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Recommended Citation
Evans, Mary F. and Georg Schaur, A Quantile Estimation Approach to Identify Income and Age Variation in the Value of Statistical Life, Journal of Environmental Economics and Management 59(3): 260-270, 2010.

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A quantile estimation approach to indentify income and age variation in the value of a statistical life

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June 11, 2009

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Thanks are due to V. Kerry Smith, Thomas Kniesner, W. Kip Viscusi, and J.R. DeShazo for providing helpful comments on this research.

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Abstract:

Theory predicts variation in the marginal willingness to pay for a mortality risk reduction with individual characteristics. Two dimensions of heterogeneity, associated with income and age differences, have recently received attention due to their policy relevance. We propose a quantile regression approach to simultaneously explore these two sources of heterogeneity and their interactions within the context of the hedonic wage model, the most common revealed preference approach for obtaining value of statistical life estimates. We illustrate the approach using data from the Health and Retirement Study (HRS). Our results confirm differences in the wage-risk tradeoff with age and across the wage distribution. In addition, we find that the effect of age on the wage-risk tradeoff varies across the wage distribution. Thus, the conventional mean hedonic wage regression, even when the mean effect is allowed to vary with age, masks important hetereogeneity.

Key words: value of a statistical life, quantile regression

I. Introduction

The valuation of mortality risk reductions has important implications for numerous policy arenas including transportation, occupational safety, food safety, and environmental quality because mortality risk reductions represent a large share of the estimated benefits of these policies. For example, for each of the three final air quality rules promulgated in 2004, reduced mortality risks represented approximately ninety percent of total monetized benefits (Robinson (2007)). Because the risk reductions associated with these policies are distributed non-uniformly across individuals, indentifying variation in the willingness to pay for mortality risk reductions across individuals is policy-relevant.

An extensive literature examines various sources of heterogeneity in estimates of the marginal willingness to pay for a fatality risk reduction, the so-called value of a statistical life (VSL). Economic theory suggests factors that influence the magnitude of the tradeoffs including (but not limited to) preferences and ability to pay. The two potential sources of VSL heterogeneity that have received the most attention in the literature are due to age and income differences.

The hedonic wage model is the dominant approach to obtaining estimates of the VSL ((Viscusi, 1993). The empirical explorations of VSL heterogeneity within this framework often involve the inclusion of an interaction between the fatality risk measure and a variable that captures the relevant dimension of heterogeneity (e.g., age) as a regressor in the hedonic wage specification. Income heterogeneity is not amenable to this interaction technique with hedonic wage models. As Hammitt et al. (2003) note, "Because income (or the wage rate) is the dependent variable, it cannot be used as an explanatory variable, and so these studies typically do not provide information about income elasticity" (p. 1). Existing techniques for exploring income heterogeneity of the VSL either rely on revealed preference data from several samples (e.g., hedonic wage meta-analyses) or on stated preference data.

We propose a quantile regression approach to examine income (i.e., wage) heterogeneity. To our knowledge, our framework represents the only revealed preference approach to exploring wage heterogeneity in the VSL with individual-level data. By including additional controls to account for age heterogeneity, our empirical models also allow for a differential effect of age on the wage-risk tradeoff at different points in the wage distribution. This is important because numerous important changes, some of which affect the jobs individuals choose and thus their income and/or their valuation of mortality risks, occur in parallel with aging (Riley and Chow (1992), DeShazo and Cameron (2005), Aldy and Viscusi (2007), Evans and Smith (2008)).

Previous revealed preference applications that examine the impact of either wage or age heterogeneity on VSL estimates without controlling for the other source of variation are unable to isolate the specific influence of either source. Quantile regressions solve this identification problem and parse these two policy-relevant dimensions of heterogeneity. We motivate the use of quantile regressions with a conceptual model based on the conventional hedonic wage framework. Our conceptual framework supports an empirical model, such as the quantile regression, that identifies the risk-wage tradeoff across different percentiles of the wage distribution.

The topic of VSL heterogeneity with respect to age differences motivated a recent symposium in the *Review of Environmental Economics and Policy*. The introduction to the symposium describes the VSL-age relationship as "an issue of considerable controversy in policy circles and keen interest within the research community" (p. 169, Stavins et al. (2007)). To illustrate the potential policy relevance of age variation in the VSL, Evans and Smith

(2006) mention four economically significant air quality rules for which mortality risk reductions for individuals over age 65 account for between 65 and 70 percent of the estimated total benefits. Robinson (2007) notes that for policies that decrease particulate matter concentrations, roughly 80 percent of the mortality risk reductions accrue to individuals over age 65. Thus, adjustment to VSL estimates on the basis of age, as reported for example in the "alternative" benefit analyses of the *Clear Skies Initiative*, can give rise to vast differences in total monetized benefits (U.S. Environmental Protection Agency (2002)).

Following the controversy surrounding the so-called "senior death discount", John Graham, then Administrator of the Office of Information and Regulatory Affairs, issued a memorandum discouraging the adjustment of VSL for age differences (2003).[1] The U.S. Environmental Protection Agency's (EPA) recently revised *Guidelines for Preparing Economic Analyses* reiterate this recommendation and refer to the mixed theoretical and empirical findings with regard to the relationship between age and the VSL (U.S. Environmental Protection Agency (2008)).[2] Aldy and Viscusi (2007) and Krupnick (2007) provide informative discussions of the empirical techniques that exist for exploring variation in the VSL with age using revealed and stated preference data, respectively.

The responsiveness of the VSL with respect to income variation has implications for inter-temporal and cross-country benefit transfers. The EPA's practice of longitudinal adjustment represents an example of the former. The EPA adjusts VSL estimates to account for anticipated income growth based on theoretical and empirical support for a

[1] See Aldy and Viscusi (2007), Robinson (2007), and Evans and Smith (2006) for more detailed discussions of the senior death discount.
[2] We received permission to cite this document from Kelly Maguire, National Center for Environmental Economics, U.S. Environmental Protection.

positive income elasticity of the value of a statistical life (IEVSL).[3] Since many current policy changes result in reductions in future mortality risks, the IEVSL is often a central component in estimating the benefits of large-scale policy changes.

