Validating Conjoint and Hedonic Preference Measures: Evidence From Valuing Reductions in Risk

Douglas Gegax*
New Mexico State University

Linda R. Stanley
Colorado State University

Economists and marketers have relied on different estimation methods for measuring consumer preferences. We attempt to show that a marketing tool, conjoint analysis, can be useful for economists in situations where hedonic estimation fails. Second, we examine convergent and theoretical validity of conjoint measures. We apply conjoint analysis to measure workers' preferences for on-the-job risk. Using survey data we obtain marginal value of safety (MVS) estimates using hedonic and conjoint techniques for four job types. The lack of a significant difference between the hedonic and conjoint MVS estimates supports convergent validity. Theoretical validity is supported because the utility function estimated from the conjoint data conforms to expectations derived from theory. The failure of hedonics to produce MVS estimates in low risk/nonunionized jobs, combined with the support of conjoint validity, suggests that conjoint analysis may be superior in assessing MVS in all job types.

INTRODUCTION

Measuring consumer preferences long has been a major concern in economics and in other business disciplines, especially marketing. Economists and marketers, however, have relied on different estimation methods. Economists typically have preferred revealed preference or indirect methods, such as hedonics, for measuring consumer preferences toward product attributes. On the other hand, direct survey methods, such as conjoint analysis, commonly are used in marketing. We believe that neither marketing nor economics has taken full advantage of the merits of the other's most commonly used estimation techniques. We attempt to bridge this gap by showing that conjoint analysis can be a useful technique for economists in situations where hedonic estimation fails.

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Second, we offer a validation of conjoint techniques by comparing conjoint estimates to hedonic estimates in a situation where hedonic methods work well.

Hedonic techniques have been widely used to value nonmarket attributes such as visibility and occupational risk. This technique imputes preferences by regressing the price of a commodity on its characteristics. As noted by Kroes and Sheldon (1988), there are limits to hedonics (as well as to other revealed preference methods). First, there are often strong correlations between explanatory variations that make it difficult to estimate the proper trade-off ratios. Second, hedonic methods cannot be used directly to evaluate potential demand under market conditions that do not yet exist. Finally, it can be difficult to obtain sufficient variation in the revealed preference data to examine all variables.

When a revealed preference approach such as hedonics is not feasible, conjoint analysis may provide a useful technique for valuing attributes and measuring demand. Broadly, *conjoint analysis* refers to a family of techniques that uses an individual's stated preference to estimate a utility function, obtain valuations of attributes of a specified object, and forecast demand. Conjoint analysis has become an important practical tool in marketing, illustrated by its extensive use in marketing research firms and internal research departments (Cattin and Wittink, 1982; Wittink and Cattin, 1989). The method also has gained wide acceptance in the transportation literature, where it is commonly referred to as the *stated preference method.*[1]

Before conjoint methods can be applied to economic issues, there must be evidence that carefully gathered conjoint data will represent individual preferences. Analyses of whether conjoint results reflect true consumer preferences or predict actual behavior (predictive validity) in the market have been scarce (Wardman, 1988). Because it is often difficult to compare preferences with the conjoint model's predictions, evaluating the construct validity of conjoint measures is crucial.[2] Construct validity concerns the degree to which the preferences measured in conjoint analysis relate to other measures as predicted by theory (Carmines and Zeller, 1979).[3]

In this article we examine two forms of construct validity of conjoint measures: convergent validity and theoretical validity. *Convergent validity* concerns whether the conjoint measure of preference is correlated with other measures of that preference. We compare results from conjoint measurement to results obtained from hedonic measurement. *Theoretical validity* concerns whether the measure is related to measures of other constructs as predicted by theory (Mitchell and Carson, 1989). For example, demand theory predicts that the quantity of a good purchased will be inversely related to the price of that good. Failure to find this relationship casts doubt on the theoretical validity of one or both measures.

We apply conjoint analysis in a new setting, measuring workers' preferences for on-the-job risk. This construct, known as the *marginal value of safety* (MVS), has a long

[1] For example, see the January 1988 issue of *Journal of Transport Economics and Policy* which is devoted to stated preference models.

[2] To the extent conjoint analysis gives a measure of preference in the form of utility, it measures a construct (a variable that is not directly observable).

[3] In economics there is a history of construct validation for the contingent valuation survey method and the hedonic price method of measuring consumer preferences for nonmarket goods (Mitchell and Carson, 1989). Also see Brookshire *et al.* (1982) and Cummings *et al.* (1986).

history in the research on hedonic wages.[4] The present study uses data from a survey initially conducted to obtain the hedonic MVS estimates found in Gegax, Gerking, and Schulze (1991), who provide some of the most recent hedonic estimates of the MVS for various groups of workers using their perceived on-the-job risk of death.[5] That study, however, does not use all the survey data. The survey obtained data for conjoint MVS estimation, and we analyze these data here for the first time. With both types of data, we have a unique opportunity to compare the MVS values obtained from both techniques. This comparison is important because the hedonic technique measures the actual wage-safety trade-off while the conjoint method measures the trade-off perceived by workers. Convergent validity suggests that the conjoint measure is equal to the hedonic measure. We also assess whether parameter estimates of the conjoint model are consistent with theoretical expectations.

BACKGROUND

HEDONIC ESTIMATION OF THE MARGINAL VALUE OF SAFETY

Workers require monetary compensation for accepting greater on-the-job risk. MVS is the maximum amount individuals will give up in income in order to reduce their risk of death by some small amount or, conversely, the minimum they would accept in order to increase their risk of death by some small amount.

MVS estimates are obtained by analyzing wage differentials across jobs with varying levels of risk. Empirical hedonic wage models regress wage rates from various jobs on a vector of worker and job characteristics. The latter includes the job-related risk of death.[6] The marginal effect of this risk on wages is the rate at which the labor market compensates workers for taking additional levels of risk. In equilibrium this marginal compensation is influenced by both the preferences of workers and firms. On the supply side it is hypothesized that workers voluntarily will accept a higher level of job-related risk for a higher wage. On the demand side firms face a trade-off of either paying higher wages for higher risk or lowering risk by purchasing safety. The hedonic wage-risk gradient describes the equilibrium levels of wage and risk with wage being positively related to risk. According to this wage-risk theory the hedonic wage gradient is a locus of tangencies between workers' wage-risk indifference curves and firms' isoprofit curves. Therefore, the rate at which the market compensates a worker for bearing job-related risk, the slope of the hedonic gradient, equals the worker's subjective MVS as described by the slope of his/her indifference curve.

The existence of a hedonic risk gradient assumes that workers are aware of the risk levels of their jobs and are able to negotiate for financial trade-off and that firms are will-

[4] For a thorough review and history of this literature, see Viscusi (1993).

[5] Workers voluntarily trade increased job-related risk for increased wages based on their perceptions of such risks; yet most hedonic studies base MVS estimates on fatal accident risks measured as industry or occupational averages. But particular jobs have greater or lesser risks than industry or occupational averages. Moreover, perceived death risks may differ from objective risk measures based on accident data. While such factors as dissemination of risk information by unions and on-the-job experience may imply that perceptions of risk approach objective risk over time, at any point in time the market comprises different vintage workers. Whether or not perceptions are finely tuned, the market outcomes are based on perceptions of risk.

[6] See Rosen (1974) for a detailed development of hedonic price theory. Thaler and Rosen (1975) were the first to apply hedonic price theory to the labor market.

ing to offer more income for increased risk assumption by workers. It has been suggested, however, that the hedonic risk gradient may not exist for all jobs (Gegax, Gerking, and Schulze, 1991; Viscusi, 1979). There are a number of reasons for this possibility.

