) provide a comprehensive discussion of the VSL, paying particular attention to the wage-hedonic technique and the problems that can arise in its implementation. Consider, for example, the role of unobservable individual heterogeneity. One particular form of such heterogeneity is worker productivity. Hwang et al (1992) demonstrate that if workers can be classified as high or low productivity (i.e., if there is positive correlation in wage draws across occupations) and if high productivity workers choose to take some of their compensation in the form of lower fatality risk, wages in low-risk occupations will look too high and the estimated fatality risk premium will be too low. This problem has been dealt with in earlier work by using longitudinal data, identifying individual fixed effects with either (i) workers who switch jobs or (ii) time-varying fatality rates within a job. [See, for example, Brown (1980), Black and Kneisner (2003), and Kniesner et al (2006)] The first estimation approach we describe below will, conveniently, account for this source of bias in that (i) it assumes workers take account of both wages and job attributes (including fatality risk) when choosing an occupation, and (ii) it is robust to any form of correlation in workers' wage draws (i.e., workers can have differing productivities).

A separate problem arises if there is unobservable heterogeneity in individuals' ability to avoid risk. Shogren and Stamland (2002) note that estimates of the VSL will be biased up if there is heterogeneity in unobservable safety-related skills. The presence of safety-related skills means that not all workers face the same risk on the same job – alternatively, some workers may simply be better at avoiding accidents than others. The compensating differential is determined by the marginal worker, who will have the least amount of safety-related skill among workers in the risky job and thus will face the highest risk. If the average risk faced by workers in the risky job is instead used to calculate the estimate of the VSL, that estimate will be biased upward. Our estimators, in their current form, are unable to allow for idiosyncratic exposure to risk.

A third problem arises when individuals have heterogeneous preferences for risk. In particular, workers who put less value on safety are more likely to sort into risky jobs, biasing downward wage-hedonic estimates of the compensating risk premium. While panel data and individual fixed effects provide one solution to this sort of preference-based sorting, researchers have also used information about seatbelt use [Hersch and Viscusi (1990), Hersch and Pickton (1995)] or smoking behavior [Viscusi and Hersch (2001)] to control for risk preferences.[5]

There are a number of other problems that may arise when using wage-hedonics to measure the VSL. For example, wage-hedonic techniques often ignore quality of life impacts, as well as the effects of life expectancy.[6] They usually measure the disutility of facing a particular kind of death that is neither slow nor protracted, and which does not involve a significant latency period. These techniques may not, therefore, be good for valuing avoided deaths from cancer. [Savage (1993), Revesz (1999)] Scotten and Taylor (2007) demonstrate that one should not even treat different sources of on-the-job fatality risk (e.g., accidental, transportation related, and death from violent assault) homogenously in a wage-hedonic equation. Because they focus on labor market outcomes, wage-hedonic techniques are not useful for valuing the lives of children and the elderly. For these and other problems, there are a variety of alternative techniques for calculating VSL's including stated preference, human capital approaches, and quantifying the risk tradeoffs agents make in non-labor market settings.[7] Finally, it is unclear how well actual

---

[5] Note that our approach does allow distaste for fatality risk to vary with *observable* sources of worker heterogeneity. DeLeire and Levy (2004) provide empirical support for the notion that workers who, based on their observable characteristics such as sex, marital status, and whether they have children, likely have a greater distaste for dangerous work tend to choose safer occupations.

[6] Notable exceptions include Viscusi and Aldy (2006), who find that VSL's follow an inverted-U pattern in age, and Alberini et al (2004), who find lower VSL's for those over the age of 70 using stated preference techniques. Other researchers have also found that the VSL declines at higher ages – see Table 10 in Viscusi and Aldy (2003) for a summary. In contrast, Smith et al (2004) find no evidence of lower VSL's for older individuals.

[7] Ashenfelter and Greenstone (2004), for example, use states' decisions to raise speed limits as evidence that the median voter was willing to incur an increased risk of driver death in exchange for lower travel times. Atkinson and Halvorsen (1990), Dreyfus and Viscusi (1995), and Li (2006) look at the willingness of automobile buyers to trade-off risk of death with operating expenditures and purchase price. Blomquist (1979) and Hakes and Viscusi (2007) use drivers' decisions to employ seatbelts in order to recover estimates of the VSL, and Carlin and Sandy (1991) do so with data on individuals' decisions to use child

on-the-job fatality risks proxy for the risks a worker perceives when he decides to accept or reject a wage offer.

Even with all these problems, wage-hedonics remains prevalent in policy making. The EPA currently uses a VSL of $6.2 million, which is based on the results of twenty-six different studies surveyed by Viscusi (1992). Twenty-one of those studies use wage-hedonic techniques. Wage-hedonic results are especially relevant (and transferable) when valuing risk reductions from OSHA regulations.

4. IDENTIFICATION

We begin by describing our identification strategy with a simple model of sorting by individuals into one of two occupations (j = 1, 2). We indicate the wage earned by individual i should he choose to work in occupation #1 or #2 as $\omega_{i,1}$ and $\omega_{i,2}$, respectively. In contrast to the classic Roy model, where sorting across occupations is driven entirely by an individual's pecuniary compensation, we model sorting as determined by his wage draw in each occupation and by non-wage determinants of utility specific to each particular occupation. We summarize the latter (for now) as "tastes". The conventional wisdom, based on Heckman and Honore (1990) is that there is no additional information in conditional wage distributions with which to identify these taste parameters. In the following model, we show how they are, in fact, identified with the help of a simple assumption.

We begin by modeling individual i's utility from choosing occupation j as the sum of wages ($\omega_{i,j}$) and tastes (τ_j):

$$U_{i,j} = \omega_{i,j} + \tau_j \tag{7}$$

safety seats. Portney (1981) and Gayer, Hamilton, and Viscusi (2000) use tradeoffs between housing expenditures and mortality from air pollution and cancer (caused by proximity to Superfund sites), respectively.

The first important restriction we impose on the model is that there is no idiosyncratic component to the taste parameter (i.e., we estimate τ_j instead of $\tau_{i,j}$).[8] After first explaining how to recover estimates of these taste parameters, we describe how they can be used to recover the value workers place on particular non-pecuniary occupation attributes (e.g., fatality risk).

Without loss of generality, we normalize $\tau_1 = 0$.[9] At this point, the goal of our exercise is to recover an estimate of τ_2.[10] The difficulty in doing so arises from the fact that we only see (i) wage distributions conditional upon optimal sorting behavior, and (ii) an indicator of which occupation an individual chooses. In particular, for an individual *i*, we only observe $\omega_{i,2}$ if:

$$\omega_{i,2} + \tau_2 \geq \omega_{i,1} \tag{8}$$

Alternatively, we only observe $\omega_{i,1}$ if:

$$\omega_{i,2} + \tau_2 < \omega_{i,1} \tag{9}$$

Denote the smallest wage (i.e., the minimum order statistic, or extreme quantile) that we observe from someone choosing occupation #1 or #2 by $\underline{w}_1$ and $\underline{w}_2$, respectively. Assuming that the unconditional distributions of ω_1 and ω_2 have finite lower points of supports (denoted by ω_1^* and ω_2^*), we know the smallest value of ω_1 that we could ever see, given that individuals maximize utility:

$$\begin{aligned} \underline{w}_1 &= \omega_1^* && \text{if} \quad \omega_1^* > \omega_2^* + \tau_2 \\ \underline{w}_1 &= \omega_2^* + \tau_2 && \text{if} \quad \omega_1^* \leq \omega_2^* + \tau_2 \end{aligned} \tag{10}$$

[8] Relaxing this assumption may be possible with the use of explicit (un-testable) distributional assumptions. Exploring these assumptions is the subject of our continuing research.

[9] As in all random-utility frameworks, utility is only identified up to an additive constant. This requires some sort of a normalization, which we use to eliminate one of the τ's from the two-occupation example. In the more general N occupation case, we estimate (N-1) distinct τ's.

[10] Bayer, Khan, and Timmins (2007) show how, by making an additional assumption of independence, non-parametric estimates of the unconditional wage distributions can be recovered as well.

Similarly, the smallest value of ω_2 that we could ever observe would be:

$$(11) \qquad \begin{aligned} &\underline{w}_2 = \omega_2^* && if && \omega_1^* \le \omega_2^* + \tau_2 \\ &\underline{w}_2 = \omega_1^* - \tau_2 && if && \omega_1^* > \omega_2^* + \tau_2 \end{aligned}$$

In order to make sense of (10) and (11), define the following two cases:

$$(12) \qquad \begin{aligned} &A: \quad \omega_1^* > \omega_2^* + \tau_2 \\ &B: \quad \omega_1^* \le \omega_2^* + \tau_2 \end{aligned}$$

We are not able to tell whether case A or B prevails in the data without first recovering an estimate of τ_2, which is the object of the estimation procedure. Conveniently, we are able to recover an estimate of τ_2 in either case. In particular:

$$(13) \qquad \tau_2 = \underline{w}_1 - \underline{w}_2$$

Equation (13) therefore describes our minimum order statistic estimator for τ_2 in the simplest two-occupation case. Figures 7 and 8 illustrate the intuition underlying this estimator for cases A and B, respectively. The heavy dashed lines in each figure correspond to the minimum order statistics that would be observed in the data (i.e., $\underline{w}_1 = \omega_1^*$ and $\underline{w}_2 = \omega_1^* - \tau_2$ in case A, and $\underline{w}_1 = \omega_2^* + \tau_2$ and $\underline{w}_2 = \omega_2^*$ in case B). In each case, the difference between the heavy dashed lines identifies τ_2.

We reiterate at this point that, at no point in the preceding discussion were we required to say anything about the relative sizes of the variances of wage draws across occupations or the correlation in an individual's wage draws across occupations. Correlations that are positive, negative, or zero are all consistent with this model. Identification comes off of only differences in the supports of different conditional wage distributions.

