Factorial Survey Methods for Studying Beliefs and Judgments

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This article develops a unified framework, based on Rossi's factorial survey method, for studying positive beliefs and normative judgments. The framework enables estimation of individuals' positive-belief and normative-judgment equations, leading to analysis of the components of beliefs and judgments, assessment of interpersonal variability in the components, and estimation of two further equations, representing, respectively, the determinants and consequences of the components. We describe procedures for data collection, assemble a set of tools for estimating the positive-belief and normative-judgment equations and carrying out the corresponding homogeneity tests, and propose ways of estimating the determinants and consequences equations. To illustrate the framework, we investigate both a positive-belief equation (describing adolescents' views concerning determination of marital happiness) and a normative-judgment equation (describing judgments of the justice of earnings). This article thus provides a guide to contemporary factorial survey analysis, and points the way to its further development.

Keywords: *factorial survey analysis; vignettes; marital happiness; justice; inequality*

1. INTRODUCTION

Consider the equation representing determination of a behavioral or social outcome of interest:

$$Y_j = \beta_0 + \sum \beta_k X_{kj} + \epsilon_j, \qquad (1)$$

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where j denotes the unit in which the outcome Y is observed and there are K explanatory regressors X. This type of equation, which we will call a Type I equation, is routinely estimated by social scientists. The outcome Y might represent earnings, healthiness, marital happiness, admission to graduate school, grade point average, labor force participation, the decision to vote, and so on. When social scientists specify and estimate such an equation, they are systematically seeking to learn something about reality—about how, in fact, healthiness or earnings are attained, about the determinants of employment, and so on.

But social scientists are not alone in seeking to understand reality. People in general seek knowledge about external reality, both for its own sake and to alter the possibilities for their own lives. As a sociologist of knowledge might say, humans form beliefs about the nature of the world. Thus, to every Type I equation, there corresponds an equation representing an individual's belief about the determination of the outcome Y. This new equation—the *positive-belief* equation, termed a Type II equation and sometimes referred to as a "what is" equation—may be written as follows:

$$Y_{ij}^{\mathrm{POS}} = \beta_{0i} + \sum \beta_{ki} X_{kj} + \epsilon_{ij}, \tag{2}$$

where the subscript i denotes the individual-observer, who is acting as a *lay scientist*.

One might say that a Type I equation represents a collective and systematic approximation to "truth" and that a Type II equation represents a solitary and less explicitly systematic approximation—in Platonic terms, an "appearance" as seen by a given individual. For example, if an earnings function is regarded as an instance of a Type I equation, then it is possible to find, inside the heads of individuals, beliefs concerning its parameters, to find, that is, the corresponding Type II equation held by each individual-observer. Similarly, one might specify a Type I equation to describe the probability that an applicant for an immigrant visa is selected for permanent residence in the United States and a parallel Type II equation embodying Americans' (and others') beliefs about the probability of selection to U.S. permanent residence.

Of course, both scientists' and ordinary people's ideas about the way the world works may be far more complicated than the representations in the Type I and Type II equations. These ideas may be more faithfully represented by a multiequation system, say, or a tree structure. These more elaborate representations include single equations, and it is these single equations on which this article focuses. To illustrate, the Type I earnings function may be embedded in a two-equation system in which the other equation describes the determinants of schooling; the ordinary person's belief may parallel this two-equation system.[1]

In addition to the positive-belief (Type II) equation, the original (Type I) equation of Y may be accompanied by a third equation, an equation expressing an individual's opinion concerning the correct or proper or just determination of Y. For example, humans not only form ideas about the determination of earnings, but they also form ideas about the just distribution of earnings; humans not only form ideas about how prospective immigrants are selected but also about the ideal system for selecting them. These ideas are expressed in a new equation—the *normative-judgment* equation, termed a Type III equation and sometimes referred to as a "what ought to be" equation:

$$Y_{ij}^{\text{NOR}} = \beta_{0i} + \sum \beta_{ki} X_{kj} + \epsilon_{ij}, \quad (3)$$

In this case, the individual-observer is acting as a *lay judge* (or *guardian*).[2]

Note that the Type II and Type III equations for any given individual may be shorter than the corresponding Type I equation—if (some) individuals pay attention to a restricted set of stimuli (Kahneman and Tversky 1979; Miller 1956). However, the full set of explanatory regressors X in all the individuals' Type II or Type III equations may be larger than that in the Type I equation. Individuals may mistakenly believe that some characteristics affect Y when, in fact, they do not or may judge that they ought to affect Y.

In both the positive-belief (Type II) and the normative-judgment (Type III) equations, three components are of interest: (a) the lay scientist/judge's view concerning the location parameter of the Y distribution, represented by the equation intercept β_{0i}; (b) the lay scientist/judge's view concerning the relevant determinants of Y and their quantitative effects, represented by the regression slopes β_{ki}; and (c) the degree of certitude with which the lay scientist/judge holds the view embodied in the equation, represented in the ordinary least squares case by R^2.[3] These three components of the positive-belief and normative-judgment equations, together with functions of the intercept and slope coefficients, are collectively denoted θ. Thus, the set θ may include not only the parameter estimates but also the difference between two slope coefficients, the sum of two or more slope coefficients, a nonlinear function of a slope coefficient, and so on.

Equations of Type II and Type III—which might be considered second-order equations or "shadows" of the Type I equation, expressing, respectively, the human's drives to *know* and to *judge*—are in turn important to social scientists, triggering what might be considered third-order equations. For the positive-belief and normative-judgment equations are themselves the product of sociobehavioral processes of interest to social science and also influence many behaviors also of interest to social science. To illustrate, the lay scientist's view of the determinants of marital happiness may be influenced by childhood observation of parental behavior; the decision to stop smoking or to eat cabbage may be influenced by the perceived determinants of healthiness. Similarly, the lay judge's view of the just prison sentence may be influenced by religious experiences in early childhood, and the financial contribution to an anti–capital punishment lobby group may be influenced by the certitude with which a normative view concerning offender rehabilitation is held.

Thus, we may write two further equations, one representing *determinants* of an element of the set θ and the other representing *consequences* of an element of the set θ.

To represent the determinants of an element θ associated with the positive-belief (Type II) and normative-judgment (Type III) equations, we specify

$$\theta_i = \gamma_0 + \sum \gamma_k Q_{ki} + \nu_i, \tag{4}$$

where Q denotes the determinants of θ, and γ_k denotes the effects of Q. For example, the perceived effect of smoking on life expectancy, estimated via a Type II equation, may be shaped or influenced by the individual's age and schooling. This equation will be called a Type IV equation.

To specify the consequences of an element of the set θ associated with the positive-belief (Type II) and normative-judgment (Type III) equations, we write

$$S_i = \alpha + \delta\theta_i + e_i, \tag{5}$$

where S denotes the behavioral consequences of the elements of the belief/judgment structure, and δ expresses the quantitative effect of θ. For convenience, we have omitted further subscripts to indicate which θ from among the possibly large set of estimated θs is being studied. For example, the perceived effect of smoking on life expectancy may influence a variety of behavioral consequences, such as the decision to smoke, the decision to stop smoking, the number of cigarettes smoked per day, choice of marital partner, choice of friends, and parenting behaviors. This kind of equation will be called a Type V equation.

This set of five equations is a fundamental set. It begins with the objective attempt to understand reality, proceeds to the two subjective "shadow" equations, and ends with objective relations between the shadow equations and their causes and effects.

The connections between elements of the set θ and their determinants and consequences may be represented diagrammatically:

$$\text{Determinants } Q \rightarrow \ \theta \rightarrow \ \text{Consequences } S. \qquad (6)$$

Note, however, that if all observers can be described by the same shadow equation of Type II or Type III, then there are no determinants or consequences to study via equations of Type IV or Type V. Accordingly, an important task is to assess the extent to which a population of interest holds the same beliefs or reaches the same judgments and can be characterized by the same degree of certitude.

Of course, we cannot even begin to make such an assessment of population homogeneity unless we can obtain reasonable estimates of the positive-belief and normative-judgment equations implicitly held by individuals. Our first task, then, is to ascertain the equation-inside-the-head for each person in a reasonable sample. This task is not prima facie easy, for it requires, ceteris paribus, estimates of a rather sophisticated nature. Consider, for example, what one might respond to an interviewer who asked, "Now I want you to tell me what you think is the effect of an extra year of schooling on the wage rate, holding everything else constant," and then proceeded to ask about the effects of 10 other variables, concluding with "How sure are you about this process?"[4]

The factorial survey method pioneered by Peter H. Rossi (1951, 1979) and developed in many applications (Rossi et al. 1974; Sampson and Rossi 1975; Berk and Rossi 1977; Jasso and Rossi 1977; Alves and Rossi 1978; Alves 1982; Nock and Rossi 1978; Rossi and Anderson 1982; Bose and Rossi 1983; Rossi and Berk 1985; Jasso 1988, 1990; Jasso and Opp 1997; Jasso and Webster 1999; Hechter et al. 1999) enables estimation of an individual observer's positive-belief and normative-judgment equations. The Rossi method yields estimates of the intercept and slopes of Type II and Type III equations that are unbiased and, under specified conditions, best linear unbiased estimates (BLUE) and yields a consistent estimate of the third component of interest, the equation R^2.

The purpose of this article is to formalize the framework for the systematic study of equations of Types II, III, IV, and V, incorporating advances in measurement and estimation strategies. We build on the approach developed by Rossi and his associates, who in a long series of papers have obtained estimates of positive-belief and normative-judgment equations and have explored ways of estimating the third-order Type IV equation. We begin with a brief review of the factorial survey method, describe procedures for data collection, assemble a set of tools for estimating Type II and Type III equations and carrying out the corresponding homogeneity tests, and propose ways of estimating Type IV and Type V equations—incorporating such advances as seemingly unrelated regression estimators (Zellner 1962, 1963) and random-parameters estimators (Hildreth and Houck 1968; Swamy 1970) for the Type II and Type III equations and joint multilevel estimation (DiPrete and Forristal 1994; Goldstein 2003; Hox 1995; Rabe-Hesketh, Pickles, and Skrondal 2005; Raudenbush and Bryk 2002; Snijders 2003a, 2003b; Snijders and Bosker 1999) for the pair of equations formed by a Type IV equation and a Type II or Type III equation.

To illustrate, we provide two examples. The first example is of a positive-belief Type II equation. We retrieve adolescents' implicit equations of the determination of marital happiness; on the basis of statistical tests, we reject homogeneity and then estimate Type IV equations of the determinants of the adolescents' idiosyncratic beliefs. The second example is of a normative-judgment Type III equation. We show how Rossi's factorial survey method makes it possible to estimate respondent-specific just earnings functions and just earnings distributions, together with their parameters—principally, the just base salary, the just rate of return to schooling, and the just gender multiplier embodied in just earnings functions and the amount of inequality embodied in just earnings distributions—and to investigate the effects of respondents' gender and schooling on these components via Type IV equations. These examples illustrate the possibilities of the Rossi method for extending the territory of estimable socio-behavioral relationships.[5]

2. ESTIMATING THE POSITIVE-BELIEF (TYPE II) AND NORMATIVE-JUDGMENT (TYPE III) EQUATIONS

In the factorial survey approach, each respondent is asked to rate the level of a specified outcome variable (such as healthiness or wage attainment or just prison sentence) corresponding to a fictitious unit (a person, say, or a family), which is described in terms of potentially relevant characteristics such as age, gender, study or eating habits, access to medical care or housing, and the like. The respondent is presented a large set of these fictitious units, termed *vignettes*. Statistical techniques are used to retrieve the equation implicitly used by each respondent in assigning the level of the outcome variable to each vignette.

There is a tight correspondence between the objective—to obtain estimates, with the best possible statistical properties, of the Type II or Type III equation in the respondent's head—and elements of the research design. For example, as will be seen, the inputs in the Type II or Type III equation are embodied in the vignettes, the dependent variable in the Type II or Type III equation is measured via the rating task, and the precision of the estimates depends, in part, on the relation between the number of regressors and the number of vignettes rated by each respondent (i.e., on the degrees of freedom in the respondent-specific equation). Decisions about particular design features—for example, how many characteristics and levels of characteristics to include in the vignettes and how many vignettes to present to each respondent—are made with the explicit goal of obtaining the statistically best possible estimates of the Type II and Type III equations.[6]

An important feature of the factorial survey method, formulated by Rossi, is that it permits construction of a richly varied population of vignettes. Rossi's early innovation was to propose that random sampling be used to draw samples from the large vignette population;

given that respondents would be presented with *samples* of vignettes, there is no need to restrict the size or complexity of the vignette population. Accordingly, the vignettes are described in terms of many characteristics; each characteristic is represented by many possible realizations (excepting, of course, cases where the characteristic has few possible levels, such as gender), and the characteristics are fully crossed. Two additional important features of the Rossi design are the following: (a) in the population of vignettes, the correlations between vignette characteristics are all zero or close to zero, thus reducing or eliminating problems associated with multicollinearity, and (b) the vignettes presented to a respondent are under the control of the investigator (i.e., they are "fixed"), so that endogeneity problems in the estimation of Type II and Type III equations arise only if respondents do not rate all the vignettes presented to them.

In the case of a positive-belief (Type II) equation, the factorial survey method yields estimates of each respondent's belief concerning the direction and magnitude of the effect of each input factor on the outcome variable. In the case of a normative-judgment (Type III) equation, the factorial survey method yields estimates of each respondent's judgment concerning the correct weight (positive, negative, or zero) to be placed on an input factor in deciding the outcome variable. For example, as will be seen below, the factorial survey method yields estimates of the beliefs of adolescents concerning the determinants of marital happiness; and as shown in Jasso (1988), the factorial survey method yields estimates of the judgments of each member of a decision-making body concerning the appropriate criteria for the selection of immigrants.