Firms will be willing to offer more income for increased risk assumption if the marginal product of risk to the firm is positive. In jobs where risk is low (e.g., white collar jobs), increased risk of a fatal accident may not enter the production function; thus, no hedonic gradient exists. There may be, however, an incentive to provide safety even if risk does not enter the production function. Safety will be increased if the marginal cost of providing it is less than the marginal wage reduction associated with safety. In jobs that are already safe (e.g., white collar jobs), however, the marginal cost of providing more safety is relatively high. On the other hand, the marginal wage reduction associated with safety is likely to be small in low risk jobs because MVS is positively related to the current risk of death. Given the high marginal cost and low marginal benefit of safety associated with low risk jobs, the market trade-offs between risk and wage may not be observed. In low-risk job categories the hedonic regression technique may be thwarted because in these subsamples there is little variation in on-the-job risk. Without sufficient variation in risk it is difficult to impute MVS due to the lack of statistical significance between wage and risk in the hedonic regression equation.

Viscusi (1979) has argued that hedonic gradients are more likely to exist in union jobs than in nonunion jobs. Unions may be able to accumulate and disseminate information about safety hazards better than individual workers can, and collective bargaining provides opportunities to negotiate financial trade-offs for job safety.

In summary, hedonic estimation may not generate reliable MVS estimates in white collar/nonunionized jobs. On the other hand, for blue collar and/or unionized job categories the hedonic procedure may work well. Comparing hedonic MVS estimates with conjoint MVS estimates for these job types may show that conjoint methods may be relied upon in situations where hedonic gradients do not exist (e.g., white collar jobs).

CONJOINT ANALYSIS

Conjoint analysis is a practical method for predicting consumer preferences in a wide variety of product and service contexts.[7] It assumes that attributes are known and then attempts to attach values or *part worths* to the levels of each attribute. The theoretical basis for conjoint analysis is provided by both Lancaster's characteristics model (Lancaster, 1966; Ratchford, 1975) and the Fishbein-Rosenberg class of expectancy-value models (Fishbein, 1963; Rosenberg, 1970).[8] These theoretical models measure utility based upon a compositional approach, where utility for some multi-attribute object is a function of the attributes of the object and the attributes' valuations. Conjoint analysis, in contrast, is based on a decompositional approach: respondents rate or rank various combinations of levels of previously identified attributes or profiles of the object. The researcher extracts the value or part worth of each attribute from these ratings or rankings.

[7] See Green and Srinivasan (1978, 1990) and a special edition of *Journal of Transport Economics and Policy* (January 1988) for a review of conjoint methods.

[8] In relation to standard economic consumer theory, Hensher *et al.* (1988) and Bates (1988) show that conjoint data generally fall within the overall scope of random utility models.

Conjoint analysis involves six steps. [See Green and Srinivasan (1990) for a review of these steps.] The first step is selecting the functional form to model individual preferences.[9] The second step is to choose a method for data collection. A choice typically is made between full profile and two-factor-at-a-time trade-off procedures. In the trade-off procedure the respondent is asked to rank various combinations of a pair of factor or attribute levels (e.g., tread life and tire brand) from most preferred to least preferred. The individual does this for all possible pairs of attributes. A more common approach is the full profile approach where the respondent is shown a complete set of attributes and asked to rate each profile. For example, if five attributes were being used to profile an object, the respondent would be shown a number of profiles each with a different combination of attribute levels and asked to rate each profile. Because there may be too many possible combinations for each respondent to rate, the researcher must reduce the number of profiles (step 3), to usually not more than 30, while retaining enough combinations to measure part worths. A more recent data collection method reviewed by Louviere (1988) is to develop choice data experiments where the individual identifies one set of alternatives out of several as best or most likely to be chosen.

The fourth step is to develop the stimulus presentation. Possible presentations are a verbal or written description, pictorial or three dimensional model, or actual physical products. Profile cards with terse attribute-level descriptions are by far the more popular stimulus presentation method. Step five involves choosing the measurement scale of the dependent variable. Rating and ranking scales are used most frequently.

Finally, the estimation procedure must be chosen. Multiple regression, nonmetric methods, or logit and multinomial logit methods are used, depending on the measurement scale of the dependent variable. Green and Srinivasan (1990) review a number of studies comparing different estimation procedures and conclude that the estimation procedures do not differ much in their predictive validity.

During the early 1980s the most common applications of conjoint analysis in marketing were new product design, pricing, market segmentation, competitive analysis, and repositioning (Wittink and Cattin, 1989). Green and Srinivasan (1990) note that its applications are becoming increasingly diverse; conjoint analysis recently was used as a primary input to the settlement of disputes in telecommunications, pharmaceuticals, and airline industries. It also has been applied to employee benefit packages and personnel administration (Sawtooth Software, 1989), to measuring employees' perceived managerial power (Steckel and O'Shaughnessy, 1989), salespersons' trade-offs between income and

[9] Three general preference models typically have been used to model preferences of consumers and thus estimate the value of attributes to these consumers: the vector model or linear model, the ideal point model, and the part worth function (Green and Srinivasan, 1990). The part worth function provides the greatest flexibility in allowing different shapes for the preference function and includes as special cases the vector model and the ideal point model. The part worth function is defined as:

$$s_j = \sum_{p=1}^{t} f_p(y_{jp})$$

where:

s_j = The preference for the jth stimulus; and

f_p = The function denoting the part worth of different levels of y_{jp} for the pth attribute.

leisure (Darmon, 1979), and predicting the outcomes of buyer-seller negotiations (Neslin and Greenhalgh, 1983).

There also have been a number of applications in the public sector area. One application involved evaluating gasoline conservation policies (Green and Srinivasan, 1990). In another application conjoint analysis was used to help determine the number, locations, and physical and operational characteristics of a set of health care facilities to be added to an existing health care delivery system (Parker and Srinivasan, 1976). It has been used in the transportation area to evaluate passenger priorities for various characteristics of public transportation systems, develop market share analyses, and undertake route choice studies (Kroes and Sheldon, 1988).

THE VALIDITY OF THE CONJOINT MODEL

Studies have shown conjoint analysis to be relatively robust to data collection type, structural perturbations, and estimation procedures.[10] Few studies, however, have compared the respondents' predicted choices from a conjoint model to the actual choices made by these respondents because assessing the predictive validity of conjoint methodology is inherently difficult.[11] Attributes or attribute levels not currently available to individuals often are included in conjoint studies to discover marketing opportunities. Cattin and Wittink (1982) report that most applications of conjoint analysis (72 percent prior to 1982) are for new product/concept identification. By the time the product is on the market, however, changes in market structure or consumer preferences may have occurred, making comparisons between the conjoint results and actual consumer behavior impossible. In addition, actual behavior may differ from the intention to act. For examples, not all objects and/or attributes of these objects included in the conjoint study may be available to the consumer; there may be attributes excluded from the model that are relevant to consumers making an actual choice; or brand image or perceptions that are difficult to model may influence consumer choice. In light of the difficulties in assessing predictive validity, this study examines the construct validity of conjoint methodology as applied to the marginal value of job safety.

THEORY

To assess the construct validity of the conjoint measure (as well as the hedonic measure), we derive a set of conditions that are implied by a utility maximization model, where an individual is assumed to trade income and risk. We use the theoretical model to

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[10] For a more thorough review of this research, see Safizadeh (1989). Some researchers have found results questioning the reliability and internal validity of some methods of data collection and analysis. For example, Safizadeh (1989) questions the internal validity of preferences obtained via the trade-off method, and Darmon and Rouzies (1989) find that internal validity depends upon the spacing of attribute levels.

