ROY MODEL SORTING AND NON-RANDOM SELECTION IN THE VALUATION OF A STATISTICAL LIFE

Thomas DeLeire

Shakeeb Khan

and

Christopher Timmins

July 2011

Abstract

Wage-hedonics is used to recover the value of a statistical life (VSL) by exploiting the fact that workers who choose riskier occupations will be compensated with a higher wage. However, Roy (1951) suggests that observed wage distributions will be distorted if individuals select into jobs according to idiosyncratic returns. We describe how this type of sorting may bias wage-hedonic VSL estimates and then implement a pair of new estimation strategies that correct that bias. Using data from the CPS, we recover VSL estimates that are three to four times larger than those based on the traditional techniques, 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, Matt Kahn, John List, Chris Rohlfs, Laura Taylor, Joe Terza, and all the participants in the Duke Applied Microeconomics Lunch, the Yale and Earth Institute Environmental Economics Seminars, the ASHE biannual meetings, the NBER Summer Institute, and the University of Chicago econometrics workshop for their helpful comments. *Contacts*: Thomas DeLeire, La Follette School of Public Affairs and Department of Population Health Sciences, University of Wisconsin-Madison, 1225 Observatory Drive, Madison, WI 53706. deleire@wisc.edu. Shakeeb Khan and Christopher Timmins, Department of Economics, Duke University, PO Box 90097, Durham, NC 27708. shakeebk@econ.duke.edu, christopher.timmins@duke.edu.

ROY MODEL SORTING AND NON-RANDOM SELECTION IN THE VALUATION OF A STATISTICAL LIFE

Abstract

Wage-hedonics is used to recover the value of a statistical life (VSL) by exploiting the fact that workers who choose riskier occupations will be compensated with a higher wage. However, Roy (1951) suggests that observed wage distributions will be distorted if individuals select into jobs according to idiosyncratic returns. We describe how this type of sorting may bias wage-hedonic VSL estimates and then implement a pair of new estimation strategies that correct that bias. Using data from the CPS, we recover VSL estimates that are three to four times larger than those based on the traditional techniques, statistically significant, and robust to a wide array of specifications.

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

JEL Classification: J17, J31

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 pair of new empirical strategies to correct for this source of bias. In particular, we employ methodology introduced by Bayer, Khan, and Timmins (2011) to control for polychotomous selection when individuals care about more than just pecuniary returns. This technique extends 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. For example, we estimate the VSL for men aged 18-60 to be roughly three

[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.

to four times larger (and statistically significant) when we correct for "Roy sorting" than the VSL based on the same data but estimated with traditional techniques. We find this bias, moreover, in age-specific VSLs that exhibit patterns similar to those found by previous researchers. Our estimates of VSLs 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 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 estimators deal with (or fails to address) some other well-known problems with the wage-hedonic approach. Section 4 describes the data we use to implement our modeling strategies, 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 5 outlines our estimation strategies, which identify workers' risk preferences in the presence of Roy sorting. The first is based on standard Roy modeling assumptions – linearity and independence; the second relaxes the strong distributional assumptions and replaces independence with a weaker condition – extreme quantile independence. Section 6 reports the results of our estimation procedures alongside results derived from a traditional wage-hedonic procedure, and discusses the results of a number of alternative model specifications. Section 7 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 the 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 can be illustrated in a simple example. In an economy 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). In particular, 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.[3] Heckman and Honoré (1990), however, prove that these unconditional distributions cannot be recovered without first assuming a value for the correlation in individuals' wage draws across occupations. 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 needs 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 5, we demonstrate how one can avoid this problem and correct the sorting bias in the VSL (i) without knowing the unconditional wage distributions and (ii) with only very weak assumptions about the correlation in individuals' wage draws across occupations. Our proposed procedures yield estimates of the VSL that are three times larger than that derived from the traditional wage-hedonic technique.

Before proceeding, we pause briefly to note that our focus is on identification strategies that do not rely upon covariates. Identification of the Roy model is difficult (even without the introduction of non-pecuniary tastes) under the sorts of arbitrary correlation patterns that we allow for; it has generally been shown to require some form of "identification at infinity". We rely on a similar argument. That said, the introduction of covariates (if motivated by a valid exclusion restriction) could relax, to a certain extent,

[3] 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.

the need for such an assumption. We do not, however, have such a motivation for any of the covariates available to us in this application.

While our preferred estimator is straightforward to implement and does not depend upon covariates, it does require a lot from the data – in particular, estimates of the minimum order statistics associated with each of a number of conditional wage distributions. While the quality of the wage data we use in our empirical application is quite high, we concede that in many applications measurement error and outliers can make it difficult to accurately estimate the minimum order statistic, which would complicate the implementation of our extreme quantile estimator.

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

The wage-hedonic technique has been both extensively used and rigorously scrutinized for decades. Even with all its problems, however, it remains prevalent in policy making. In this section, we present a brief overview of the large literature on the VSL. Viscusi and Aldy (2003) provide a comprehensive discussion, 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 addressed in earlier work with 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)] Our preferred estimation approach 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 upward 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 estimator, in its current form, is 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. While we do not employ data of this sort, our estimation approach does permit distaste for fatality risk to be modeled as a function of these sorts of observable characteristics.[4]

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.[5] 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.[6] 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 VSLs 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

[4] 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.

[5] Notable exceptions include Viscusi and Aldy (2006), who find that VSLs follow an inverted-U pattern in age, and Alberini et al (2004), who find lower VSLs 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 VSLs for older individuals.

[6] Lott and Manning (2000) use a hedonic wage method to estimate compensating differentials for exposure to environmental concinogens in the workplace.

[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.

4. DATA

We use data from three different sources for our estimate strategy. 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,

---

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.

including the median number of days missed from work per injury within an occupation.[8] 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.[9] 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).[10] 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. Average annual risk of death on 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. 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

[8] Note that simply being able to miss days from work after a non-fatal injury may be a positive amenity associated with many jobs.
[9] 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.
[10] A full-time worker is assumed to work 2,000 hours/year, so that the risks we calculate are per 200,000 hours worked.

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 less than one death per 10,000 workers each year.

The data used to construct hourly wage rates for our analyses 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).[11] 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.[12] The focus of our investigation is therefore on "hourly" workers. This group has received much of the attention in previous VSL studies. [Viscusi and Aldy (2003)]

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.[13] 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,

[11] 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.
[12] In Section 6.3, we do report a separate set of results for salaried workers.
[13] 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).

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 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.

5. IDENTIFICATION

5.1 Estimation Strategy #1: Normality and Independence

We begin by describing a simple estimation strategy that corresponds to the traditional normal Roy model, but incorporating non-pecuniary returns; for a detailed description, see Bayer, Khan and Timmins (2011). Unlike the estimator described in the following subsection, this model relies on an independence assumption, but requires no assumptions about wage distributions' supports. Instead, it relies upon two alternative identifying assumptions: (i) the unconditional distribution of log-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.[14]

To explain this estimator, we consider a simple model of individuals sorting over two occupations, indexed by #1 and #2. Without loss of generality, we normalize the

[14] This latter assumption also underlies the traditional wage-hedonic model estimated with cross-sectional data (with panel data, individual fixed effects have been used to control for unobserved worker productivity).

taste for occupation #1 to zero ($\tau_1 = 0$). We also assume that there is no idiosyncratic component to the taste parameter (i.e., we assume that utility is a function of τ_j instead of $\tau_{i,j}$). There are two important points to make about this assumption. First, a similar assumption underlies the derivation of the traditional hedonic model.[15] As is the case for that model, we can run our estimator separately for different observable types of individuals, subsequently allowing taste parameter estimates to vary with observable individual attributes. Allowing tastes to vary with idiosyncratic individual unobservables is more difficult. If utility is a function of idiosyncratically unobservable tastes, our model (and likewise the traditional wage-hedonic model) may yield biased estimates of average tastes, τ_j. In our model, there is no reason *a priori* to expect that bias to go in a particular direction when τ_j is decomposed into its constituent job attributes (one of which is fatality risk). We describe this decomposition procedure below, along with the circumstances under which we would expect the bias in τ_j to be upward or downward in a simple two-sector model.