Evans and Smith (2008) cite the prospective report on the costs and benefits of the Clean Air Act Amendments for 1990 to 2010 to illustrate the implications of this adjustment. The report includes a sensitivity analysis using IEVSL estimates of 0.08, 0.4, and 1.0, which result in VSL estimates for 2010 of $4.9, $5.3, and $6.3 million (in undiscounted 1990 dollars) respectively. Because mortality risk reductions represent a large fraction of the benefits of improved air quality, the more than $1 million difference between the estimated VSL for 2010 based on the upper and lower IEVSL translates into drastically different aggregate benefit estimates.

To illustrate the implications of the IEVSL for cross-country benefit transfer, we present an example using parameters from a study by Strukova et al. (2006) that estimates the mortality costs of air pollution in major Ukrainian cities. The lack of VSL estimates based on Ukrainian data necessitated the benefit transfer. The authors assume that the ratio of VSLs in Ukraine and in a group of higher income countries equals the ratio of associated per-capita incomes, an assumption that is equivalent to setting the IEVSL to one. With 22,000 deaths annually attributed to air pollution in Ukraine, they obtain an estimated annual mortality cost of air pollution of $2 billion (2004 dollars). Consider the implications of alternate assumptions about the IEVSL. Values of 0.08 and 0.4 (the same values used in the EPA report) imply estimated annual mortality costs of air pollution in Ukraine of $40.7 billion and $27.3 billion respectively. The policy implications of different values of the IEVSL are striking.

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[3] The EPA does not, however, adjust for cross-sectional variation in income. See. http://yosemite.epa.gov/ee/epa/eed.nsf/webpages/Mortality%20Risk%20Valuation.html#WhatAdjustments

Several empirical studies, adopting various strategies, estimate the size of VSL responsiveness to income changes and confirm the theoretical sign prediction although estimates of the IEVSL vary in magnitude across studies. The empirical studies vary along several dimensions, including the way in which income is measured. Some studies exploit variation in unearned income while others use variation in earned income or in total income. We are aware of four methodologies used to estimate the IEVSL. Examples of the first methodology, which exploit variation in (sample mean) incomes across the hedonic wage studies included in meta-analyses to estimate the IEVSL, include Mrozek and Taylor (2003), Viscusi and Aldy (2003), and Bowland and Beghin (2001). A second method, employed by Hammitt et al. (2006) and Costa and Kahn (2004), estimates the IEVSL by comparing VSL estimates, based on hedonic wage studies, at different points in time for a single country (Taiwan for the Hammitt et al. study and the U.S. for the Costa and Kahn analysis). A third technique, also discussed in Hammitt et al. (2006), involves cross-country comparisons of VSL estimates from hedonic wage studies. These first three methods are akin to estimating second stage demand models, a technique more common in the hedonic property value literature. As a result, they require VSL estimates from multiple hedonic wage regressions. The final methodology relies on stated preference (i.e., contingent valuation), rather than revealed preference (i.e., hedonic wage), data. For examples, see Hammitt and Graham (2000), Hammitt and Zhou (2000), and Mitchell and Carson (1986).

While these methods differ in their use of revealed or stated preference, individual or aggregate data, they each focus on the responsiveness of the VSL to changes in income at a specific point in the wage distribution. Our quantile specifications allow us to estimate the wage-risk tradeoff at various points in the wage distribution. By introducing a standard method used to explore other dimensions of heterogeneity into our quantile framework, our models also examine age variation in the VSL. Comparisons across income quantiles and different ages provide insight into how the VSL varies with income and age.

Section II presents a conceptual model to motivate our use of quantile models for exploring income heterogeneity in the VSL. Our conceptual framework focuses on the income-VSL relationship since there is general consensus in the literature that the VSL is likely to vary with age (see the discussion in Hammitt (2007) and the citations therein). Section III discusses the empirical specifications and introduces the data we exploit to illustrate our methodology. Section IV contains our empirical results and section V concludes.

II. Conceptual framework

The conventional hedonic wage model estimates the wage-risk tradeoff at a single point in the wage distribution (i.e., the mean). One might conclude from this that either (1) we care only about the wage-risk tradeoff at this point or (2) we expect little variation in the wage-risk tradeoff across the wage distribution and therefore the wage-risk tradeoff at the mean is a reasonable proxy for the wage-risk tradeoff at other points of the distribution. The policy implications discussed above contradict (1). The discussion in this section provides grounds for questioning (2) and motivates the quantile regressions to identify variation in the estimated wage-risk tradeoff across the wage distribution. We motivate our quantile approach by exploring the implications of a wage change for the wage-risk tradeoff within the conceptual model typically used to motivate the hedonic wage framework.

Let $U_s(c), s = A, D$ represent the state-dependent utilities associated with the consumption of a numeraire good, denoted *c*, in *alive* (*A*) and *dead* (*D*) states, respectively. In addition, assume, as is standard in the literature (Jones-Lee, 1974), $U_A(c) > U_D(c)$,

$U_s'(c) > 0$ for $s = A, D$, and $U_A'(c) > U_D'(c)$. The probability of death is denoted *p* where we assume the sole source of mortality risk is occupational.[4] The individual budget constraint is $c = W(p)$ where $W(p)$ is the equilibrium wage function. Substitution yields the expected utility function defined in equation (1).

$$EU = pU_D(W(p)) + (1-p)U_A(W(p)) \tag{1}$$

Assuming EU is strictly concave in *p*, the first order condition for a maximum is given in (2).

$$EU_p = U_D - U_A + \frac{dW}{dp}(1-p)U_A'(W) + pU_D'(W) = 0 \tag{2}$$

Following Thaler and Rosen [1976], define an acceptance wage θ as the amount of money that makes the worker indifferent to jobs with different levels of risk. With EU_0 representing a specific level of expected utility, expression (3) implicitly defines θ as a function of *p* and EU_0:

$$pU_D(\theta) + (1-p)U_A(\theta) - EU_0 = 0 \qquad (3).$$

The slope of the acceptance wage with respect to *p* is equal to the marginal rate of substitution between *p* and θ, or the value of a statistical life (VSL) as in equation (4).

$$\theta_p = \frac{[U_A(\theta) - U_D(\theta)]}{(1-p)U_A'(\theta) + pU_D'(\theta)} = VSL \tag{4}$$

Thaler and Rosen show $\theta_p > 0$ and derive the following additional properties associated with θ:

$$\theta_{pp} > 0, \theta_{pEU} > 0\,. \tag{5}$$

[4] See Evans and Smith (2006) for a discussion of multiple sources of mortality risk.