[11] There are four studies often cited that attempt to test for predictive validity. Parker and Srinivasan (1976) compare a conjoint model's prediction of the most preferred physician at a rural primary health care facility with the individual's actual choice of doctor. They find that 50 percent of individuals went to the first, second, third, or fourth preferred physician as predicted by the conjoint model. Wittink and Montgomery (1979) compare actual job choices of MBA students with their rankings of job offers as predicted by a conjoint model of job preferences. Using individual utility functions, 63 percent of the individual choices are predicted correctly by the conjoint model as compared to 26 percent correct predictions under a random choice model. Wardman (1988) reports that the conjoint model correctly explains 77 percent of individuals' actual transportation choices. On the other hand, tests of predictive validity by Leigh, MacKay, and Summers (1984) of both conjoint analysis and self-explicated weights fail to support the superiority of conjoint techniques.

test for convergent validity; we identify conditions under which the conjoint and hedonic measures of MVS converge. The theoretical validity of conjoint analysis can be assessed by testing whether the utility function estimated from the conjoint data, combined with the hedonic gradient estimated using wage-risk data, meets conditions derived from the model.

BASIC MODEL

Suppose a worker maximizes utility, U:

(1) $U(R, X)$

where:

R	=	The perceived risk level associated with the individual's job; and
X	=	The composite commodity (assuming a unit price equal to 1).

We assume the worker prefers less risk to more and prefers more X to less: $U_R < 0$ and $U_X > 0$ where subscripts denote first partial derivatives.

An individual chooses R and X to maximize utility in equation (1) subject to the budget constraint

(2) $Y(R) - X \geq 0$

where:

Y	=	Income; and
Y(R)	=	The hedonic risk gradient which is assumed to be continuous and differentiable.[12]

To allow for nonnegative values of R, maximization of equation (1) subject to equation (2) requires us to consider the first order Kuhn-Tucker conditions for this utility maximization problem:

(3) $Y(R) - X \geq 0;$ $\quad (Y(R) - X) * \lambda = 0;$ $\quad \lambda \geq 0$

(4) $U_R + \lambda Y_R \leq 0;$ $\quad (U_R + \lambda Y_R) * R = 0;$ $\quad R \geq 0$

(5) $U_X - \lambda \leq 0;$ $\quad (U_X - \lambda) * X = 0;$ $\quad X \geq 0$

where:

λ = The Lagrange multiplier.

[12] Although other factors, such as education, age, experience and the like would affect both Y and U, their omission here does not alter the theoretical results of interest.

For an interior solution (R, X > 0), the first order conditions imply:

(6) $-(U_R/U_X) = Y_R$.

By definition, the individual spends all of his/her income on the composite commodity X. Consequently, $U_X = U_Y$. Thus, for an interior solution, equation (6) can be rewritten as

(7) $-U_R/U_Y = Y_R$.

where:

$-U_R/U_Y$ = The slope of the indifference curve; and
Y_R = The slope of the hedonic gradient.

The left side of equation (7) measures the change in income required for a change in risk (holding utility constant) and is, therefore, the marginal value of safety.

Figure 1 illustrates equation (7). The vertical axis measures the quantity of the composite commodity, X, in dollars. Perceived risk is on the horizontal axis. Worker A has preferences represented by indifference curves, $I_A^* > I_A$. Worker A's budget constraint is given by the curve Y(R) - X = 0. Individual A will maximize utility at point a by choosing a risk level equal to R_a and X equal to X_a.

Second order sufficient conditions for an interior solution require

(8) $U_{RR} + U_{YY}Y_R^2 + 2\,U_{YR}Y_R + U_YY_{RR} < 0$.

A hedonic gradient may not exist for low risk jobs. This situation approximates a corner solution (R = 0) in the utility maximization problem, in which case equation (7) becomes

(9) $-(U_R/U_Y) > Y_R$.

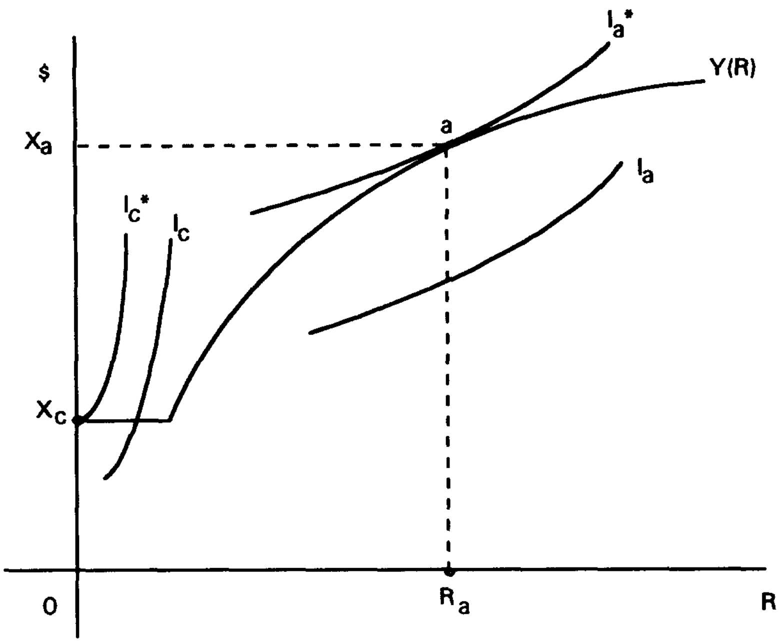
Moreover, the nonexistence of a hedonic gradient implies $Y_R = 0$ so that equation (9) becomes

(10) $-(U_R/U_Y) > 0$.

For this corner solution to yield a maximum, U_R must be less than zero and U_Y must be greater than zero.

Figure 1 also illustrates the corner solution. The hedonic gradient is nonexistent at low levels of R; $Y_R = 0$. Worker C has preferences represented by indifference curves $I_C^* > I_C$. Individual C maximizes utility by choosing R = 0 and X = X_c. The indifference curve for individual C is steeper at any level of risk than that of individual A, indicating that C has a greater aversion to risk than does A. Accordingly, C maximizes utility by choosing a lower level of risk than that chosen by A.

Figure 1—Interior and Corner Solution Values for Constrained Utility Maximization



CONVERGENT VALIDITY: COMPARISON OF CONJOINT AND HEDONIC ESTIMATES

From the utility function estimated using the conjoint data, one can measure the trade-off an individual is willing to make between specified values of any two attributes. This trade-off represents the slope of the indifference curve at the point defined by the values of the attributes. As applied here, conjoint analysis measures the trade-off workers make between risk and income as represented by the left side of equation (7). The hedonic technique, on the other hand, indirectly measures this trade-off as realized in the labor market, which is represented by the right side of equation (7). In situations where a hedonic risk gradient is likely to exist (relatively high risk/union jobs), equation (7) hypothesizes that the conjoint method should generate marginal value of safety estimates equivalent to those generated from the hedonic technique.

If a hedonic risk gradient is nonexistent for some subset of jobs, the conjoint method still will provide marginal value of safety estimates for workers in these jobs because it gives a direct measure of the slope of the indifference curve. As long as workers prefer less risk and more income, these MVS estimates will be some positive amount and thus will be greater than the hedonic estimates which for this case are zero.