The theory used to describe the simple two-occupation case scales-up naturally to any number of potential occupations. With more than two potential occupations, however, we require some additional notation. Consider the following three-occupation system with wages for individual i denoted by $\omega_{1,i}$, $\omega_{2,i}$, and $\omega_{3,i}$. We denote the lower supports of each occupation's wage distribution by ω_1^*, ω_2^*, and ω_3^*. We therefore normalize $\tau_1 = 0$. For individual i, we observe w_i, where:

$$
\begin{aligned}
w_i \quad = \quad & \omega_{1,i} I[\omega_{1,i} > \max(\omega_{2,i} + \tau_2, \omega_{3,i} + \tau_3)] + \\
& \omega_{2,i} I[\omega_{2,i} + \tau_2 > \max(\omega_{1,i}, \omega_{3,i} + \tau_3)] + \\
& \omega_{3,i} I[\omega_{3,i} + \tau_3 > \max(\omega_{1,i}, \omega_{2,i} + \tau_2)]
\end{aligned} \tag{14}
$$

We also observe an indicator corresponding to which occupation individual i has selected – i.e., $d_{1,i}$, $d_{2,i}$, and $d_{3,i}$. We note that, under convex supports for all random variables and assuming finite lower support points (ω_1^*, ω_2^*, ω_3^*), we have the following conditional minimum order statistics:

$$
\begin{aligned}
\underline{w}_1 &= \min(w_i \mid d_{1,i} = 1) = \max(\omega_1^*, \omega_2^* + \tau_2, \omega_3^* + \tau_3) \\
\underline{w}_2 &= \min(w_i \mid d_{2,i} = 1) = \max(\omega_1^*, \omega_2^* + \tau_2, \omega_3^* + \tau_3) - \tau_2 \\
\underline{w}_3 &= \min(w_i \mid d_{3,i} = 1) = \max(\omega_1^*, \omega_2^* + \tau_2, \omega_3^* + \tau_3) - \tau_3
\end{aligned} \tag{15}
$$

Notice that τ_3 is equal to $(\underline{w}_1 - \underline{w}_3)$, while τ_2 is equal to $(\underline{w}_1 - \underline{w}_2)$.

With estimates of τ for multiple occupations $j = 1, 2, \ldots$, it becomes possible to decompose the taste parameter into the utility effects of multiple non-pecuniary occupation characteristics, X (including fatality risk), along with an unobserved occupation attribute, ε_j, by way of regression analysis.

$$
\tau_j = X_j'\beta + \varepsilon_j \tag{16}
$$

5. DATA

We use data from three different sources for our analysis. First, we use data on hourly wage rates and occupations from the Outgoing Rotation Groups of the Current Population Surveys (CPS). Second, we use data on fatal and non-fatal risks associated with each occupation that we construct by merging Bureau of Labor Statistics data on injuries and deaths with CPS data in a procedure described below. Third, we use data on the occupational characteristics (besides injury risks) from the Dictionary of Occupational Titles (DOT).

We record wages and occupations from the CPS Outgoing Rotation Groups Surveys from 1983 through 2002. We restrict the data to these years because 1983 and 2002 are the first and last years that the 1980 occupational classification was used in the CPS. In particular, to determine occupation we use responses to the question "What kind of work was … doing [last week]?" Our sample includes all individuals who were employed during the survey week. This yields data on 3,434,820 workers.

We assign fatal and non-fatal injury risks to each occupation using data from the BLS Survey of Occupational Injuries and Illnesses and the Census of Fatal Occupational Injuries. These data provide counts of injuries and fatalities at the 3-digit occupation level from 1992 to 1999; there is also information on the severity of non-fatal injuries, including the median number of days missed from work per injury within an occupation. In some cases the data are aggregated across 3-digit occupations; we aggregate all data to correspond to the 2-digit detailed occupation recodes in the CPS.[11] We use monthly CPS data to calculate hours worked over this period in each category to transform the counts into risks (the number of injuries per 100 full-time workers).[12] We also calculate "anticipated" days of work lost due to nonfatal injury by multiplying the risk of nonfatal injury by the median days lost per injury within an occupation. We then average over the period 1992-1999 in order to minimize the effects of year-to-year noise (recall that we do not need time variation in fatality risk for identification). Average annual risk of death on

[11] The categories do not correspond perfectly to the Census detailed occupation recodes; we collapse codes 40, 41, and 42 into a single category since the fatality data are not available for these categories in a way that can be disaggregated.

[12] A full-time worker is assumed to work 2,000 hours/year, so that the risks we calculate are per 200,000 hours worked.

the job is 0.005 for all men (or one for every 25,000 men) and 0.002 for all women (or one for every 50,000 women).

We also use data on other job attributes from the Dictionary of Occupational Titles. The DOT is a reference manual compiled by the U.S. Department of Labor that provides information about occupations. It attempts both to define occupations in a uniform way across industries and to assess the characteristics of occupations. While the occupational characteristics in the DOT were not collected from a nationally representative survey of firms and little detail on sampling or response rates is available, they are the best data available on the characteristics of occupations. The analysis of occupational characteristics was conducted through on-site observation and interviews with employees. The DOT data were constructed by analysts assigning numerical codes to 43 job traits. We create six aggregate variables from the underlying DOT variables to describe occupational characteristics: substantive complexity, motor skills, physical demands, working conditions, creative skills, and interactions with people. A detailed list of the variables used to construct these data is provided in Table 1. Table 2 summarizes the attributes of each occupation. The highest risk occupations (in order) are (1) forestry and fishing, (2) motor vehicle operations, (3) other transportation occupations, (4) farm workers, and (5) construction, freight, labor. All other occupations average fewer than one death per 10,000 workers each year.

The data used to construct hourly wage rates for this analysis come from the Bureau of the Census, Current Population Survey, Outgoing Rotation Groups files from 1983 through 2002. Wages are inflated to 2005 dollars using the CPI-U-RS. Workers' hourly wage rates are either (i) the reported hourly wage (for the 60 percent of workers paid on that basis) or (ii) weekly earnings divided by weekly hours (for the other 40 percent of workers).[13] To avoid measurement error from using wages derived from salary and "usual" hours data, we drop the latter group of workers for our primary analysis.[14] The focus of our investigation is therefore on "blue collar" workers. This group has received much of the attention in previous VSL studies. [Viscusi and Aldy (2003)]

[13] Imputed data on wage rates were used to describe some hourly workers. In cases where individuals do not provide complete responses to the Census Bureau interviewers, the Census Bureau imputes the missing data using the information provided by a different respondent with some of the same characteristics, when those characteristics were likely to be associated with the missing data.

[14] In Section 6.2, we do report a separate set of results for salaried workers.

Table 3 summarizes the data describing hourly workers. In particular, the table reports means for attributes of men and women, broken down according to whether the individual works in a high or low risk occupation.[15] There are a few interesting points that can be made simply by looking at these raw data. Men in high risk occupations earn more on average than those in low risk occupations, even though the latter are more likely to be college educated. This suggests the sort of variation in the data that would yield a positive VSL. Men in high risk occupations are, however, also more likely to be older, married, union members, fulltime workers, and white – all of which are factors that would likely contribute to their being paid a higher wage. This highlights the importance of controlling for individual heterogeneity when applying our minimum order statistic estimator. We describe how this is done in the following section.

Unlike their male counterparts, women in high risk occupations tend to earn lower wages. Like men, women with any college training are less likely to work in those jobs. Across most other attributes, women are similar irrespective of whether they work in a high or low risk occupation. Finally, note that 83% of men work in occupations classified as high risk, while only 35% of women do so.

6. ESTIMATION AND RESULTS

In this section, we describe the results of two sets of estimation procedures. The first is based on the traditional wage-hedonic model for recovering marginal willingness-to-pay for reductions in fatality risk. In particular, we estimate a regression of the form:

$$(17) \qquad w_{i,j} = \alpha_0 + Z_i'\alpha_1 + \alpha_2\, FATAL_j + X'_j\alpha_3 + \varepsilon_{i,j}$$

where i indexes workers and j indexes forty-three occupation categories. Z is a vector of variables describing worker i, including:

[15] The individual is considered to be in a high risk occupation if that occupation has fatality risk above the median risk across all 43 occupations (i.e., 1.571 deaths per 100,000 workers each year).

HSDROP	worker is a high-school dropout
HSGRAD	worker is a high-school graduate
SOMECOLL	worker has completed < 4 years of college
COLLGRAD	worker has a four year college degree
AGE	age measured in years
AGE2	age-squared
MARRIED	worker is married and lives with spouse
UNION	worker is a union member
MSA	worker lives in a metropolitan area
FULLTIME	fulltime worker (i.e., hours > 35 per week)
PUBLIC	worker is in the public sector
BLACK	worker is African-American
OTHER	worker is other race (non-white)
HISPANIC	worker is of Hispanic decent
NEW ENGLAND	worker lives in New England census region
MID-ATLANTIC	worker lives in Mid-Atlantic census region
EAST NORTH CENTRAL	worker lives in East North Central census region
WEST NORTH CENTRAL	worker lives in West North Central census region
SOUTH ATLANTIC	worker lives in South Atlantic census region
EAST SOUTH CENTRAL	worker lives in East South Central census region
WEST SOUTH CENTRAL	worker lives in West South Central census region
MOUNTAIN	worker lives in Mountain census region
PACIFIC	worker lives in Pacific census region

X is a vector of non-pecuniary occupation attributes other than fatality risk. These include:

NONFATAL	"Anticipated" days of work lost due to nonfatal injury.
SCMPLX	Substantive complexity, including complexity of function in relation to data, general educational development, intelligence, numerical aptitude, adaptability to performing repetitive work, sensor or judgmental criteria, specific vocational preparation, and verbal aptitude.
MSKILL	Motor skills, including color discrimination, finger dexterity, manual dexterity, motor coordination, and complexity in relation to things.
PHYDDS	Physical demands, including climbing and balancing, eye-hand-foot coordination, dealing with hazardous conditions or outside working conditions, stooping, kneeling, crouching, or crawling.

WORCON	Working conditions, including extreme cold, extreme heat, wetness, or humidity.
CSKILL	Creative skills, including abstract and creative activities, feelings, ideas, or facts.
INTPEOPLE	Worker interactions with people.

The main variable of interest is the fatality risk associated with occupation *j*, represented by FATAL (the number of deaths per 100 full-time workers) which we defined above.

Recognizing that the value placed on certain job attributes may differ with worker attributes, we also estimate a regression of the form:

$$(18) \qquad w_{i,j} = \alpha_0 + Z_i'\alpha_1 + \alpha_2\, FATAL_j + X_j'\alpha_3 + (X_j d_{coll})'\alpha_4 + (X_j d_{AGE>40})'\alpha_5 + \varepsilon_{i,j}$$

where d_{coll} is a dummy variable indicating that SOMECOLL = 1 or COLLGRAD = 1, and $d_{AGE>40}$ is a dummy variable indicating that the individual is over 40 years of age. We restrict our estimate of the compensating differential in wages (and, hence, the VSL) to be constant across worker attributes.

We then take the estimate of the marginal willingness-to-pay to avoid fatality risk, α_2, and scale this up by the typical maximum number of hours worked in a year (2,000) and by the number of workers over whom the annual fatality risk was measured (100). This provides us with our estimated VSL.

Tables 4 and 5 describe the results of regression equations (17) and (18) for both men and women. In each case, we estimate two specifications – one in which we use worker-occupation attribute interactions, and another in which we do not. All results reported in this section of the paper are based on a trimmed sample that drops all individuals reporting wages lower than the federally mandated minimum wage in the year of observation.[16, 17]

[16] In many years, CPS wages are top-coded at a nominal value of $99.99. We drop all observations nominally at or above this top-coded value in every year. Dropping observations with wages below the federally mandated minimum wage reduces the influence of mis-measured wages, particularly in the lower tail of the wage distribution. Results without lower trimming are reported in the sub-section 6.2.