In this section, we summarize the essential elements of the procedures for generating the vignettes, obtaining the ratings, and estimating the positive-belief (Type II) and normative-judgment (Type III) equations.

2.1. INSTRUMENT PREPARATION AND DATA COLLECTION

2.1.1. The Vignette Samples

A vignette is a description of a unit or actor—such as a person or a family—in terms of the unit's characteristics, such as age, school grade, or marital duration. The characteristics used to describe the unit are the regressors in the Type II or Type III equation, and the first objective will be to estimate the effects of these characteristics on the outcome of interest.

The procedure developed by Rossi for constructing the vignettes and assembling the vignette packs presented to respondents consists of the following steps:

1. *Selection of input factors/vignette characteristics*. The investigator first selects the variables believed to influence the outcome variable of interest. This set—the variables corresponding to the regressors X in the Type I, II, and III equations—includes variables suggested by prior theory and research, extra-theoretical reasonings, and conventional wisdom.[7] Note the critical importance of including variables popularly thought to be determinants, even if working scientists believe they are irrelevant.

   There is a rich literature concerning the number of characteristics people use in reaching their judgments (Kahneman and Tversky 1979; Miller 1956). The factorial survey method makes it possible to assess the number and identity of the characteristics a person uses in reaching a judgment and hence the extent of interpersonal variability on these matters and its etiology.
2. *Measurement of input factors/vignette characteristics*. The investigator next assigns to each selected characteristic a domain as well as realizations from within that domain; for example, the characteristic "age" of a vignette adult might be assigned a domain from 25 to 65 years inclusive, with nine realizations at 5-year intervals. The decision of how many realizations to include in the vignettes reflects one consideration—the number of regressors in the equations to be estimated (which, via the relation to the number of vignettes rated by each respondent, affects the precision of the estimates)—and differs according to whether the characteristic is quantitative or qualitative.[8] Quantitative characteristics may be assigned as many levels as one pleases, given that they are represented by a single regressor X in Type II and Type III equations, no matter how many realizations; qualitative characteristics, on the other hand, will be represented in the equations by binary variables, and thus the number of realizations is selected with an eye to the total number of regressors.[9]
3. *Generation of full factorial vignette population*. The investigator generates the full factorial population of all possible combinations of the realizations assigned to the characteristics (i.e., the Cartesian product). This population may contain millions of fictitious individuals,

each representing a unique combination of realizations of characteristics. The full factorial design ensures that the intercorrelations among vignette characteristics are zero in the vignette population.[10]

4. *Deletion of logically impossible vignettes*. Subject to the specific substantive context, the investigator next removes from the vignette population those combinations that are not logically possible—for example, a physician with only an eighth-grade education. If such deletion occurs, then the population intercorrelations among vignette characteristics are no longer all zero.[11,12]
5. *Drawing random samples from the vignette population*. At this step, the investigator draws random samples of a specified size V from the vignette population. The size V of the samples is usually in the range of 40 to 60—large enough to enable precise estimation of respondent-specific Type II and Type III equations even when the input factors number 10 or 15, yet small enough to prevent respondent fatigue.

   In drawing the vignette samples, the investigator may draw a unique sample for each respondent or may, to obtain multiple ratings on each vignette, draw only a few samples, for example, one for each 20 respondents. Each unique vignette sample is called a *deck* of vignettes. To illustrate, in Jasso and Rossi's (1977) research on the justice of earnings, 10 distinct vignette decks were drawn, each containing 60 vignettes ($V = 60$) and each presented to 20 respondents; in contrast, in Alves and Rossi's (1978) research on the same topic, unique vignette decks were drawn for each respondent, each deck containing 50 vignettes ($V = 50$). Note that there are trade-offs between the two strategies. Certain questions can only be answered by presenting the same deck to many respondents—for example, investigation of the question of whether certain types of persons (say, women or the foreign born) elicit greater variation in judgments of just earnings requires computation of measures of dispersion in the just earnings assigned to particular vignettes.[13] On the other hand, a richer collection of vignettes is rated when each respondent receives a unique deck. The set of vignettes presented to each respondent—which may be a unique deck (as in the Alves and Rossi 1978 research) or may be a copy of a deck (as in the Jasso and Rossi 1977 research)—is called a *pack* (like a pack of cards).
6. *Shuffling the vignette pack*. It has been standard practice since the early days of the factorial survey method to shuffle the pack of vignettes before presenting it to a respondent to prevent order effects. However, subsequent detection of serial correlation requires that a record be kept of the order in each respondent's pack.

Recent advances in computer hardware and software enable smooth and efficient generation of the vignette population and drawing of the random samples. Examples of vignettes are included in the appendix. Tables A1 through A4 present vignettes, respectively, of married couples, such as were used in the study of adolescents' perceptions of marital happiness; of immigrant visa applicants, such as were used in the policy study of an immigration point system; of adolescents, proposed for use in a study of adolescent investment in schooling and health; and of chief executive officers, drawn from a study of both perceptions of actual total compensation and of just compensation.[14]

2.1.2. The Rating Task

Each pack of vignettes is accompanied by a rating task. The respondent is asked to assign the value of the outcome variable to each of the V fictitious units in the pack. Note that it is the rating task that generates the dependent variable and defines the positive or normative character of the equations to be estimated. In a positive-belief (Type II) context, the respondent is asked to estimate, say, the earnings or happiness of the fictitious vignette. In contrast, in a normative-judgment (Type III) context, the task is to judge the just or desirable outcome.

The rating task also determines the measurement properties of the outcome variable and hence has important consequences for the subsequent analysis. Measurement of the outcome variable may be fundamental (e.g., life expectancy in years) or quasi-fundamental (e.g., money earnings) or nonfundamental (e.g., happiness). The outcome variable may define an amount (e.g., earnings), a probability (e.g., probability of divorce), a set of unordered categories (e.g., different concentrations for a college degree), or a set of ordered categories (e.g., verbal health assessments).[15]

Tables A5 through A9 in the appendix contain examples of the rating task instructions for equations of marital cohesiveness, healthiness, scholastic attainment, perceptions of CEO compensation, and justice of CEO compensation. The two marital cohesiveness examples include a happiness scale as well as the probability of divorce. The two healthiness outcomes include life expectancy in years and a nonfundamental scale of healthiness. The two scholastic attainment outcomes shown in the appendix are high school grade point average and highest degree.

The nonfundamentally measurable (or inherently subjective) outcomes, unlike the fundamentally measurable (or objective) ones, present special problems. Early work using the factorial survey method employed nine-point category scales. Such scales have high field utility in the survey research context. On the other hand, the literature on constructing scales and obtaining judgments of inherently subjective magnitudes suggests that category scales produce distortions and that the preferred technique is one that more faithfully represents the response variable continuum in the respondent's head and that allows the rater maximum freedom in estimating magnitudes (Hamblin 1974; Shinn 1974; S. S. Stevens 1975). Moreover, from a statistical perspective, the scale form—and the resultant properties of the response variable—determines the properties of the estimated models, coefficients, and hypothesis tests.

To avoid the distortions potentially induced by category scaling of the nonfundamentally measurable outcomes, factorial survey research has increasingly used a scale form called "number matching" pioneered by S. S. Stevens (1975)—the respondent matches a number to a point on the response-variable continuum.[16] The number matching scale form capitalizes on the prior experience of the respondent. As Stevens argued,

> The observer brings one of the continua with him as the system of numbers that he has learned and practiced so very thoroughly in memorizing the multiplication table, counting his change, and in measuring many things. With the number system thoroughly drummed into him, the observer can match numbers from that continuum to items on any other continuum with which he is confronted. . . . [M]ost people seem to achieve a firm grasp of the knack of assigning numbers to match apparent magnitude. (P. 30)

Thus, S. S. Stevens (1975) believed that the number continuum is activated when the number assignment task is given to suitably prepared individuals. Of course, this may depend on the characteristics of the respondent sample, for example, on their age, education, and experience. If the number continuum is not activated by the number assignment task, then the ratings must be regarded as representing only an ordinal sequence. To activate the number continuum, factorial survey rating task instructions explicitly mention fractions and decimals (Tables A5, A6, A7, and A9 in the appendix).

S. S. Stevens (1975) developed two main forms of number matching: a "with standard" form and a "with no standard" form. In the "with no standard" or purest form, the scale is completely respondent devised (except for the origin, which may be dictated by the context); the respondent chooses the domain and the end-points. In the "with standard" form, the investigator provides the end-points, which are then interpreted as linear transformations of the respondent's own end-points.

Vignette studies of justice can use the "with no standard" form (Table A9) because justice theory accommodates respondent-specific scales and provides the requisite equations for transforming expressed justice evaluations into experienced justice evaluations (Jasso 1990). In other topical areas, the "with standard" form has been more widely used. The marital happiness (Table A5) and general healthiness (Table A6) scales exemplify spartan versions of the "with standard" scale form, in which only the end-points are provided by the investigator.

Notwithstanding the presumed superiority of magnitude estimation techniques, it is useful to keep the category scale in the tool kit, both because of its field utility and for use with less mathematically prepared populations. Further work might establish precise links between the two scale forms.

To preserve independence of the ratings, the rating task instruction typically includes the sentence "You may rate the vignettes in any order; and you may change any of your ratings."

2.2. ESTIMATION OF THE TYPE II AND TYPE III EQUATIONS AND ASSESSMENT OF RESPONDENT HOMOGENEITY

Design of the estimation strategy for Type II and Type III equations takes into account a number of factors: the number of respondents, whether the respondents constitute a random sample, measurement properties of the dependent variable, assumptions concerning the respondent-specific errors in the multirespondent context, and features specific to the substantive domain. In this section, we develop a set of tools for estimating Type II and Type III equations. We begin with estimation of the equation-inside-the-head for a single individual. Next we consider the system of equations corresponding to a set of respondents, describing four main approaches: (a) classical least squares, assuming equal variances across the respondent-specific equations; (b) generalized least squares, allowing the respondent-specific equations to have different error variances; (c) seemingly unrelated regressions, in which the errors from the respondent-specific equations may be correlated; and (d) random parameters, in which the respondents constitute a random sample and the parameters of the respondent-specific equations are viewed as coming from a distribution. The homogeneity testing framework is described for all approaches.

There is, however, a prior task that must be undertaken before estimating the equation, and this is to examine the pattern of ratings. Accordingly, our discussion of the respondent-specific equation begins with the respondent-specific distribution of ratings.

2.2.1. The Type II or Type III Equation Inside the Head of a Single Individual

Before turning to estimation of the Type II or Type III equation, we briefly consider the respondent-specific distribution of ratings. As has been recognized since the early days of the Rossi factorial survey (see, e.g., Rossi and Anderson 1982:42-4), the respondent-specific distribution of ratings is important for at least two reasons: First, depending on the substantive context, it may reveal important information. Second, the pattern of ratings may constrain choice of estimation procedure or even estimation itself.

To appreciate the usefulness of the ratings distribution, we consider four examples. The first is drawn from the study of norms. The pattern of ratings indicates (a) whether the estimated respondent-specific norm is prescriptive, proscriptive, or bipolar; (b) whether the norm is conditional or unconditional; (c) the intensity of the norm; and (d) whether the respondent in fact adheres to a norm (Jasso and Opp 1997:954-7). Second, in the study of values, the pattern of ratings indicates the polarity, conditionality, and existence of a value (Hechter et al. 1999:416-8). Third, in studies of the justice of actual rewards, the pattern of ratings reveals whether the respondent has uniform or nuanced views; for example, some respondents judge every rewardee to be justly rewarded, and others view everyone as underrewarded. Finally, in studies of ideas of the just reward, the judgments indicate whether the respondent views just rewards as conditional or unconditional; for example, some respondents are strict egalitarians and assign identical just rewards to every target rewardee.

In terms of the mechanics of estimation, the examples above suggest that in some cases, the respondent-specific ratings are constant. These "zero-variance" respondents require thoughtful handling. It is obvious that in the case of a single respondent, the equation cannot be estimated, but what to do in the multiple-respondent case is less obvious and will depend on the substantive context and on theoretical guidance.

The Type II or Type III equation inside the head of an individual is the most elementary starting point, and estimation of respondent-specific Type II or Type III equations is a fundamental starting point for several reasons. First, the behavioral model underlying the Rossi factorial survey method posits the existence of these equations inside the head, and a faithful analytic strategy begins with them. Second, respondent-specific equations constitute an analytic benchmark and are used to form other estimators (such as the random-effects estimator, which can be thought of as combining the respondent-specific, or within, estimator and the between estimator, as discussed by Mundlak 1978a). Third, there is interest in gauging the respondent's certitude, which is approximated by an element of the respondent-specific equation, such as R^2. Fourth, in some research contexts, there is indeed only a single respondent; one can imagine, for example, the usefulness of estimating certain Type II and Type III equations in Rust's (1987) superintendent of maintenance to complement the optimal stopping model of bus engine replacement. Fifth, the factorial survey method may become a useful diagnostic tool both for self and for clinicians.

The data matrix may be visualized as a matrix of size $V \times K$, where V denotes the number of vignettes rated by the respondent, and K denotes the number of regressors plus one. The statistical model may be written

$$y = XB + \epsilon, \tag{7}$$

with restrictions, to be tested, placed on the error.

The actual estimation of the single respondent-specific Type II or Type III equation can be carried out in several ways, corresponding to the measurement properties of the ratings collected from respondents.