THEORETICAL VALIDITY: TESTING THE ASSUMPTIONS OF THE BASIC MODEL

Conjoint analysis measures the utility of an individual as a function of attributes, holding all else constant. There are two classes of solutions to the utility maximization problem. In the first class an individual chooses a positive level of R. The hedonic gradient exists and $Y_R > 0$. Moreover, equations (11) through (13) are sufficient for a unique utility maximization solution.

(11) $U_Y > 0$

(12) $U_R < 0$

(13) $U_{RR} + U_{YY}Y_R^2 + 2\, U_{YR}Y_R + U_Y Y_{RR} < 0.$

In the second class the hedonic gradient is nonexistent and $Y_R = 0$. In this case only equations (11) and (12) must hold for the optimal X and R (R = 0) to yield a point of utility maximization. Therefore, we can assess the theoretical validity of conjoint analysis by testing whether the utility function estimated from the conjoint data meets equations (11) and (12) when $R \geq 0$ and, when combined with estimates from the hedonic gradient, meets equation (13) when $R > 0$.

EMPIRICAL ANALYSIS

DATA

We use data previously collected by a national mail survey during summer 1984 using Dillman's (1978) total design method.[13] Gegax, Gerking, and Schulze (1991) initially conducted this survey to obtain data for calculating hedonic MVS estimates. They did not use all the survey data in that study, however. The survey obtained data for conjoint MVS estimation, and we analyze these data here for the first time. Using both types of data gives us a unique opportunity to directly compare the conjoint and hedonic techniques.

Gegax *et al.* (1991) sent survey materials to a random sample of 3,000 U.S. household heads and to 3,000 additional household heads randomly selected from 105 counties with disproportionately large concentrations of high risk industries.[14] The second subsample includes an equal number of households from the northeast, north central, west, and south regions of the U.S. Of the 6,000 questionnaires mailed, 749 (12.5 percent) were returned as undeliverable, and a total of 2,103 were returned in completed form. Thus, the net response rate is approximately 40 percent. Not all completed questionnaires, however,

[13] The total design method is aimed at minimizing response bias and procuring a high response rate. It includes recommendations for pretesting the survey instrument, designing the questionnaire, mailing the questionnaires, and all follow-up procedures. The total design method commonly is accepted as the standard for mail surveys. For a description of the technique, see Dillman (1978).

[14] States within each of the four regions that are known to have concentrations of lumbering, mining, oil, steel mills, and construction (high risk industries) are selected. Within these states, counties with the highest concentrations of these industries are selected (for a total of 105 counties). Finally, 750 households are drawn randomly from the selected counties in each of the four regions. These additional 3,000 households ensure an adequate response from households employed in high risk occupations.

could be used in the empirical analysis. We exclude responses from household heads (1) who are retired, unemployed, or otherwise not in the labor force, (2) who receive more than 20 percent of total income from transfer payments, (3) who worked fewer than 1250 hours in 1983, (4) who are self-employed, (5) who did not report their income, or (6) who did not complete the conjoint section of the survey. This results in a total of 519 observations.[15]

The survey yielded several types of information from each respondent. First, it measures each household head's perceived risk of a fatal accident in his/her job (RISK). Respondents are shown an illustration of a ladder, reproduced in Figure 2, with ten equally spaced steps. Several well-known example occupations are placed on the ladder according to their average levels of job-related risk of death. These examples range from relatively safe jobs such as school teachers to more dangerous jobs such as lumberjacks. The respondent then is asked to specify the step number closest to describing the riskiness (in terms of accidental death) of his or her job.[16]

The next section of the survey gathered data used in the conjoint analysis. Respondents were asked to compare 15 hypothetical jobs to their current one. They were told that each hypothetical job is identical to their current job except for the risk and salary levels. For each hypothetical job, respondents were presented with a risk level represented by a step on the ladder, and a salary level, represented by their 1983 salary plus or minus some percentage of that salary. On a scale from 1 (much worse job) to 9 (much better job), respondents circled the number that indicated how each job compared to their current job.[17]

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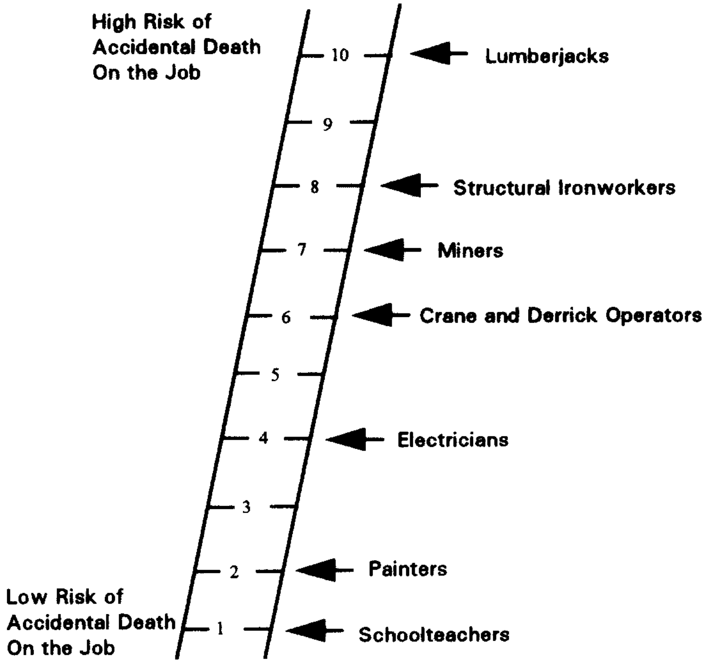
[15] We exclude household heads with significant transfer payments because Gerking and Weirick (1983) note that households receiving a significant percentage of their income in the form of transfer payments face non-convex budget constraints. Further, Gerking and Weirick state that "casual workers ... may be out of equilibrium because their asking wage may exceed their offered wage." This leads us to exclude household heads working part time.

[16] Gegax *et al.* (1991) chose the scale on the risk ladder (1 - 10) for its simplicity while basing the positioning of the example occupations on the ladder on data presented in Thaler and Rosen (1975, p. 288). These data measure extra deaths per 100,000 policy years of life insurance underwriting experience. Extra deaths are measured as the actual death rate minus the expected death rate given age and social class characteristics based on sample records and standard life tables. In the Thaler and Rosen sample lumberjacks are the highest risk occupation, with a value of 256 extra deaths per 100,000 policy years (i.e., annual probability of death = .0025). Because lumberjacks are the highest risk occupation in the Thaler and Rosen study, this sample occupation is placed on the highest step of the risk ladder in Figure 1, step 10. In order for this step to correspond with the same probability of death for lumberjacks implied by Thaler and Rosen, step 10 is interpreted to mean 10 deaths per 4,000 workers (i.e., 10/4000 = .0025). Similarly, each step number on the risk ladder is interpreted as the number of deaths per 4,000 workers per year. Other sample occupations from Thaler and Rosen are positioned by the step that corresponds to the Thaler and Rosen probabilities. Even though steps on the ladder are associated with fatal accident probabilities, respondents are neither required to make numerical calculations nor told the implied absolute probability values. Instead, the respondent is asked only to place his/her job in an appropriate position relative to the example occupations. Only during the process of constructing the marginal value of safety estimate is the RISK variable converted to a probability measure (by dividing the step number by 4000). We use such a rescaling method to make the respondent's task of estimating his or her job's risk as simple as possible while still retaining a meaningful and useful measure of risk. Using a 10 step ladder and assigning the highest risk occupation to step 10 did imply that step 1, the lowest risk, would somewhat overestimate the risk of the least risky occupation. This could cause underestimation of the MVS estimates (Viscusi, 1993). This should not affect our test for convergent validity because in this paper both the conjoint and hedonic measures use the same risk ladder.