We define a variable d_i, which functions as an indicator that individual i chose occupation #1:

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

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

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

[15] One exception to this is the model described in Bajari and Benkard (2005).

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

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

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

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

Focusing on the expression for $\Psi_1(t)$, we exploit the assumption that wage draws (conditional on observable individual attributes) are assumed to be independent across sectors to re-write it as follows:

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

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

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

This means that $\psi_1(t)$ can be defined as:

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

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

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

Going back to the final integral in equation (5) and carrying out integration-by-parts yields:

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

Performing a change of variables, $u = s - \tau_2$, equation (8) becomes:

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

Next, we use the expressions for $\psi_1(t)$ and $\psi_2(t)$ defined in (6) and (7) to re-write equation (9) as follows:

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

Noting that the integral term in (10) is simply $\Psi_2(t-\tau_2)$, we can solve for the distribution of ω_1 as a function of τ_2:

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

where $\lambda_1(t)$ is a function of the unconditional wage distribution in location #1. (11) is a single equation in two unknowns ($\lambda_1(t)$ and τ_2) when evaluated at a particular value of t, and therefore we ***cannot*** identify both of these values without making an additional assumption. Thus we first attain identification by assuming normality of the wage distributions. Assuming $F_1(t)$ is the cumulative normal distribution with mean μ_1 and variance σ_1^2 would, however, reduce equation (11) to three parameters. That number of parameters does 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 therefore have more equations than unknowns and can easily identify the model's parameters. In fact, the overidentification immediately allows for the possibility dropping the independence assumption, and assuming a bivariate normal distribution in the two location model. However, as the number of locations increases, estimating all the pairwise correlation parameters in a multivariate normal distribution becomes intractable for a large number of locations as in our empirical setting.

The preceding derivations scale-up naturally to any number of occupations. We can, therefore, estimate the model in our occupational sorting context by forming a minimum-distance criterion function based on equation (11). In our application, minimizing this objective function would require us to search over a high-dimensional parameter space (i.e., forty-three means, forty-three variances, and forty-two taste parameters, which could then be regressed on a vector of job attributes).[16] As mentioned, the dimension grows even larger if we were to dropt the independence assumption. We therefore maintain independence and make one further simplifying assumption in order to facilitate estimation; in particular, we write the taste parameter as a function of observable occupation attributes, $\tau_j = X'_j\beta$, normalizing the intercept in the taste decomposition to zero. We therefore need to only estimate eight β parameters instead of a separate τ_j for each occupation.

5.2 Estimation Strategy #2: Extreme Quantile Estimator

Our second approach to identification relaxes the strong assumption of independence across wage draws (which recall was not required theoretically but needed for implementation with a large number of locations) as well as the normality assumption on the marginal distributions of wages. As will be described below, we replace these two assumptions with a support condition as well as a quantile independence condition. Relaxing the complete independence assumption of the previous section can prove important in properly controlling for the bias in the estimated value of fatality risk reduction. As in the previous sub-section, we describe our identification strategy with a simple model of sorting by individuals into one of two occupations (j = 1, 2). We begin by modeling individual i's utility from choosing occupation j as the sum of wages ($\omega_{i,j}$) and tastes (τ_j):

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

(12) $U_{i,j} = \omega_{i,j} + \tau_j$

As in the previous subsection, we assume that there is no idiosyncratic component to the taste parameter. Without loss of generality, we again normalize $\tau_1 = 0$. At this point, the goal of our exercise is to recover an estimate of τ_2. 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:

(13) $\omega_{i,2} + \tau_2 \geq \omega_{i,1}$

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

(14) $\omega_{i,2} + \tau_2 < \omega_{i,1}$

Denote the smallest wage (i.e., the minimum order statistic) that we observe from someone choosing occupation #1 or #2 by $\underline{w}_1$ and $\underline{w}_2$, respectively.

Next, we assume that the unconditional distributions of ω_1 and ω_2 have finite lower points of supports (or extreme quantiles) denoted by ω_1^* and ω_2^*. Our main assumption used for identification is that the lowest possible wage draw an individual can receive in one occupation is independent of the actual wage draws received in other occupations. We refer to this condition as "extreme quantile independence". That is, one particular conditional quantile of the first random variable (in our case, the extreme lower support point), does not vary with the value of the other random variable. Note this assumption is weaker than the full independence assumption, which would impose that every conditinal quantile of the first random variable is invariant to the value taken by the second random variable. Under this assumption, we know the smallest value of ω_1 that we could ever see, given that individuals maximize utility, is:

$$(15) \qquad \begin{aligned} \underline{w}_1 &= \omega_1^* && \text{if} \quad \omega_1^* > \omega_2^* + \tau_2 \\ \underline{w}_1 &= \omega_2^* + \tau_2 && \text{if} \quad \omega_1^* \le \omega_2^* + \tau_2 \end{aligned}$$

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

$$(16) \qquad \begin{aligned} \underline{w}_2 &= \omega_2^* && \text{if} \quad \omega_1^* \le \omega_2^* + \tau_2 \\ \underline{w}_2 &= \omega_1^* - \tau_2 && \text{if} \quad \omega_1^* > \omega_2^* + \tau_2 \end{aligned}$$

In order to make sense of (15) and (16), define the following two cases:

$$(17) \qquad \begin{aligned} A&: \quad \omega_1^* > \omega_2^* + \tau_2 \\ B&: \quad \omega_1^* \le \omega_2^* + \tau_2 \end{aligned}$$

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.[17] In particular:

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

Equation (18) therefore describes our minimum order statistic estimator for τ_2 in the simplest two-occupation case. Figures 1 and 2 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 return briefly to the question of bias if the true data generating process is characterized by idiosyncratic tastes ($\tau_{i,j}$), whereas the model assumes common tastes (τ_j). If case A prevailed, there could be some individual with both a very low wage draw and a very high draw for $\tau_{i,2}$. If this individual's draw for $\tau_{i,2}$ was large enough, she could be compelled to accept a wage draw as low as ω_2^* (i.e., $\underline{w}_2 = \omega_2^*$). In this case, our estimator would report $\tau_2 = \underline{w}_1 - \underline{w}_2 = \omega_1^* - \omega_2^*$, which would be the largest possible case of upward bias in the average τ_2.

Alternatively, in case B, there may be some individual who gets a very small wage draw in both sectors (i.e., ω_1^* and ω_2^*), but who also has a very small value of $\tau_{i,2}$ (in

[17] By exploiting information contained in the extreme tails of the wage distribution, this approach has much in common with the "identification at infinity" strategy for estimating treatment effects under selection described in Heckman (1990).

particular, $\tau_{i,2} < \omega_1^* - \omega_2^*$). This individual would be compelled to accept a wage draw in sector #1 equal to ω_1^*, so that $\underline{w}_1 = \omega_1^*$. Presuming there are other individuals with larger $\tau_{i,2}$'s, $\underline{w}_2 = \omega_2^*$. Our model would therefore yield an estimate of the mean taste $\tau_2 = \underline{w}_1 - \underline{w}_2 = \omega_1^* - \omega_2^*$, which is downwardly biased.

While it is simple to explain the direction of the bias in each case for the simple two-sector model, things become far more complicated in our application with forty-three occupations. The estimation remains straightforward, but the number of potential "cases" becomes very large. Moreover, there is no reason to expect that any particular τ_j (or the subsequent estimates of the marginal disutility of fatality risk based on those τ_j estimates) should be biased in one direction or the other because of idiosyncratic tastes. We therefore proceed assuming that utility is a function of common tastes.

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 (except at the extreme quantile). Correlations at all other quantiles that are positive, negative, or zero are all consistent with this model. Identification relies only on differences in the supports of different conditional wage distributions. This requires that the wage draw in one sector does not affect the lower support of the wage distribution in the other sector. The strength of this approach is, however, that it does not require us to make any assumptions about the dependence of any other quantile of one wage distribution on draws from another.