If the ratings are reasonably assumed to constitute a continuous scale of a quantitative variable, then the estimation procedures of classical ordinary least squares (OLS) are appropriate and, indeed, for respondents who rate all vignettes in their pack or if any missing data are missing completely at random, yield respondent-specific estimates that, under the classical assumption that the errors are independently distributed with mean zero and constant variance (within respondent), are BLUE.[17] For each respondent, a measure of the associated certitude, in the form of R^2, is also obtained; as is well known, this sample estimate is biased but consistent. To take into account the number of regressors and the consequent reduction in degrees of freedom, it is prudent to obtain as well the adjusted R^2.[18] Depending on the substantive context, the investigator may estimate several versions of the equation, representing alternative functional form assumptions.

If the ratings are thought to constitute an ordinal scale, then the assumptions for OLS fail, and the appropriate estimation procedure entails recasting the equation into its counterpart in an ordered-response framework (McKelvey and Zavoina 1975; Amemiya 1981; Maddala 1983; Winship and Mare 1984).

If the ratings are unordered categories, then the equation is recast into a multinomial logit or probit equation.

A problem endemic to estimation of respondent-specific equations is the small sample size (20-60 vignettes)—“micronumerosity,” as Goldberger (1991) has termed it—which leads to estimates with less than robust precision. In survey research, the standard remedy is to “get more data.” But in the case of estimating the equation inside the head of a single individual, there are barriers to obtaining more data: Presenting more vignettes may induce fatigue, error, or breakoff of the interview. However, if there are multiple respondents, the additional information may be used to improve efficiency, as will be discussed below. Moreover, best practice may evolve in the direction of presenting 40 to 60 vignettes to the respondent, a number less likely to lead to problems of micronumerosity than 20 vignettes.[19]

2.2.2. The Type II or Type III Equation as a System of Equations Pertaining to a Set of Individuals

Consider now the more usual case in which there are multiple respondents. In this case, the existence of multiple respondents provides new information that can be used to improve the precision of the respondent-specific estimates. This new information may take any of several forms; for example, the researcher may have reason to believe that the equation error variances differ across respondents or that, when several respondents see the same deck of vignettes, their responses are correlated. The three approaches we describe invoke differing sets of assumptions concerning these and related matters. In some substantive contexts, one or the other approach will be unambiguously preferred. But in other substantive contexts, choice of preferred estimator may depend on issues of interpretation.

In the multiple-respondent context, the data may be visualized as a matrix, where, as before, V denotes the number of vignettes and K the number of regressors plus one, and N denotes the number of respondents. This is the "giant" stacked model.

Our discussion will focus on the case in which the dependent variable is continuous; extensions to limited dependent variable cases are straightforward.

Of course, there is an important new question when there are a set of individuals, and this is whether all of them can be described by the same equation—in the positive-belief context, whether they differ in their perceptions of the external world and, in the normative-judgment context, whether they disagree concerning ideas of justice or desirable policies. This issue of "aggregation bias," which was raised in a classic paper by Zellner (1962), pertains to many substantive domains.

Addressing the question of aggregation bias requires systematic assessment of interrespondent homogeneity. Accordingly, an important focus is on the homogeneity testing apparatus in each approach. In general, we begin with four classical models, building on Johnston and DiNardo's (1997:129-30) three-model classification.

Model 1 specifies that all respondents can be characterized by the same equation:

$$R_{iv} = \beta_0 + \sum \beta_k X_{kiv} + \epsilon_{iv}, \tag{8}$$

where R_{iv} denotes the rating made by the ith respondent about the vth vignette, β_0 denotes the common intercept, the X_{kiv} are the K regressors representing attributes of the fictitious vignette units, the β_k are the (common) slope coefficients associated with the vignette characteristics, and ϵ_{iv} is an error assumed to vary independently across respondents and vignettes. Model 1 imposes the restriction that the behavior of all respondents obeys the same rules, that is, can be described by the same intercept and the same slope vector. The number of parameters estimated in Model 1 is $(K + 1)$.

Model 2a specifies an equation with a common vector of slope coefficients but different intercepts for each respondent:

$$R_{iv} = \beta_{0i} + \sum \beta_k X_{kiv} + \epsilon_{iv}, \tag{9}$$

This model (also known as a fixed-effects or dummy-variable model) removes the restriction of a common intercept, thereby increasing the number of parameters estimated to $(K + N)$.

Model 2b specifies that respondents have common intercepts but different slopes:

$$R_{iv} = \beta_0 + \sum \beta_{ki} X_{kiv} + \epsilon_{iv}. \tag{10}$$

The number of parameters estimated is $NK + 1$.

Model 3 is fully unrestricted, specifying that respondents have both different intercepts and different slopes:

$$R_{iv} = \beta_{0i} + \sum \beta_{ki} X_{kiv} + \epsilon_{iv}, \tag{11}$$

The number of parameters estimated increases to $[N(K + 1)]$.

Each of the approaches we consider provides tests for assessing which of these models best fits the data, that is, tests of parameter homogeneity.

2.2.2.1. Classical OLS approach. In this approach, the stacked multiple-respondent equation is estimated by OLS. There are a variety of techniques for obtaining the OLS estimates in some of the models. For example, Model 2a is a fixed-effects equation and can be estimated via any of several equivalent techniques, such as (a) including a dummy variable for each respondent or (b) transforming the regressors into deviations from unit means. Similarly, Model 3 can be estimated in several ways, including (a) estimating each respondent-specific equation separately and (b) specifying a full set of interactions between regressors and respondent-specific dummies.

The homogeneity tests are conventional *F* tests of a set of linear restrictions (Johnston and DiNardo 1997). The test between Models 1 and 3 is popularly known as the Chow test, after Chow (1960). These tests assume that the errors are distributed independently and identically across both vignettes and respondents. It is likely that the equation error variances differ across respondents; a number of tests appropriate to this situation have been proposed, and we consider some of them in our discussion of the generalized least squares approach in the next section.

2.2.2.2. Generalized least squares and seemingly unrelated regressions approach. The generalized least squares (GLS) approach is characterized by relaxation of restrictions on the error variances and is compatible with all four models introduced above. The seemingly unrelated regressions (SUR) approach, as applied to factorial survey analysis, pertains to Model 3 and posits correlation between the respondent-specific equations. Because of the overlap between these two estimation approaches, we consider them jointly in this section. All the models considered here can be estimated by feasible generalized least squares (FGLS), including both two-step GLS and iterated GLS, which yields maximum likelihood (ML) estimates.

Unequal variances. The first assumption we relax is that of equal variances across the respondent-specific equations. All four models can be straightforwardly estimated. A variety of estimators for the standard errors have been proposed, their suitability depending on the fit between their properties and sample size (degrees of freedom) considerations. For example, a simple procedure that has asymptotic validity is to correct for the heteroskedasticity by dividing all observations by the square root of the corresponding respondent-specific equation error variances.

Tests of unequal variances include the Lagrange multiplier test, a likelihood ratio test, and White's test (Greene 2003:323-4). These, as well as tests of parameter homogeneity under unequal variances, are described in Greene (2003), Judge et al. (1985), and Kmenta (1986).

Cross-equation correlation. Suppose that when respondents rate the same vignette, they are subject to some of the same unobservables.

The respondent-specific equations would then be linked via their errors. This is the classical case Zellner (1962, 1963) considered and to which he gave the name "seemingly unrelated regressions." Factorial survey analysis presents an interesting situation in that SUR estimation is substantively appropriate when respondents rate the same vignettes, but when they rate the same vignettes, SUR produces identical estimates to OLS, providing no efficiency gain whatever. Yet SUR estimation is still useful because it yields an estimate of the cross-equation correlation and enables tests of the cross-equation correlation (Greene 2003:350). Given the substantive interest in exploring agreements and disagreements across respondents, these constitute a valuable piece of information.

There are a number of tests of parameter homogeneity in the literature. These include tests based on two-step FGLS estimates and on iterated FGLS estimates (Greene 2003:350). Note that it is possible to argue that cross-equation correlation can also arise, besides arising from common disturbances when judging the same vignette, in a way quite similar to the classical time-series contemporaneous correlation—namely, if respondents rating vignettes at the same time in a hall or classroom are subject to similar disturbances when they rate the ith vignette. In this case, SUR estimation can be applied to all factorial survey data, whether or not respondents see the same vignette deck, provided that the order in which they see vignettes is recorded (recall that the order is usually different for different respondents, as the vignette packs are shuffled). If the vignettes differ across respondents, the respondent-specific regressor matrices are no longer identical, and SUR estimation would produce efficiencies.

Autocorrelation. It has long been thought that factorial survey data are not very susceptible to autocorrelation. This view arises in part from a battery of early studies (Rossi and Anderson 1982:33) and in part because of the protection afforded by the instructions to rate the vignettes in any order and to feel free to change any ratings. Nonetheless, statistical and computational advances of the past several years enable renewed scrutiny. All that is required is that the order of presentation of vignettes be recorded; this can easily be accomplished when the vignette instruments are prepared.

Estimation of the four models under the assumption of autocorrelation can be conducted with one of several additional assumptions concerning the form of the autocorrelation, for example, whether it is assumed to be the same for all respondents or different across respondents.

Tests can be carried out (a) for nonautocorrelation and (b) for parameter homogeneity, with corrections for autocorrelation (Greene 2003:360-2).

2.2.2.3. Random-parameters approach. The last approach we consider views some or all of the parameters in the equation as drawn from a probability distribution rather than as fixed parameters. The random-effects specification of Model 2a is well known; here we focus on the random-parameters (RP) specification of Models 1 and 3. Random-parameter estimates of Model 3 are matrix-weighted averages of OLS estimates of the separate Model 3 equations. These are again matrix weighted to yield the Model 1 estimates. The literature provides a number of formulations and estimators, starting with the classical Hildreth and Houck (1968) and Swamy (1970) estimators (Greene 2003:285-6; Judge et al. 1985:538-45).

These procedures also provide tests of parameter homogeneity.

* * *

The suite of procedures just described yields a rich portrait of the positive-belief Type II or normative-judgment Type III equations inside the heads of respondents and the links between them. In particular, the tests of parameter homogeneity help the investigator decide whether all respondents can be described by the same equation.

If, based on these statistical tests, the investigator concludes that all respondents can be described by the same equation, then there are no further analyses to be performed. The only remaining task is to select the various estimates that survive the tests, for example, incorporating autocorrelation or not, unequal variances or not, and presenting both OLS/GLS and RP estimates. To illustrate, if statistical tests fail to reject parameter homogeneity and nonautocorrelation and the hypothesis of no cross-equation correlation, rejecting only equal variances, then the final task is to present Model 1 estimates with standard errors corrected for heteroskedasticity due to clustering by respondent (Huber 1967; White 1980, 1984). That is, in such case, there is little variation either to explain or to use in explaining respondent behavior.

On the other hand, if the statistical tests suggest respondent heterogeneity, then there are two further statistical analyses to be performed, probing, respectively, the determinants and consequences of the belief/judgment structure. Of course, these two further analyses can only be performed if data on respondent characteristics and behavior have been collected. In some studies, such data cannot be collected—the quintessential example being the case in which complete respondent anonymity is required (e.g., in the study of Washington policy makers reported in Jasso 1988)—and perforce the analysis must end without probing further for the determinants and consequences of the belief/judgment structure.

Note that the equation components of interest—and population homogeneity—may change over time. A longitudinal design would enable assessment of the effects of age and experience on both the θ and the interrespondent variability.

3. DETERMINANTS OF VARIABILITY IN THE POSITIVE-BELIEF (TYPE II) AND NORMATIVE-JUDGMENT (TYPE III) EQUATIONS

The respondent-specific positive-belief (Type II) and normative-judgment (Type III) equations have three kinds of components: the intercept, the slopes, and, in the OLS case, the coefficient of multiple correlation, plus combinations and functions of these—a set collectively termed θ. To search for the determinants of these components, we specify an equation in which the dependent variable is one of the θ. The righthandside variables in this Type IV equation include whatever respondent and contextual characteristics are regarded as potentially relevant.

We begin our consideration of the Type IV determinants equation with a look at the set θ. Our main interest (aside from interest in R^2 or another measure of certitude) is in components of beliefs and components of judgments; these, however, need not be identical with the intercept and slopes of the positive-belief (Type II) or normative-judgment (Type III) equation. There are (at least) two ways in which new kinds of θ may arise.

The first new kind of θ occurs when a single belief component or judgment component consists of more than one slope. Two cases of multislope belief/judgment components may be distinguished. In the first case of a multislope component, a single variable requires for its representation more than one regressor, and hence its effect is appropriately described by more than one slope coefficient; examples include (a) categorical variables with more than two categories, such as a three-category religious affiliation variable, which is represented by two binary variables, and (b) quantitative variables whose operation in the equation is specified by a polynomial, such as experience in an earnings equation, which is usually represented by two regressors, a linear term and a quadratic term. The second case of a multislope component involves belief/judgment components, which refer to a combination of the effects of two or more variables. For example, in the marital happiness illustration below, it is of interest to learn whether the effect of the husband's earnings is thought to be greater than that of the wife's earnings, and hence the belief component is defined as the difference between two slopes.

The second new kind of θ arises when the basic positive-belief (Type II) or normative-judgment (Type III) equation can be used to derive estimates of new quantities that are also considered to be belief components or judgment components. For example, in the just earnings illustration below, the respondent-specific estimates of just earnings for particular workers can be used to build a respondent-specific just earnings *distribution*, a distribution whose parameters—mean, dispersion, and so on—also constitute important judgment components. Because sets of 20 respondents rated the same vignettes, it is possible to study the determinants of the inequality in the respondent-specific distributions, thus exploring why individuals differ in the amount of inequality they regard as just.