[17] The particular conjoint method used in this survey is consistent with commercial use of conjoint analysis as surveyed by Cattin and Wittink (1989). Ratings scales are used more often (49 percent) than rankings (36 percent). Verbal descriptions of alternatives account for 70 percent of applications. Finally, most applications use the full profile approach as opposed to trading off two attributes at a time. In this survey the only characteristics changing are the risk and wage levels of the respondent's current job.

Figure 2—Risk Ladder Shown to Survey Respondents



The final two sections collected information on the respondent's human capital (H), work environment (W), personal characteristics (P), and labor earnings and hours. We include these data in the estimated hedonic wage equations to avoid omitted variable bias. Table 1 lists and defines individual variables measuring human capital, work environment and personal characteristics. We combine data on annual labor earnings, exclusive of overtime pay, from the respondent's primary job in calendar 1983 with data on hours worked during the same year to yield an hourly wage figure. This hourly nominal wage variable is adjusted for regional price differences to form the dependent variable, RWAGE, used in the hedonic labor market analysis.[18]

[18] In order to construct a set of 1983 regional price indices, we use two separate U.S. Department of Labor Consumer Price Index tables (Table 1 = 1980, p. 291; Table 2 = 1983, p. 49). Table 1 gives eight 1977 regional price indices for urban and rural areas within each of these four regions (base = 100 = 1977 U.S. urban average). Table 2 shows four 1983 regional indices for the northeast, north central, south, and west (base = 100 = 1977). Table 2 reveals price changes since 1977 in each of the four regions but assumes equal price levels for each region in that year. Table 1 reveals cross-regional price differences in 1977. By multiplying each index in (1) with its appropriate regional index in (2), eight regional price indices are constructed. These indices then are adjusted so that the lowest index is the base; i.e., 1977 rural-south = 100.

Table 1—Means and Definitions of Variables, Full Sample (N = 519)

Variable		Mean
Dependent Variable		
RWAGE	Hourly real wage in 1977 dollars of primary job exclusive of overtime	$10.01
Risk Variable		
RISK	Perceived risk of a fatal accident at work. Takes on an integer value between 1 and 10 as shown on risk ladder. Corresponds to the number of deaths per 4,000 workers	2.490
Human Capital Variables (H)		
SCHOOL1	1 if schooling ended in grades 1-8	.025
SCHOOL2	1 if schooling ended in grades 9-11	.047
SCHOOL3	1 if schooling ended in grade 12	.214
SCHOOL4	1 if schooling ended with a trade school program	.071
SCHOOL5	1 if schooling ended with some college	.257
SCHOOL6	1 if schooling ended with BS or BA and/or graduate training or degrees*	.386
YRSPO	Years worked in present occupation	12.60
YRSFT	Years worked full time since age 18	20.37
YRSPE	Years worked for present employer	11.76
Work Environment Variables (W)		
RQSCHL1	1 if 0-8 years of schooling are required for job	.040
RQSCHL2	1 if 9-11 years of schooling are required	.048
RQSCHL3	1 if 12 years of schooling are required	.367
RQSCHL4	1 if some college is required	.187
RQSCHL5	1 if one or more college degrees are required*	.358
WKEXP	1 if work experience or special training required	.842
SUPER	Number of persons supervised on primary job	14.50
GOVT	1 if public sector employee	.195
UNION	1 if union member	.362
YRSQUAL	Years required to become fully trained and/or qualified on primary job	3.28
MILES	Road mileage from home to place of work	11.76
NUMBER	Number of employees at primary work place	746.3
CENTRAL	1 if primary job site is in central city or suburban area	.756
SERVICE	1 if employed as a service worker	.084
LABOR	1 if employed as a laborer	.080
TRANS	1 if employed as a transportation operator	.036
EQUIP	1 if employed as an equipment operator	.058
CRAFT	1 if employed as a craft worker	.157
CLERIC	1 if employed as a clerical worker	.052
SALES	1 if employed as a sales worker	.057
MANAGE	1 if employed as a manager or administrator	.156
PROF	1 if employed as a professional or technical worker*	.316
Personal Characteristic Variables (P)		
AGE	Years of age	41.2
RACE	1 if white	.934
SEX	1 if male	.831
DISAB	1 if physical or nervous conditions limit amount or type of work that can be done	.108
VET	1 if respondent is veteran	.380
LIVE	1 if respondent lives in a central city or suburban area	.708

*Dummy variable deleted in hedonic regression equations

We initially divide the data into four subsamples selected in light of persistent empirical differences between white and blue collar workers and union members and non-members found in previously estimated marginal safety values. (See Gegax, Gerking, and

Table 2—Means and Standard Deviations for RISK[a]

Sample	Mean	Standard Deviation	N[b]
Blue Union	4.016	2.657	107
Blue Nonunion	2.950	2.310	138
White Union	1.694	1.895	36
White Nonunion	1.658	1.245	238
Full Sample	2.490	2.169	519

[a]RISK ranges from 1 (lowest possible perceived risk) to 10 (highest possible perceived risk) as shown on the risk ladder. RISK corresponds to the number of deaths per 4,000 workers
[b]N is the number of observations in a subsample

Schulze, 1991; Moore and Viscusi, 1990; Viscusi, 1979).[19] Table 2 shows means and standard deviations for RISK and the number of observations for the full sample and for the four subsamples. Unionized blue collar workers have the highest average level of perceived risk (4.016 deaths in 4,000). This figure is over twice as large as the average level of perceived risk for nonunionized white collar workers who have the lowest level of perceived risk (1.658 in 4,000). In addition, there is much less variation among the individual reported RISK values for workers in the nonunion and white collar subsamples. Sixty-seven percent of white collar workers report a risk value of 1 (i.e., position their job at step 1 on the risk ladder) while 93.9 percent report risk values of 3 or less. Likewise, 83 percent of nonunion workers report risk levels of 3 or less. This contrasts to the blue union sample where less than 50 percent report risk levels under 4.

A hedonic risk gradient most likely exists for those jobs that require the worker to assume some risk of death (i.e., blue collar jobs) and for those jobs that are unionized. Therefore, we expect the hedonic method to estimate MVS best for the blue union subsample. Assuming the method is valid, conjoint analysis should be equally capable of providing MVS estimates for the blue union subsample as well as for all other subsamples of the worker population. Thus, comparing the hedonic MVS estimate for blue union with the conjoint MVS estimate for this same subsample offers the best test of the convergent validity of the measures.

HEDONIC ESTIMATION

The general form of the hedonic wage equation is

(14) WAGE = f(H, P, W).

Based on tests of functional form, equation (14) is specified as semilogarithmic.[20] The first column of Table 3 gives the empirical results from estimating a semilogarithmic

[19] Individuals are asked to choose one of ten occupational categories that most closely reflect the type of work done in their job. White collar workers are managers, administrators, or professional and technical workers. The remaining workers are classified as blue collar.

[20] We ran the full sample regression using two alternative specifications. (1) The dependent variable is subjected to a Box and Cox (1962) transformation defined as $(RWAGE^{\lambda} - 1)/\lambda$ where λ is a parameter to be estimated. Significance tests can be performed on λ to check for special cases of functional form. For example, if $\lambda = 0$, the functional form becomes semilogarithmic because the limit of $(RWAGE^{\lambda} - 1)/\lambda$ as λ approaches zero is ln(RWAGE). The estimated λ is equal to -.04. Based on a likelihood ratio test with computed value of 1.27 (distributed $\chi^2_{(1)}$), we fail to reject the null hypothesis that $\lambda = 0$. A quadratic term, $RISK^2$, is added to the full sample equation. Its coefficient is -.0024 with corresponding t-statistic of -.697. Thus, it is not significantly different from zero at conventional levels.