6.1. Minimum Order Statistic Estimator

We carry-out a comparable set of specifications of our minimum order statistic estimator. The practical difficulty in applying this estimator in the current context arises in controlling for the rich set of worker attributes provided by the CPS. One alternative is to divide the data up into very small groups and apply the estimator non-parametrically to each group. The problem that arises, however, is that for a particular group (e.g., black, non-hispanic, married men aged 18-30 with a high-school education, living in an MSA in New England, who are fulltime workers but not in the public sector), we may be unlikely to see many individuals in a particular occupation (e.g., machine operators). The estimator becomes very sensitive to the wages of the few individuals we do see, and fails if we see no workers in a group. Alternatively, we could choose not to control for individual attributes at all, but then we would be deriving our measure of the VSL from the wages and occupation choices of a potentially unrepresentative group. We therefore adopt a two-stage estimation procedure that introduces some parametric modeling.[18] We first estimate a regression of the form:

(19) $$\hat{w}_{i,j} = \beta_0 + Z_i'\beta_1 + u_{i,j}$$

where $\hat{w}_{i,j}$ is individual *i*'s observed wage in occupation *j*, having differenced out the mean of all wages earned by workers in occupation *j*. $\xi_{i,j}$ measures worker *i*'s wage in occupation *j*, purged of the effects of observable individual attributes Z_i:[19]

(20) $$\xi_{i,j} = w_{i,j} - \beta_0 - Z_i'\beta_1$$

---

[17] Keep in mind that, in the traditional wage-hedonic model, a disamenity enters the wage equation positively, indicating a positive wage differential paid to compensate for the unattractive job attribute.
[18] This two-step approach is similar to that employed by Bajari and Kahn (2005), who face a similar problem of needing to perform non-parametric estimation with an abundance of covariates.
[19] Note that we use $w_{i,j}$, not $\hat{w}_{i,j}$, in deriving $\xi_{i,j}$. $\xi_{i,j}$ should be purged of the effects of observable individual attributes, but not of the level-effects attributable to being in different occupations.

We then use $\xi_{i,j}$ as our "wage" in implementing the lower bound estimator. This allows us to compare different individuals without having to divide them into unreasonably small sub-groups.[20]

In particular, normalizing the taste parameter for a large occupation (i.e., occupation #34 – construction trades) to be zero, we recover estimates of the taste parameters for the remaining sectors according to the formula:[21]

$$(21) \qquad \tau_j = \underline{\xi}_{34} - \underline{\xi}_j$$

and carry out the second-stage regression to recover the value of non-pecuniary job attributes:

$$(22) \qquad \tau_j = \theta + \beta_2 \, FATAL_j + X'_j \beta_3 + \upsilon_j$$

where θ accounts for the arbitrary choice of normalization in deriving the τ's. In a final specification, we also include interactions between X_j and d_{coll} and between X_j and $d_{AGE>40}$ in the estimation of equation (19).

Bayer, Khan, and Timmins (2007) describes the asymptotic distribution of the minimum order statistic estimates. We rely, however, on M/N bootstrapping techniques to recover confidence intervals.[22] In particular, we conduct 1000 M/N bootstrap simulations of each specification, from which we derive symmetric 95% confidence

---

[20] This assumption does impose the constraint that job attributes and worker characteristics enter additively in determining a worker's wage. This is restrictive, but not significantly different from the assumption usually maintained in the VSL literature.

[21] We choose an occupation with a lot of observations for our normalization, as the minimum order statistic is likely to provide us with the cleanest estimate of the lower bound of the wage distribution for this occupation. That predicted lower bound will enter into the calculation of τ for every other occupation, so picking the occupation with the most observations for normalization is prudent.

[22] Inference is complicated by the fact that the lower bound estimator does not have an asymptotically normal distribution. The traditional bootstrap algorithm, moreover, is invalid when the estimate is not asymptotically normal. This problem is overcome by the use of the M/N bootstrap, a variant on sub-sampling (here, we use bootstrapped sub-samples that are ¼ the size of the full data set). While yielding inefficient (i.e., overly large) estimates of the confidence interval, the M/N bootstrap does produce confidence interval estimates that are consistent.

intervals.[23] Results are consistent with expectations – workers exhibit a strong and statistically significant disutility from increased fatality risk.[24]

Tables 6 and 7 report the results of our minimum-order-statistic estimator, for both men and women. The first and third columns refer to the specification that does not include worker-occupation attribute interactions; the second and fourth columns include these interactions. Table 6 reports results for equation (19), while Table 7 reports the results of equation (22), including 95% confidence intervals derived from the M/N bootstrap.

Table 8 summarizes the VSL estimates from both the traditional wage hedonic and minimum order statistic estimation techniques, for each of the specifications described above. Looking only at point estimates for men, the minimum order statistic estimator produces VSL estimates that are 3.3 and 4.3 times greater than those produced by the traditional wage hedonic procedure. The minimum order statistic estimates are, moreover, statistically significant with a 95% confidence interval ranging from approximately \$5 million to almost \$16 million. None of traditional wage-hedonic VSL estimates for men are statistically significant.

Turning our attention to the results for women, the difference between the two models is even more stark. The minimum order statistic estimator yields results that are similar to those for men – \$8.62 or \$12.26 million, depending upon whether worker-occupation attribute interactions are included in the first stage estimation. Moreover, these results are statistically significant. By contrast, the wage-hedonic procedure yields *negative* VSL point estimates, with 95% confidence intervals ranging from -\$53.17 million to \$24.42 million.

[23] Specifically, a bootstrap simulation consists of taking a random ¼ sub-sample (drawn with replacement) from the population of $\xi_{i,j}$'s. We then determine the values of τ_j, j = 1, 2,…, 43, and regress these values on the vector of occupation attributes. We record the resulting estimates and repeat the entire process 1000 times. The bootstrapped confidence interval is then found by taking the 2.5th and 97.5th percentiles of the distribution of bootstrapped parameter estimates.

[24] In contrast to the traditional wage-hedonic model, we are here estimating structural utility function parameters. Disutility is therefore indicated by a negative parameter value. Recall, moreover, that these parameter estimates are already normalized by the marginal utility of wages, so that they can be interpreted as marginal willingnesses-to-pay, and are comparable across sub-populations.

6.2 Alternative Specifications

Because our estimator is based on the minimum order statistic, it is possible that our results may be sensitive to the particular choice of model specification (including the criteria used to draw a data sample). In this sub-section, we explore that sensitivity with a variety of alternative specifications. Table 9 reports the VSL estimates arising from ten alternatives. We note at the outset that in no case does the traditional wage-hedonic procedure produce a statistically significant estimate, and for women, most of the point-estimates have the wrong sign. The first row of Table 9 reports estimates based on the sample of salaried workers. Minimum order statistic estimates remain significant, but fall relative to their values for wage workers (more so for men than for women). Wage-hedonic estimates, on the other hand, rise dramatically but have large confidence intervals. The second row reports results based on a sample of hourly workers that does not drop those reporting wages below the federally mandated minimum. These low wages may be real observations, but might also simply reflect measurement error. Including these low wages has the effect of collapsing across-occupation variation at the bottom of the wage distribution, with the effect of reducing the VSL estimate based on the minimum order statistic. Even with this reduction, however, the estimate is still statistically significant and larger than that based on the traditional wage hedonic technique.

The next four rows describe results based on samples drawn to include only individuals in a certain age range.[25,26] In particular, we perform the exact same estimation procedure described in the previous sub-section (including estimating parameters on AGE and AGE2), but do so only on a sub-set of workers (e.g., aged 20 to 29). It is reassuring that the same inverted-U pattern found in previous work is apparent in our results. The inverted-U is, moreover, shifted upward for the minimum order statistic estimates relative to the wage-hedonic estimates.

The next two rows describe how the VSL varies with marital status. Using the minimum order statistic estimator, we find that married men have a higher VSL. This

[25] In these results (and in the remainder of the results in this section), we use the trimmed sample of hourly workers as a starting point.

[26] Besides age, researchers have also calculated VSL's that differ with respect to race [Viscusi (2003)], income, and union status [summarized in Viscusi and Aldy (2003)].

difference goes away when considering women, and is not present for men or women when using the traditional wage-hedonic estimator.

The final two rows of Table 9 illustrate two cases in which our model may not perform well. In the first, we restrict ourselves to using a limited set of worker attributes (AGE, AGE2, HSDROP, SOMECOLL, COLLGRAD). This has the effect of reducing the variability across occupations in the lower bound of our wage distributions.[27] The result is to provide a sort of lower bound on the VSL estimate. While the minimum order statistic estimate falls below that found with the wage-hedonic model, it does remain statistically significant. This result highlights the importance of explaining as much of the variation in wages as possible with observable worker attributes.

The final row of Table 9 illustrates the effects of having little cross-occupation variation in fatality risk. In particular, we eliminate the relatively risky occupation categories #41 - #43 (i.e., farm managers, farm workers, and forestry & fishing). The result is to increase the confidence intervals for the estimates derived from both techniques (particularly for the minimum order statistic estimator). The change has little effect on the point estimate for men based on the wage-hedonic technique, but the point estimate based on the minimum order statistic jumps dramatically.