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:

$$
\begin{aligned}
w_i \quad = \quad & \omega_{1,i} I[\omega_{1,i} > \max(\omega_{2,i} + \tau_2, \omega_{3,i} + \tau_3)] + \\
& \omega_{2,i} I[\omega_{2,i} + \tau_2 > \max(\omega_{1,i}, \omega_{3,i} + \tau_3)] + \\
& \omega_{3,i} I[\omega_{3,i} + \tau_3 > \max(\omega_{1,i}, \omega_{2,i} + \tau_2)]
\end{aligned} \tag{19}
$$

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:

$$
\begin{aligned}
\underline{w}_1 &= \min(w_i \mid d_{1,i} = 1) = \max(\omega_1^*, \omega_2^* + \tau_2, \omega_3^* + \tau_3) \\
\underline{w}_2 &= \min(w_i \mid d_{2,i} = 1) = \max(\omega_1^*, \omega_2^* + \tau_2, \omega_3^* + \tau_3) - \tau_2 \\
\underline{w}_3 &= \min(w_i \mid d_{3,i} = 1) = \max(\omega_1^*, \omega_2^* + \tau_2, \omega_3^* + \tau_3) - \tau_3
\end{aligned} \tag{20}
$$

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, …, 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.[18]

$$\tau_j = X'_j \beta + \varepsilon_j \tag{21}$$

6. RESULTS

6.1 Traditional Wage-Hedonic Model

In this section, we describe the results of three 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:

$$w_{i,j} = \alpha_0 + Z'_i \alpha_1 + \alpha_2\, FATAL_j + X'_j \alpha_3 + \varepsilon_{i,j} \tag{22}$$

where i indexes workers and j indexes forty-three occupation categories.[19] Z is a vector of variables describing worker i including:

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

[18] This assumes, of course, that E[εX] = 0, which may be violated if there are important omitted job characteristics. In our application, we deal with this concern directly by employing the best available data describing occupation attributes. Alternatively, if one believed that correlated unobservable job attributes were time invariant, and if one could exploit time variation in fatality risk, it would be possible to estimate multiple taste parameters (i.e., a different vector for each time period), pool them over time, and include occupation fixed effects in equation (16) to deal with the endogeneity. See, for example, the data used by Costa and Kahn (2004) in their analysis of changes in the VSL from 1940-1980.

[19] We also estimated a set of traditional wage-hedonic specifications using the natural log of hourly wages as the dependent variable. These specifications yield a statistically significant and positive relationship between fatal risk and male wages and a statistically significant, but negative relationship between fatal risk and female wages.

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:

$$(23) \qquad w_{i,j} = \alpha_0 + Z_i'\alpha_1 + \alpha_2\, FATAL_j + X_j'\alpha_3 + (X_j d_{coll})'\alpha_4 + (X_j d_{AGE>40})'\alpha_5 + \varepsilon_{i,j}$$

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. At this stage of the analysis, we restrict our estimate of the compensating differential in wages (and, hence, the VSL) to be constant across worker attributes, but we relax this assumption below.

We then take the estimate of the marginal willingness-to-pay to avoid fatality risk, α_2, and scale this up by a typical 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.

Table 4a describes the results of regression equations (22) and (23) for both men and women where the dependent variable is the hourly wage. Table 4b describes the corresponding results where the dependent variable is the log hourly wage. 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.[20,21] 95% confidence intervals, which were calculated allowing for clustering at the occupation level, were computed using an $m(n)/n$ bootstrap method.

6.2 Results: Normality and Independence

The practical difficulty in applying each of the estimators discussed in section 5 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 (we provide some results along these lines in subsection 6.4). An advantage of such an approach would be that we would be able to estimate taste parameters that vary with observable individual attributes. 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. At the other extreme, we could choose not to control for individual attributes at all, but then we would derive our measure of the VSL from the wages and occupation choices of a potentially unrepresentative group. In this and the following subsection, we therefore

[20] 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 mismeasured wages, particularly in the lower tail of the wage distribution. Results without lower trimming are reported in the sub-section 6.2.

[21] 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.

adopt a two-stage estimation procedure that introduces some parametric modeling.[22] We first estimate a regression of the form:

$$(24) \qquad \hat{w}_{i,j} = \beta_0 + Z_i'\beta_1 + u_{i,j}$$

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:[23]

$$(25) \qquad \xi_{i,j} = w_{i,j} - \beta_0 - Z_i'\beta_1$$

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.[24]

Table 5 describes the outcome of the normal Roy sorting model with non-pecuniary returns applied to the sample of male hourly workers earning more than the federal minimum wage.[25] We evaluate a minimum distance criterion function based on

[22] 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.
[23] 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.
[24] 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. We have also estimated specifications that relax this assumption as well as specifications that allow the effect of worker characteristics to vary by occupation. These specifications, available upon request, yield minimum order statistics that are very similar to those obtained from the specification presented in this paper.
[25] 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 (25)).

equation (11) at 200 values of log-wages evenly spaced between 0.25 and 4.25.[26] 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 for men rate in the sample ($13.16). The result is a statistically significant VSL estimate of $8.05 million; we compare this result to the results of our extreme quantile and traditional wage-hedonic procedures below.

6.3 Results: Extreme Quantile Estimator

We carry-out a comparable set of specifications of our extreme quantile estimator. 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:

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

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

(27) $$\tau_j = \theta + \beta_2\, FATAL_j + X_j'\beta_3 + \upsilon_j$$

[26] Bayer, Khan, and Timmins (2011) 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.

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 (27).

Bayer, Khan, and Timmins (2011) describes the asymptotic distribution of these estimates, which proves to be quite complicated. A natural alternative for inference is the bootstrap. We cannot, however, employ the naive bootstrap, as it has been well established that the bootstrap distribution of an extreme order statistic converges in distribution to a random probability measure. Papers that have established the inconsistency of the bootstrap in the extreme quantile setting include Bickel and Friedman (1981), Angus (1993), Knight (1989), and Andrews (2000). It is also well known, however, that a modified bootstrap procedure based on choosing a bootstrap sample of size $m(n)$, where $m(n)$ converges to infinity and $m(n)/n$ converges to 0, will work; see Swanepoel (1986) as well as Bretagnolle (1983) and Datta and Mc Cormick (1995). Recently, Deheuvels et al. (1993) have derived a natural range of rates for $m(n)$. In particular, we conduct 1000 of these bootstrap simulations for each specification, from which we derive symmetric 95% confidence intervals.[27] Results are consistent with expectations – workers exhibit a strong and statistically significant disutility from increased fatality risk.[28]

[27] 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.

[28] 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.

One might reasonably be concerned with the effect of measurement error and outliers on the performance of this estimator. Put simply, if the differences between minimum order statistics are driven by outliers or mis-measured data, this will filter through the model and drive our point estimate of the marginal utility associated with each job attribute. We take comfort, however, from the fact that our estimates are nearly always statistically significant. If our estimates were, in fact, being driven by outliers or many forms of measurement error, we would expect this to be reflected in large standard errors calculated by our bootstrap procedure.[29]

Tables 6 and 7 report the results of our extreme quantile 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. Tables 6a and 6b report results where the dependent variable is the hourly wage, while Tables 7a and 7b report results where the dependent variable is the log hourly wage. Tables 6a and 7a report results for equation (24), while Tables 6b and 7b report the results of equation (27). Also reported are 95% confidence intervals derived from the $m(n)$ bootstrap.

Table 8a summarizes the VSL estimates from both the traditional wage hedonic and extreme quantile estimators for each of the specifications described above when the dependent variable is the hourly wage. Looking only at point estimates for men, the extreme quantile estimator produces VSL estimates ($13.43 and $12 million) that are 2.7 and 4.3 times greater than those produced by the traditional wage hedonic procedure. These estimates are, moreover, statistically significant with a 95% confidence interval

[29] That is, any particular m(n) sample would be unlikely to contain the problematic observation, producing a very different point estimate.

ranging from approximately $5 million to almost $16 million. The log-wage hedonic specification (see Table 7b) yields estimates of the VSL for men that are even lower than those based on the wage level ($1.76 and $1.02 million). The extreme quantile estimates of the VSL are, however, still much larger ($10.48 and $9.28 million), allowing us to reject the hypothesis that the VSLs estimated by traditional wage-hedonic methods are equal to those estimated from extreme quantiles.