Accordingly, in any given study, the number of θ equations may differ considerably from the number of slopes plus two. Because the investigator may seek to isolate the operation of many varieties of belief/judgment components, including many multislope combinations, the number of θ equations may in fact considerably exceed $(K + 2)$.

Moreover, recall from the previous section that typically we obtain several estimates of the parameters of the Type II and Type III equations (e.g., OLS estimates, GLS estimates, and random-parameters estimates, under a variety of assumptions about the error structure).

While in some situations, it will be possible to designate one set of estimates as the preferred estimate, in other cases, two or more sets of estimates may remain viable candidates. Thus, the number of (versions of) θ equations may grow even larger.

Each θ equation and the companion equation on which θ is based form a multilevel system of equations:

$$Y_{ij} = \beta_{0i} + \sum \beta_{ki} X_{kj} + \epsilon_{ij},$$
$$\theta_i = \gamma_0 + \sum \gamma_k Q_{ki} + v_i, \tag{12}$$

where the first equation is the positive-belief (Type II) or normative-judgment (Type III) equation, the second equation is the determinants (Type IV) equation, and the two equations are linked because the dependent variable in the second equation is generated by the first equation.

Estimation of the Type IV equation presents new challenges. For example, estimation is subject to bias if the righthandside Q vector contains any endogenous characteristics (e.g., any characteristics related to omitted relevant factors or jointly determined with the outcome). What might appear to be the effect of, say, working part-time during the school year on a belief concerning the effect of gender on achievement could conceivably be instead the effect of the belief on the employment behavior; alternatively, it could be that both the belief and the employment behavior are jointly determined. To correct for such endogeneity, the investigator might use instrumental variable procedures or might field a longitudinal design. For example, with a longitudinal design, endogeneity bias can be controlled in part by statistical procedures, which hold constant the operation of time-invariant unobservables (such as persistent components of "ability," "ambition," or unmeasured background characteristics).

The longitudinal version of the Type IV equation used for investigating the determinants of the belief structure has the following form:

$$\theta_{it} = \sum \gamma_k Q_{kit} + \mu_i + v_i, \tag{13}$$

where μ_i denotes the individual-specific time-invariant fixed effect, N denotes the number of respondents, and T denotes the number of time periods. Comparison of estimates obtained from the cross-sectional and longitudinal versions of the Type IV equation reveals the sensitivity to the operation of persistent latent factors. The two specifications can be formally tested using a Hausman-type (Hausman 1978) specification test.

In the special case in which the θ of interest is the intercept or one of the slopes of the positive-belief (Type II) or normative-judgment (Type III) equation, the multilevel system of equations above reduces to a form introduced by Raudenbush and Bryk (2002) and Goldstein (2003), which has received extensive attention in recent years, both substantive, methodological, and computational (e.g., Greene 2003:444-7; Kreft, de Leeuw, and van der Leeden 1994; Rabe-Hesketh et al. 2005; Rice, Jones, and Goldstein 2002):

$$\begin{aligned} Y_{ij} &= \beta_{0i} + \sum \beta_{ki} X_{kj} + \epsilon_{ij}, \\ \beta_i &= \gamma_0 + \sum \gamma_k Q_{ki} + v_i. \end{aligned} \tag{14}$$

In this multilevel system, the first equation is known as a Level 1 equation and the second as a Level 2 equation.

As before, the β of interest may have been estimated in a variety of ways. However, the literature on the system in (14) has for the most part recommended random-parameters estimation of the Level 1 equation.

Note that the multilevel systems in (12) and (14) suggest that there is a general class of multilevel systems of equations, of which the form in (14)—the form commonly thought of as “the” multilevel system (Raudenbusch and Bryk 2002; Goldstein 2003)—is a special case.

4. CONSEQUENCES OF THE BELIEF/JUDGMENT STRUCTURE

The second set of analyses that are performed if the statistical tests suggest respondent heterogeneity in the positive-belief (Type II) or normative-judgment (Type III) equation consists of assessing the behavioral effects of the belief/judgment structure. These effects include (a) the effects of the estimated slope coefficient associated with each input on the respondent’s own choices and behaviors vis-à-vis that input, (b) the effects of the intercept, and (c) the effects of the estimated certitude on a wide range of behaviors. As shown earlier, the basic consequences (Type V) equation for this set of analyses has the estimated respondent-specific parameter on the righthand side and the respondent's own behavior on the lefthand side.

To illustrate, if the investigator has obtained each respondent's estimated slope describing the perceived effect of smoking on healthiness, then the respondent's own smoking behavior would be regressed on the estimated slope, including, as appropriate, other relevant regressors. In this case, δ would measure the effect on smoking behavior of the belief β_{ki} concerning the effect of smoking on healthiness. Similarly, one can investigate the effects of the certitude with which the lay theorist holds a theory. For example, it is possible that the greater the certitude with which an adolescent respondent holds a theory of marital happiness, the lower will be his or her expected as well as actual age at marriage.[20]

Exactly as described in the previous section, there may be a large number of relevant consequences (Type V) equations, given that the several θ, each potentially estimated in a variety of ways, may be thought to affect different outcomes.

The combination of the positive-belief (Type II) or normative-judgment (Type III) equation with the companion consequences (Type V) equation gives rise to a new system of equations:

$$\begin{aligned} Y_{ij} &= \beta_{0i} + \sum \beta_{ki} X_{kj} + \epsilon_{ij}, \\ S_i &= \alpha + \delta\theta_i + e_i, \end{aligned} \qquad (15)$$

where the first equation is the positive-belief (Type II) or normative-judgment (Type III) equation, the second equation is the consequences (Type V) equation, and the two equations are linked because the regressor in the second equation is generated by the first equation. This new system may, but need not, be multilevel.

Estimation of the Type V equation presents new challenges. Because θ is measured with error, the consequences (Type V) equation is subject to the classical errors-in-variables problem (discussed in all standard sources, such as Judge et al. 1985). It can be shown that if the problem is left untreated and if θ is the only measured-with-error explanatory variable in the equation, then the estimate of δ the effect of θ is biased to zero, and the coefficients of other included explanatory variables may be biased in either direction (and the bias is calculable). Thus, in this simple case, estimation of the consequences (Type V) equation would yield information concerning the *direction* of the effect of the belief.

A longitudinal design would make possible analyses that test for the operation of age, experience, and, in the case of adolescents, of pubertal and other growth, as well as for the effects of endogenous characteristics (e.g., among adolescents, family, school, and workplace characteristics). The basic longitudinal form of the Type V equation for investigating the consequences of the respondents' beliefs and judgments and of the associated certitude is written as follows:

$$S_{it} = \delta\theta_{it} + \Omega_i + e_{it}. \tag{16}$$

By combining fixed-effects and instrumental variables techniques, it would become possible to assess the effects of changes in beliefs on changes in behaviors, conditional on a prior behavior, enabling quantitative estimation of the magnitude of a belief change required to offset the effects of habituation.

In the special case in which the θ of interest is the intercept or one of the slopes of the positive-belief (Type II) or normative-judgment (Type III) equation, the system of equations above reduces to the following form:

$$\begin{aligned} Y_{ij} &= \beta_{0i} + \sum \beta_{ki} X_{kj} + \epsilon_{ij}, \\ S_i &= \alpha + \delta\beta_i + e_i. \end{aligned} \tag{17}$$

In a way that parallels the two multilevel systems presented in the previous section, the system in (17) is a special case of the system in (15). If these are multilevel, then the idea of a multilevel system can now be generalized even further, for now there are two distinct types of multilevel systems, one focused on the determinants of the θ and the other on the consequences of the θ.[21]

5. EXAMPLE OF POSITIVE-BELIEF EQUATION: ADOLESCENTS' BELIEFS CONCERNING THE DETERMINANTS OF MARITAL HAPPINESS

In June 1985, a pilot study of adolescents' positive beliefs about the determinants of marital happiness was conducted at the annual

Junior Leadership Conference sponsored by a state organization of 4-H Clubs. Fifteen students (8 girls and 7 boys, subsequently known to range in age from 14 to 17 years) were asked to rate the marital happiness of fictitious married couples described in terms of variables highlighted in the family literature—spouses' age, education, earnings, and sibling configuration, as well as the couple's offspring configuration (Cherlin 1981; Spanier and Glick 1981; Sweet and Bumpass 1987). The respondents were each given a packet containing 40 vignettes and the instructions for the rating task. The sample married couple vignette and a version of the marital happiness rating task in the appendix (Tables A1, A5) were used in the pilot study.

The following sections illustrate analysis of the positive-belief (Type II) equation and the determinants (Type IV) equation developed above. First, we report estimates of the respondent-specific (Model 3) positive-belief (Type II) equations, examining both OLS, GLS, and RP estimates. Second, we report a variety of estimates of the pooled (Model 1) positive-belief (Type II) equation, based on OLS, GLS, and RP approaches, and carry out tests of respondent homogeneity, almost all of which reject homogeneity. Third, we examine two belief components (concerning the effects on marital happiness of spouses' earnings and of offspring gender) and investigate the determinants of one of them and of the certitude associated with the belief; that is, we obtain estimates of two determinants (Type IV) equations.

5.1. RESPONDENT-SPECIFIC MODELS OF MARITAL HAPPINESS

The pilot test produced 599 ratings. That is, only one vignette was unrated by one respondent; physical signs suggest that it was inadvertently left unrated. Table 1 reports the OLS estimates of the respondent-specific (Model 3) equations. As discussed earlier, under the classical assumption that the errors are independently distributed with mean zero and constant variance, the estimates are best linear unbiased for respondents who rated all the vignettes; if the single vignette left unrated was inadvertently left unrated, then the estimates for that respondent (Respondent 6), too, are best linear unbiased. Even if there is heteroskedasticity in the respondent-specific equation, the estimates remain unbiased and consistent. The values of R^2 for the

15 regressions range from .53 to .96; the median is .79. Only one lies below .6 and only four below .7. The values of the adjusted R^2 are, as expected, lower, ranging from .24 to .93; the median is .66, and only 4 are smaller than .6. Together, these values of R^2 and adjusted R^2 indicate that the characteristics chosen to describe the fictitious married couples were perceived by all the respondents as relevant to marital happiness and, indeed, that they account for a substantial portion of the variation in marital happiness—well over half on average for both measures.[22]

Table 1 affords a view of what Baker (1982) has called "the adolescent as theorist." By inspecting Table 1, the reader can visually compare the 15 adolescents' models of marital happiness. Each column represents a respondent's model; each row contains all respondents' coefficients for a given characteristic, together with the absolute values of the corresponding *t* ratios. Thus, the reader will notice the main areas of agreement and disagreement across respondents' views of the attainment of marital happiness.

In general, for each respondent-specific equation, one would want to test the significance of particular single coefficients and subsets of coefficients. For example, there are substantive reasons for carrying out the following tests in the coefficients reported in Table 1 separately for each respondent: single tests of the six coefficients of the wife's and husband's age, schooling, and earnings; joint test of the wife's age-schooling-earnings coefficients; joint test of the husband's age-schooling-earnings coefficients; joint test of the wife's sibling configuration coefficients; joint test of the husband's sibling configuration coefficients; joint test of both the wife's and husband's sibling configuration coefficients; and joint test of the couple's offspring configuration coefficients. Space considerations do not permit such detailed analysis here. For purposes of illustration, we carried out the joint test on the three offspring coefficients; these reach unambiguous statistical significance only for one respondent (Respondent 2, with a p level of .0013) and borderline significance for five respondents (Respondents 4, 7, 8, 9, and 12, with p levels ranging from .0518 to .116). Meanwhile, of the six demographic characteristics of the two spouses, only the earnings variables reach significance, doing so, however, at quite high probability levels.