Figure 1 illustrates the risk-earnings indifference curves, $\theta(p;EU)$, for different levels of expected utility with $EU_0 < EU_1 < EU_2$. In equilibrium, $\theta_p = \frac{dW}{dp}$. With data on wages and occupational fatality risk measures, $\frac{dW}{dp}$ can be estimated using a hedonic wage model (see Rosen [1974]) that characterizes the equilibrium locus of wage/job attributes (including job-related risks).

We consider the implications of this basic conceptual framework to explore how a specific form of income variation, holding preferences constant, affects the marginal rate of substitution between *p* and θ. Our empirical specifications introduced in the next section exploit cross sectional (i.e., between) variation as well as temporal (i.e., within) variation in income. Thus, the conceptual exercise we present here, based on Thaler and Rosen (1976), illustrates an extreme case: even with fixed preferences, differences in income are associated with differences in θ_p.

Following Thaler and Rosen, parameterize $W(p)$ such that

$$W(p) = \gamma + \omega(p)$$

with $\omega(p)$ an increasing function of *p*. We consider the effect of an increase in γ on θ_p where γ represents a component of the wage unrelated to the job's riskiness. As noted by Thaler and Rosen, a change in γ parallels a pure income effect in demand theory. Thus an increase in γ leads the worker to choose a safer job; job safety is a normal good with respect to changes in γ (see Proposition I of Thaler and Rosen, p. 276). With respect to θ_p, an increase in γ has three effects, the relative magnitudes of which determine the net effect of an increase in earnings on the VSL.

Figure 1 provides a graphical illustration of these effects. Begin at point A, where the individual, faced with the budget line labeled $W_0(p)=\gamma_0+\varpi(p)$, optimally chooses a job with risk p_0. Her choice yields expected utility of EU_0. From here, consider an increase in γ from γ_0 to γ_1. This implies a parallel upward shift in the budget line from $W_0(p)=\gamma_0+\varpi(p)$ to $W_1(p)=\gamma_1+\varpi(p)$. With *p* fixed at p_0, the increase in earnings moves the individual from point A, with expected utility of EU_0, to point B, where expected utility is $EU_1 > EU_0$. Although expected utility is higher at point B, given the change in the budget line, point B does not represent an optimum. Note, however, that by (5), θ_p (the VSL) is higher at point B than at point A.

Since point B is suboptimal given $W_1(p)$, the individual will not remain at B; she will reoptimize by choosing the level of risk at which the risk-earnings indifference curve is tangent to $W_1(p)$. This occurs at point C with a risk level of p_1 and expected utility of EU_2. The movement from point B to point C results in decreased risk *and* increased expected utility. To isolate these two effects on θ_p, we add a fourth point, labeled point D, to the figure. At point D, the level of risk is the same as at point C (p_1) but expected utility is the same as at point B (EU_1). As we move from point B to point D, risk decreases (from p_0 to p_1) but expected utility is constant at EU_1. Since $\theta_{pp} > 0$, θ_p at point D is lower than at point B (i.e., the movement from B to D decreases the VSL).[5] Pratt and Zeckhauser (1996) refer to this as the dead anyway effect. On the other hand, as we move from point D to point C, expected utility increases (from EU_1 to EU_2) but risk is constant. Since

[5] Since points B and D do not represent tangencies, they are unobserved for this particular worker. However, they may be observed in the data if these points represent optima for other workers.

$\theta_{pEU} > 0$, θ_p at point C is higher than at point D (i.e., the movement from D to C increases the VSL). A comparison of θ_p at points A and C requires accounting for the magnitudes of these three effects. Unless the dead anyway effect, which decreases the VSL as γ increases, dominates the other two effects, which both increase the VSL as γ increases, then we expect to observe higher VSL estimates as earnings increase.

Regardless of the magnitudes of the effects, the model motivates consideration of empirical specifications that allow the estimated wage-risk tradeoff to vary with earnings. Since a conventional hedonic wage model provides an estimate of θ_p at the mean of the earnings/wage distribution, it may inaccurately reflect the wage-risk tradeoff for individuals at other points in the wage distribution. The quantile estimation approach we discuss in the next section allows us to estimate θ_p at different points in the wage distribution. To simultaneously explore income and age heterogeneity, we augment our quantile specifications using the interaction technique mentioned above and described in more detail in the next section.

III. Data and empirical specifications

Conventional hedonic wage models relate the logarithm of the hourly wage of worker *i* to individual and job characteristics, including a measure of the occupational job risk faced by *i*. With cross sectional variation in wages and risks, ordinary least squares (OLS) estimates the wage-risk tradeoff at the mean of the wage distribution. Our conceptual model suggests variation in the wage-risk tradeoff at different points of the wage distribution. Quantile regressions identify the empirical significance of such variation. To account for age heterogeneity, our quantile models include an interaction term between job risk and age, a technique first proposed for conventional hedonic wage models by Thaler and Rosen (1976).[6]

We use data from the Health and Retirement Study (HRS).[7] The HRS is a national panel survey representative of those individuals between the ages of 51 and 61 (and their spouses) in 1991. The first interview occurred in 1992 (wave 1) with subsequent interviews every two years. Our sample consists of any HRS respondent over age 30 who worked in at least one of waves 2 (1994), 3 (1996), or 4 (1998).