Table 3—Coefficients, T-statistics, and Summary Statistics of Estimated Hedonic Wage-Risk Equations*

	Full Sample	Blue Union	White Union	Blue Nonunion	White Nonunion
Risk Variable					
RISK	.009	.023*	.006	.013	-.017
	(.976)	(1.80)	(.055)	(.718)	(-.776)
Human Capital Variables (H)					
SCHOOL1	-.321*	-.285	2.41*	.683	
	(-1.65)	(-1.27)	(1.77)	(1.44)	
SCHOOL2	-.379**	-.164		-.777*	
	(-2.98)	(-1.12)		(-2.31)	
SCHOOL3	-.129*	-.044	.436	-.021	-.204*
	(-2.01)	(-.39)	(.413)	(-.174)	(-1.68)
SCHOOL4	-.030	-.136		.193	-1.73
	(-.382)	(-1.09)		(1.44)	(-1.10)
SCHOOL5	-.071	-.055		.023	-.107
	(-1.28)	(-.559)		(.210)	(-1.22)
YRSPO	-.005*	.008*	.056*	-.007	-.008*
	(-1.83)	(1.65)	(2.15)	(-1.30)	(-2.00)
YRSFT	-.00001	.008	.019	-.013	.009
	(-.003)	(.820)	(.444)	(-1.24)	(.947)
YRSPE	.011**	.004	.005	.015**	.011**
	(4.36)	(.763)	(.246)	(2.95)	(2.86)
Work Environmental Variables (W)					
RQSCHL1	-.316**	.254		-.853**	-.914*
	(-2.73)	(1.01)		(-3.90)	(-2.26)
RQSCHL2	-.188	.060	-.786	-.315	-.358
	(-1.58)	(.240)	(-.410)	(-1.41)	(-.845)
RQSCHL3	-.124*	.178	-.875	-.270*	-.178
	(-1.86)	(.774)	(-1.25)	(-1.83)	(-1.55)
RQSCHL4	-.089	.079	-.908	-.214	-.015*
	(-1.44)	(.322)	(-1.01)	(-1.42)	(-1.72)
WKEXP	.080*	.139*	.201	.034	.122
	(1.64)	(1.65)	(1.03)	(.351)	(1.34)
SUPER	.0004*	.0009	.003	-.004	.003
	(2.03)	(1.35)	(.723)	(-1.00)	(1.48)
GOVT	-.006	-.038	.220	.225*	-.147*
	(-.122)	(-.482)	(1.22)	(1.98)	(-2.01)
UNION	.089*				
	(2.08)				
YRSQUAL	.027**	-.008	-.003	.034*	.027**
	(4.81)	(-.799)	(-.057)	(1.74)	(3.56)
MILES	.004**	.004*	.013	.002	.006**
	(3.37)	(2.12)	(1.43)	(.687)	(2.74)
NUMBER	.00025**	.00002	.00005	.00008**	.00002
	(2.37)	(1.24)	(.854)	(2.38)	(1.33)
CENTRAL	.102**	.057	.007	.124	.040
	(2.36)	(.810)	(.039)	(1.38)	(.496)
SERVICE	-.227**	-.073			
	(-2.86)	(-.731)			
LABOR	.023	.014		.096	
	(.264)	(.183)		(.651)	
TRANS	-.047	-.050		-.154	
	(-.416)	(-.413)		(-.884)	
EQUIP	-.075	-.115		.094	
	(-.837)	(-1.23)		(.695)	
CRAFT	-.093				
	(-1.35)				
CLERIC	-.124	.098		-.132	
	(-1.35)	(.553)		(-1.00)	

Table 3 (cont.)—Coefficients, T-statistics, and Summary Statistics of Estimated Hedonic Wage-Risk Equations[a]

	Full Sample	Blue Union	White Union	Blue Nonunion	White Nonunion
Work Environmental Variables (W) (cont.)					
SALES	-.145*	.586**		-.158	
	(-1.88)	(2.62)		(-1.42)	
MANAGE	.009		.599		-.031
	(.189)		(1.23)		(-.535)
Personal Characteristics Variables (P)					
AGE	.006	-.010	-.055	.017	.001
	(.977)	(-.896)	(-1.36)	(1.61)	(.105)
RACE	.073	-.189	-.129	-.244	.308*
	(.781)	(-1.08)	(-.144)	(-1.01)	(2.14)
SEX	.180**	.305*	.325	.186*	.174*
	(3.51)	(2.05)	(1.58)	(1.72)	(2.12)
DISAB	-.055	-.050	.086	.094	-.188
	(-.820)	(-.464)	(.349)	(.638)	(-1.48)
VETS	.043	.012*	-.347	.022	.042
	(1.05)	(1.80)	(-1.14)	(.238)	(.630)
LIVE	-.090*	-.147*	-.208	-.044	-.028
	(-2.20)	(-2.21)	(-1.11)	(-.520)	(-.378)
Sample Size	519	107	36	138	238
R^2	.45	.53	.74	.50	.45
F-Statistic	11.26**	2.60**	1.33	3.23**	6.99**

[a]Variables with no corresponding coefficients are constants for the subsample.
* $\rho < .05$ (one tail test)
** $\rho < .01$ (one tail test)

version of equation (14) for the full sample. The coefficient on RISK is not significant at conventional levels.

A Chow (1960) test statistic of F(81, 402) = 1.32 indicates that the null hypothesis of no wage structure shifts over the subsamples can be rejected at the 5 percent level. This suggests that pooling the subsamples may not be appropriate and may explain the poor performance of RISK in the full sample.

The second through fifth columns of Table 3 present the empirical results from estimating equation (14) for each subsample. The H, W, and P variables perform roughly as expected, with generally significant coefficients and correct signs. For the most part, as the years of schooling of a respondent (SCHOOL1 - SCHOOL5) increase, so does the wage rate.[21] For unionized workers the years in present occupation (YRSPO) show a positive and significant relationship to wages, while years with the present employer (YRSPE) are positively related to wages for nonunionized workers.

As years of schooling required for the respondent's job (RQSCHL1 - RQSCHL4) increase, the wage rate increases for all subsamples except blue union. If work experience or special training (WKEXP) is required for the present job, wages increase for all samples but the effect is significant only for blue union. Years required to become fully trained or qualified (YRSQUAL) have a significant and positive effect on wages for the

[21] The glaring exception is the significant and positive coefficient on SCHOOL1 for white union. One explanation is the small number of observations in this subsample.

nonunionized workers. Bigger firms (NUMBER) appear to pay better, as do jobs in central or suburban areas (CENTRAL).

The personal characteristic (P) variable that shows a consistent relationship to wages is SEX; males are paid more than females in all subsamples. In addition, for nonunionized, white collar jobs whites are paid significantly more than other races.

Table 3 indicates that only blue collar, union workers are able to capture a wage premium for accepting greater levels of perceived risk. In all other equations the coefficients of RISK are not significantly different from zero at any acceptable level. This result is consistent with the assertion above that a hedonic risk gradient may not exist for nonunionized jobs and for jobs where RISK does not enter the production function. The latter is consistent with the relatively low mean values of RISK, with little variation among the individually reported values for workers in the nonunion and white collar subsamples.[22]

CONJOINT ANALYSIS

As noted above, conjoint studies usually use one of three preference models to estimate the value of attributes to consumers: a linear or vector model, an ideal point model or the part worth function. We have chosen one form of the ideal point preference function, a quadratic function, for several reasons. First, Peckelman and Sen (March 1979, May 1979) use simulation analysis to show that the quadratic utility function is superior for predictive purposes over a part worth function. Second, a quadratic function is more general than a linear function and allows for convex indifference curves.