TABLE 1: Adolescents' Views of the Determinants of Marital Happiness: Ordinary Least Squares Estimates (Absolute Values of *t* Ratios in Parentheses)

Variable/Respondent	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Wife's age	−3.675	−3.421	−0.114	−2.476	−0.0583
	(1.22)	(1.25)	(0.02)	(0.51)	(0.024)
Husband's age	4.697	0.0234	−0.824	−2.149	7.324
	(1.50)	(0.01)	(0.12)	(0.43)	(1.79)
Wife's education	−3.459	0.811	−2.730	4.479	−3.778
	(1.48)	(0.38)	(0.53)	(1.19)	(1.23)
Husband's education	−3.897	−0.502	−1.332	−0.479	−1.888
	(1.67)	(0.24)	(0.26)	(0.13)	(0.62)
Wife's earnings	2.137	2.068	3.279	2.399	3.213
	(4.14)	(4.40)	(2.90)	(2.89)	(4.76)
Husband's earnings	3.218	2.985	2.104	2.824	4.193
	(6.47)	(6.60)	(1.94)	(3.54)	(6.45)
Husband has older brother	16.512	−31.950	21.391	9.344	16.419
	(1.42)	(3.03)	(0.84)	(0.50)	(1.08)
Husband has older sister	10.464	−0.170	21.078	−24.367	32.979
	(0.85)	(0.02)	(0.79)	(1.24)	(2.05)
Husband has younger brother	2.241	−4.130	21.340	13.668	41.286
	(0.18)	(0.36)	(0.78)	(0.68)	(2.52)
Wife has older brother	6.142	−3.178	−51.562	36.265	9.755
	(0.48)	(0.28)	(1.86)	(1.78)	(0.59)
Wife has older sister	−2.753	27.303	−38.105	−16.999	11.075
	(0.25)	(2.72)	(1.58)	(0.96)	(0.77)
Wife has younger brother	8.278	25.490	−18.593	−1.878	40.689
	(0.66)	(2.22)	(0.68)	(0.09)	(2.47)
Couple has two daughters	−17.941	19.290	18.624	−43.709	−19.552
	(1.14)	(1.35)	(0.54)	(1.73)	(0.95)
Couple has two sons	−2.663	−34.597	19.028	35.689	−18.636
	(0.20)	(2.83)	(0.65)	(1.66)	(1.06)
Couple has older daughter,	−5.183	−27.441	−5.256	−12.506	−24.640
younger son	(0.34)	(2.01)	(0.16)	(0.52)	(1.26)
Intercept	37.129	106.858	22.774	93.319	−298.789
	(0.24)	(0.76)	(0.07)	(0.38)	(1.49)
R^2	0.788	0.857	0.532	0.665	0.856
Adjusted R^2	0.656	0.768	0.239	0.456	0.765
F ratio	5.95	9.60	1.81	3.18	9.48

(continued)

As discussed earlier, the limited sample size of respondent-specific equations in factorial survey analysis (39-40 in this case), leading to reduced degrees of freedom (23-24 here), prevents many of the coefficients from reaching statistical discernibility. Some reassurance

TABLE 1: (continued)

Variable/Respondent	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Wife's age	−3.342	−3.401	−0.151	3.680	−5.279
	(0.80)	(1.19)	(0.04)	(0.77)	(1.90)
Husband's age	2.817	−1.404	−3.320	−4.417	1.308
	(0.65)	(0.47)	(0.95)	(0.89)	(0.45)
Wife's education	−0.834	−4.976	0.322	1.218	−1.383
	(0.25)	(2.22)	(0.12)	(0.33)	(0.64)
Husband's education	−3.952	−4.778	−2.125	2.234	1.775
	(1.23)	(2.14)	(0.81)	(0.60)	(0.82)
Wife's earnings	0.222	3.488	2.218	1.434	1.220
	(0.31)	(7.07)	(3.82)	(1.75)	(2.56)
Husband's earnings	5.104	3.544	3.699	4.353	3.808
	(7.36)	(7.46)	(6.62)	(5.52)	(8.29)
Husband has older brother	4.241	6.022	4.150	6.422	15.764
	(0.25)	(0.54)	(0.32)	(0.35)	(1.47)
Husband has older sister	−6.810	−1.531	21.040	−14.376	5.359
	(0.40)	(0.13)	(1.53)	(0.74)	(0.47)
Husband has younger brother	−17.950	19.144	19.420	1.227	13.586
	(1.04)	(1.60)	(1.38)	(0.06)	(1.17)
Wife has older brother	26.608	10.727	19.772	31.436	−1.247
	(1.52)	(0.88)	(1.38)	(1.56)	(0.11)
Wife has older sister	−0.393	14.952	16.422	39.769	−14.056
	(0.02)	(1.42)	(1.33)	(2.27)	(1.38)
Wife has younger brother	7.766	22.156	34.069	27.604	−9.157
	(0.45)	(1.84)	(2.40)	(1.38)	(0.79)
Couple has two daughters	−12.781	−28.354	−42.500	−49.664	−12.837
	(0.55)	(1.89)	(2.41)	(1.99)	(0.88)
Couple has two sons	11.609	5.854	−28.427	−47.433	17.831
	(0.63)	(0.46)	(1.88)	(2.23)	(1.44)
Couple has older daughter,	1.882	−28.342	−35.299	−12.107	0.193
younger son	(0.09)	(1.98)	(2.09)	(0.51)	(0.01)
Intercept	69.561	249.006	94.115	−49.329	127.012
	(0.33)	(1.70)	(0.54)	(0.20)	(0.90)
R^2	0.767	0.853	0.814	0.775	0.814
Adjusted R^2	0.615	0.761	0.697	0.634	0.697
F ratio	5.04	9.28	6.98	5.50	6.99

(continued)

is provided by the fact that the estimates are unbiased and consistent (and, under homoskedastic errors, best linear unbiased). However, it is useful to search for gains in efficiency. This requires combining information from all the respondents and exploiting features of the

TABLE 1: (continued)

Variable/Respondent	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*
Wife's age	−0.912	0.356	2.728	−1.771	0.210
	(0.28)	(0.07)	(1.43)	(0.55)	(0.04)
Husband's age	−0.723	−1.216	3.346	5.990	−4.856
	(0.21)	(0.22)	(1.69)	(1.78)	(0.97)
Wife's education	0.582	−4.255	2.514	1.187	−3.897
	(0.22)	(1.04)	(1.69)	(0.47)	(1.03)
Husband's education	1.243	−1.277	3.237	−2.047	−1.205
	(0.48)	(0.31)	(2.18)	(0.81)	(0.32)
Wife's earnings	1.555	4.951	3.623	3.204	2.323
	(2.71)	(5.50)	(11.03)	(5.75)	(2.80)
Husband's earnings	2.119	4.334	3.325	3.927	3.622
	(3.84)	(5.00)	(10.52)	(7.32)	(4.53)
Husband has older brother	26.628	52.836	2.317	23.544	0.354
	(2.07)	(2.61)	(0.31)	(1.88)	(0.02)
Husband has older sister	2.135	27.300	−5.137	17.570	−7.735
	(0.16)	(1.28)	(0.66)	(1.33)	(0.39)
Husband has younger brother	5.050	28.578	−3.683	28.924	6.767
	(0.36)	(1.31)	(0.46)	(2.14)	(0.34)
Wife has older brother	−4.553	46.785	8.108	−26.793	−21.103
	(0.32)	(2.11)	(1.00)	(1.95)	(1.03)
Wife has older sister	−8.683	−16.468	−0.041	8.834	−16.008
	(0.71)	(0.86)	(0.00)	(0.74)	(0.90)
Wife has younger brother	3.229	22.801	13.508	8.568	6.651
	(0.23)	(1.04)	(1.69)	(0.63)	(0.33)
Couple has two daughters	1.534	−72.791	−6.208	3.683	8.328
	(0.09)	(2.66)	(0.62)	(0.22)	(0.33)
Couple has two sons	25.453	3.852	−9.892	−12.418	47.693
	(1.71)	(0.16)	(1.16)	(0.86)	(2.21)
Couple has older daughter,	8.632	−31.448	1.904	−10.532	16.726
younger son	(0.52)	(1.20)	(0.20)	(0.65)	(0.69)
Intercept	−0.0959	4.185	−397.022	−228.239	231.276
	(0.00)	(0.02)	(4.07)	(1.38)	(0.94)
R^2	0.629	0.782	0.955	0.885	0.665
Adjusted R^2	0.397	0.646	0.927	0.814	0.456
F ratio	2.71	5.74	34.26	12.34	3.18

data, such as cross-respondent heteroskedasticity, or introducing the random-parameters assumption.

To take advantage of the additional information in the multiple-respondents context, we estimated the respondent-specific equations jointly in four different versions: OLS estimation assuming equal variances across the respondent-specific equations, GLS estimation allowing cross-respondent heteroskedasticity, SUR estimation allowing cross-respondent correlation, and RP estimation. The first three produce the same parameter estimates, as we know, and marginal gains in efficiency only in the analysis of covariance and the GLS analysis assuming heteroskedasticity (in this case of identical regressors, as discussed above, there is no efficiency gain from SUR estimation). The random-parameters estimation, as expected, produces different parameter estimates (matrix-weighted averages of the OLS estimates) and some gains in efficiency.

To illustrate, we report in Table 2 the means, minimums, and maximums for the distributions of the 16 estimated parameters, separately for the OLS (/GLS/SUR) estimation (from Table 1) and the RP estimation. The RP estimates may be thought of as transformations of the OLS estimates for one respondent, taking into account the OLS estimates for all the other respondents. Accordingly, the RP estimates tend to be compressed relative to the OLS estimates. As shown in Table 2, the distributions of the RP estimates have a larger minimum and a smaller maximum than the corresponding OLS estimates in every case except, trivially, one (the minimum of the wife's earnings coefficient distributions).

5.2. DIFFERENCES ACROSS RESPONDENTS IN THE POSITIVE-BELIEF EQUATION

Can all respondents be characterized by the same positive-belief (Type II) equation? Table 1 provides initial evidence that the adolescents' equations differ both in their equation R^2s and in their parameters. In this section, we systematically address respondent heterogeneity.

Unequal variances. Variation in the R^2s signals variation in the equation error variances. We carried out an array of tests of heteroskedasticity, with and without the assumption of parameter homogeneity. The hypothesis of equal variances is rejected in every test. For example, the likelihood ratio test (Greene 2003:330-1) yields a chi-squared statistic of 78.74 when based on the Model 1 equation and a chi-squared statistic of 110.4 when based on the Model 3 equation, both of which, at 14 degrees of freedom, dictate rejection of equal variances at well beyond the .0001 probability level.

TABLE 2: Summary of Ordinary Least Squares/Generalized Least Squares (OLS/GLS) and Random Parameters (RP) Estimates of Adolescents' Views of the Determinants of Marital Happiness

	OLS/GLS			*RP*		
Variable	*Mean*	*Minimum*	*Maximum*	*Mean*	*Minimum*	*Maximum*
Wife's age	−1.176	−5.279	3.680	−1.387	−3.264	1.996
Husband's age	0.440	−4.856	7.324	0.866	−1.944	5.108
Wife's education	−0.947	−4.976	4.478	−0.829	−3.072	2.221
Husband's education	−0.999	−4.778	3.237	−0.824	−2.712	2.356
Wife's earnings	2.489	0.222	4.951	2.475	0.0799	4.718
Husband's earnings	3.544	2.104	5.104	3.517	2.551	4.475
Husband has older brother	11.600	−31.950	52.836	10.427	−26.068	34.000
Husband has older sister	5.187	−24.367	32.979	4.618	−13.178	26.210
Husband has younger brother	11.696	−17.950	41.286	10.644	−6.086	29.455
Wife has older brother	5.811	−51.562	46.785	5.759	−27.851	29.072
Wife has older sister	0.323	−38.105	39.769	1.353	−20.013	31.571
Wife has younger brother	12.745	−18.593	40.689	12.837	−3.471	31.893
Couple has two daughters	−16.992	−72.791	19.290	−15.780	−47.271	14.232
Couple has two sons	0.863	−47.433	47.693	0.363	−34.638	26.923
Couple has older daughter, younger son	−10.894	−35.299	16.726	−10.217	−26.792	3.503
Constant	4.117	−397.022	249.006	−8.044	−307.794	153.586

Parameter homogeneity. It is useful to begin by inspecting the coefficients. Coefficients that singly portray an effect can be examined for differences in sign and magnitude. For example, among the six coefficients representing the effects of the wife's and husband's age, schooling, and earnings, only two have the same sign across all respondent-specific equations—the two earnings coefficients, which are uniformly positive (Table 1). The family structure variables, which require three coefficients each, can be assessed by looking at the orderings of the coefficients. For example, the offspring configuration variable gives rise to 24 distinct orderings, of which 9 are represented in the regressions (Table 1).

More systematically, we carry out an array of homogeneity tests. Almost all of the homogeneity hypotheses, in all the estimation approaches, are rejected. To illustrate, Table 3 provides a summary of OLS- and GLS-based estimates of the four models and 5 tests described above. As shown, homogeneity is rejected in 9 of the 10 tests. For example, the OLS-based test contrasting Models 1 and 3 yields an F statistic of 2.45, with 224 and 359 degrees of freedom, leading to rejection of the null hypothesis at well beyond the .0001 level of significance, and the corresponding GLS-based test yields a chi-squared statistic of 1075.48, which again dictates rejection of the null hypothesis at well beyond the .0001 level of significance.[23,24] Other tests, not shown, produce the same results. For example, an F test contrasting Models 1 and 3, using a correction for heteroskedasticity, yields an F statistic of 2.88, with 224 and 359 degrees of freedom, again leading to rejection of the null hypothesis at well beyond the .0001 level of significance, and a test based on the random-parameters formulation yields a chi-squared statistic of 644.02, which, at 224 degrees of freedom, again leads to rejection of the null hypothesis at well beyond the .0001 level.