Comparing these results with the results of the estimator based on normality and independence, it is clear that controlling for Roy sorting (even with strong distributional and independence assumptions) has important implications for measuring the VSL. Assuming independence and normality, and using log-wages as the dependent variable, our estimated VSL for the sample of males ($8.05 million) is significantly larger than either of the wage-hedonic estimates ($1.76 and $1.02 million). This result is, however, similar to that derived from the extreme quantile estimator ($10.48 and $9.28 million), even though the assumptions and methodology used to arrive at the two sets of estimates differ dramatically. Taken together, the results of these two methodological approaches support one another, leading us to conclude that the VSL based on traditional wage-hedonic techniques is indeed biased downward by Roy sorting.

Up to this point in the discussion, we have focused our attention on results for males (as does most of the literature on the VSL). For women, however, the difference in results between the modeling strategies is even starker. The extreme quantile estimator yields results that are similar to those for men – $7.95 or $11.76 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 for women. In all cases, we can reject the hypothesis that the VSLs estimated by traditional wage-hedonic methods are equal to those estimated from minimum order statistics.

6.4 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. Tables 9a and 9b report the VSL estimates arising from twelve alternatives. We note at the outset that in these subsamples, the traditional wage-hedonic procedure typically does not produce a statistically significant estimate, and for women, most of the point-estimates have the wrong sign. Table 9a reports the results from the hourly wage specifications while Table 9b reports the results from the log hourly wage specifications. The first row of Table 9a 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.[30,31] 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 difference goes away when considering women, and is not present for men or women when using the traditional wage-hedonic estimator.

The next two rows describe how the VSL estimates vary with the time period of analysis. If we restrict our data to the 1983 to 1992 period, we obtain larger estimates for men of the VSL based on minimum order statistics while if we restrict the data to the 1993 to 2002 period, we get smaller estimates for men.[32] For women, the estimates of the VSL based on minimum order statistics are, by contrast, larger in the latter period.

The final two rows of Tables 9a and 9b illustrate two cases in which our method may not perform well. In the first, we restrict ourselves to using a limited set of worker

[30] 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.

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

[32] The occupational risk measure we use is based on the average occupation mortality rate from 1992-1999 (the data are not available prior to 1992). To the extent that occupational mortality rates were substantially higher in the 1983-1992 period than in the 1993-2003 period, the use of occupational mortality rates from the late period may lead to an overestimate of the VSL in the early period.

attributes (AGE, AGE2, HSDROP, SOMECOLL, COLLGRAD). This has the effect of reducing the variability across occupations in the lower bound of our wage distributions.[33] 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 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. 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

[33] 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.

empirical problem that depends partly upon the relative variances of the unconditional sector-specific wage distributions.

We demonstrate a way to deal with Roy sorting bias without recovering the unconditional wage distributions and without relying upon distributional assumptions. Doing so requires the relatively innocuous assumptions that wage distributions have finite lower support points, and that those lower support points are independent of draws in other sectors (i.e., extreme quantile independence). Note, however, that our approach does not assume anything about the correlation between wage draws in different sectors for any other quantiles. As such, in addition to controlling for the biases induced by Roy sorting, this 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 strong practical assumption that we can accurately measure the minimum order statistic associated with conditional wage distribution. For some (small, noisy) data sets, this will clearly not be the case.

The conclusions of our empirical application are that traditional wage-hedonic techniques yield significantly 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 while estimates for women become positive and of similar magnitude as those for men.

The EPA has recently reduced the VSL it uses for policy analysis to $7.22 million from $8.04 million. This reduction will have important implications for which policies pass EPA cost-benefit analysis. Both numbers are based on meta-analyses of VSL studies, which focus almost exclusively on hedonic-wage techniques. Our 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.

Andrews, D.W.K. (2000). "Notes and Comments: The Inconsistency of the Bootstrap when a Parameter is on the Boundary of the Parameter Space." *Econometrica*. 68(2):399-405.

Angus, J.E. (1993). "Asymptotic Theory for Bootstrapping the Extremes." *Commun. Statist. Theory Meth*. 22(1):15–30.

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 (2011). "Nonparametric Identification and Estimation in a Roy Model With Common Nonpecuniary Returns." Journal of Business and Economic Statistics. 29(2): 201–215.

Bajari, P. and C.L. Benkard (2005). "Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach." *Journal of Political Economy*. 113(6):1239-1276.

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.

Bickel, P.J. and Freedman, D.A. (1981). "Some Asymptotic Theory for the Bootstrap." *Annals of Statistics*. 9:1196–1217.

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.

Bretagnolle, J. (1983). "Lois Limites du Bootstrap de Certaines Fonctionnelles". *Ann. Inst. Henri Poincaré.* 19:281–296.

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.

Costa, D. and M. Kahn (2004). "Changes in the Value of Life, 1940-1980." *The Journal of Risk and Uncertainty*. 29(2):159-180.

Datta, S. and W.P. McCormick (1995). "Bootstrap Inference for a First-Order Autoregression with Positive Innovations." *Journal of the American Statistical Association*. 90:1289–1300

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

Deheuvels, P., D.M. Mason, and G.R. Shorack (1993). "Some results on the influence of extremes on the bootstrap." *Ann. Inst. Henri Poincaré*. 29:83–103.

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. (1990). "Varieties of Selection Bias." *American Economic Review*. 80(2):313-18.

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.

Knight, K. (1989). "On the Bootstrap of the Sample Mean in the Infinite Variance Case." *Annals of Statistics.* 17:1168-1175.

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

Lott, J.R. and R.L. Manning (2000). "Have Changing Liability Rules Compensated Workers Twice for Occupational Hazards? Earnings Premiums and Cancer Risks." *Journal of Legal Studies*. 29:99-130.

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	SUBSTANTIVECOMPLEXITY
	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	MOTOR SKILLS
	CLRDISC (color discrimination)
	FNGRDXT (finger dexterity)
	MNLDXTY (manual dexterity)
	MTRCRD (motor coordination)
	THINGS (complexity in relation to things)
Factor 3	PHYSICAL DEMANDS
	CLIMB (climbing, balancing)
	EYHNFTC (eye-hand-foot coordination)
	HAZARDS (hazardous conditions)
	OUT (outside working conditions)
	STOOP (stooping, kneeling, crouching, crawling)
Factor 4	WORKING CONDITION
	COLD (extreme cold)
	HEAT (extreme heat)
	WET (wet, humid)
Factor 5	CREATIVE SKILLS
	ABSCREAT (abstract & creative activities)
	FIF (feelings, ideas or facts)
Factor 6	INTPEOPLE
	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	-0.2694
7-22: Other Exec.	0.0020	1.4982	0.6143	1.1082	-0.4853	-0.3941	-0.1763	-0.3935
23-37: Management	0.0009	1.3879	0.9138	1.1947	-0.7276	-0.4849	-0.1829	-0.2586
44-59: Engineers	0.0023	1.0150	1.3207	-0.9070	-0.4879	-0.4232	0.4608	-1.3702
64-68: Mathematical and Comp Sci	0.0004	0.6365	1.1708	1.3192	-0.6439	-0.5881	-0.0977	-0.2871
69-83: Natural scientists	0.0023	0.8725	1.3793	-0.9374	-0.3347	0.3333	0.0038	-1.3461
84-89: Health diagnosers	0.0011	1.8691	1.8017	-3.1622	-0.5097	-0.5521	-0.4203	-3.1264
95-106: Health assess & treat	0.0007	5.1230	0.6012	-0.9513	-0.4469	-0.5923	-0.3494	-0.4050
113-154: Professors	0.0005	0.2670	1.6046	1.4303	-0.8375	-0.5982	-0.1342	-0.8641
155-159: Teachers (exc. coll.)	0.0005	1.2979	0.9016	0.3525	-0.3597	-0.5881	0.9809	-1.0559
178-179: Lawyers & judges	0.0012	0.3306	2.0665	1.7181	-0.9118	-0.6018	4.1324	-1.6702
43,63,163-177,183-199: Oth. prof. spec.	0.0011	2.2276	1.1812	0.1353	-0.5487	-0.0945	4.1225	-1.2298
203-208: Health tech.	0.0009	8.6382	0.0277	-1.0334	-0.3174	-0.4868	-0.3592	-0.1885
213-225: Eng/sci tech.	0.0020	4.2027	0.5435	-1.4970	-0.4499	-0.4413	-0.0645	-0.7843
226-235: Tech, not eng/sci	0.0096	5.5567	0.7081	0.4057	-0.5408	-0.5718	-0.0134	-0.5043
243: Sales supervisors	0.0033	3.5027	0.4089	1.0263	-0.2950	-0.3658	-0.0998	-0.2668
253-257: Sales reps and business	0.0012	1.5427	0.6899	1.2582	-0.8207	-0.5888	-0.3644	0.2252
258-259: Sales reps, non-retail comm.	0.0016	2.0476	0.2529	1.0859	-0.8616	-0.5615	-0.3929	0.3773
263-278: Sales work, retail & svc.	0.0020	5.3078	-0.4732	-0.2793	-0.7061	-0.5062	-0.3788	0.4036
283-285: Sales-related occupations	0.0000	5.8560	-0.0287	-0.0613	-0.8066	-0.5784	0.7758	0.2225