7. ESTIMATION WITHOUT THE MINIMUM ORDER STATISTIC

While the CPS provides high-quality data on wages, one might still be concerned about the potential for measurement error to prevent us from observing the true minimum order statistic. A similar concern might arise in settings where one has a relatively small sample to work with. In this section, we employ an alternative estimation strategy that instead uses data from the entire conditional wage distribution and makes no assumption about the distributions' supports. [Bayer, Khan, and Timmins (2007)] Instead, it relies upon two alternative identifying assumptions: (i) the unconditional distribution of log-

[27] Consider an extreme example. When we trim all observations below the federally mandated minimum wage and use no covariates, it will likely be the case that there is no variation at all across sectors in the lower point of support. The VSL recovered with our minimum order statistic estimator would therefore be $0.

wage in occupation *j* is normal with mean μ_j and variance σ_j^2, and (ii) wage draws for individual *i* are independent across occupations.[28]

To explain this estimator, we return to the simple model of individuals sorting over two occupations, indexed by #1 and #2. Without loss of generality, we again normalize the taste for occupation #1 to zero ($\tau_1 = 0$). We define a variable d_i, which functions as an indicator that individual *i* chose occupation #1:

$$(23) \qquad d_i = I[\omega_{1,i} > \omega_{2,i} + \tau_2]$$

Using this indicator, we can write down an expression for individual *i*'s observed wage:

$$(24) \qquad w_i = d_i \omega_{1,i} + (1 - d_i)\omega_{2,i}$$

i.e., the individual receives his draw from occupation #1 if it was utility maximizing to choose that occupation. Next, define the following joint probability distributions, both of which are easily observed in the data:

$$(25) \qquad \Psi_1(t) = P(d_i = 1, w_i \le t) \qquad\qquad \Psi_2(t) = P(d_i = 0, w_i \le t)$$

We will also work with the derivatives of these expressions, denoted by:

$$(26) \qquad \psi_1(t) = \frac{\partial}{\partial t} P(d_i = 1, w_i \le t) \qquad\qquad \psi_2(t) = \frac{\partial}{\partial t} P(d_i = 0, w_i \le t)$$

Focusing on the expression for $\Psi_1(t)$, we can exploit the independence assumption to re-write it as follows:

[28] Using panel data to relax the independence assumption is a focus of our current research.

$$\Psi_1(t) = P(d_i = 1, w_i \le t)$$

(27) $$= P(\omega_{1,i} > \omega_{2,i} + \tau_2, \omega_{1,i} \le t) \quad = \quad P(\omega_{1,i} - \tau_2 > \omega_{2,i}, \omega_{1,i} \le t)$$

$$= \int_{-\infty}^{t} f_1(\omega_1) d\omega_1 \int_{-\infty}^{\omega_1 - \tau_2} f_2(\omega_2)\, d\omega_2 \quad = \quad \int_{-\infty}^{t} f_1(\omega_1)\, F_2(\omega_1 - \tau_2)\, d\omega_1$$

This means that we can define $\psi_1(t)$ as follows:

(28) $$\psi_1(t) \; = \; \frac{\partial}{\partial t} \int_{-\infty}^{t} f_1(\omega_1)\, F_2(\omega_1 - \tau_2)\, d\omega_1 = f_1(t)\, F_2(t - \tau_2)$$

An analogous argument defines $\psi_2(t)$:

(29) $$\psi_2(t) \; = \; \frac{\partial}{\partial t} \int_{-\infty}^{t} f_2(\omega_2)\, F_1(\omega_2 + \tau_2)\, d\omega_2 = f_2(t)\, F_1(t + \tau_2)$$

Going back to the final integral in equation (27) and carrying out integration-by-parts yields:

(30) $$\Psi_1(t) = \int_{-\infty}^{t} f_1(\omega_1) F_2(\omega_1 - \tau_2) d\omega_1 \; = \; F_1(t) F_2(t - \tau_2) - \int_{-\infty}^{t} F_1(s)\, f_2(s - \tau_2) ds$$

Performing a change of variables $u = s - \tau_2$, equation (30) becomes:

(31) $$\Psi_1(t) = F_1(t) F_2(t - \tau_2) - \int_{-\infty}^{t - \tau_2} F_1(u + \tau_2)\, f_2(u) du$$

Next, we use the expressions for $\psi_1(t)$ and $\psi_2(t)$ defined in (28) and (29) to re-write equation (31) as follows:

$$(32)\qquad \Psi_1(t) = \frac{F_1(t)\psi_1(t)}{f_1(t)} - \int_{-\infty}^{t-\tau_2} \psi_2(u)du$$

Noting that the integral term in (32) is simply $\Psi_2(t-\tau_2)$, we can solve for the distribution of ω_1 as a function of τ_2:

$$(33)\qquad \lambda_1(t) = \frac{f_1(t)}{F_1(t)} = \frac{\psi_1(t)}{\Psi_1(t) + \Psi_2(t-\tau_2)}$$

where $\lambda_1(t)$ is a function of the unconditional wage distribution in location #1. (33) is a single equation in two unknowns ($\lambda_1(t)$ and τ_2) when evaluated at a particular value of t, and it is therefore not surprising that we cannot identify both of these values without making an additional assumption. Bayer, Khan, and Timmins (2007) show how the equation can be estimated in a model of spatial sorting by assuming that workers living in the same location receive a wage draw from the same distribution irrespective of where they migrated from. That source of variation is not available in the data used to recover the VSL. Instead, we make a parametric assumption about $F_1(t)$. Assuming $F_1(t)$ is the cumulative normal distribution with mean μ_1 and variance σ_1^2 would reduce equation (33) to three parameters. The number of parameters would not increase, moreover, as we consider the expression evaluated at different values of t. By forcing the equation to hold for many values of t, we would have more equations than unknowns and could identify the model's parameters.

The preceding arguments scale-up to any number of occupations (although the denominator in the right-hand-side expression of (33) becomes more complicated). We can, therefore, estimate the model in our occupational sorting context by forming a minimum-distance criterion function based on equation (33). Minimizing this objective function requires us to search over a high-dimensional parameter space (i.e., forty-three means, forty-three variances, and forty-two taste parameters).[29] We make one further simplifying assumption in order to facilitate estimation – that the taste parameter can be

[29] In this unrestricted specification, one of the taste parameters must still be normalized to zero.

written as a function of observable occupation attributes: $\tau_j = X'_j\beta$. We therefore need to only estimate eight β parameters instead of a separate τ_j for each occupation.

Table 10 describes the outcome of this estimation procedure applied to the sample of male hourly workers earning more than the federal minimum wage.[30] We evaluate a minimum distance criterion function based on (33) at 200 values of log-wages evenly spaced between 0.25 and 4.25.[31] Standard errors are bootstrapped from 800 re-samples. Because we are modeling log-wages, the coefficient on fatality risk needs to be multiplied by the wage rate before being converted into a VSL. We use the average wage rate in the sample ($13.16). The result is a statistically significant VSL estimate of $8.05 million.

Although the assumptions and methodology used to arrive at this estimate differ dramatically from those in the previous section, the result is remarkably similar. Controlling for Roy sorting, we recover a VSL that is two to four times greater than that derived from traditional wage-hedonics. Taken together, the results of these two methodological approaches lead us to conclude that the VSL based on traditional wage-hedonic techniques is indeed biased downward by Roy sorting.

8. CONCLUSIONS

The effect of individual unobservable heterogeneity (i.e., productivity) on estimates of the value of a statistical life has been addressed in previous work, but occupational (Roy) sorting based on idiosyncratic returns is absent from the literature on VSL. We demonstrate that this type of sorting has the potential to bias wage-hedonic estimates of the VSL. Recovering the size and direction of that bias is a difficult empirical problem that depends partly upon the relative variances of the unconditional sector-specific wage distributions. But as Heckman and Honore (1990) demonstrate, one cannot recover those unconditional wage distributions without first making an assumption

[30] Specifically, we apply the procedure to the "purged" wage data that were created by removing the variation in wages explained by observable worker attributes (i.e., $\xi_{i,j}$ from equation (20)).
[31] Bayer, Khan, and Timmins (2007) describe the details of this procedure. For example, we use normal density kernels and a Silverman's rule of thumb to approximate $\psi_j(t)$. $\Psi_j(t)$ is measured non-parametrically as a step-function.

about the correlation of wage draws across occupations. This is problematic, since the assumed value of the correlation affects the size of the Roy sorting bias.

We demonstrate a way to deal with Roy sorting bias without recovering the unconditional wage distributions. Doing so requires the relatively innocuous assumption that wage distributions have finite lower bounds. In addition to controlling for the biases induced by Roy sorting, this semi-parametric estimator also corrects for biases resulting from unobserved productivity, of the sort described by Hwang et al (1992). It is, moreover, easy to use – everything (except standard errors) can be calculated with a spreadsheet. Finally, it can be expanded to use better data sets (e.g., a finer gradation of occupation/sector, like those used by Kniesner et al. (2006) or Scotten and Taylor (2007). In so doing, however, it does also require the stronger practical assumption that we can actually see the lower bound of each conditional distribution in the form of a minimum order statistic. For some (small, noisy) data sets, this will clearly not be the case. In response to this concern, we offer an alternative estimation strategy that does not impose strict data requirements (but does require an independence assumption on wage draws). The conclusions of both models are that traditional wage-hedonic techniques yield downwardly biased estimates of the VSL. That bias is big enough, moreover, to matter for policy. Estimates for men rise by more than a factor of three and become statistically significant. Estimates for women take on the expected sign and become statistically significant as well. These estimates suggest that substantially larger valuations should be used in cost-benefit analyses of environmental, workplace, and job safety regulations than is current practice.

REFERENCES

Alberini, A., M. Cropper, A. Krupnick, and N. Simon (2004). "Does the value of a statistical life vary with age and health status? Evidence from the US and Canada." *Journal of Environmental Economics and Management*. 48:869-792.

Ashenfelter, O. and M. Greenstone (2004). "Using Mandated Speed Limits to Measure the Value of a Statistical Life." *Journal of Political Economy*. 112:S226-S267.

Atkinson, S.E. and R. Halvorsen (1990). "The Valuation of Risks to Life: Evidence from the Market for Automobiles." *Review of Economics and Statistics*. 72(1):133-136.

Bayer, P., S. Khan, and C. Timmins (2007). "Nonparametric Identification and Estimation in a Generalized Roy Model." Mimeo, Duke University Department of Economics.

Bajari, P. and M.E. Kahn (2005). "Estimating Housing Demand With an Application to Explaining Racial Segregation in Cities." *Journal of Business and Economic Statistics*. 23(1):20-33.

Black, D.A. and T.J. Kniesner (2003). "On the Measurement of Job Risk in Hedonic Wage Models." *Journal of Risk and Uncertainty*. 27(3):205-220.

Blomquist, G. (1979). "Value of Life Saving: Implications from Consumption Activity." *Journal of Political Economy*. 87(3):540-58.

Brown, C. (1980). "Equalizing Differences in the Labor Market." *Quarterly Journal of Economics*. 94(1):113-34.

Carlin, P. and R. Sandy (1991). "Estimating the Implicit Value of a Young Child's Life." *Southern Economic Journal*. 58(1): 186-202.

DeLeire, T. and H. Levy (2004). "Worker Sorting and the Risk of Death on the Job." *Journal of Labor Economics*. 22(4): 925-954.

Dreyfus, M.K. and W.K. Viscusi (1995). "Rates of Time Preference and Consumer Valuations of Automobile Safety and Fuel Efficiency." *Journal of Law and Economics*. 38(1):79-105.

Gayer, T., J.T. Hamilton, and W.K. Viscusi (2000). "Private Values of Risk Tradeoffs at Superfund Sites: Housing Market Evidence on Learning About Risk." *Review of Economics and Statistics*. 82(3):439-451.

Gill, R.D. (1980). Censoring and Stochastic Integrals. Mathematical Centre Tracts, 124. Mathematical Centrum, Amsterdam.

Hakes, J. and W.K. Viscusi (2007). "Automobile Seatbelt Usage and the Value of Statistical Life." *Southern Economic Journal*. 73(3):659-676.