As a benchmark for comparison, we estimate a log-linear hedonic wage regression with an interaction term to allow for variation in the estimated wage-risk tradeoff with age as in Aldy and Viscusi (2003). This specification relates the log of the real wage of individual *i* at time *t* to individual and job characteristics including on-the-job fatality risk, age, gender, experience, occupation-specific indicators collected in the vector OC_{it}, education-specific indicators collected in vector E_i, race-specific indicators collected in vector R_i, and time period-specific (or wave-specific) indicators collected in vector T_t to obtain

$$\begin{aligned}\ln\left(wage_{it}\right) &= \alpha + \beta_1 risk_{it} + \beta_2 age_{it} + \beta_3 age_{it} * risk_{it} \\ &\quad + \phi male_i + \xi \exp_{it} + \gamma OC_{it} + \delta E_i + \theta R_i + \omega T_t + u_{it}\end{aligned} \quad (6)$$

The HRS provides information on nominal hourly wages, actual for workers paid hourly and imputed for salaried workers. From these data, we calculate real hourly wages, with 1998 as the base year, using the annual average Consumer Price Index provided by the U.S. Bureau of Labor Statistics. Table 1 contains summary statistics on real wages as well as other demographic variables of interest for our sample.

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[6] See Aldy and Viscusi (2007) for a discussion of other studies that have used this technique.

[7] The HRS (Health and Retirement Study) is sponsored by the National Institute of Aging (grant number NIA U01AG09740) and conducted by the University of Michigan. We rely on the RAND Corporation's cleaned version of the HRS available at http://www.rand.org/labor/aging/dataprod/#randhrs.

Our measure of on-the-job fatality risk is industry- and age-differentiated as in Viscusi and Aldy (2007) and Evans and Smith (2008). That is, we structure fatality risk cells for each industry (by 2-digit SIC code) and age group using data from the Bureau of Labor Statistics (BLS) Census of Fatal Occupational Injuries (CFOI) to develop a more refined measure of job risk than is typical of hedonic wage studies. Our risk measure gives the number of fatalities, from the CFOI, per 10,000 workers, from the Current Population Survey, in the respondent's industry and age group.[8]

Our benchmark model employs the standard approach of minimizing the sum of squared residuals to estimate the coefficients in (6). In the absence of the interaction term, β_1 measures the marginal impact of job risk on the conditional mean of the log wage, $E(\ln(wage_{it})|X_{it})$, where X denotes the included covariates. With the inclusion of the interaction term, the marginal impact of job risk on the conditional mean of the log wage for an individual with mean age, denoted $\overline{age}$, is given by $\beta_1 + \beta_3 \overline{age}$.

Instead of evaluating the impact of risk on the mean, our quantile regressions estimate the marginal impact of risk on the log wage at the 10th, 25th, 50th, 75th, and 90th percentiles of the wage distribution. We specify the conditional quantile function for quantile τ, denoted Q_τ, as in (7):

$$\begin{aligned} Q_\tau(\ln(wage_{it})|X_{it}) = {} & \alpha_\tau + \beta_{1\tau} risk_{it} + \beta_{2\tau} age_{it} + \beta_{3\tau} age_{it} * risk_{it} \\ & + \phi_\tau male_i + \xi_\tau \exp_i + \gamma_\tau OC_{it} + \delta_\tau E_i + \theta_\tau R_i + \omega_\tau T_t \end{aligned} \tag{7}$$

As is standard in the literature, expression (7) represents a linear approximation for the conditional quantile (see, for example, Koenker and Basset (1982), Abrevaya and Dahl

[8] The risk measures are formed for the following age groups according to the CFOI data availability: 16-19, 19-24, 24-34, 34-44, 44-54, 54-64, and over 64. The first age group is not represented in the HRS data. The wave 2 risk measure uses data from 1994. The measures for waves 3 and 4 average data from 1995/1996 and 1997/1998 respectively.

(2008)). The slope coefficients represent the marginal impacts of the explanatory variables on the τ^{th} quantile of the log wage. Consistent with the theory, the model does not assume that an individual at the τ^{th} quantile will remain at that point of the wage distribution if any of the explanatory variables change.

In our pooled quantile regression, the coefficients minimize

$$\sum_i \sum_t \rho_\tau \left(\ln(wage_{it}) - Q_\tau \left(\ln(wage_{it}) \middle| X_{it} \right) \right) \tag{8}$$

where $\rho_\tau(u) = u\tau$ if $u > 0$ and $\rho_\tau(u) = u(\tau - 1)$ if $u < 0$. See Koenker (2005) for a more detailed discussion. We estimate two quantile models based on the specification described by (7). The models differ in the bootstrapping method we employ to obtain standard errors. For our first quantile model, we obtain standard errors through bootstrapping using a simple sub-sampling method (see, for example, Cameron and Trivedi (2005)). This bootstrapping technique treats observations from the same individual as independent. In our second quantile model, we obtain the standard errors using a bootstrapping technique that recognizes the potential dependence of wages within individuals. We follow Abrevaya and Dahl (2008) and draw random subsamples of individuals repeatedly with replacement. For consistency, we use the same bootstrapping techniques to obtain standard errors for our benchmark log-linear hedonic wage models.

To summarize, our empirical strategy to simultaneously explore age and income heterogeneity involves estimating two sets of models. First, we estimate pooled OLS and pooled quantile hedonic wage models, bootstrapping the standard errors using a technique that assumes independence among observations from the same individual. Second, we estimate the same pooled OLS and pooled quantile specifications but employ a block bootstrapping technique that recognizes the potential dependence of wages within individuals. Before turning to these results, we begin in the next section by reporting results from a series of benchmark models.