We specify the preference function as:

$$(15)\ \text{RATING}_{ijk} = \beta_{0j} + \beta_{1j} * \text{RWAGE}_{ijk} + \beta_{2j} * \text{RWAGE}^2_{ijk} + \tau_{1j} * \text{RISK}_{ijk} + \tau_{2j} * \text{RISK}^2_{ijk} + \phi_{1j} * X_{ijk} + \phi_{2j} * X^2_{ijk}$$

where:

- i = The job;
- j = The subsample;
- k = An individual in subsample j;
- RATING_{ijk} = The rating or preference given by respondent k in subsample j based on the utility of the ith job;
- ϕ_{ij} = A column vector of coefficients; and
- X_{ijk} = A vector of characteristics (other than risk) of the ith job for individual k in subsample j.[23]

[22] An objective measure of fatal accident rates (FATAL) was obtained from Bureau of Labor Statistics data on work-related deaths per thousand employees in SIC two digit industries. Respondents were matched with their appropriate value of FATAL. FATAL was substituted for the subjective RISK measure in regressions otherwise specified identically to those reported in the paper. As with the RISK variable, the coefficient on FATAL was not significantly different from zero at any reasonable significance level.

[23] Because utility as such is unmeasurable, conjoint analysis typically starts with a specified interval scale to measure preference for a specified profile. Such scales have the properties of order and difference. For example, on a 5 point interval scale if option A is rated 1 and option B is rated 3, then B is three times better

The ratings chosen by respondent k are based on a comparison of a new (hypothetical) job with the respondent's current job. The survey rating of the new (hypothetical) job compared to the current job given by individual k in subsample j, $SURVRATE_{njk}$, can be expressed as

$$(16)\ SURVRATE_{njk} = RATING_{njk} - RATING_{cjk}$$

where:

n	=	The new hypothetical job;
c	=	The respondent's current job;
$RATING_{njk}$	=	The rating of the respondent's job at the new wage and risk level;
$RATING_{cjk}$	=	The rating of the respondent's job at the current wage and risk level.[24]

For a given j and k, there are 15 new hypothetical jobs, each of which is compared to the respondent's current job. Letting i equal c in equation (15) and subtracting from that equation (15) when i equals n gives

$$(17)\ SURVRATE_{njk} = \beta_{1j}(RWAGE_{njk} - RWAGE_{cjk}) + \beta_{2j}(RWAGE^2_{njk} - RWAGE^2_{cjk})$$
$$+ \tau_{1j}(RISK_{njk} - RISK_{cjk}) + \tau_{2j}(RISK^2_{njk} - RISK^2_{cjk}).$$

The X's disappear because for a given k and j, these are held constant across the current and new jobs. The parameters, β_{1j}, β_{2j}, τ_{1j}, and τ_{2j} in equation (17) are the same as those in equation (15).[25]

We estimate equation (17) for the four subsamples using the survey conjoint data where $RWAGE_{njk}$ and $RISK_{njk}$ are the wage and risk levels of the new hypothetical job presented to the respondent in the survey and $RWAGE_{cjk}$ and $RISK_{cjk}$ are the wage and risk levels of the current job. Because each sample consists of 15 observations for each individual, the disturbances across observations for an individual may be correlated. The *error component model* (also commonly referred to as *the random effects model*) describes how the behavior of different individuals varies due to an individual-specific disturbance. The two component model assumes that the regression disturbance is composed of two independent components: one random component associated with cross-sectional units and another associated with the entire sample. Assuming this error structure, parameters in

than A. Alternatively, A could be rated 2 and B rated 6 on a ten point scale. Hence, while the specific interval scale is arbitrary, the relative intensity of preference must be maintained. Therefore, ratings in conjoint analysis have both a cardinal and ordinal aspect. In this sense, RATING is a proxy for utility in that intensity of preference is captured.

[24] The survey rating scale (a nine point scale ranging from 1 to 9) was transformed to have a mean of zero and a range of -4 to 4.

[25] Another justification for the quadratic utility function is that other nonlinear transformations of the dependent variable that generate convex indifference curves, such as a translog function, pose a problem because RATING is not known in equation (15). Only SURVATE is known from the survey data. Taking the natural log of RATING in equation (15) and subtracting (15) when i = c from (15) when i = n would give a left side variable that is not known from the survey data.

Table 4—Conjoint Statistical Results for Each Subsample[a]

Variable	Blue Union	Blue Nonunion	White Union	White Nonunion
$(RWAGE_{ajk} - RWAGE_{cjk})$	1.87*	2.90*	1.83*	1.19*
	(7.31)	(17.30)	(7.57)	(29.50)
$(RWAGE^2_{ajk} - RWAGE^2_{cjk})$	-.026*	-.074*	-.023*	-.011*
	(-2.21)	(-9.69)	(-2.49)	(-15.00)
$(RISK_{ajk} - RISK_{cjk})$	-.265*	-.464*	-.650*	-.580*
	(-4.68)	(-9.29)	(-9.17)	(-17.80)
$(RISK^2_{ajk} - RISK^2_{cjk})$	-.010**	.010*	.029*	.022*
	(-1.89)	(2.30)	(4.42)	(7.40)
R^2	.35	.32	.39	.26
Breusch-Pagan Lagrange Multiplier	227.20	1480.9	268.0	2332.1
$\frac{\partial SURVRATE}{\partial RISK}$	-.344	-.405	-.552	-.502
$\frac{\partial SURVRATE}{\partial RWAGE}$	1.390	1.775	1.353	.928

[a]t-statistics in parentheses
* Significant at $\rho < .05$
** Significant at $\rho < .06$

equation (17) are estimated using generalized least squares according to Kmenta (1986, p. 628).

Table 4 contains the estimated parameters and t-ratios. The test for the appropriateness of the error structure implied by the random effects model is based on the Breusch and Pagan Lagrange multiplier which is distributed $\chi^2_{(1)}$. The calculated Breusch and Pagan Lagrange multipliers, presented in Table 4, range from 268 to 2332. Based upon these values, we reject the null hypothesis that there is no individual-specific disturbance.[26]

For all samples the coefficients on the unsquared variables in equation (17) are significantly different from zero at $\rho < .01$ and are the expected signs. In addition, the coefficients on the squared terms are significantly different from zero at $\rho < .06$.[27] The negative coefficient on $RWAGE^2$ for all samples indicates diminishing marginal utility of income. The negative coefficient on $RISK^2$ for blue union indicates increasing marginal disutility of risk, while the positive coefficient on $RISK^2$ for the other three subsamples indicates diminishing marginal disutility of risk.[28]

[26] An alternative to the error component model is the dummy variable or fixed effects model where the difference across individuals is assumed to be fixed. The difference between the two is that the specific characteristics of a cross-sectional unit is a normally distributed random variable in the error component model whereas the specific characteristic of a cross-sectional unit is a parameter in the fixed effect model. With this particular sample, the loss in the number of degrees of freedom if a fixed effects model is assumed is large (the loss being the number of individuals in each sample), resulting in possibly large losses in efficiency.

[27] We calculate F-statistics to test the hypothesis that equation (17) is linear for each subsample. F-statistics range between 3.94 and 8.33; thus, we are able to reject the hypothesis of linearity at $\rho < .05$.