Heckman, J.J. and B. Honore (1990). "The Empirical Content of the Roy Model." *Econometrica*. 58:1121-1149.

Hersch, J. and T.S. Pickton (1995). "Risk-Taking Activities and Heterogeneity in Job-Risk Tradeoffs." *Journal of Risk and Uncertainty*. 11(3):205-217.

Hersch, J. and W.K. Viscusi (1990). "Cigarette Smoking, Seatbelt Use, and Differences in Wage-Risk Tradeoffs." *Journal of Human Resources*. 25(2):202-227.

Hwang, H., W.R. Reed, and C. Hubbard (1992). "Compensating Wage Differentials and Unobserved Productivity." *Journal of Political Economy*. 100(4): 835-858.

Kniesner, .J., W.K. Viscusi, C. Woock, and J.P. Ziliak (2006). "Pinning Down the Value of Statistical Life." Center for Policy Research Working Paper 85, Maxwell School, Syracuse University.

Li, S. (2006). "The Social Costs of the "Arms Race" on American Roads: Evidence from Automobile Demand." Mimeo, Duke University Department of Economics.

Portney, P.R. (1981). "Housing Prices, Health Effects, and Valuing Reductions in Risk of Death." *Journal of Environmental Economics and Management*. 8:72-78.

Revesz, R. (1999). "Environmental Regulation, Cost-Benefit Analysis, and the Discounting of Human Lives." *Columbia Law Review*. 99:941-1017.

Rosen, S. (1986). "The Theory of Equalizing Differences." In Handbook of Labor Economics, Vol. 1. ed. Orley C. Ashenfelter and Richard Layard, pp.641-92. Amsterdam: North-Holland.

Roy, A.D. (1951). "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers*. 3:135-146.

Savage, I. (1993). "An Empirical Investigation into the Effect of Psychological Perception on the Willingness to Pay to Reduce Risk." *Journal of Risk and Uncertainty*. 6:75-90.

Scotten, C. and L. Taylor (2007). "Of Cab Drivers and Coal Miners: Accounting for Risk Heterogeneity in Value of Statistical Life Estimates." Mimeo.

Shogren, J.F. and T. Stamland (2002). "Skill and the Value of Life." *Journal of Political Economy*. 110(5):1168-1197.

Smith, V.K., M. Evans, H. Kim, and D. Taylor (2004). "Do the Near-Elderly Value Mortality Risks Differently?" *Review of Economics and Statistics*. 86(1):423-429.

Thaler, R. and S. Rosen (1975). "The Value of Saving a Life: Evidence from the Labor Markets." In N.E. Terleckyj (ed.), *Household Production and Consumption*. New York: Columbia University Press. pp.265-300.

Viscusi, W.K. (1992). *Fatal Tradeoffs: Public and Private Responsibilities for Risk*. New York: Oxford University Press.

________. (2003). "Racial Differences in Labor Market Values of a Statistical Life." *Journal or Risk and Uncertainty*. 27:3:239-256.

Viscusi,, W.K. and J. Aldy (2003). "The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World." *Journal of Risk and Uncertainty*. 27(1):5-76.

________. "Adjusting the Value of a Statistical Life for Age and Cohort Effects." RFF Discussion Paper 06-19.

Viscusi, W.K. and J. Hersch (2001). "Cigarette Smokers as Job Risk Takers." *Review of Economics and Statistics*. 83(2):269-280.

Table 1
Determinants of Job Characteristics Based on DOT Data

Factor 1	<u>SUBSTANTIVECOMPLEXITY</u>
	DATAL (complexity of function in relation to data)
	GED (general educational development)
	INTELL (intelligence)
	NUMERCL (numerical aptitude)
	REPCON (Adaptability to performing repetitive work)
	SJC (sensor or judgmental criteria)
	SVP (specific vocational preparation)
	VERBAL (verbal aptitude)
Factor 2	<u>MOTOR SKILLS</u>
	CLRDISC (color discrimination)
	FNGRDXT (finger dexterity)
	MNLDXTY (manual dexterity)
	MTRCRD (motor coordination)
	THINGS (complexity in relation to things)
Factor 3	<u>PHYSICAL DEMANDS</u>
	CLIMB (climbing, balancing)
	EYHNFTC (eye-hand-foot coordination)
	HAZARDS (hazardous conditions)
	OUT (outside working conditions)
	STOOP (stooping, kneeling, crouching, crawling)
Factor 4	<u>WORKING CONDITION</u>
	COLD (extreme cold)
	HEAT (extreme heat)
	WET (wet, humid)
Factor 5	<u>CREATIVE SKILLS</u>
	ABSCREAT (abstract & creative activities)
	FIF (feelings, ideas or facts)
Factor 6	<u>INTPEOPLE</u>
	PEOPLE (interaction with people)

Table 2 (a)
Occupation Attributes

Occupation	FATAL	NONFATAL	SCMPLX	MSKILL	PHYDDS	WORCON	CSKILL	INTPEOPLE
3-6: Pub. Admin.	0.0018	0.0000	0.6879	1.1353	-0.2425	0.6505	-0.1907	-0.7855
7-22: Other Exec.	0.0020	1.4982	0.6143	1.1082	-0.4853	-0.3941	-0.1763	-0.9577
23-37: Management	0.0009	1.3879	0.9138	1.1947	-0.7276	-0.4849	-0.1829	-1.3500
44-59: Engineers	0.0023	1.0150	1.3207	-0.9070	-0.4879	-0.4232	0.4608	-0.2709
64-68: Mathematical and Comp Sci	0.0004	0.6365	1.1708	1.3192	-0.6439	-0.5881	-0.0977	-1.0983
69-83: Natural scientists	0.0023	0.8725	1.3793	-0.9374	-0.3347	0.3333	0.0038	-0.1951
84-89: Health diagnosers	0.0011	1.8691	1.8017	-3.1622	-0.5097	-0.5521	-0.4203	0.3824
95-106: Health assess & treat	0.0007	5.1230	0.6012	-0.9513	-0.4469	-0.5923	-0.3494	0.6415
113-154: Professors	0.0005	0.2670	1.6046	1.4303	-0.8375	-0.5982	-0.1342	-1.3198
155-159: Teachers (exc. coll.)	0.0005	1.2979	0.9016	0.3525	-0.3597	-0.5881	0.9809	-0.9455
178-179: Lawyers & judges	0.0012	0.3306	2.0665	1.7181	-0.9118	-0.6018	4.1324	-2.1331
43,63,163-177,183-199: Oth. prof. spec.	0.0011	2.2276	1.1812	0.1353	-0.5487	-0.0945	4.1225	-0.7069
203-208: Health tech.	0.0009	8.6382	0.0277	-1.0334	-0.3174	-0.4868	-0.3592	0.2528
213-225: Eng/sci tech.	0.0020	4.2027	0.5435	-1.4970	-0.4499	-0.4413	-0.0645	-0.2571
226-235: Tech, not eng/sci	0.0096	5.5567	0.7081	0.4057	-0.5408	-0.5718	-0.0134	-0.7532
243: Sales supervisors	0.0033	3.5027	0.4089	1.0263	-0.2950	-0.3658	-0.0998	-0.7847
253-257: Sales reps and business	0.0012	1.5427	0.6899	1.2582	-0.8207	-0.5888	-0.3644	-1.0679
258-259: Sales reps, non-retail comm.	0.0016	2.0476	0.2529	1.0859	-0.8616	-0.5615	-0.3929	-1.2436
263-278: Sales work, retail & svc.	0.0020	5.3078	-0.4732	-0.2793	-0.7061	-0.5062	-0.3788	-0.2030
283-285: Sales-related occupations	0.0000	5.8560	-0.0287	-0.0613	-0.8066	-0.5784	0.7758	-0.4289

Table 2 (b)
Occupation Attributes

Occupation	FATAL	NONFATAL	SCMPLX	MSKILL	PHYDDS	WORCON	CSKILL	INTPEOPLE
303-307: Admin. Supervisors	0.0004	2.6672	0.1349	0.3182	-0.6802	-0.4804	-0.3788	-0.6197
308-309: Computer operators	0.0000	1.7641	-0.0650	-0.4041	-0.5568	-0.6022	-0.4023	0.0712
313-315: Secretaries	0.0003	2.0029	0.3957	-1.9561	-0.9030	-0.5939	-0.4176	-0.0692
337-344: Fin. record process	0.0002	2.1631	-0.1916	-0.4688	-0.8965	-0.5598	-0.4209	-0.8874
354-357: Mail/msg dist.	0.0025	11.5449	-1.1516	0.5619	-0.6374	-0.4628	-0.4289	-0.0914
316-336,345-353,359-389: other admin.	0.0005	6.3292	-0.3962	0.5455	-0.7559	-0.4331	-0.3810	-0.6918
403-407: Pvt. hh service	0.0007	0.0000	-1.3641	0.7072	0.2214	-0.5826	-0.4251	-0.0018
413-427: Protective svc.	0.0086	7.7154	-0.6374	0.6563	0.7423	1.0386	-0.4224	0.4060
433-444: Food service	0.0009	8.8127	-0.8628	0.4484	-0.3909	2.1472	-0.1096	-0.0835
445-447: Health service	0.0008	24.1017	-0.8532	-0.2811	0.6658	-0.3933	-0.3731	1.2654
448-455: Cleaning/bldg svc.	0.0020	13.8845	-1.5140	0.3170	1.1338	-0.2767	-0.4196	1.4381
456-469: Personal svc.	0.0014	9.1429	-0.4508	-0.5895	-0.2467	-0.4406	1.3130	0.3233
503-549: Mechanics & repairers	0.0053	15.2240	-0.0444	-1.3110	0.7587	0.3971	-0.4063	1.6128
553-599: Construction trades	0.0068	22.5577	-0.0188	-0.9502	2.2933	-0.1960	-0.3797	1.8767
613-699: Other precision production	0.0029	13.6475	-0.5258	-1.0338	0.0501	1.6055	-0.3601	0.4448
703-779: Machine operators	0.0024	22.6953	-1.2204	-0.3437	-0.1057	0.8997	-0.3738	0.0608
783-799: Fabricators, inspectors	0.0028	17.8286	-1.2994	-0.4417	-0.0571	0.6781	-0.3785	0.2925
803-814: Motor vehic. Operators	0.0176	35.6393	-1.3383	-0.3606	0.7426	-0.4457	-0.4160	0.6131
823-859: Other transportation	0.0166	29.2157	-1.1876	-0.0819	1.1613	0.4532	-0.4187	0.7212
864-889: Construction, freight, labor	0.0110	34.9962	-1.6291	0.4910	1.0768	3.8833	-0.4244	0.8275
473-476: Farm managers	0.0094	0.3968	0.4685	0.2723	2.3756	-0.4168	-0.4280	2.3884
477-489: Farm workers	0.0117	11.4986	-1.3619	0.3021	2.6532	-0.1571	-0.3915	1.5870
494-499: Forestry & fishing	0.0872	35.0779	-1.2595	0.2617	2.6898	2.9723	-0.4088	1.7403