Thus, we conclude that the respondents cannot be described by the same equation. Of course, it is possible that respondents may agree on the effects of some of the regressors and disagree on the effects of others. To assess the possibility that disagreement is confined to some of the coefficients, we tested interrespondent homogeneity on all variables singly and on all substantively meaningful subsets (such as all the wife's characteristics, both spouses' sibships, etc.). In the GLS-based tests, homogeneity is rejected for all subsets of characteristics

TABLE 3: Adolescents' Beliefs Concerning the Determinants of Marital Happiness: Summary of OLS-Based and GLS-Based Estimated Models and Homogeneity Tests (15 Respondents and 599 Ratings)

	Ordinary Least Squares (OLS)		*Generalized Least Squares (GLS)*	
Model/Test	R^2	*F Ratio (df)*	*Log Likelihood*	*Chi-Square (df)*
Model 1: Common intercept and common slopes (16 parameters)				
$R_{iv} = \beta_0 + \Sigma\beta_k X_{kiv} + \epsilon_{iv}$	0.512	40.8 (15, 583)	−2969.651	629.07(15)
Model 2a: Different intercepts and common slopes (30 parameters)				
$R_{iv} = \beta_{0i} + \Sigma\beta_k X_{kiv} + \epsilon_{iv}$	0.638	34.6 (29, 569)	−2838.579	1352.57(29)
Model 2b: Common intercept and different slopes (226 parameters)				
$R_{iv} = \beta_0 + \Sigma\beta_{ki} X_{kiv} + \epsilon_{iv}$	0.801	6.67 (225, 373)	−2655.093	2994.74 (225)
Model 3: Different intercepts and different slopes (240 parameters)				
$R_{iv} = \beta_{0i} + \Sigma\beta_{ki} X_{kiv} + \epsilon_{iv}$	0.807	6.28 (239, 359)	−2636.732	3511.80 (239)
Test of different intercepts, conditional on common slopes				
Model 1 vs. Model 2a $\beta_{01} = \cdots = \beta_{015}$		14.2 (14, 569)		245.23 (14)
Test of different slopes, conditional on common intercept				
Model 1 vs. Model 2b $\beta_{k1} = \cdots = \beta_{k15}$		2.58 (210, 373)		943.60 (210)
Test of different slopes, conditional on different intercepts				
Model 2a vs. Model 3 $\beta_{k1} = \cdots = \beta_{k15}$		1.49 (210, 359)		613.77 (210)
Test of different intercepts, conditional on different slopes				
Model 2b vs. Model 3 $\beta_{01} = \cdots = \beta_{015}$		0.80 (14, 359)		42.37 (14)
Test of different regressions				
Model 1 vs. Model 3 $B_1 = \cdots = B_{15}$		2.45 (224, 359)		1075.48 (224)

and for all single characteristics except the two spouses' ages. In the OLS-based tests, however, homogeneity fails to be rejected for the two spouses' education, the husband's earnings, and the husband's sibship, as well as, among the subsets, for the wife's characteristics, the husband's characteri-stics, and the husband's combined characteristics and sibship. To the extent that the GLS-based tests mirror more faithfully the unequal error variances, the GLS-based results may be preferred.

Thus, we cannot rule out differences in the adolescents' equations on anything except spouses' ages. Simply put, each of the 15 adolescents has his or her own model of the production of marital happiness; while the models may have some similarities, the direction and magnitude of the effects "theorized" by the adolescents appear to vary significantly.[25]

Cross-equation correlation. Notwithstanding substantial parameter heterogeneity, the adolescents' equations are not complete isolates. The Breusch-Pagan test of cross-equation correlation yields a chi-squared statistic of 233.5, which at 105 degrees of freedom leads to rejection of independence at well beyond the .0001 level of significance.

5.3. PARTICULAR BELIEF COMPONENTS AND THEIR DETERMINANTS

The parameter estimates reported in Table 1 (and summarized in Table 2) exemplify the observation above that the class of belief components contains not only the slopes associated with particular regressors but also sets of slopes corresponding to two or more regressors. For example, the models contain three categorical variables (the sibling and offspring configuration variables), each represented by three binary regressors, and several quantitative variables whose effects may combine to form interesting belief components, as we shall see below.

The pilot study obtained information from the adolescent respondents on a small set of characteristics (the Qs in the determinants [Type IV] equation discussed above), which the literature suggests may play a part in shaping beliefs, behaviors, and a variety of educational, marital, and socioeconomic outcomes. These include the adolescent's sex and age, whether the adolescent lives on a farm, whether the parents are divorced, and the sibling configuration (Bumpass and Sweet 1972; Zajonc 1976; Featherman and Hauser 1978; Blake 1981; Furstenberg et al. 1983; Alwin 1984; Alwin and Thornton 1984; Heer 1985; Furstenberg and Seltzer 1986). To the extent that these factors may be reasonably regarded as exogenous, the estimated Type IV equations are free of endogeneity bias.[26]

5.3.1. The Effect of Spouses' Earnings on Marital Happiness

As Tables 1 and 2 show, all respondents assigned positive weights to both spouses' earnings, and all but 3 of the 30 estimated coefficients are highly statistically significant (notwithstanding the relatively small sample sizes). However, the pattern of *within-respondent* magnitudes differs across respondents, statistically significantly so for the wife's earnings in all tests. As estimated in both the OLS and the RP specifications, 12 of the 15 respondents assigned larger weights to the husband's than to the wife's earnings, and the difference between the two weights varies considerably. Hence, it is of interest to discern what factors in the respondent's background and experience account for this variation.

To address this question, we set up the multilevel system of two equations presented in expression (12) above. The belief component of interest is the difference between two slopes, and thus the dependent variable in the determinants (Type IV) equation is θ, not β.[27] Next we constructed two variables defined as the coefficient for the husband's earnings minus the coefficient for the wife's earnings—one based on the OLS estimates, the other on the RP estimates—and regressed them on respondent characteristics. Tables 4 and 5 report estimates of five specifications, separately for the OLS-based and RP-based estimates of the dependent variable. All specifications include a basic set of respondent characteristics—adolescent's sex and age, whether the adolescent lives on a farm, and whether the adolescent's parents are divorced. Specifications (2) to (5) incorporate three additional respondent characteristics—sibsize (defined as the total number of children in the adolescent's family) and binary variables for whether the respondent is a first-born or last-born child. The values of adjusted R^2 indicate that the basic set of characteristics explains about one

TABLE 4: Sources of Cross-Individual Variation in the Perceived Differential Effects of Spouses' Earnings on Marital Happiness—Based on Ordinary Least Squares (OLS) Estimates of the Respondent-Specific Marital Happiness Equations

	Specification				
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Respondent's sex (1 = female)	0.650	0.648	1.078	0.936	0.869
	(0.93)	(0.85)	(1.58)	(1.41)	(1.23)
Respondent's age (years)	0.679	0.677	1.153	1.087	1.03
	(1.53)	(1.33)	(2.40)	(2.29)	(2.03)
Lives on farm (1 = yes)	2.197	2.196	2.606	2.434	2.44
	(2.47)	(2.34)	(3.06)	(2.93)	(2.82)
Parents divorced (1 = yes)	0.721	0.721	0.917	0.401	0.387
	(0.50)	(0.48)	(0.64)	(0.30)	(0.28)
Sibsize (number of children)	—	0.0028	—	—	0.187
		(0.01)			(0.54)
First born (1 = yes)	—	—	1.876	1.155	1.28
			(1.86)	(1.68)	(1.70)
Last born (1 = yes)	—	—	0.797	—	—
			(0.98)		
Intercept	−10.322	−10.306	−19.012	−17.221	−16.9
	(1.49)	(1.36)	(2.44)	(2.28)	(2.14)
R^2	0.651	0.651	0.763	0.734	0.744
Adjusted R^2	0.511	0.457	0.585	0.587	0.552
F ratio	4.66	3.35	4.28	4.97	3.87

NOTE: The dependent variable is constructed from the estimated coefficients of the husband's and wife's earnings ($\beta_H - \beta_W$) in the OLS-based respondent-specific equations of the perceived determinants of marital happiness, reported in Table 1. Absolute values of t ratios appear in parentheses under the corresponding estimates. Sample size is 15 respondents.

half of the variation in the husband-wife slope coefficient differential. Inclusion of the first-born binary variable increases adjusted R^2 by 4.5 to 7.6 percentage points.[28]

Across all specifications, the coefficients for the basic set of variables are positive. The point estimates indicate that the belief that the husband's earnings matter more for marital happiness than the

TABLE 5: Sources of Cross-Individual Variation in the Perceived Differential Effects of Spouses' Earnings on Marital Happiness—Based on Random Parameters Estimates of the Respondent-Specific Marital Happiness Equations

	Specification				
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Respondent's sex (1 = female)	0.303	0.214	0.534	0.525	0.407
	(0.49)	(0.32)	(0.89)	(0.86)	(0.67)
Respondent's age (years)	0.560	0.467	0.904	0.876	0.773
	(1.42)	(1.05)	(1.96)	(2.01)	(1.75)
Lives on farm (1 = yes)	1.927	1.908	2.183	2.112	2.12
	(2.45)	(2.33)	(2.68)	(2.78)	(2.82)
Parents divorced (1 = yes)	0.723	0.742	0.690	0.474	0.450
	(0.57)	(0.56)	(0.50)	(0.39)	(0.37)
Sibsize (number of children)	—	0.167	—	—	0.327
		(0.53)			(1.10)
First born (1 = yes)	—	—	1.196	0.896	1.12
			(1.24)	(1.42)	(1.71)
Last born (1 = yes)	—	—	0.332	—	—
			(0.42)		
Intercept	−8.251	−7.265	−14.348	−13.601	−13.0
	(1.35)	(1.36)	(1.92)	(1.96)	(1.89)
R^2	0.657	0.668	0.726	0.720	0.757
Adjusted R^2	0.520	0.480	0.521	0.565	0.574
F ratio	4.79	3.62	3.54	4.63	4.15

NOTE: The dependent variable is constructed from the estimated coefficients of the husband's and wife's earnings ($\beta_h - \beta_W$) in the random-parameters-based respondent-specific equations of the perceived determinants of marital happiness; the mean, minimum, and maximum of the underlying estimates are reported in Table 2. Absolute values of t ratios appear in parentheses under the corresponding estimates. Sample size is 15 respondents.

wife's earnings increases with age and is more strongly held by girls than boys, by farm dwellers than non–farm dwellers, and by children whose parents are divorced. The results also indicate that this belief is stronger the greater the number of children, stronger in first-born children than in all other children, and, interestingly, stronger in last-born children than in middle children. This being a pilot study, sample

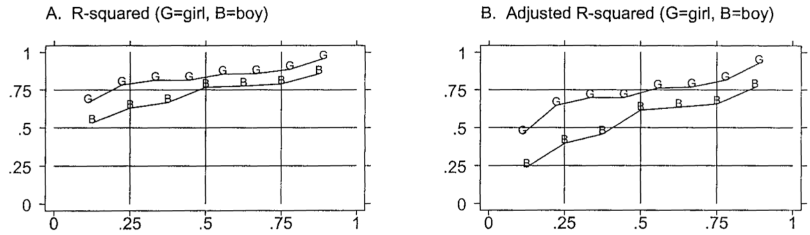


Figure 1: Values of *R*-squared and Adjusted *R*-squared by Gender

size is small; thus, only the farm dweller coefficients reach statistical significance in all specifications, with age approaching it and reaching it in some.

If larger studies of adolescents' views of marital happiness yield similar results, then such results would provide useful insights, to be more rigorously studied in future work, concerning both (a) the process by which adults attain marital happiness and (b) the process by which adolescents form their ideas about how adults attain marital happiness.

5.3.2. Degree of Certitude Concerning the Beliefs

As noted earlier, the values of R^2 in the 15 respondent-specific OLS equations range from .53 to .96, and those of adjusted R^2 range from .24 to .93 (Table 1). A striking result is that the girls appear to have significantly higher values of both R^2 and adjusted R^2 than the boys, as depicted in Figure 1, which presents quantile functions of the sex-specific distributions of these measures. The mean value of R^2 for the girls (.83) is 11 percentage points higher than that for the boys (.72); looking at adjusted R^2, the mean value for the girls (.72) is 18 percentage points higher than that for the boys (.54). In both measures, the lowest observed value belongs to a boy and the highest to a girl.

This sex differential raises many questions. Do adolescent girls think they know more about the world than adolescent boys? Do adolescent girls hold more rigid views than adolescent boys? Do sex differences in certitude vary with the substantive topic? Do girls know more than boys about marital happiness because, feeling perhaps a greater stake, they have thought more about it? While the pilot study cannot answer these questions—it would be necessary to estimate *several* positive-belief equations and to do so longitudinally—it is possible to explore the sources of variation in values of R^2.

Again, we set up a multilevel system of the kind presented in expression (12) above. Here, θ is the R^2 and the adjusted R^2 from the respondent-specific OLS equations (Table 1). Tables 6 and 7 report estimates of five specifications of the certitude with which adolescents hold their models of marital happiness, separately for two measures of certitude, R^2 and adjusted R^2. All specifications include the basic set of exogenous variables, the respondent's sex and age, whether he or she lives on a farm, and whether the parents are divorced. Other specifications add sibsize and binary variables for whether the respondent is a first-born or last-born child. The results support the initial hint concerning the effect of sex: In all specifications, the effect of sex is strong, in the expected direction (females have higher values of R^2 and adjusted R^2) and, despite the small sample size, strongly statistically significant. As would be expected, age is positively related to certitude—older children are more sure concerning the determinants of marital happiness. The binary variable for living on a farm is also positively signed, suggesting effects on certitude not only of a stable human environment but also of the observed orderliness of the natural world. Finally, the effect of divorced parents, though small and not statistically significant, is negative, suggesting the part divorce plays in disrupting the child's growing knowledge of the world of marital relations and suggesting also that disruption in the process of forming beliefs about the determination of marital happiness may be one of the mechanisms by which the propensity to divorce is inherited (a legacy documented by Bumpass and Sweet 1972).