[28] Diminishing marginal utility of risk reduction (increasing marginal disutility of risk) is intuitively appealing and strongly supports the satisfaction of equation (13). On the other hand, increasing marginal utility of risk reduction is not intuitively appealing. Where the hedonic gradient is nonexistent, however, we only need equations (11) and (12) satisfied. Therefore, we have no *a priori* reason to expect any particular sign on U_{RR}. The three groups have significantly lower risk levels than blue union so that this increasing marginal utility of risk reduction occurs at low levels of risk. Individuals may self-select into these lower risk occupations because of a strong aversion to risk. Most individuals in these three subsamples perceive themselves to be at step 1 on the risk ladder. Accepting that first step increase in risk represents a significant loss in utility with less loss for the next step. Given blue union's results, if forced to move to risk levels above the range of risk in

Table 5—Hedonic and Conjoint MVS Estimates for Each Sample[a]

	Hedonic MVS	Conjoint MVS
Blue Union	\$2,248,480	\$2,504,311
Blue Nonunion	–	\$2,310,635
White Union	–	\$4,131,624
White Nonunion	–	\$5,565,602

[a]No estimate for the MVS is given where the coefficient of RISK is not significantly different from zero. MVS estimates are in 1990 dollars

THEORETICAL VALIDITY

Table 4 shows the marginal effects of RWAGE and RISK on SURVRATE evaluated at the mean values of RISK and RWAGE for each of the four subsamples. The signs of these marginal effects are consistent with the hypothesized signs in equations (11) and (12). For white union, white nonunion, and blue nonunion, satisfaction of equations (11) and (12) ensures that the utility function estimated from the conjoint data is consistent with a unique utility maximization solution. We test the conjoint model estimated for blue union for satisfaction of equation (13). Equation (13) evaluated at the subsample's means is negative. Therefore, in all samples, the utility function estimated from the conjoint data is consistent with a unique utility maximization solution.

MARGINAL VALUE OF SAFETY ESTIMATES

HEDONIC MVS

The MVS estimate implied by the semilogarithmic hedonic function is

$$(18)\quad \frac{\partial \text{RWAGE}}{\partial \text{RISK}} = \frac{\partial \ln(\text{RWAGE})}{\partial \text{RISK}} * \text{RWAGE} * 2{,}000 * 4{,}000.$$

The number 2,000 assumes a 40 hour work week, 50 weeks per year. The number 4,000 is included because the unit change in deaths (ΔRISK) is one per 4,000 workers. The first column of Table 5 gives the MVS estimate evaluated at the mean real wage for the subsample blue union.[29] We calculate the MVS only for this subsample because it is the only subsample where the coefficient of RISK is significantly different from zero at $\rho < .05$.

CONJOINT MVS

From the conjoint analysis, the average MVS estimate for an individual k in subsample j is equal to

$$(19)\quad \frac{|\partial \text{SURVRATE}_{jk}/\partial \text{RISK}_{jk}|}{|\partial \text{SURVRATE}_{jk}/\partial \text{RWAGE}_{jk}|} * 4{,}000 * 2{,}000.$$

these occupations, these results may not hold. We may get, as in the case of blue union, diminishing marginal utility of risk reduction.

[29] All marginal value of safety estimates in this paper are expressed in 1990 dollars.

Evaluating the partial derivatives in equation (19) at the mean values for RWAGE and RISK gives the conjoint MVS estimates for each subsample, as presented in the second column of Table 5. The largest conjoint marginal value of safety estimate, \$5,565,602, is for the subsample, nonunion white, while the smallest, \$2,310,635 and \$2,504,311, are for the subsamples blue nonunion and blue union, respectively. These differences reflect the differences in both how workers in each subsample value an increase in income and how they value a decrease in risk. For example, workers with the highest MVS, white nonunion workers, value a small increase in income less than other subsamples while the decrease in utility coming from a one unit increase in RISK is greater than the other subsamples. These workers are also, on average, the highest paid and have the lowest risk levels.

The MVS estimates in Table 5 are consistent with other MVS estimates from labor market studies. A summary of these estimates by Viscusi (1993) shows the middle two-thirds of these estimates ranging from \$1.1 million to \$9.7 million (1990 dollars) with a mean of \$5.1 million.[30]

CONVERGENT VALIDITY

We compare the hedonic MVS estimate from the blue union sample to the corresponding conjoint MVS estimate for significant differences. The standard error of the hedonic MVS estimate can be calculated from the results in Table 3, while a Taylor series expansion is used to find the standard error of the conjoint MVS estimate (Kmenta, 1986, p.486). A paired t-test ($t = 1.50$) reveals that the hypothesis of no significant difference between the two estimates cannot be rejected at a reasonable level of confidence.[31]

In addition, a comparison of the hedonic MVS estimate calculated for each worker with the conjoint MVS estimate for that same worker provides further support for convergent validity. The Pearson correlation coefficient between the individual conjoint and hedonic MVS measures is .94, which is significant at $\rho < .001$.

CONCLUSION

The lack of a significant difference between the hedonic and conjoint MVS estimates for blue union provides support for the convergent validity of conjoint methods. Theoretical validity is also supported because the preference function estimated from the conjoint data conforms to expectations derived from economic theory. These results are especially noteworthy because of the type of conjoint study used. Risk is an intangible attribute of a job and not easily quantified. Many conjoint studies gather data on attributes of consumer

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[30] Gegax *et al.* (1991) report an MVS estimate for blue collar, unionized workers of \$1.6 million. The difference between their estimate and the corresponding estimate in this paper is due to a difference in the sample size. Our sample size is smaller due to deletions of respondents that did not fully complete the conjoint section of the survey.

[31] The hedonic and conjoint MVS estimates for individuals one standard deviation above the average wage and risk levels and the estimates for individuals one standard deviation below these average levels are also not significantly different. The difference between the MVS estimates for individuals two standard deviations above the averages, however, is approximately 15 percent and significant at $\rho = .05$. This difference is due, in part, to the standard error of the hedonic MVS estimate being larger than the standard error of the conjoint MVS estimate. In imputing the relationship between wage and risk through hedonic regression analyses, there are many intervening factors that can increase the estimated standard error of the coefficient on risk, e.g., multicollinearity between the independent variables. In addition, the market may not perfectly trade off increased wages for increased risk, especially for low risk jobs.

products that are more tangible and thus have attribute levels that are more easily quantified or on attributes where respondents are familiar with what constitutes high versus low levels of the attributes. In comparison with conjoint exercises where respondents are familiar with attributes and attribute levels, the conjoint exercise used in this paper is relatively difficult. Even with these difficulties, however, this study produces significant support for both convergent and theoretical validity of the conjoint methodology. Therefore, the growing use of conjoint analysis as a decision-making tool and the resulting trust that academicians and practitioners place in the conjoint results appears to be supported.

There is another important implication of this work for those who estimate individuals' marginal values of safety. This paper uses the conjoint method to measure the MVS for all types of workers, whereas the hedonic technique failed for low risk, nonunion jobs. The apparent failure of the hedonic method to produce MVS estimates in low risk/nonunionized jobs combined with the support of validity of the conjoint results in this study suggest that conjoint analysis may be superior in assessing the MVS of workers in all types of jobs.

Although conjoint analysis may have applications in many economic valuation studies, further validation of its results should be pursued.[32] Louviere (1988) calls for further research to determine where conjoint techniques are likely to exhibit external or predictive validity and whether some conjoint techniques are likely to produce more valid results than others.

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