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	-0.1069
308-309: Computer operators	0.0000	1.7641	-0.0650	-0.4041	-0.5568	-0.6022	-0.4023	-0.4457
313-315: Secretaries	0.0003	2.0029	0.3957	-1.9561	-0.9030	-0.5939	-0.4176	-0.4713
337-344: Fin. record process	0.0002	2.1631	-0.1916	-0.4688	-0.8965	-0.5598	-0.4209	0.1085
354-357: Mail/msg dist.	0.0025	11.5449	-1.1516	0.5619	-0.6374	-0.4628	-0.4289	1.1268
316-336,345-353,359-389: other admin.	0.0005	6.3292	-0.3962	0.5455	-0.7559	-0.4331	-0.3810	0.3642
403-407: Pvt. hh service	0.0007	0.0000	-1.3641	0.7072	0.2214	-0.5826	-0.4251	1.4478
413-427: Protective svc.	0.0086	7.7154	-0.6374	0.6563	0.7423	1.0386	-0.4224	0.7100
433-444: Food service	0.0009	8.8127	-0.8628	0.4484	-0.3909	2.1472	-0.1096	0.6795
445-447: Health service	0.0008	24.1017	-0.8532	-0.2811	0.6658	-0.3933	-0.3731	0.9321
448-455: Cleaning/bldg svc.	0.0020	13.8845	-1.5140	0.3170	1.1338	-0.2767	-0.4196	1.4232
456-469: Personal svc.	0.0014	9.1429	-0.4508	-0.5895	-0.2467	-0.4406	1.3130	0.3487
503-549: Mechanics & repairers	0.0053	15.2240	-0.0444	-1.3110	0.7587	0.3971	-0.4063	-0.6087
553-599: Construction trades	0.0068	22.5577	-0.0188	-0.9502	2.2933	-0.1960	-0.3797	-0.2826
613-699: Other precision production	0.0029	13.6475	-0.5258	-1.0338	0.0501	1.6055	-0.3601	0.2105
703-779: Machine operators	0.0024	22.6953	-1.2204	-0.3437	-0.1057	0.8997	-0.3738	0.9643
783-799: Fabricators, inspectors	0.0028	17.8286	-1.2994	-0.4417	-0.0571	0.6781	-0.3785	1.2154
803-814: Motor vehicle operators	0.0176	35.6393	-1.3383	-0.3606	0.7426	-0.4457	-0.4160	0.7532
823-859: Other transportation	0.0166	29.2157	-1.1876	-0.0819	1.1613	0.4532	-0.4187	1.1319
864-889: Construction, freight, labor	0.0110	34.9962	-1.6291	0.4910	1.0768	3.8833	-0.4244	1.7816
473-476: Farm managers	0.0094	0.3968	0.4685	0.2723	2.3756	-0.4168	-0.4280	-1.0789
477-489: Farm workers	0.0117	11.4986	-1.3619	0.3021	2.6532	-0.1571	-0.3915	1.5059
494-499: Forestry & fishing	0.0872	35.0779	-1.2595	0.2617	2.6898	2.9723	-0.4088	1.0820

Table 3: Worker Attributes[34]

	Men		Women	
	Low Risk	High Risk	Low Risk	High Risk
Sample Size	107,140	519,970	412,307	281,131
Wage	13.12	13.17	12.14	9.81
AGE	31.82	34.03	35.77	35.38
MARRIED	0.39	0.54	0.56	0.51
UNION	1.97	1.96	1.97	1.98
MSA	0.81	0.70	0.74	0.70
FULLTIME	0.71	0.85	0.63	0.66
WHITE	0.82	0.86	0.85	0.82
HSDROP	0.13	0.22	0.08	0.20
HSGRAD	0.27	0.45	0.38	0.46
SOMECOLL	0.36	0.26	0.38	0.25
COLLGRAD	0.24	0.07	0.17	0.08
NEW ENGLAND	0.08	0.08	0.09	0.09
MID ATLANTIC	0.12	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	0.07
W. S. CENTRAL	0.08	0.10	0.08	0.09
MOUNTAIN	0.12	0.10	0.09	0.09
PACIFIC	0.16	0.12	0.12	0.11

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

Table 4a
Wage-Hedonic Model Estimates
Dependent variable: wage

	(1)	(2)	(3)	(4)
Sample	Men Age 18-60	Men Age 18-60	Women Age 18-60	Women Age 18-60
Worker Attributes				
HSDROP	-1.450	-1.492	-0.794	-1.017
	(-1.521, -1.378)	(-1.562, -1.419)	(-0.860, -0.723)	(-1.081, -0.947)
SOMECOLL	0.320	0.692	1.076	1.199
	(0.240, 0.392)	(0.548, 0.830)	(1.016, 1.145)	(1.040, 1.342)
COLLGRAD	3.013	2.856	4.423	4.156
	(2.828, 3.218)	(2.648, 3.079)	(4.292, 4.558)	(3.963, 4.344)
AGE	0.574	0.644	0.433	0.452
	(0.553, 0.595)	(0.622, 0.644)	(0.417, 0.450)	(0.435, 0.470)
AGE2	-0.006	-0.006	-0.005	-0.005
	(-0.006, -0.005)	(-0.006, -0.005)	(-0.005, -0.004)	(-0.005, -0.004)
BLACK	-1.335	-1.303	-0.503	-0.516
	(-1.444, -1.231)	(-1.417, -1.199)	(-0.577, -0.415)	(-0.593, -0.433)
OTHER	-0.990	-0.896	-0.204	-0.199
	(-1.190, -0.782)	(-1.084, -0.691)	(-0.378, -0.048)	(-0.362, -0.048)
HISPANIC	-1.367	-1.416	-0.548	-0.584
	(-1.464, -1.272)	(-1.509, -1.322)	(-0.638, -0.459)	(-0.673, -0.497)
MARRIED	1.242	1.183	0.206	0.187
	(1.164, 1.323)	(1.106, 1.262)	(0.145, 0.267)	(0.130, 0.245)
PUBLIC	1.157	1.040	0.499	0.448
	(1.011, 1.304)	(0.897, 1.190)	(0.392, 0.607)	(0.344, 0.553)
UNION	-2.489	-2.486	-1.877	-1.834
	(-2.689, -2.300)	(-2.684, -2.296)	(-2.096, -1.658)	(-2.050, -1.625)
MSA	0.966	0.974	1.022	1.049
	(0.894, 1.036)	(0.902, 1.045)	(0.964, 1.085)	(0.993, 1.111)
FULLTIME	1.112	1.084	0.651	0.715
	(1.010, 1.206)	(0.980, 1.172)	(0.591, 0.711)	(0.657, 0.775)