Consistent with the findings and speculations of numerous authors, it is not unreasonable to conjecture that the number of siblings and especially the position in the offspring configuration affect the child's knowledge of the world and certitude about it (Zajonc 1976; Blake 1981; Alwin 1984; Alwin and Thornton 1984; Heer 1985). In these data, the effect of being the first-born child is particularly strong—almost as large as the effect of being a girl and also highly statistically significant. A variety of specifications were estimated, with differing combinations of definitions (e.g., a quantitative variable for birth

TABLE 6: Sources of Cross-Individual Variation in the R^2 Values for Adolescents' Models of Marital Happiness

	Specification				
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Respondent's sex (1 = female)	0.162	0.178	0.203	0.207	0.208
	(2.39)	(2.51)	(4.09)	(4.48)	(4.20)
Respondent's age (years)	0.0044	0.0209	0.0660	0.0675	0.0689
	(0.10)	(0.44)	(1.88)	(2.05)	(1.93)
Lives on farm (1 = yes)	0.103	0.106	0.136	0.140	0.139
	(1.19)	(1.22)	(2.19)	(2.43)	(2.29)
Parents divorced (1 = yes)	−0.0252	−0.0287	−0.0869	−0.0749	−0.0745
	(0.18)	(0.20)	(0.83)	(0.81)	(0.76)
Sibsize (number of children)	—	−0.0296	—	—	−0.0044
		(0.89)			(0.18)
First born (1 = yes)	—	—	0.162	0.179	0.176
			(2.21)	(3.76)	(3.32)
Last born (1 = yes)	—	—	−0.0186	—	—
			(0.31)		
Intercept	0.603	0.428	−0.424	−0.466	−0.474
	(0.90)	(0.61)	(0.75)	(0.89)	(0.85)
R^2	0.389	0.438	0.765	0.762	0.763
Adjusted R^2	0.144	0.125	0.589	0.631	0.586
F ratio	1.59	1.40	4.35	5.78	4.30

NOTE: The dependent variable is the value of R^2 from the ordinary least squares (OLS)−based respondent-specific equations describing the perceived determinants of marital happiness, reported in Table 1. Absolute values of t ratios appear in parentheses under the corresponding estimates. Sample size is 15 respondents.

order) and variables, yet none altered the basic results of specifications (3), (4), and (5). As shown in Tables 6 and 7, the presence of the first-born binary variable increases the equation R^2 by 32 to 49 percentage points (contrasting specification (4) with specification (1) and specification (5) with specification (2)). Thus, if these results are replicated in larger studies, they would provide yet further evidence of the pervasive effects of birth order and position in the offspring configuration.

TABLE 7: Sources of Cross-Individual Variation in the Adjusted R^2 Values for Adolescents' Models of Marital Happiness

	Specification				
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Respondent's sex (1 = female)	0.263	0.288	0.329	0.335	0.337
	(2.39)	(2.50)	(4.06)	(4.45)	(4.17)
Respondent's age (years)	0.00634	0.0330	0.106	0.109	0.111
	(0.09)	(0.43)	(1.85)	(2.02)	(1.90)
Lives on farm (1 = yes)	0.165	0.171	0.218	0.225	0.225
	(1.18)	(1.20)	(2.16)	(2.40)	(2.26)
Parents divorced (1 = yes)	−0.0396	−0.0452	−0.141	−0.120	−0.120
	(0.17)	(0.20)	(0.82)	(0.79)	(0.75)
Sibsize (number of children)	—	−0.0477	—	—	−0.00675
		(0.88)			(0.17)
First born (1 = yes)	–	–	0.261	0.290	0.285
			(2.18)	(3.74)	(3.30)
Last born (1 = yes)	—	—	−0.0319	—	—
			(0.33)		
Intercept	0.366	0.0841	−1.29	−1.37	−1.38
	(0.34)	(0.07)	(1.40)	(1.60)	(1.52)
R^2	0.388	0.436	0.763	0.760	0.761
Adjusted R^2	0.143	0.123	0.586	0.627	0.582
F ratio	1.59	1.39	4.30	5.70	4.25

NOTE: The dependent variable is the value of the adjusted R^2 from the ordinary least squares (OLS)−based respondent-specific equations describing the perceived determinants of marital happiness, reported in Table 1. Absolute values of t ratios appear in parentheses under the corresponding estimates. Sample size is 15 respondents.

Whether first-borns indeed learn more about the world for a given age, whether they develop rigidities in their views of the world, and whether they become very sure of themselves—these are questions for future research to address rigorously and systematically, and in this effort, the factorial survey method can play an important part.

5.3.3. Beliefs Concerning the Effects of Offspring Gender

As a final look at the adolescent data, consider the students' views of the effects of offspring configuration on marital happiness. We permitted the fictitious couples in the vignettes to each have two children, yielding four different configurations: two daughters, two sons, a son older than a daughter, and a daughter older than a son. If we rank-order the coefficients for each respondent, we find that, in the OLS-based estimates, 8 respondents assigned their own highest weight β to the two-boy family, and another 8 respondents assigned their own lowest weight β to the two-girl family. In the RP-based estimates, 9 respondents assigned their own highest weight β to the two-boy family, and another 10 respondents assigned their own lowest weight β to the two-girl family. Thus, more than half of the adolescents appear to believe that "getting" two boys in this natural lottery produces much marital happiness, while "getting" two girls produces much marital *un*happiness. In each case, roughly equal numbers of boys and girls shared these beliefs (in the OLS-based estimates, exactly 4 boys and 4 girls; in the RP-based estimates, exactly 5 boys and 5 girls with respect to the two-girl family and 5 boys and 4 girls with respect to the two-boy family). This result is consistent with Spanier and Glick's (1981) finding that couples whose children are all daughters have a higher probability of divorce, a proposition subsequently investigated by Morgan, Lye, and Condran (1988) and that has recently attracted considerable new attention (Dahl and Moretti 2004; Morgan and Pollard 2003).[29]

Again, if these results are replicated in larger studies, they suggest many new possibilities for research. These span directions as diverse as the effect of farm dwelling on son preference and the perceived relative difficulty of raising boys versus raising girls. Note that a longitudinal design, in which the adolescents were followed into their own marital formation and reproductive years, would enable assessment not only of shifts in the belief that offspring gender affects marital happiness but also of its role in fertility and other marital decisions, permitting estimation of the consequences (Type V) equation.

6. *EXAMPLE OF NORMATIVE-JUDGMENT (TYPE III) EQUATION: JUDGMENTS OF JUST EARNINGS*

To illustrate estimation of normative-judgment (Type III) equations, together with computation of derived quantities and investigation of the determinants (Type IV equations) of the components of normative judgments, we turn to questions of distributive justice. Since the early factorial survey analyses of the justice of earnings (Jasso and Rossi 1977; Alves and Rossi 1978; Jasso 1978; Alves 1982), it has been known that Rossi's factorial survey method makes it possible to estimate three quantities: (a) the *justice evaluation*, namely, the judgment that a specified individual receiving a specified reward is fairly or unfairly rewarded and, if unfairly rewarded, the type (underreward vs. overreward) and degree of injustice; (b) the *just reward*, namely, the amount of a reward thought just for an individual of given characteristics; and (c) the *just reward function*, namely, the formula that converts reward-relevant characteristics into the just reward for an individual of specified characteristics. The early work reported estimates of all three quantities for the case of the reward earnings, based on judgments collected from probability samples of the civilian non-institutionalized adult population. Only later, and gradually, however, was it realized that there are two justice evaluations rather than one—the *experienced* and the *expressed* justice evaluations—and two just rewards rather than one—the *true* and the *disclosed* just rewards—and that Rossi's factorial survey method provides a unified, parsimonious framework for approximating all of these quantities (Jasso 1990, 1996; Jasso and Wegener 1997). Moreover, only later was it realized that the just reward function is a mathematization of ideas developed earlier by Berger et al. (1972), as shown in Jasso (1983).

Meanwhile, it also came to be seen that two important additional directions for further investigation are uniquely amenable to analysis via Rossi's method. These involve, first, the classic idea that all the quantities of interest may be *observer specific* and, second, the *just reward distributions* that are generated from observers' judgments of the just rewards for a set of rewardees.

Arguments for the observer-specific view were reinvigorated by Walster, Berscheid, and Walster's (1976) observation, "Equity is in the eyes of the beholder" (p. 4), and appear in Robinson and Bell (1978), Hamilton and Rytina (1980), Jasso (1980), and Alwin (1987). The early estimates of just earnings and of just earnings functions reported by Alves, Jasso, and Rossi were calculated either for entire respondent samples or for selected subsets of respondents, based on such characteristics as sex and schooling. In terms of the analytic framework developed above, the early work produced Model 1 equations. The next generation of factorial survey studies of justice obtained estimates of respondent-specific Model 3 versions of justice evaluation equations and carried out tests of interrespondent agreement. These estimates and tests all show that the hypothesis of respondent homogeneity is rejected and that observers have both idiosyncratic notions of what constitutes just earnings for specified vignette persons and idiosyncratic styles of expressing the justice evaluation. Thus, both just earnings and the justice evaluation appear to be observer specific.

As for the just reward distributions, Rossi's factorial survey method, given that each respondent judges a large set of vignettes, immediately generates the set of respondent-specific just reward amounts, thus generating a just reward distribution; its parameters, especially its inequality, also can be isolated and studied. Similarly, whenever multiple ratings are obtained on each distinct vignette, a just reward distribution is generated for each vignette; one can then investigate whether, say, some rewardees experience greater variability in what is thought just for them than other rewardees. Stated more precisely, whenever each deck of vignettes is presented to several respondents, Rossi's method generates a *just reward matrix*. Assigning the respondents to the rows and the vignettes to the columns, each row represents an *observer-specific just reward distribution*, and each column represents a *rewardee-specific just reward distribution*.[30]

The early work by Alves, Jasso, and Rossi approached the question of the just earnings distribution for a collectivity by using the estimated just earnings functions to calculate just earnings for a variety of hypothetical earners, including persons combining exclusively least-remunerated and exclusively most-remunerated attributes—yielding, respectively, the *minimum just earnings* and the *maximum just earnings*. By this method, they were able to establish that the just distribution of earnings has a higher mean and lower variance (including a smaller range between the minimum and maximum earnings) than either the actual distribution of earnings or the distribution of earnings put empirically into the vignettes (Jasso and Rossi 1977:649-50; Alves and Rossi 1978:556-7; Jasso 1978:1411-4; Alves 1982:215-8). But Rossi's factorial survey method enables a more direct approach, namely, to estimate respondent-specific just reward distributions and their principal parameters (such as Gini's coefficient, etc.). We illustrate this approach below.

In the following sections, we situate estimation of justice equations in the context of multilevel models and investigate observer-specific versions of just reward functions and of just reward distributions using data collected by Jasso and Rossi (1977). First, we provide a brief overview of the main elements from justice analysis to be used in the illustration. Second, we discuss the work to be presented from the perspective of multilevel methods. Third, we report estimates of the (true) just earnings matrix. Fourth, we estimate three major components of the observer-specific just earnings functions—the just base wage, the just rate of return to schooling, and the just gender multiplier—and explore the effects of the respondent's sex and schooling on each component. Fifth, we calculate four measures of inequality in the observer-specific just earnings distributions—the Gini coefficient, the ratio of the maximum earnings to the minimum earnings (the measure suggested by Plato), and the minimum and maximum relative earnings (relative to the mean)—again obtaining estimates of the effects of the respondent's sex and schooling on each of these components of justice judgments. Finally, we briefly report a sensitivity analysis.

Because the present purpose is to illustrate the Rossi method with as much detail as possible, we restrict analysis to 1 of the 10 decks (Deck 06) used in the Jasso and Rossi (1977) research and to the 10 vignettes describing unmarried persons. Half the vignettes describe men age 37, the other half women age 35. The vignette person's education was described as years of formal schooling completed, ranging from completion of the seventh grade to college graduation, in increments of one year. The vignette person's occupation was drawn from a list of 96 occupational titles spanning the full spectrum of occupational prestige. Each vignette deck was presented to a subsample of 20 respondents drawn randomly from the full sample of 200 respondents, which was itself a probability sample drawn from the population of

White adults residing in private households in Baltimore in 1974. Thus, the data analyzed below consist of 200 ratings, 10 provided by each of 20 respondents.

6.1. BRIEF OVERVIEW OF JUSTICE ANALYSIS

The sense of justice is thought to involve four distinct operations: (a) formation of ideas about what is just; (b) use of these ideas about what is just to make allocation decisions; (c) judgments about whether recipients of benefits or burdens are fairly or unfairly rewarded and, if unfairly rewarded, whether overrewarded or overrewarded and to what degree (the justice evaluations introduced above); and (d) behavioral consequences of the justice evaluations. These four operations correspond to the four central questions compiled by Jasso and Wegener (1997).

In the first operation, the observer forms an idea of the just reward for a rewardee. In the third operation, the observer compares the rewardee's actual reward, denoted A, to the just reward, denoted C, producing the experienced justice evaluation, denoted J^*:

$$J^* = \ln\left(\frac{A}{C}\right). \tag{18}$$

Extensive investigation of the logarithmic ratio form of the justice evaluation function has established eight useful properties. The first three were noted from the start (Jasso 1978). The first is the natural mapping that the justice evaluation function provides onto the justice evaluation variable, where zero represents the point of perfect justice, negative numbers represent degrees of unjust underreward, and positive numbers represent degrees of unjust overreward. Second, the justice evaluation function integrates the previously competing views of the justice evaluation function as a ratio and as a difference (Berger et al. 1972). Third, the justice evaluation function quantifies the common opinion that deficiency is felt more keenly than comparable excess, a property discussed by Wagner and Berger (1985) and Whitmeyer (2004), among others. Twelve years later, a new theoretical analysis showed that two other properties desirable in a justice evaluation function are scale invariance and additivity, that the log-ratio form possesses them and, indeed, in the case of a cardinal reward, it is the only functional form that simultaneously satisfies both properties (Jasso 1990). The sixth and seventh properties, noted six years later in Jasso (1996), are symmetry and the property that the log-ratio specification is the limiting form of the difference between two power functions; this latter property not only provides a new way of representing the unification of the ratio and difference perspectives but also unifies the power and log forms that have long been seen as competitors. Along the way, the property of deficiency aversion was extended to cover loss aversion. And recently, it was shown that the log-ratio function yields a connection to the Golden Number, $(\sqrt{5}-1)/2$ (Jasso 2005). Together, these properties serve to strengthen the foundation for the log-ratio form of the justice evaluation function and its use in both theoretical and empirical justice analyses.