Table 3: Worker Attributes[32]

	Men		Women	
	Low Risk	High Risk	Low Risk	High Risk
Sample Size	105259	522782	410823	217218
Wage	12.93	13.21	12.11	9.99
AGE	31.60	34.07	35.74	35.09
MARRIED	0.38	0.54	0.56	0.51
UNION	0.03	0.04	0.02	0.02
MSA	0.81	0.70	0.74	0.72
FULLTIME	0.71	0.84	0.63	0.64
WHITE	0.82	0.86	0.85	0.83
HSDROP	0.13	0.22	0.08	0.18
HSGRAD	0.27	0.45	0.38	0.45
SOMECOLL	0.36	0.26	0.38	0.28
COLLGRAD	0.24	0.07	0.17	0.10
NEW ENGLAND	0.08	0.08	0.09	0.09
MID ATLANTIC	0.13	0.11	0.13	0.11
E. N. CENTRAL	0.14	0.14	0.16	0.15
W. N. CENTRAL	0.10	0.10	0.12	0.10
SOUTH ATLANTIC	0.16	0.19	0.16	0.19
E. S. CENTRAL	0.04	0.06	0.05	0.06
W. S. CENTRAL	0.08	0.10	0.08	0.09
MOUNTAIN	0.11	0.10	0.09	0.09
PACIFIC	0.16	0.12	0.12	0.12

[32] This table describes the sample of hourly wage workers, excluding all those who earn less than the federal minimum wage.

Table 4
Wage-Hedonic Model Estimates (Worker Attributes)[33]

	(1)	(2)	(3)	(4)
Sample	Men Age 18-60	Men Age 18-60	Women Age 18-60	Women Age 18-60
Worker-Occupation Attribute Interactions	No	Yes	No	Yes
Constant	-0.603	-1.132	1.421	1.045
	(1.344)	(1.128)	(1.279)	(1.043)
HSDROP	-1.347	-1.397	-0.643	-0.898
	(0.167)	(0.162)	(0.173)	(0.133)
SOMECOLL	0.235	0.614	1.019	1.317
	(0.109)	(0.315)	(0.306)	(0.557)
COLLGRAD	2.775	2.762	4.290	4.201
	(0.522)	(0.507)	(0.823)	(0.794)
AGE	0.569	0.569	0.419	0.404
	(0.060)	(0.059)	(0.060)	(0.058)
AGE2	-0.006	-0.006	-0.004	-0.004
	(6.8×10^{-4})	(7.0×10^{-4})	(6.7×10^{-4})	(6.5×10^{-4})
BLACK	-1.258	-1.261	-0.420	-0.448
	(0.154)	(0.140)	(0.150)	(0.132)
OTHER	-0.942	-0.889	-0.196	-0.204
	(0.167)	(0.167)	(0.123)	(0.118)
HISPANIC	-1.384	-1.443	-0.523	-0.567
	(0.133)	(0.129)	(0.124)	(0.127)
MARRIED	1.260	1.213	0.250	0.217
	(0.074)	(0.071)	(0.077)	(0.066)
PUBLIC	1.089	0.988	0.379	0.344
	(0.367)	(0.368)	(0.373)	(0.343)
UNION	2.669	2.665	1.946	1.902
	(0.190)	(0.196)	(0.228)	(0.226)
MSA	0.802	0.811	0.976	0.998
	(0.099)	(0.098)	(0.129)	(0.128)
FULLTIME	1.430	1.378	0.764	0.797
	(0.119)	(0.109)	(0.223)	(0.198)
Regional Indicators	Yes	Yes	Yes	Yes
R^2	0.316	0.331	0.317	0.334
N	628217	628217	695051	695051

[33] Standard errors (in parentheses) are clustered to reflect the fact that occupation attributes are the same for all workers in a particular occupation.

Table 5
Wage-Hedonic Model Estimates (Occupation Attributes)[34]

	(1)	(2)	(3)	(4)
	Men Age 18-60	Men Age 18-60	Women Age 18-60	Women Age 18-60
FATAL	20.506	13.804	-65.183	-44.251
	(-37.893, 78.904)	(-35.100, 62.708)	(-265.855, 135.489)	(-210.577, 122.076)
NONFATAL	0.094	0.057	0.098	0.061
	(0.041, 0.147)	(0.026, 0.088)	(-0.017, 0.212)	(-0.007, 0.129)
SCMPLX	5.422	3.318	4.283	1.530
	(3.287, 7.557)	(1.869, 4.767)	(0.469, 8.098)	(0.273, 2.788)
MSKILL	-1.397	-1.478	-0.393	-0.027
	(-2.426, -0.368)	(-2.157, -0.800)	(-1.814, 1.028)	(-0.346, 0.292)
PHYDDS	-0.328	-0.119	0.951	0.112
	(-0.794, 0.139)	(-0.423, 0.185)	(-0.164, 2.067)	(-0.619, 0.842)
WORCON	0.156	0.036f	0.147	-0.016
	(-0.179, 0.490)	(-0.160, 0.232)	(-0.331, 0.625)	(-0.343, 0.311)
CSKILL	-0.353	-0.327	-0.798	-0.583
	(-0.782, 0.076)	(-0.944, 0.289)	(-1.289, -0.308)	(-0.942, -0.225)
INTPEOPLE	2.529	1.983	0.799	-0.116
	(0.252, 4.806)	(0.405, 3.560)	(-2.729, 4.328)	(-1.485, 1.253)

[34] Confidence intervals (in parentheses) are based on clustered standard errors, reflecting the fact that occupation attributes are the same for all workers in a particular occupation.

Table 6
Minimum Order Statistic Estimator, First Stage (Worker Attributes)

	(1)	(2)	(3)	(4)
Sample	Men Age 18-60	Men Age 18-60	Women Age 18-60	Women Age 18-60
Worker-Occupation Attribute Interactions	No	Yes	No	Yes
Constant	-10.578 (0.080)	-10.915 (0.080)	-6.836 (0.062)	-7.242 (0.062)
HSDROP	-1.203 (0.018)	-1.254 (0.020)	-0.553 (0.018)	-0.706 (0.018)
SOMECOLL	0.058 (0.018)	0.203 (0.031)	0.180 (0.013)	0.388 (0.030)
COLLGRAD	1.311 (0.026)	1.872 (0.036)	2.078 (0.018)	2.533 (0.032)
AGE	0.449 (0.004)	0.458 (0.005)	0.299 (0.003)	0.308 (0.003)
AGE2	-0.004 (5.9×10^{-5})	-0.005 (5.9×10^{-5})	-0.003 (4.5×10^{-5})	-0.003 (4.5×10^{-5})
BLACK	-1.008 (0.025)	-1.129 (0.025)	-0.195 (0.018)	-0.278 (0.018)
OTHER	-0.759 (0.035)	-0.813 (0.035)	-0.088 (0.028)	-0.188 (0.028)
HISPANIC	-1.185 (0.023)	-1.275 (0.023)	-0.455 (0.021)	-0.531 (0.021)
MARRIED	0.884 (0.016)	0.958 (0.016)	0.039 (0.012)	0.097 (0.012)
PUBLIC	0.341 (0.025)	0.392 (0.025)	0.159 (0.018)	0.286 (0.018)
UNION	2.486 (0.040)	2.464 (0.040)	1.567 (0.036)	1.552 (0.036)
MSA	0.761 (0.017)	0.825 (0.017)	0.869 (0.013)	0.928 (0.013)
FULLTIME	0.841 (0.019)	0.897 (0.019)	0.492 (0.012)	0.561 (0.012)
Regional Indicators	Yes	Yes	Yes	Yes
R^2	0.146	0.153	0.096	0.104
N	628041	628041	694930	694930

Table 7
Minimum Order Statistic Estimator, Second Stage (Occupation Attributes)[35]

	(1)	(2)	(3)	(4)
Sample	Men	Men	Women	Women
	Age 18-60	Age 18-60	Age 18-60	Age 18-60
Constant	-2.194	-1.613	1.409	1.603
	(-3.43, 0.41)	(-3.02, 0.70)	(0.46, 2.68)	(0.63, 3.13)
FATAL	-66.737	-59.371	-43.116	-61.275
	(-78.91, -29.17)	(-79.60, -23.22)	(-66.21, -22.80)	(-70.29, -37.63)
NONFATAL	0.073	0.033	0.013	0.006
	(0.01, 0.09)	(-0.03, 0.07)	(-0.05, 0.04)	(-0.06, 0.03)
SCMPLX	-0.768	-1.937	-0.740	-2.075
	(-1.30, 0.89)	(-2.39, 0.03)	(-1.22, 0.52)	(-2.41, -0.60)
MSKILL	0.399	0.640	0.225	0.393
	(-0.22, 0.61)	(-0.11, 0.77)	(-0.43, 0.31)	(-0.30, 0.46)
PHYDDS	0.101	0.323	-0.371	-0.352
	(-0.31, 0.47)	(-0.14, 0.70)	(-0.63, -0.01)	(-0.62, 0.01)
WORCON	0.279	0.547	0.088	0.091
	(-0.12, 0.61)	(0.19, 0.89)	(-0.16, 0.36)	(-0.20, 0.36)
CSKILL	-0.066	0.230	0.169	0.217
	(-0.35, 0.27)	(-0.04, 0.65)	(-0.01, 0.54)	(0.06, 0.59)
INTPEOPLE	-0.589	-1.195	-0.273	-0.903
	(-1.03, 1.30)	(-1.42, 1.10)	(-0.49, 1.36)	(-0.98, 1.00)

[35] Confidence intervals (in parentheses) are based on the 2.5th and 97.5th percentiles of the distribution of bootstrapped parameter estimates.