IV. Results

Our first set of results isolates the role of income hetereogeneity. That is, we begin by estimating a quantile hedonic wage model without the age-risk interaction term. For comparison, we estimate a similarly specified ordinary least squares model. Table 2 reports these results. Results from the quantile regressions with bootstrapped standard errors are given in columns two through six and the OLS results are reported in the final column. All specifications include occupational fixed effects.[9] The excluded categories for the respective indicator variables are operator/handlers from the occupation indicators, college education and above from the education indicators, a broad other category from the race indicators, and the final time period (wave 4) from the wave indicators. The estimated marginal impact of risk on the conditional mean of the (log) real wage distribution, 0.021, implies a VSL of $6.7 million (1998$), which falls within the range identified in hedonic wage meta-analyses by Mrozek and Taylor (2002) and Viscusi and Aldy (2003).

Turning to the results from the quantile regressions in Table 2, the coefficient on job risk is insignificant for the 10th and 25th percentiles but positive and significant for the 50th, 75th, and 90th percentiles. The marginal impact of risk at the 75th and 90th percentiles exceeds that at the median of the real wage distribution. Note that a comparison of the quantile and OLS results indicate about a fifty percent increase in the estimated wage-risk tradeoff at the median compared with the mean of the wage distribution. Figure 2 illustrates the results of the OLS and quantile models. The shaded area in the figure represents the 95 percent

[9] We do not report the coefficient estimates on the occupational fixed effects. Full results are available by request from the authors.

confidence interval for the estimated risk coefficients in the quantile regressions. The comparison suggests that while the OLS results may represent the sample at lower percentiles of the wage distribution well, the impact on the conditional mean falls below the estimate at the 75th and 90th percentiles.

The results for the other covariates in the pooled OLS and quantile regressions coincide with the previous hedonic wage literature. The education indicators indicate positive returns to schooling. That is, across all specifications, individuals with less than college education make lower wages than individuals with college education or higher (the excluded category). The positive and generally significant coefficients on the race indicators show that the ethnicities included in the specification tend to make higher wages than a broad other category. The occupational indicators absorb unobserved job characteristics without interpretation. The consistently positive and significant coefficient on experience is intuitive. Given the inclusion of a control for experience in the models, the negative and significant coefficients on age suggest lower wages among older workers of similar experience levels. The coefficient on the male indicator variable is consistently positive and increases over the wage distribution. This suggests a higher male-female wage gap at the upper end of the wage distribution, a finding consistent with Garcia et al. (2001). The time indicators generally indicate lower real wages in the first two sample periods (wave 2 and 3) compared to the final sample period (wave 4).

Table 3 reports our primary results, from quantile hedonic wage regressions that account for age (and of course wage) heterogeneity. The standard errors reported in parentheses below the coefficient estimates assume independence whereas those in brackets are obtained using the block bootstrapping technique described above. The final column of Table 3 reports results from comparable OLS models. The general pattern of results is similar to that of Table 2. We focus our discussion on the results with respect to variation in the wage-risk tradeoff with age and across the wage distribution. First, the consistently negative coefficient on the risk-age interaction suggests a lower wage-risk tradeoff among older individuals at each wage quantile. Second, a comparison of the estimated coefficients on the risk-age interactions across the quantiles suggests a differential effect of age on the wage-risk tradeoff across the wage distribution. The results suggest that the dampening effect of age on the wage-risk tradeoff is strongest at the lowest quantiles. Thus, the mean hedonic wage regression (i.e., OLS), even when we include an age-risk interaction term, masks important hetereogeneity.

To explore the impact of age and wage heterogeneity on VSL estimates, we use the (marginally) statistically significant estimated wage-risk tradeoffs reported in Table 3 to calculate VSL estimates for representative 50, 55, and 60 year old individuals with real wages at different points in the wage distribution. [10] The VSL estimates assume the individual works forty hours per week for fifty weeks per year. Table 4 reports these results. Comparisons across points of the real wage distribution for an individual at a given age reveal the considerable effect of income heterogeneity on the VSL estimates. Variation in the real wage affects VSL estimates in two ways, through its impact on the marginal effect of risk and by affecting the wage used in calculating the VSL estimate. Focus on the results for a 50 year old individual and consider these effects as we move from the 10th to 75th percentile of the wage distribution. Assuming the same marginal impact of risk, we expect the VSL estimates to increase in proportion to the increase in real wages (the second effect). However, this is not the case since the marginal impact of risk first increases then decreases as we move up the wage distribution (the first effect). The substantial increase in the VSL

[10] Since the distribution of age is similar across the different quantiles of the real wage distribution, we focus on three ages of which the HRS is intended to be representative.

estimates between the 25th and 50th percentiles, across all three ages, is due more to the almost three-fold increase in the marginal impact of risk than to the approximately $4 increase in the real hourly wage. Restricting attention to a given point in the real wage distribution and comparing across the three ages suggests that the effect of age heterogeneity, which results in lower VSL estimates with age in our application, is less pronounced than the effect of income variation.

We note several caveats with respect to our findings. First, Smith et al. (2001) estimate hedonic wage models with data from the HRS and note the importance of controlling for sample selection given the age profile of the sample. Our models do not do so, as sample selection in quantile regression is a challenging open research topic (Koenker and Hallock 2001a). Buchinsky (2001) represents an example of significant progress in this direction. His method includes all explanatory variables of the target specification in the selection equation. We are unable to satisfy this data requirement because we do not observe job risk or occupation for those HRS respondents who are not working. Applications that account for sample selection or different populations represent an important complement to our research.

Second, while the pooled quantile regression approach is consistent with the theory in that it allows the marginal impact of risk and age to vary across the wage distribution, it does not account for unobserved heterogeneity that may contribute to variations in earnings. A recent paper by Kneisner et al. (2005) that compares conventional VSL estimates obtained from cross sectional data to VSL estimates from panel data models highlights the importance of controlling for unobserved heterogeneity in conventional (i.e., mean) hedonic wage models. While the literature examining the treatment of unobserved effects in quantile regressions is in its naissance, there currently exist a few candidate approaches. As an important recent addition to the literature, Abrevaya and Dahl (2008) develop a correlated random effects approach. Alternatively, Koenker (2004) suggests a dummy variable regression that restricts the impacts of the unobserved effects across quantiles. Bache, Dahl, and Kristensen (2008) propose augmenting the quantile specifications to allow for correlated random effects based on the so-called Mundlak-device (1978). Identification of the marginal impact of risk on the wage in these models requires sufficient variation within individuals. The nature of the industry/age job risk measure we employ and the low incidence of job switching among the HRS respondents limit this variation and preclude the panel quantile approaches for our data.[11] An alternative panel dataset with more variation in the job risk measure, both between and within, such as that used in Kneisner et al. (2006), may broaden the set of applicable panel quantile models. A comparison of the approaches for modeling unobserved heterogeneity within the context of the hedonic wage framework represents an interesting extension of our results.