Table 4a (continued)
Wage-Hedonic Model Estimates[35]
Dependent variable: wage

Occupation Attributes	(1)	(2)	(3)	(4)
FATAL	24.531	14.128	-46.452	-24.612
	(16.930 , 32.667)	(6.495 , 22.219)	(-58.770 , -33.982)	(-37.084 , -12.707)
NONFATAL	0.098	-0.009	0.100	0.022
	(0.093 , 0.104)	(-0.025 , 0.006)	(0.094 , 0.106)	(0.005 , 0.039)
SCMPLX	5.679	-1.362	4.274	-1.200
	(5.443 , 5.908)	(-2.098 , -0.642)	(4.088 , 4.457)	(-1.824 , -0.593)
MSKILL	-1.447	-1.080	-0.388	-0.111
	(-1.541 , -1.354)	(-1.372 , -0.784)	(-0.435 , -0.340)	(-0.270 , 0.048)
PHYDDS	-0.413	0.655	0.734	-0.744
	(-0.456 , -0.373)	(0.535 , 0.767)	(0.668 , 0.814)	(-0.988 , -0.534)
WORCON	0.125	0.011	0.153	-0.087
	(0.096 , 0.153)	(-0.075 , 0.098)	(0.124 , 0.182)	(-0.177 , -0.002)
CSKILL	-0.346	-0.328	-0.805	-0.248
	(-0.437 , -0.248)	(-0.650 , -0.007)	(-0.864 , -0.744)	(-0.441 , -0.034)
INTPEOPLE	2.738	0.228	0.852	-0.228
	(2.497 , 2.962)	(-0.465 , 0.919)	(0.610 , 1.069)	(-1.046 , 0.529)
Constant	4.728	2.524	4.934	3.803
	(4.192 , 5.328)	(1.997 , 3.148)	(4.391 , 5.477)	(3.224 , 4.375)
Worker-Occupation Attribute Interactions	No	Yes	No	Yes
Regional Indicators	Yes	Yes	Yes	Yes
R^2	0.3283	0.3502	0.3293	0.3513
N	627110	627110	693438	693438

[35] Bootstrapped 95% confidence intervals (in brackets) are clustered to reflect the fact that occupation attributes are the same for all workers in a particular occupation.

Table 4b
Wage-Hedonic Model Estimates
Dependent variable: log wage

	(1)	(2)	(3)	(4)
Sample	Men Age 18-60	Men Age 18-60	Women Age 18-60	Women Age 18-60
Worker Attributes				
HSDROP	-0.118	-0.119	-0.089	-0.102
	(-0.124, -0.113)	(-0.124, -0.114)	(-0.094, -0.083)	(-0.108, -0.097)
SOMECOLL	0.019	0.048	0.083	0.089
	(0.014, 0.024)	(0.038, 0.057)	(0.079, 0.087)	(0.079, 0.100)
COLLGRAD	0.128	0.134	0.274	0.257
	(0.120, 0.138)	(0.123, 0.146)	(0.267, 0.281)	(0.245, 0.269)
AGE	0.048	0.051	0.037	0.038
	(0.047, 0.049)	(0.049, 0.052)	(0.036, 0.038)	(0.037, 0.039)
AGE2	-0.001	-0.001	0.000	0.000
	(-0.001, 0.000)	(-0.001, -0.001)	(0.000, 0.000)	(0.000, 0.000)
BLACK	-0.103	-0.100	-0.043	-0.044
	(-0.110, -0.096)	(-0.108, -0.093)	(-0.049, -0.038)	(-0.049, -0.038)
OTHER	-0.071	-0.067	-0.021	-0.021
	(-0.083, -0.060)	(-0.078, -0.056)	(-0.032, -0.012)	(-0.031, -0.012)
HISPANIC	-0.105	-0.106	-0.046	-0.047
	(-0.111, -0.098)	(-0.112, -0.099)	(-0.052, -0.040)	(-0.054, -0.042)
MARRIED	0.096	0.093	0.021	0.019
	(0.091, 0.101)	(0.088, 0.098)	(0.017, 0.025)	(0.016, 0.023)
PUBLIC	0.084	0.079	0.047	0.044
	(0.077, 0.092)	(0.071, 0.087)	(0.040, 0.054)	(0.038, 0.051)
UNION	-0.173	-0.172	-0.145	-0.142
	(-0.184, -0.162)	(-0.184, -0.161)	(-0.158, -0.131)	(-0.155, -0.129)
MSA	0.068	0.069	0.090	0.091
	(0.064, 0.073)	(0.064, 0.073)	(0.085, 0.094)	(0.087, 0.095)
FULLTIME	0.114	0.112	0.087	0.089
	(0.109, 0.120)	(0.106, 0.118)	(0.083, 0.090)	(0.085, 0.093)

Table 4b (continued)
Wage-Hedonic Model Estimates[36]
Dependent variable: log wage

Occupation Attributes	(1)	(2)	(3)	(4)
FATAL	0.667	0.388	-2.280	-1.123
	(0.190 , 1.194)	(-0.098 , 0.893)	(-3.103 , -1.486)	(-1.984 , -0.345)
NONFATAL	0.008	0.004	0.009	0.006
	(0.008 , 0.009)	(0.003 , 0.005)	(0.008 , 0.009)	(0.004 , 0.007)
SCMPLX	0.372	0.166	0.312	0.064
	(0.359 , 0.383)	(0.129 , 0.205)	(0.302 , 0.323)	(0.030 , 0.098)
MSKILL	-0.110	-0.110	-0.029	-0.012
	(-0.115 , -0.104)	(-0.127 , -0.093)	(-0.032 , -0.026)	(-0.022 , -0.001)
PHYDDS	-0.027	0.030	0.041	-0.025
	(-0.029 , -0.024)	(0.022 , 0.038)	(0.036 , 0.045)	(-0.040 , -0.010)
WORCON	0.003	-0.007	0.004	-0.007
	(0.001 , 0.005)	(-0.013 , -0.001)	(0.002 , 0.006)	(-0.014 , 0.000)
CSKILL	-0.027	-0.038	-0.066	-0.047
	(-0.031 , -0.022)	(-0.055 , -0.022)	(-0.070 , -0.063)	(-0.059 , -0.035)
INTPEOPLE	0.176	0.148	0.049	0.005
	(0.163 , 0.189)	(0.112 , 0.186)	(0.036 , 0.061)	(-0.040 , 0.049)
Constant	1.724	1.630	1.743	1.688
	(1.692 , 1.760)	(1.595 , 1.669)	(1.709 , 1.776)	(1.652 , 1.725)
Worker-Occupation Attribute Interactions	No	Yes	No	Yes
Regional Indicators	Yes	Yes	Yes	Yes
R^2	0.3944	0.4046	0.3977	0.4106
N	627110	627110	693438	693438

[36] Bootstrapped 95% confidence intervals (in brackets) are clustered to reflect the fact that occupation attributes are the same for all workers in a particular occupation.