Table 8: Value of a Statistical Life ($ millions)
95% Confidence Interval in Parentheses

Sample	Men Age 18-60	Men Age 18-60	Women Age 18-60	Women Age 18-60
Worker-Occupation Attribute Interactions	No	Yes	No	Yes
Wage-Hedonic Model	4.10 (-7.58, 15.78)	2.76 (-7.02, 12.54)	-13.04 (-53.17, 27.10)	-8.85 (-42.12, 24.42)
Minimum Order Statistic Estimator	13.35 (5.83, 15.78)	11.87 (4.64, 15.92)	8.62 (4.56, 13.24)	12.26 (7.53, 14.06)

Table 9: Sensitivity Analysis, Value of a Statistical Life ($ millions)
95% Confidence Interval in Parentheses

Specification	Men		Women	
	Minimum Order Statistic Estimator	Wage-Hedonic Model	Minimum Order Statistic Estimator	Wage-Hedonic Model
Salaried Workers	6.98	10.66	7.94	37.12
	(0.88, 14.30)	(-4.95, 26.28)	(-5.87, 21.64)	(-10.82, 85.06)
Un-trimmed Sample	6.85	4.53	6.44	-7.42
	(3.26, 14.50)	(-7.66, 16.72)	(0.02, 19.10)	(-50.31, 35.46)
Age [20,30)	7.17	2.73	7.62	-11.09
	(2.78, 10.70)	(-6.09, 11.54)	(4.26, 18.28)	(-43.31, 21.13)
Age [30, 40)	9.01	5.58	8.86	-10.43
	(5.57, 14.92)	(-6.81, 17.97)	(5.13, 17.60)	(-55.98, 35.12)
Age [40, 50)	13.23	6.19	11.19	-13.48
	(5.24, 20.26)	(-8.96, 21.34)	(5.83, 27.22)	(-61.04, 34.09)
Age [50, 60)[36]	7.33	2.94		-17.39
	(2.57, 19.04)	(-15.45, 21.32)		(-70.93, 36.14)
Married	13.62	4.27	7.98	-18.55
	(5.96, 18.71)	(-7.99, 16.53)	(3.92, 16.85)	(-65.56, 28.46)
Unmarried	7.71	3.73	8.54	-5.13
	(3.20, 12.40)	(-7.13, 14.60)	(5.01, 13.64)	(-36.51, 26.25)
Limited Individual Attributes	2.05	5.54	4.85	-11.40
	(0.86, 8.43)	(-7.47, 18.55)	(2.63, 11.37)	(-53.22, 30.41)
No Ag, Forestry, Fishing	19.45	2.25	5.25	-11.56
	(-11.18, 138.70)	(-26.79, 31.30)	(-4.81, 30.92)	(-60.27, 37.16)

[36] In the case of women aged 50 – 59 years, there were some occupations in which we observed no workers. The minimum order statistic estimator could not be run in this case.

Table 10: Parameter Estimates Based on Normality and Independence Assumptions

Param	Est	S.E.	Param	Est	S.E.	Param	Est	S.E.
μ_1	0.04	0.01	σ_1	3.52	1.12	FATAL	-3.06	0.85
μ_2	2.14	0.61	σ_2	3.17	1.02	NONFATAL	-0.31	0.02
μ_3	-2.78	0.81	σ_3	2.92	0.81	SCMPLX	-3.05	0.30
μ_4	-2.34	0.62	σ_4	2.97	0.83	MSKILL	-0.73	0.08
μ_5	1.22	0.35	σ_5	2.72	0.80	PHYDDS	2.94	0.21
μ_6	0.43	0.14	σ_6	2.39	0.64	WORCON	0.18	0.05
μ_7	1.29	0.60	σ_7	3.29	0.91	CSKILL	0.61	0.04
μ_8	-0.57	0.16	σ_8	2.19	0.54	INTPEOPLE	2.05	0.22
μ_9	3.37	1.19	σ_9	3.93	0.91			
μ_{10}	-2.24	0.67	σ_{10}	1.93	0.50			
μ_{11}	0.49	0.14	σ_{11}	2.38	0.61			
μ_{12}	1.62	0.44	σ_{12}	3.20	1.01			
μ_{13}	0.99	0.30	σ_{13}	2.88	0.77			
μ_{14}	-2.91	0.81	σ_{14}	3.51	0.99			
μ_{15}	2.86	0.77	σ_{15}	2.76	0.93			
μ_{16}	-2.07	0.55	σ_{16}	2.75	0.70			
μ_{17}	-1.35	0.44	σ_{17}	1.35	0.43			
μ_{18}	-2.60	0.68	σ_{18}	2.88	0.89			
μ_{19}	-1.94	0.53	σ_{19}	1.72	0.50			
μ_{20}	-0.64	0.18	σ_{20}	1.23	0.36			
μ_{21}	0.99	0.29	σ_{21}	3.62	1.02			
μ_{22}	1.21	0.34	σ_{22}	3.37	0.94			
μ_{23}	0.58	0.15	σ_{23}	2.34	0.66			
μ_{24}	-1.60	0.45	σ_{24}	2.05	0.62			
μ_{25}	0.43	0.12	σ_{25}	2.17	0.71			
μ_{26}	-2.89	0.74	σ_{26}	2.54	0.80			
μ_{27}	-0.80	0.24	σ_{27}	3.21	0.84			
μ_{28}	-0.32	0.08	σ_{28}	2.11	0.62			
μ_{29}	2.20	0.58	σ_{29}	2.18	0.60			
μ_{30}	1.09	0.37	σ_{30}	3.43	1.03			
μ_{31}	-0.26	0.08	σ_{31}	2.84	0.74			
μ_{32}	0.83	0.24	σ_{32}	1.47	0.35			
μ_{33}	1.89	0.53	σ_{33}	2.55	0.58			
μ_{34}	-0.07	0.02	σ_{34}	1.56	0.41			
μ_{35}	0.44	0.14	σ_{35}	4.10	1.18			
μ_{36}	-0.23	0.07	σ_{36}	0.81	0.26			
μ_{37}	0.80	0.21	σ_{37}	1.52	0.35			
μ_{38}	3.42	0.96	σ_{38}	3.58	0.87			
μ_{39}	-1.05	0.33	σ_{39}	1.97	0.61			
μ_{40}	-1.01	0.30	σ_{40}	2.58	0.66			
μ_{41}	-1.59	0.42	σ_{41}	2.18	0.49			
μ_{42}	-3.43	1.05	σ_{42}	3.69	1.12			
μ_{43}	-0.03	0.01	σ_{43}	1.83	0.51			

Figure 1 – Unconditional Wage Distributions
Equal Variances Across Occupations, No Correlation

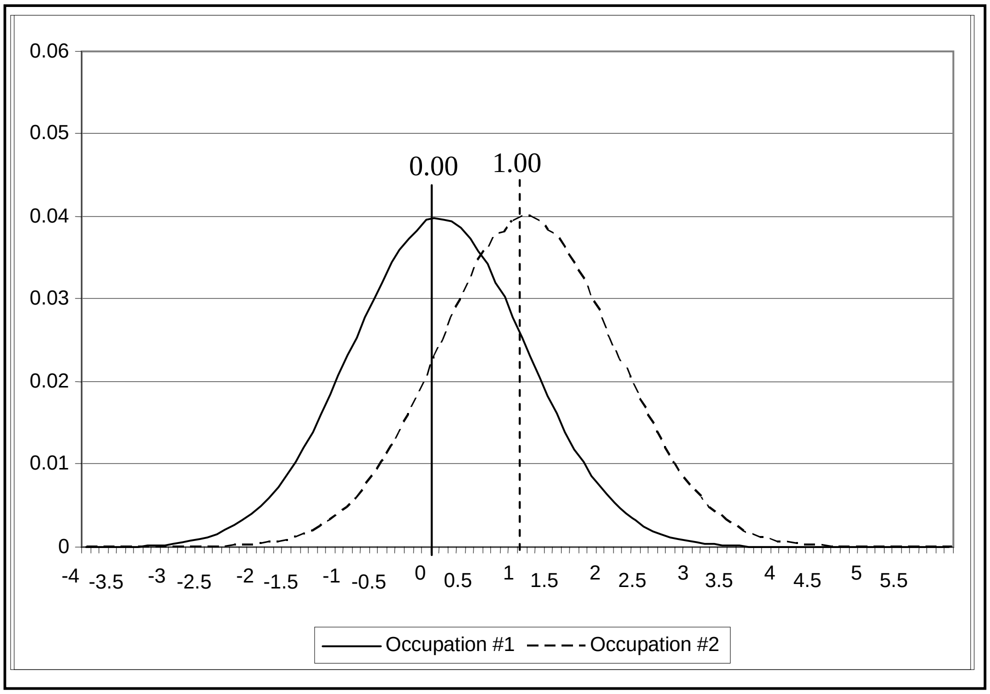

Figure 2 – Conditional Wage Distributions
Equal Variances Across Occupations, No Correlation

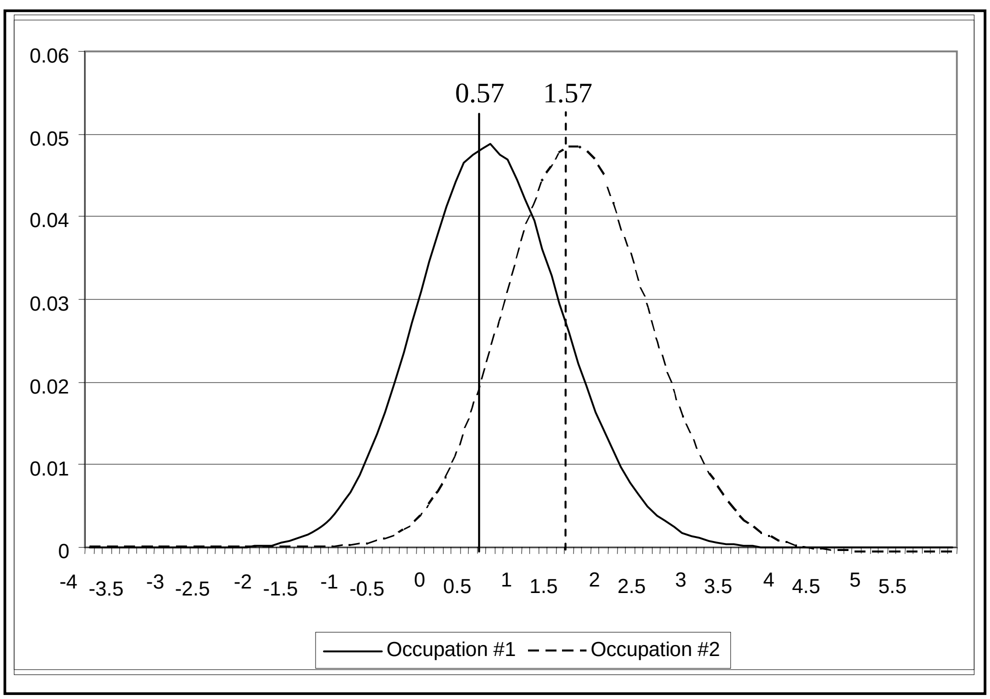

Figure 3 – Unconditional Wage Distributions
Unequal Variances Across Occupations, No Correlation