V. Conclusion

Our quantile regression approach provides insight into the relevance of earnings and age variation for estimates of the marginal willingness to pay for mortality risk reductions. Our approach has several advantages over other techniques used to explore income or age heterogeneity in the VSL. First, most approaches either focus on income or age heterogeneity, rather than exploring both dimensions within a single framework.[12] Our unified model allows us to examine the relative importance of these two dimensions of

[11] In an effort to explore the potential importance of controlling for unobserved heterogeneity in our application, we also estimated a standard fixed effects model where we obtain an estimated coefficient on risk similar to the OLS estimated wage-risk tradeoff. This result is in contrast to Kneisner et al. (2006) who use data from the Panel Study of Income Dynamics (PSID). Differences in the characteristics of the respondents represented in the HRS and those represented in the PSID may explain this divergent result.

[12] See recent work by DeShazo and Cameron (2005) for a stated preference approach to simultaneously exploring the impacts of several factors that vary with age on the valuation of risk reductions.

heterogeneity. Our results, based on the HRS data, suggest that earnings heterogeneity contributes more to variation in VSL estimates than do differences in age. Second, in contrast to other revealed preference approaches to examining income heterogeneity of the VSL, the data requirement for implementing the method we propose is less demanding. Our approach can be implemented with the same individual-level data on occupational choices that would be required to estimate a conventional hedonic wage model. Finally, because our approach is motivated by the same conceptual model used to support the conventional hedonic wage specification, comparisons between our findings and results from standard hedonic wage regressions are straightforward.

Table 1. Summary statistics

Variable name	Variable description	Mean (standard deviation)
Wage	Real hourly wage rate (1998 U.S. dollars)	15.971 (11.740)
Risk	# fatalities per 10,000 workers in the individual's industry and age category	0.651 (0.693)
Age	Individual's age in years	56.729 (5.006)
Male	Dummy variable indicating individual is male	0.519 (0.500)
Experience	Total number of years worked, self-reported	34.604 (9.865)
Less than high school	Dummy variable that equals 1 if individual obtained has less than 12 years of education (and did not obtain a GED)	0.181 (0.385)
GED	Dummy variable that equals 1 if individual obtained a GED	0.049 (0.215)
High school graduate	Dummy variable that equals 1 if individual has 12 years of education but no college degree	0.333 (0.471)
Some college	Dummy variable that equals 1 if individual has more than 12 years of education	0.218 (0.413)
White/ Caucasian	Dummy variable = 1 if individual's race is reported as white/Caucasian	0.821 (0.384)
Black / African American	Dummy variable = 1 if individual's race is reported as black/African American	0.141 (0.348)
Number of observations		11380

Table 2. Results from benchmark OLS and quantile hedonic wage regressions—bootstrapped standard errors

Variable	Quantile regression					OLS
	10%	25%	50%	75%	90%	
Risk	-0.005	0.017	0.038*	0.053*	0.052*	0.021*
	(0.019)	(0.014)	(0.011)	(0.011)	(0.012)	(0.011)
Age	-0.013*	-0.010*	-0.007*	-0.005*	-0.006*	-0.009*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Male	0.181*	0.237*	0.265*	0.278*	0.301*	0.269*
	(0.021)	(0.016)	(0.013)	(0.014)	(0.015)	(0.012)
Wave 2	-0.046*	-0.040*	-0.020	-0.021	-0.026	-0.033*
	(0.021)	(0.014)	(0.012)	(0.014)	(0.016)	(0.011)
Wave 3	-0.047*	-0.035*	-0.034*	-0.034*	-0.040*	-0.039*
	(0.020)	(0.015)	(0.012)	(0.014)	(0.016)	(0.011)
Less than high school	-0.413*	-0.460*	-0.521*	-0.506*	-0.477*	-0.494*
	(0.031)	(0.024)	(0.019)	(0.025)	(0.029)	(0.019)
GED	-0.421*	-0.428*	-0.469*	-0.390*	-0.394*	-0.434*
	(0.036)	(0.029)	(0.027)	(0.042)	(0.039)	(0.024)
High school graduate	-0.299*	-0.320*	-0.342*	-0.354*	-0.372*	-0.353*
	(0.025)	(0.019)	(0.017)	(0.021)	(0.026)	(0.016)
Some college	-0.249*	-0.262*	-0.258*	-0.255*	-0.294*	-0.265*
	(0.027)	(0.020)	(0.016)	(0.019)	(0.025)	(0.016)
Experience	0.004*	0.004*	0.005*	0.005*	0.004*	0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
White/Caucasian	0.013*	0.047*	0.027	0.045	0.060*	0.045*
	(0.037)	(0.026)	(0.031)	(0.027)	(0.030)	(0.022)
Black/African American	0.085*	0.075*	0.053	0.058*	0.068	0.063*
	(0.039)	(0.028)	(0.033)	(0.029)	(0.033)	(0.024)
Constant	2.650*	2.611*	2.704*	2.769*	3.014*	2.816*
	(0.098)	(0.074)	(0.067)	(0.085)	(0.096)	(0.066)

Occupational fixed effects included in all specifications. Excluded education category: College and above, Excluded time indicator: Wave 4, * indicates significance at the 5% level based on a standard normal distribution

Bootstrapped standard errors are reported in parentheses. Bootstrap sample size: 4000, Iterations: 1000. Nr. Of observations: 11380