Table 5: 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			

Table 6a
Extreme Quantile Estimator, First Stage (Worker Attributes)
Dependent variable: wage

	(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	-5.624 (-5.737, -5.508)	-6.006 (-6.121, -5.887)	-3.708 (-3.802, -3.610)	-4.144 (-4.240, -4.050)
HSDROP	-1.203 (-1.268, -1.140)	-1.254 (-1.321, -1.191)	-0.553 (-0.605, -0.496)	-0.706 (-0.760, -0.649)
SOMECOLL	0.058 (-0.004, 0.117)	0.203 (0.090, 0.309)	0.181 (0.131, 0.231)	0.388 (0.275, 0.486)
COLLGRAD	1.312 (1.202, 1.437)	1.873 (1.724, 2.037)	2.075 (1.993, 2.160)	2.529 (2.403, 2.651)
AGE	0.449 (0.430, 0.468)	0.458 (0.439, 0.478)	0.299 (0.289, 0.312)	0.308 (0.295, 0.321)
AGE2	-0.004 (-0.005, -0.004)	-0.005 (-0.005, -0.004)	-0.003 (-0.003, -0.003)	-0.003 (-0.003, -0.003)
BLACK	-1.007 (-1.100, -0.921)	-1.129 (-1.220, -1.041)	-0.194 (-0.255, -0.127)	-0.278 (-0.341, -0.207)
OTHER	-0.760 (-0.899, -0.603)	-0.814 (-0.955, -0.659)	-0.088 (-0.212, 0.024)	-0.189 (-0.317, -0.074)
HISPANIC	-1.184 (-1.268, -1.100)	-1.275 (-1.357, -1.190)	-0.456 (-0.526, -0.381)	-0.532 (-0.603, -0.457)
MARRIED	0.884 (0.821, 0.949)	0.958 (0.892, 1.021)	0.039 (-0.006, 0.088)	0.097 (0.052, 0.145)
PUBLIC	0.344 (0.231, 0.445)	0.395 (0.282, 0.505)	0.162 (0.086, 0.233)	0.290 (0.213, 0.362)
UNION	-2.483 (-2.651, -2.307)	-2.461 (-2.628, -2.288)	-1.564 (-1.741, -1.390)	-1.549 (-1.731, -1.375)
MSA	0.762 (0.698, 0.823)	0.826 (0.762, 0.887)	0.869 (0.824, 0.915)	0.928 (0.884, 0.974)
FULLTIME	0.847 (0.766, 0.925)	0.904 (0.820, 0.984)	0.492 (0.448, 0.537)	0.562 (0.517, 0.607)
Regional Indicators	Yes	Yes	Yes	Yes
R^2	0.1463	0.1530	0.0964	0.1037
N	627110	627110	693438	693438

Table 6b
Extreme Quantile Estimator, Second Stage (Occupation Attributes)[37]
Dependent variable: wage

	(1)	(2)	(3)	(4)
Sample	Men Age 18-60	Men Age 18-60	Women Age 18-60	Women Age 18-60
Constant	-2.203	-1.628	2.225	2.218
	(-3.500, 0.374)	(-3.042, 0.740)	(1.187, 2.764)	(1.213, 3.219)
FATAL	-67.145	-59.978	-39.747	-58.782
	(-82.070, -27.816)	(-81.406, -22.040)	(-65.413, -21.154)	(-71.257, -36.302)
NONFATAL	0.073	0.033	0.008	0.002
	(0.006, 0.093)	(-0.029, 0.063)	(-0.048, 0.034)	(-0.054, 0.026)
SCMPLX	-0.794	-1.986	-0.839	-2.149
	(-1.280, 0.860)	(-2.281, 0.041)	(-1.214, 0.561)	(-2.448, -0.593)
MSKILL	0.395	0.636	0.243	0.408
	(-0.199, 0.602)	(-0.143, 0.763)	(-0.438, 0.344)	(-0.304, 0.477)
PHYDDS	0.109	0.336	-0.446	-0.408
	(-0.298, 0.469)	(-0.144, 0.725)	(-0.650, -0.059)	(-0.639, -0.036)
WORCON	0.285	0.556	0.107	0.105
	(-0.121, 0.614)	(0.175, 0.896)	(-0.157, 0.368)	(-0.203, 0.353)
CSKILL	-0.059	0.243	0.174	0.219
	(-0.322, 0.294)	(-0.005, 0.670)	(-0.002, 0.536)	(0.050, 0.583)
INTPEOPLE	-0.617	-1.247	-0.322	-0.942
	(-0.918, 1.376)	(-1.366, 1.145)	(-0.468, 1.327)	(-0.952, 0.920)

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

Table 7a
Extreme Quantile Estimator, First Stage (Worker Attributes)
Dependent variable: log wage

	(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	-0.530	-0.564	-0.344	-0.382
	(-0.540, -0.521)	(-0.571, -0.556)	(-0.351, -0.337)	(-3.899, -3.874)
HSDROP	-0.097	-0.103	-0.061	-0.075
	(-0.101, -0.092)	(-0.107, -0.098)	(-0.065, -0.057)	(-0.080, -0.071)
SOMECOLL	0.003	0.026	0.017	0.035
	(-0.001, 0.007)	(0.018, 0.033)	(0.013, 0.020)	(0.026, 0.042)
COLLGRAD	0.048	0.100	0.121	0.160
	(0.042, 0.054)	(0.091, 0.109)	(0.116, 0.126)	(0.151, 0.168)
AGE	0.038	0.039	0.026	0.027
	(0.037, 0.040)	(0.038, 0.040)	(0.026, 0.027)	(0.026, 0.028)
AGE2	-0.000	-0.000	-0.000	-0.000
	(-0.000, -0.000)	(-0.000, -0.000)	(-0.000, -0.000)	(-0.000, -0.000)
BLACK	-0.076	-0.088	-0.019	-0.027
	(-0.082, -0.070)	(-0.094, -0.081)	(-0.024, -0.014)	(-0.031, -0.022)
OTHER	-0.049	-0.054	-0.007	-0.016
	(-0.057, -0.040)	(-0.063, -0.046)	(-0.015, 0.000)	(-0.024, -0.009)
HISPANIC	-0.087	-0.095	-0.040	-0.047
	(-0.092, -0.081)	(-0.100, -0.090)	(-0.046, -0.035)	(-0.053, -0.042)
MARRIED	0.068	0.075	0.008	0.013
	(0.064, 0.072)	(0.071, 0.079)	(0.005, 0.011)	(0.010, 0.016)
PUBLIC	0.030	0.032	0.020	0.031
	(0.024, 0.036)	(0.026, 0.039)	(0.015, 0.025)	(0.026, 0.035)
UNION	-0.168	-0.167	-0.126	-0.125
	(-0.177, -0.158)	(-0.176, -0.157)	(-0.137, -0.114)	(-0.135, -0.113)
MSA	0.060	0.065	0.077	0.082
	(0.056, 0.064)	(0.061, 0.069)	(0.074, 0.080)	(0.079, 0.085)
FULLTIME	0.096	0.101	0.065	0.072
	(0.091, 0.101)	(0.096, 0.106)	(0.062, 0.068)	(0.069, 0.075)
Regional Indicators	Yes	Yes	Yes	Yes
R^2	0.2018	0.2126	0.1385	0.1507
N	627110	627110	693438	693438

Table 7b
Extreme Quantile Estimator, Second Stage (Occupation Attributes)[38]

	(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	-0.170	-0.130	0.166	0.162
	(-0.277, 0.006)	(-0.237, 0.050)	(0.072, 0.236)	(0.068, 0.290)
FATAL	-3.980	-3.526	-1.649	-3.343
	(-6.649, -1.637)	(-6.858, -1.117)	(-6.751, -0.701)	(-6.964, -1.627)
NONFATAL	0.004	0.002	3.434E-04	-2.099E-04
	(0.001, 0.008)	(-0.002, 0.005)	(-0.004, 0.004)	(-0.005, 0.002)
SCMPLX	-0.047	-0.129	-0.082	-0.183
	(-0.124, 0.063)	(-0.192, -0.003)	(-0.127, 0.032)	(-0.225, -0.050)
MSKILL	0.006	0.023	0.012	0.026
	(-0.020, 0.049)	(-0.013, 0.062)	(-.035, 0.035)	(-0.028, 0.045)
PHYDDS	0.016	0.026	-0.037	-0.029
	(-.0178, 0.045)	(-0.006, 0.058)	(-0.056, -0.010)	(-0.062, -0.004)
WORCON	0.017	0.036	-0.005	-0.008
	(-0.010, 0.041)	(0.011, 0.062)	(-0.019, 0.026)	(-0.025, 0.026)
CSKILL	-0.015	0.021	0.027	0.033
	(-0.022, 0.014)	(-0.002, 0.048)	(-0.003, 0.054)	(0.007, 0.064)
INTPEOPLE	-0.008	-0.037	-0.024	-0.065
	(-0.081, 0.119)	(-0.098, 0.105)	(-0.055, 0.111)	(-0.082, 0.095)

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

Table 8a: Value of a Statistical Life ($ millions)
95% Confidence Interval[39]
Dependent variable: wage