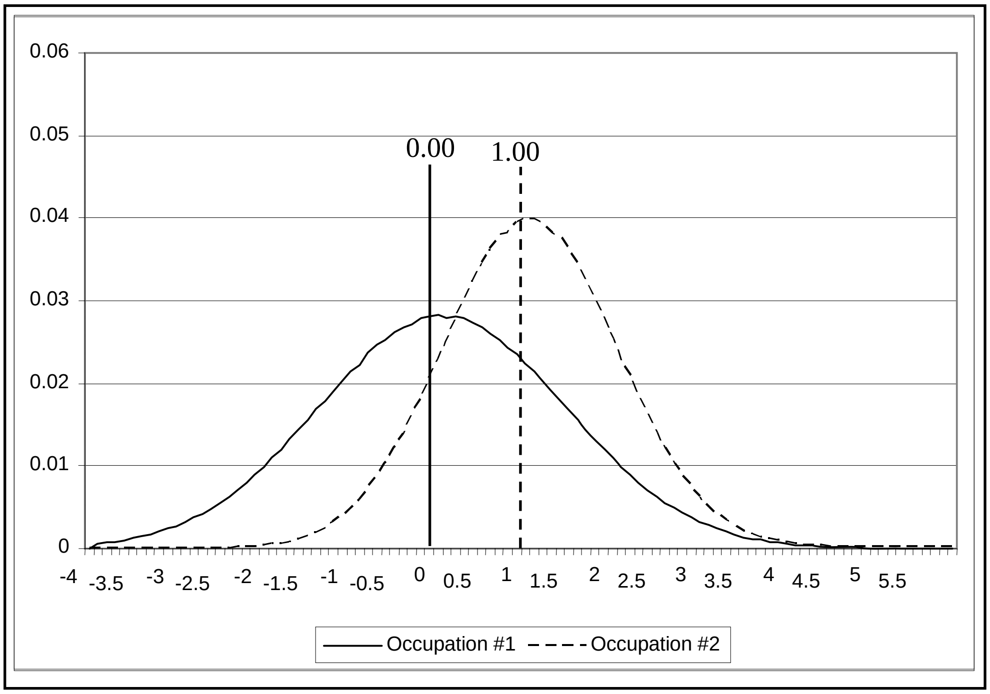

Figure 4 – Conditional Wage Distributions
Unequal Variances Across Occupations, No Correlation

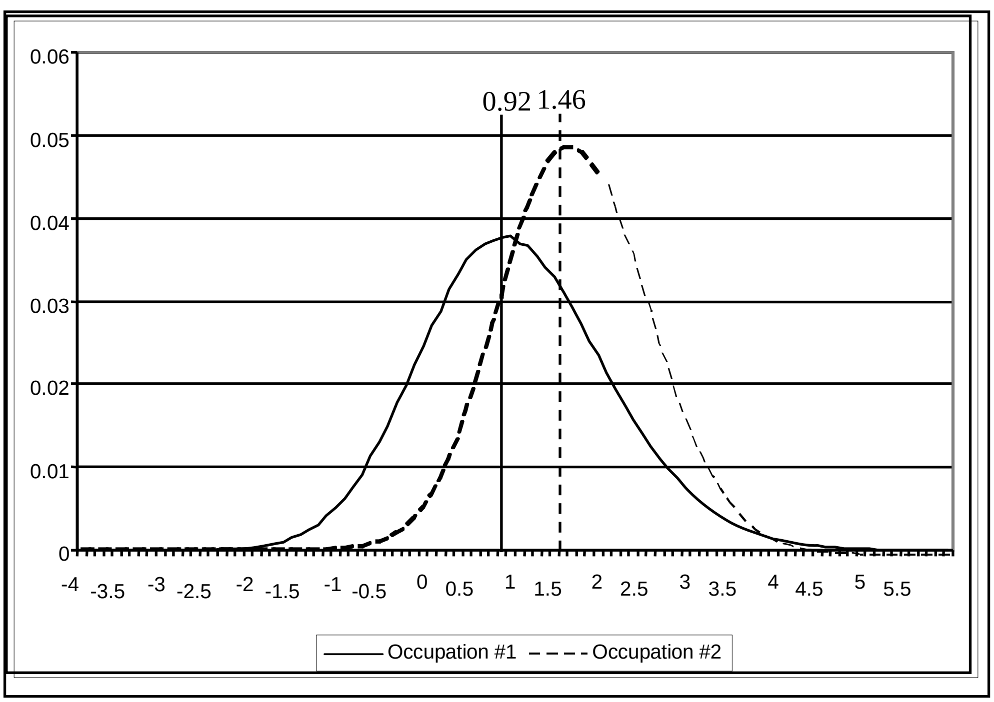

Figure 5 – Conditional Wage Distributions
Unequal Variances Across Occupations, Positive Correlation

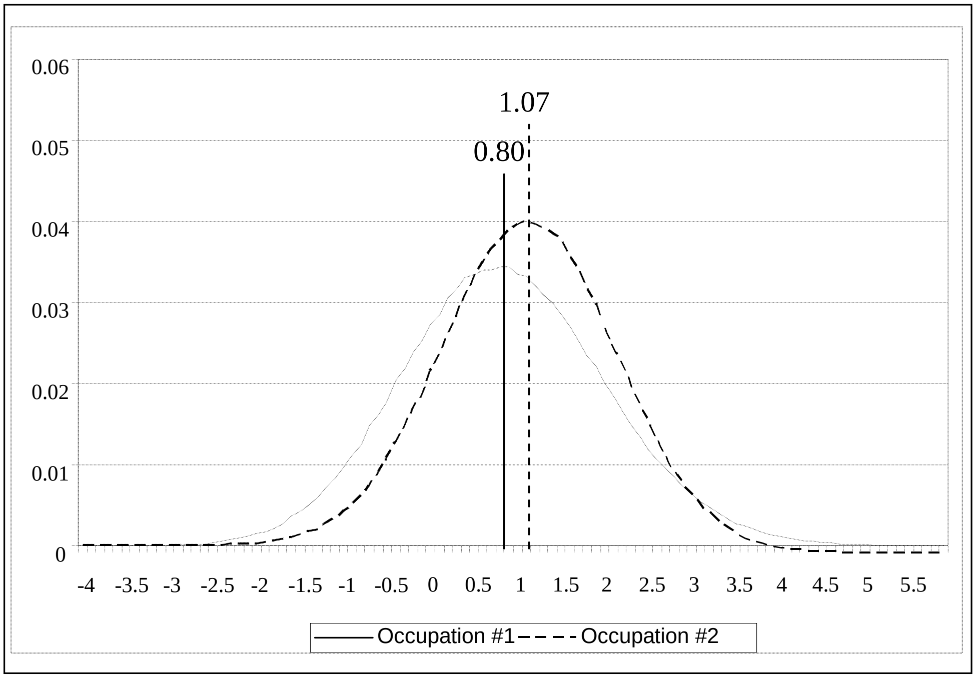

Figure 6 – Conditional Wage Distributions
Unequal Variances Across Occupations, Negative Correlation

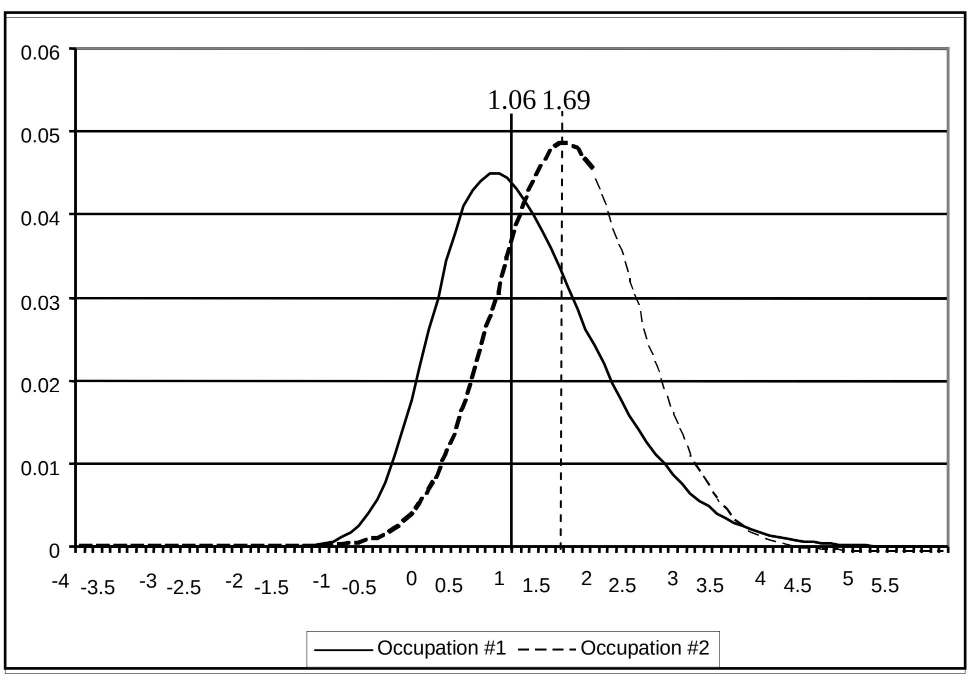

Figure 7

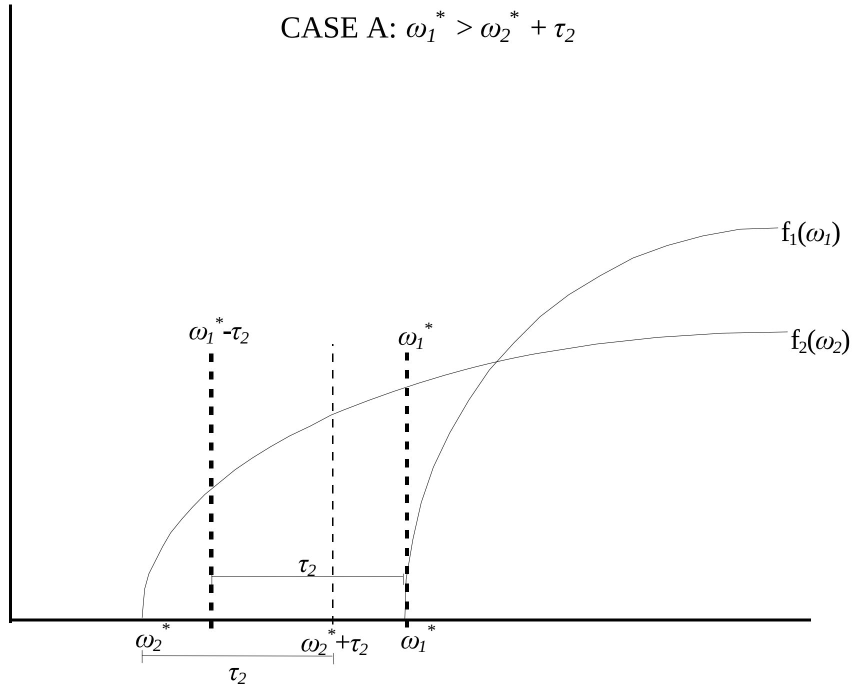

Figure 8