Table 3. Results from quantile and OLS hedonic wage regressions with age-risk interaction—bootstrapped and block bootstrapped standard errors

Variable	Quantile regression					OLS
	10%	25%	50%	75%	90%	
Risk	0.520*	0.489*	0.451*	0.306	0.152	0.346*
	(0.166)	(0.127)	(0.120)	(0.144)	(0.149)	(0.111)
	[0.198]	[0.158]	[0.153]	[0.170]	[0.179]	[0.151]
Age	-0.010*	-0.007*	-0.004*	-0.003	-0.006*	-0.006*
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]
Risk*age	-0.009*	-0.008*	-0.007*	-0.004	-0.002	-0.005
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Male	0.181*	0.230*	0.263*	0.279*	0.299*	0.265*
	(0.022)	(0.016)	(0.013)	(0.014)	(0.016)	(0.012)
	[0.027]	[0.022]	[0.018]	[0.019]	[0.021]	[0.016]
Wave 2	-0.060*	-0.049*	-0.021	-0.022	-0.029	-0.036*
	(0.020)	(0.014)	(0.012)	(0.014)	(0.017)	(0.012)
	[0.018]	[0.012]	[0.010]	[0.012]	[0.014]	[0.010]
Wave 3	-0.050*	-0.044*	-0.036*	-0.034*	-0.042*	-0.041*
	(0.019)	(0.014)	(0.012)	(0.014)	(0.017)	(0.011)
	[0.015]	[0.010]	[0.008]	[0.010]	[0.012]	[0.008]
Less than high school	-0.434*	-0.472*	-0.517*	-0.502*	-0.481*	-0.496*
	(0.030)	(0.023)	(0.019)	(0.025)	(0.030)	(0.019)
	[0.037]	[0.030]	[0.027]	[0.035]	[0.037]	[0.026]
GED	-0.404*	-0.438*	-0.464*	-0.384*	-0.391*	-0.433*
	(0.037)	(0.026)	(0.027)	(0.039)	(0.038)	(0.024)
	[0.044]	[0.035]	[0.038]	[0.056]	[0.048]	[0.035]
High school graduate	-0.309*	-0.326*	-0.336*	-0.351*	-0.372*	-0.354*
	(0.026)	(0.019)	(0.016)	(0.020)	(0.025)	(0.016)
	[0.030]	[0.025]	[0.022]	[0.028]	[0.034]	[0.021]
Some college	-0.257*	-0.261*	-0.252*	-0.254*	-0.295*	-0.266*
	(0.026)	(0.021)	(0.016)	(0.018)	(0.025)	(0.016)
	[0.031]	[0.027]	[0.023]	[0.025]	[0.032]	[0.021]
Experience	0.004*	0.004*	0.005*	0.005*	0.004*	0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
White /Caucasian	0.021	0.045	0.040	0.042	0.058	0.047
	(0.040)	(0.025)	(0.031)	(0.025)	(0.031)	(0.022)
	[0.051]	[0.034]	[0.040]	[0.035]	[0.041]	[0.031]
Black/African American	0.093	0.080*	0.067	0.053	0.067	0.064*
	(0.042)	(0.027)	(0.033)	(0.028)	(0.035)	(0.024)
	[0.055]	[0.038]	[0.044]	[0.038]	[0.041]	[0.031]
Constant	2.431*	2.413*	2.497*	2.620*	2.973*	2.635*
	(0.123)	(0.094)	(0.089)	(0.115)	(0.121)	(0.084)
	[0.145]	[0.118]	[0.114]	[0.145]	[0.155]	[0.110]

Occupational fixed effects included in all specifications. Excluded education category:

College and above, Excluded time indicator: Wave 4, * indicates significance at the 5% level based on a standard normal distribution with bootstrapped and block bootstrapped standard errors
Bootstrapped standard errors are reported in parentheses. Block bootstrapped standard errors are reported in brackets. Bootstrap sample size: 4000, Iterations: 1000. Nr. of observations: 11380

Table 4. Estimated marginal impacts of risk on the real wage and associated value of statistical life estimates by age and real wage

Point in the real wage distribution	Real hourly wage	Marginal impact of risk	VSL (million $)	Marginal impact of risk	VSL (million $)	Marginal impact of risk	VSL (million $)
		50 year old		55 year old		60 year old	
10%	$6.49	0.070	9.08	0.025	3.24	<0	<0
25%	$8.85	0.089	15.75	0.049	8.67	0.009	1.59
50%	$13.07	0.251	65.59	0.231	60.36	0.211	55.14
75%	$19.49	0.156	60.81	0.141	54.97	0.126	49.12
Mean	$15.97	0.046	14.69	0.016	5.11	<0	<0

VSL estimates are measured in 1998 dollars and are calculated as the marginal impact of risk*real wage*40*50*10,000.