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	4.906 (3.386 , 6.533)	2.826 (1.299 , 4.444)	-9.290 (-11.754 , -6.796)	-4.922 (-7.417 , -2.541)
Extreme Quantile Estimator	13.429 (5.563, 16.414)	11.996 (4.408, 16.281)	7.949 (4.231, 13.083)	11.756 (7.260, 14.251)
Difference between Wage-Hedonic and Extreme Quantile VSL estimates	-8.523 (-11.224 , -0.324)	-9.170 (-13.628 , -1.318)	-17.239 (-23.003 , -12.522)	-16.678 (-19.474 , -11.020)

39 Bootstrapped confidence intervals in brackets.

Table 8b: Value of a Statistical Life ($ millions)
95% Confidence Interval[40]
Dependent variable: log wage

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	1.756 (0.500 , 3.138)	1.021 (-0.258 , 2.345)	-5.105 (-6.950 , -3.321)	-2.515 (-4.441 , -0.771)
Extreme Quantile Estimator	10.476 (4.314, 17.524)	9.282 (2.942, 18.069)	3.692 (1.570, 15.062)	7.486 (3.644, 15.586)
Difference between Wage-Hedonic and Extreme Quantile VSL estimates	-8.720 (-15.669 , -2.482)	-8.261 (-16.998 , -2.001)	-8.797 (-19.815 , -6.231)	-10.001 (-18.029 , -5.733)

[40] Bootstrapped confidence intervals in brackets.

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

Specification	Men		Women	
	Extreme Quantile Estimator	Wage-Hedonic Model	Extreme Quantile Estimator	Wage-Hedonic Model
Salaried Workers	4.617	7.983	0.047	42.746
	(14.436, 0.473)	(-7.593, 23.559)	(21.902, -6.354)	(-5.071, 90.564)
Un-trimmed Sample	16.401	5.488	7.321	-3.404
	(23.745, 9.979)	(-7.571, 18.547)	(14.962, 4.598)	(-47.803, 40.995)
Age [20,30)	7.173	3.013	7.614	-8.427
	(10.511, 2.928)	(-6.082, 12.108)	(18.218, 3.820)	(-41.768, 24.915)
Age [30, 40)	9.080	6.422	8.873	-4.719
	(15.283, 5.079)	(-6.181, 19.025)	(17.144, 5.468)	(-49.989, 40.551)
Age [40, 50)	13.218	6.952	9.999	-11.040
	(19.892, 4.999)	(-9.422, 23.326)	(28.204, 5.510)	(-61.749, 39.669)
Age [50, 60)	7.328	2.660	3.713	-14.241
	(18.251, 2.429)	(-15.920, 21.241)	(35.953, -0.875)	(-68.023, 39.540)
Married	13.633	4.871	7.165	-14.453
	(18.658, 5.573)	(-7.671, 17.413)	(15.690, 3.843)	(-61.768, 32.861)
Unmarried	7.182	4.899	8.494	-2.680
	(11.227, 2.751)	(-6.584, 16.383)	(14.856, 4.683)	(-36.09, 30.738)
1983-1992	13.544	2.040	5.992	-9.306
	(19.107, 5.760)	(-8.189, 12.269)	(12.055, 2.607)	(-49.188, 30.575)
1993-2002	4.824	7.821	9.745	-9.157
	(13.242, 2.100)	(-6.539, 22.180)	(18.852, 5.628)	(-50.489, 32.175)
Limited Individual Attributes	2.061	6.288	4.840	-7.083
	(8.439, 1.119)	(-6.906, 19.481)	(11.454, 2.551)	(-49.021, 34.856)
No Ag, Forestry, Fishing	19.669	1.670	3.279	-7.281
	(29.477, -13.157)	(-25.815, 29.155)	(29.505, -6.436)	(-53.776, 39.213)

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

Specification	Men		Women	
	Extreme Quantile Estimator	Wage-Hedonic Model	Extreme Quantile Estimator	Wage-Hedonic Model
Salaried Workers	3.501	5.452	9.207	47.685
	(20.990, -0.824)	(-12.157, 23.060)	(33.464, -13.112)	(6.198, 89.173)
Un-trimmed Sample	30.039	2.612	25.477	7.736
	(76.427, 24.211)	(-9.027, 14.251)	(42.099, 12.077)	(-36.581, 52.052)
Age [20,30)	6.770	1.607	6.631	-5.771
	(10.950, 3.214)	(-6.933, 10.147)	(20.805, 2.890)	(-35.248, 23.705)
Age [30, 40)	12.957	3.410	9.767	0.229
	(19.599, 8.819)	(-7.872, 14.692)	(22.001, 5.689)	(-41.364, 41.822)
Age [40, 50)	16.510	1.577	8.363	-4.757
	(25.318 , 8.939)	(-12.296, 15.450)	(31.725, 4.185)	(-51.146, 41.631)
Age [50, 60)	19.629	-2.966	0.692	-8.018
	(25.353, 11.480)	(-19.314 , 13.381)	(37.066, -4.099)	(-56.734, 40.699)
Married	11.935	0.923	3.079	-9.337
	(21.250, 5.677)	(-10.523, 12.369)	(19.239, 0.577)	(-52.308, 33.634)
Unmarried	8.873	2.416	8.197	-0.224
	(12.141, 5.058)	(-7.035, 11.866)	(15.371, 4.827)	(-29.594, 29.147)
1983-1992	13.219	-0.428	3.074	-5.735
	(19.484, 5.922)	(-10.365, 9.508)	(14.057, 0.428)	(-41.116, 29.646)
1993-2002	8.994	4.074	8.033	-4.719
	(15.246, 4.568)	(-7.492, 15.640)	(22.354, 5.418)	(-41.972, 32.533)
Limited Individual Attributes	3.622	3.093	4.020	-3.259
	(10.707, 2.212)	(-8.581, 14.766)	(13.051, 1.143)	(-41.794, 35.277)
No Ag, Forestry, Fishing	16.638	-0.745	7.451	-3.484
	(30.035, -15.094)	(-28.710, 27.219)	(24.714, -10.541)	(-45.438, 38.470)

Figure 1

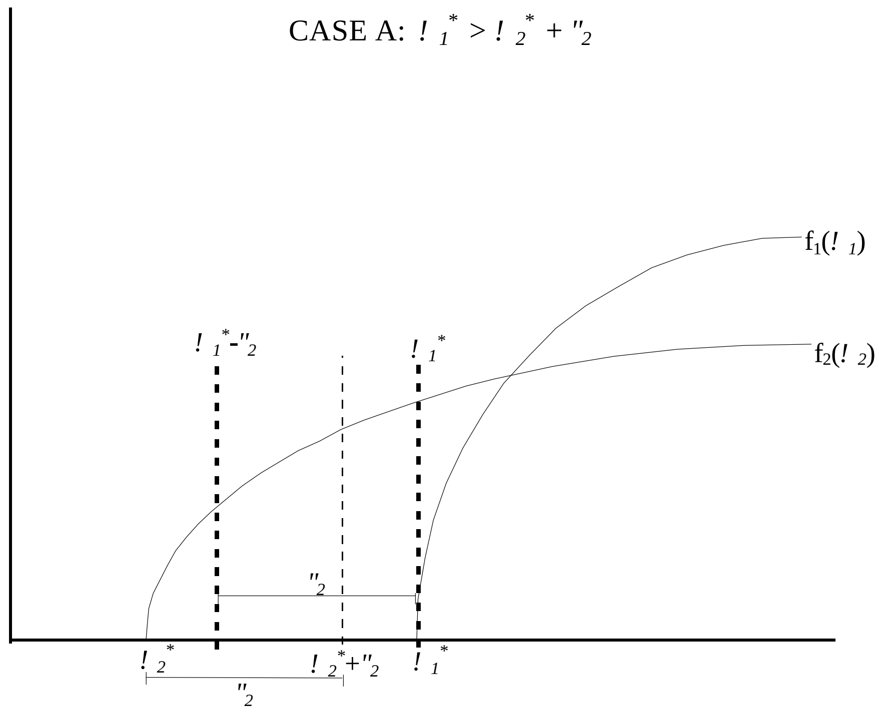

Figure 2