Figure 1. Risk-earnings indifference curves

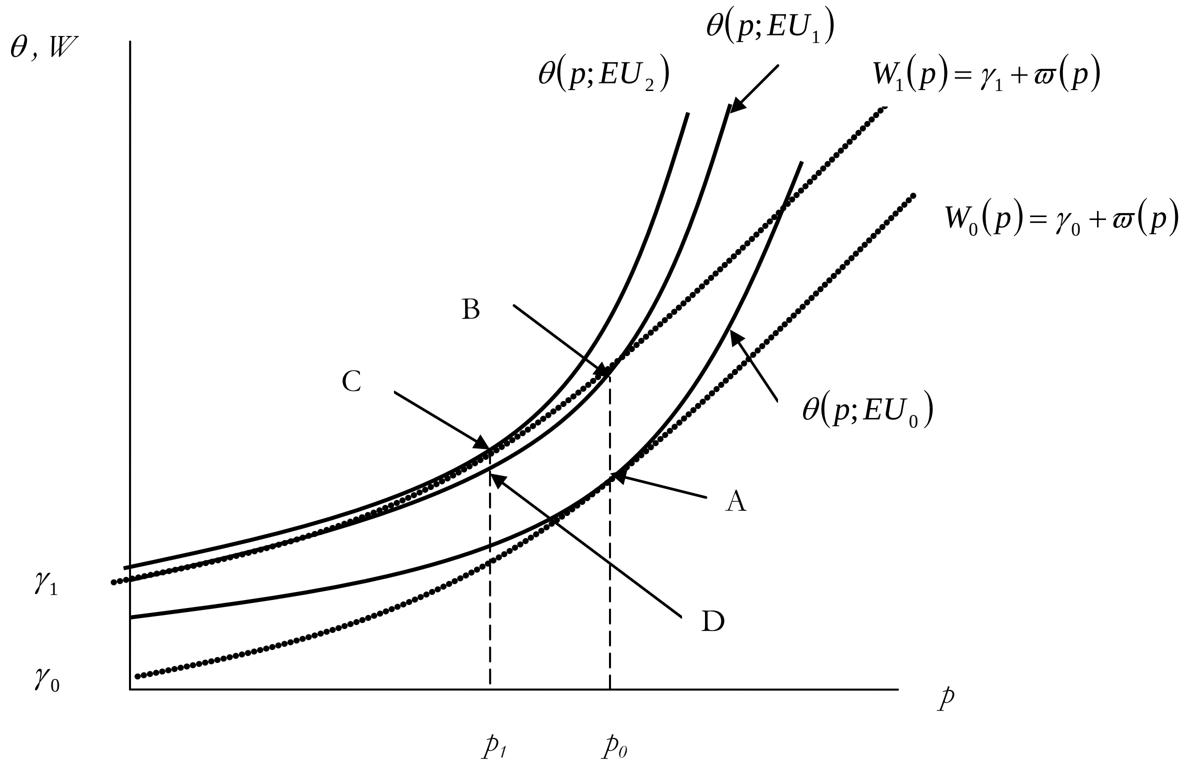
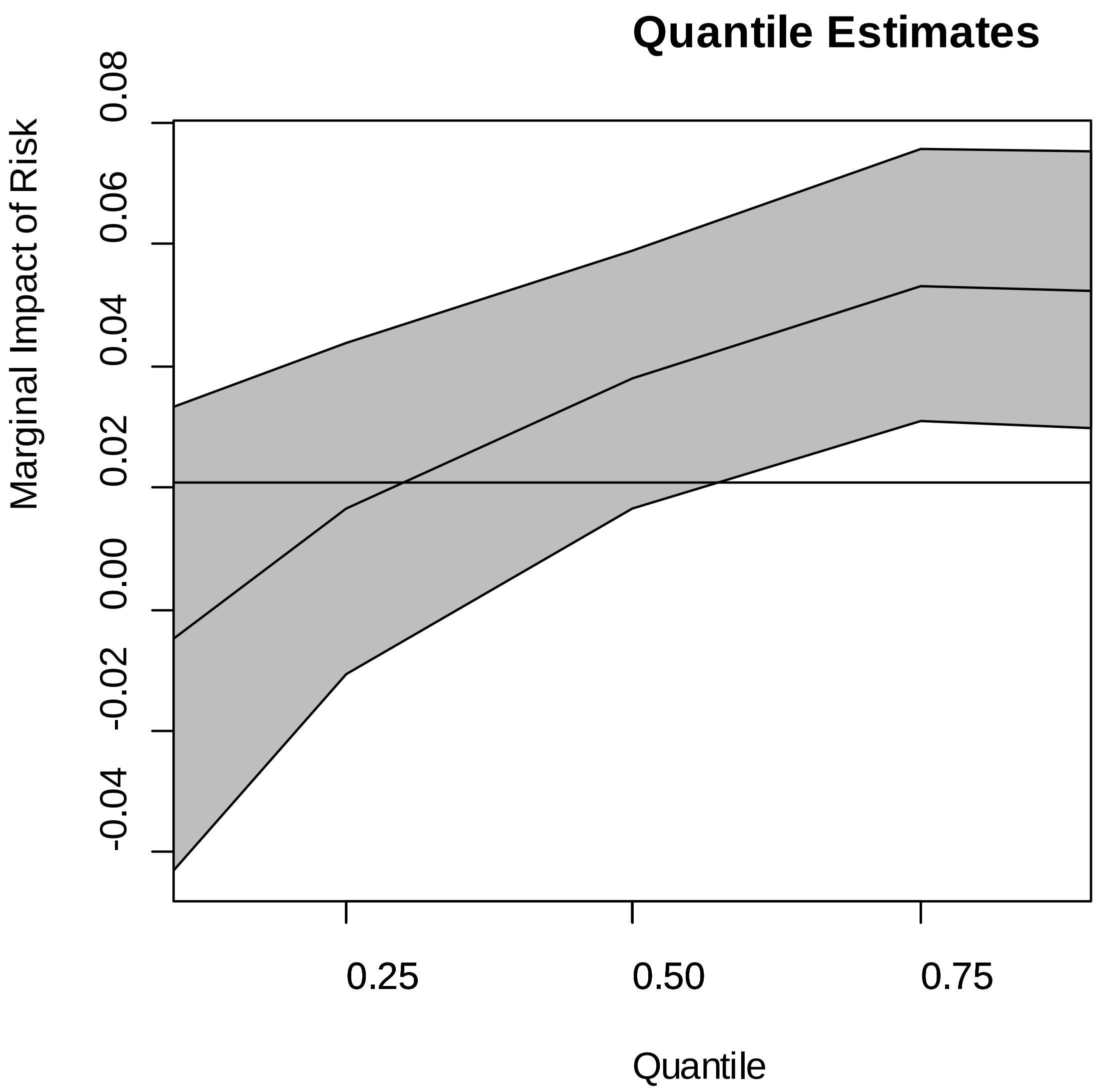


Figure 2. Comparison of estimated risk coefficients across the quantiles with the mean estimate—results from benchmark OLS and quantile hedonic wage regressions with bootstrapped standard errors



Shaded area: 95th percent confidence interval of the quantile estimates based on a standard normal distribution.

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