The justice evaluation function posits an exact relation between the actual reward, the just reward, and the justice evaluation, as shown in equation (18). Thus, the equation can be used to solve for any of the three variables, given the other two. This feature will be used below.

The experienced justice evaluation J^* is the quantity that generates behavioral consequences. However, individuals differ in their expressiveness—some shout, others whisper, for example—and thus J^* is transformed into the expressed justice evaluation J. Meanwhile, justice evaluations arise about both goods and bads. Accordingly, justice analysis introduces a quantity called the signature constant and denoted θ; by its sign, the signature constant indicates whether the observer regards the reward as a good or as a bad, and by its absolute value, the signature constant indicates expressiveness. Thus, the justice evaluation function becomes

$$J = \theta \ln \left(\frac{A}{C} \right). \tag{19}$$

Immediately, the two further equations for A and C are generated:

$$A = C \exp(J/\theta) \tag{20}$$

and

$$C = A \exp(-J/\theta). \tag{21}$$

Equation (21) plays an important part in empirical justice analysis, as it represents the just reward actually used to generate the justice evaluation and hence has come to be called the "true just reward" (Jasso and Wegener 1997). The challenge is how to estimate the true just reward.

Of course, respondents can be directly asked what they think is the just reward, as has been done in some studies, such as the International Social Justice Project. The possibility cannot be ruled out, however, that responses to a direct question—which can be called the "disclosed just reward"—incorporate a number of mechanisms such as socialization, rhetorical influences, response sets, and the like (Jasso and Wegener 1997). Accordingly, the empirical justice tradition has often relied on other designs, such as (a) studying allocation and inferring ideas of justice from allocative behavior, a design challenged by Leventhal (1976), or (b) studying reactions to violations of investigator-supplied just rewards or principles of justice, a design challenged by Jasso and Rossi (1977). Notable exceptions, designed to capture the true ideas of justice, include Kidder, Bellettirie, and Cohn (1977).

Equation (21), together with Rossi's factorial survey method, points the way to a new technique for estimating the true just reward: Ask respondents to rate the justice or injustice of the actual reward (i.e., obtain the expressed justice evaluation J for a unit with prespecified A), estimate the signature constant θ, and then use equation (21) to estimate C. This procedure, called the indirect measure of the true just reward, is implemented with the factorial survey as follows: Respondents are presented with fictitious rewardees to whom earnings amounts have been randomly attached and asked to judge the fairness or unfairness of the actual earnings. As shown in Jasso (1990, 1996), respondent-specific estimation of the justice evaluation equation—that is, regression of the expressed justice evaluation on the natural logarithm of the randomly attached actual reward, treating the true just reward C as unobservable—yields an estimate of the signature constant, denoted $\hat{\theta}$, which is unbiased and consistent and, under the classical assumption that the errors are independently distributed with mean zero and constant variance, best linear unbiased.[31] The estimated respondent-specific/rewardee-specific just reward, denoted $\hat{C}$, is then calculated. Because $\hat{C}$ is a nonlinear transformation of $\hat{\theta}$, it loses unbiasedness but, by Slutsky's theorem, remains consistent (thus strengthening the rationale for expanded number of vignettes).

The formula for calculating the estimated true just reward is thus the estimated version of equation (21):

$$\hat{C} = A \exp(-J/\hat{\theta}). \tag{22}$$

Important research tasks ahead include studying the magnitude and determinants of the discrepancy between the estimated true just reward and the disclosed just reward, thus potentially enabling calibration across studies with different designs, and searching for superior measures of the true just reward (e.g., measures using physiological measurements).

6.2. JUSTICE-JUDGMENT COMPONENTS IN MULTILEVEL PERSPECTIVE

The literature on the first operation in justice analysis—formation of ideas of the just reward—highlights a process that can be faithfully represented by a multilevel model formed by a normative-judgment (Type III) equation and a determinants (Type IV) equation, of the kind shown in expression (12). The second operation—using ideas of the just reward to make allocation decisions—can be represented by a (possibly) multilevel model formed by a normative-judgment (Type III) equation and a consequences (Type V) equation, of the kind shown in expression (15). The third operation combines the just rewards and the actual rewards to produce the justice evaluation. This process spawns a number of operations, some of which are multilevel. To illustrate, consider the signature constant. This quantity has two components, as discussed above; its sign is a framing coefficient that indicates whether the observer regards the reward as a good or as a bad, and its absolute value is an expressiveness coefficient that transforms the experience of injustice into its expression. Analysis of each component gives rise to a multilevel model of the first kind, consisting of the justice evaluation equation and an equation representing the component's determinants. Finally, the fourth operation can be represented by a two-equation system, consisting of the justice evaluation equation and a consequences (Type V) equation, a system that in some situations will be a multilevel model of the second kind.

Justice research provides an unusually rich arena for the use of multilevel models, not only because the substantive processes immediately yield both major kinds of multilevel models—both the usual kind involving determinants of the parameters of a Level 1 equation (as in expression (12)) as well as the kind involving consequences of the parameters of a Level 1 equation (as in expression (15))—but also the basic quantities produce a vast array of further quantities, such as justice indexes and components of justice indexes (poverty component, inequality component, etc.). Moreover, some approximation tasks generate situations in which an initial Level 1 equation produces a second Level 1 equation, both of which become parts of multilevel models. The data we analyze in this illustration involve this kind of elaboration, as we now discuss.

In this illustration, we are chiefly concerned with respondents' ideas of the just reward for particular rewardees and the guiding principles of justice, which are embodied in the just reward function and the just reward distribution. However, because the true just reward is estimated, as described above, we cannot begin with estimation of the Level 1 just reward equation for each respondent but must first estimate for each respondent the justice evaluation equation (also a Level 1 equation). Accordingly, there are two distinct steps at which all the discussion above of estimation of the Type II and Type III equations is pertinent—including estimation of the pertinent models, such as Models 1 and 3, and implementation via OLS, GLS, SUR, or RP.[32]

6.3. ESTIMATING THE JUSTICE EVALUATION EQUATION

Estimation of the justice evaluation equation using the wide array of combinations of models, approaches, and assumptions on the error structure, together with the appropriate statistical tests, indicates that the respondent-specific equations have unequal variances and distinctive parameters. Values of R^2 for the 20 observer-specific justice evaluation equations range from .72 to .92, indicating the possibility of unequal error variances. White's test for unequal variances (Greene 2003:324) yields a chi-squared statistic of 16.09, which, at 2 degrees of freedom, is significant beyond the .0005 level; the ML-based likelihood ratio test for unequal variances (Greene 2003:330-1) yields a chi-squared statistic of 39.19, which, at 19 degrees of freedom, is significant beyond the .005 level. These tests reject the hypothesis of equal variances.

The two substantive parameters of interest (the signature constant and the mean of the just rewards) also appear to be respondent specific, as indicated by both OLS-based and RP-based tests. Testing between the substantive models in this case requires a two-step procedure, as described in Jasso (1990:403-5). All the tests lead to rejection of the homogeneity hypotheses at very high levels of statistical significance. For example, the RP-based test constructed after estimation of the justice evaluation equation (in which the expressed justice evaluation is regressed on the log of actual earnings) yields a chi-squared statistic of 92.13, which, at 38 degrees of freedom, is significant beyond the .0001 level, indicating that respondents can be characterized by their own signature constants. The second RP-based test constructed after estimation of the adjusted justice evaluation equation (in which the experienced justice evaluation is regressed on the log of actual earnings) yields a chi-squared statistic of 93.65, which, at 38 degrees of freedom, is significant beyond the .0001 level, indicating that the respondent-specific distributions of just earnings have different means.

It is reassuring that the OLS-based and the RP-based estimates of the signature constant and of the mean of the just rewards are highly correlated (.973 for the signature constant and .995 for the mean of the just rewards). In this case, it would appear that either the OLS-based or the RP-based estimate can be used to generate the estimates of the just rewards. An important question for future research concerns development of rules for preferring one or the other estimator.[33]

6.4. THE JUST REWARD MATRIX

Once the justice evaluation equation is estimated for each respondent, the estimates of the respondent-specific/rewardee-specific true just rewards can be obtained. The just earnings amounts can then be arrayed in the form of a just reward matrix. Tables 8 and 9 report OLS-based and RP-based estimates, respectively, of the just earnings matrix for the Deck 06 vignettes. The amounts represent annual earnings and are expressed in 1974 dollars. Because $10,000 in 1974 is approximately equivalent to $38,000 in year 2005 dollars (based on the consumer price index), the reader may apply a crude inflator of 3.8 to the figures. Inflation aside, Tables 8 and 9 show vividly the idiosyncratic element in matters of the just reward. Not only do the absolute amounts vary greatly, but also the respondents differ in the orderings they produce. For example, Respondent 01 considers Vignette 01 to merit less than any other worker (yearly pay of $3,413 in the OLS-based estimate and $2,975 in the RP-based estimate). In contrast, Respondent 17 assigns Vignette 01 an annual earnings of $27,090 to $31,450—the largest amount in the RP-based estimates and tied for the largest amount in the OLS-based estimates.

As discussed above, the row vectors represent respondent-specific just reward distributions; we shall return to these below. The column vectors represent vignette-specific just reward distributions. We shall not explore the column vectors in this article. Notice, however, that the ranges vary considerably. For example, while, as noted, Vignette 01 is assigned just earnings in the range $3,413 to $31,450 (OLS) and in the range $2,975 to $27,090 (RP), Vignette 07 is assigned just earnings in a smaller range, $7,408 to $23,350 (OLS) or $7,305 to $22,638 (RP). In terms of ranks, Vignettes 05 and 10 are viewed by some respondents as meriting the smallest earnings and by others the largest earnings. In contrast, Vignette 02's just earnings range only between the third smallest and the seventh smallest (OLS).

As is visually evident, the OLS-based and RP-based estimates of the just reward are highly correlated (.985).

6.5. THE OBSERVER-SPECIFIC JUST REWARD FUNCTIONS

The just reward may be regarded as the outcome of a just reward function. The principal elements of the just reward function are the reward-relevant characteristics and the weights associated with them. Our specification of the just reward function follows the form pioneered by Mincer (1958, 1974) for the actual earnings function. We regressed, separately for each respondent, the natural logarithm of just earnings (namely, the logs of the just earnings amounts reported in the matrices in Tables 8 and 9) on the schooling (in years) and sex (binary, with $1 =$ female) of each vignette, thereby obtaining estimates of three components of the just earnings functions.

The first component, estimated by the exponential of the intercept, may be thought of as the base salary or wage the observer regards as just for a male worker.[34] In the distributive justice literature, this

(*text continues on p. 393*)

TABLE 8: Just Earnings Matrix: Estimated Ordinary Least Squares (OLS)−Based Just Earnings Amounts for 10 Hypothetical Earners, as Judged by a Probability Sample of 20 Respondents

	Earner ID									
Respondent ID	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
1	3,414	5,858	4,097	8,787	6,000	4,780	10,702	10,000	5,858	7,511
2	10,000	9,746	3,659	14,619	6,000	9,423	14,000	10,000	6,559	9,966
3	10,000	13,392	4,637	12,488	9,652	14,000	14,000	10,000	13,392	22,000
4	10,000	12,910	19,127	19,365	6,000	14,000	14,000	10,000	12,910	13,802
5	10,000	17,019	12,000	25,529	17,503	14,000	14,000	17,080	9,965	22,000
6	4,457	10,070	12,000	15,105	13,463	6,239	14,000	22,439	10,070	14,687
7	6,438	11,645	12,000	17,467	6,000	14,000	14,000	10,000	11,645	14,163
8	10,000	10,100	5,340	15,150	8,994	14,000	14,000	22,472	10,100	9,790
9	3,849	7,143	4,619	10,714	4,365	5,389	7,408	5,292	5,196	11,641
10	7,081	7,955	4,261	8,449	8,473	14,000	14,000	10,000	7,955	5,531

(continued)

TABLE 8 (continued)

	Earner ID									
Respondent ID	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
11	10,000	8,861	12,000	13,291	18,323	9,650	14,000	14,508	8,861	7,204
12	6,698	9,934	8,038	14,901	6,000	9,378	14,000	6,698	9,934	14,737
13	7,074	7,987	6,005	11,980	6,000	7,006	9,904	10,000	7,987	11,009
14	10,000	11,174	7,805	16,761	9,225	9,106	21,524	10,000	11,174	14,310
15	10,000	6,995	5,208	10,493	9,108	6,076	14,000	15,180	10,618	9,548
16	10,000	6,698	4,847	10,048	8,117	5,655	7,650	10,000	6,698	8,886
17	31,450	11,155	6,767	29,674	10,641	14,000	14,000	31,450	11,155	12,405
18	10,000	15,477	12,000	23,215	6,000	14,000	23,350	10,000	15,477	22,000
19	10,000	13,059	12,000	19,589	9,591	8,758	14,000	15,985	13,059	22,000
20	7,250	7,240	3,315	10,860	6,000	7,358	14,000	10,000	7,240	8,383

NOTE: Estimates are for the Deck 06 vignettes, which were randomly assigned to 20 of the 200 respondents. Just earnings amounts are based on OLS estimates of the justice evaluation equation and the signature constant. Just earnings amounts are in 1974 dollars. The amount $10,000 in 1974 dollars is approximately equivalent to $38,000 in year 2005 dollars. Thus, the reader may apply a crude inflator of 3.8 to the figures.

TABLE 9: Just Earnings Matrix: Estimated Random Parameters (RP) Based Just Earnings Amounts for 10 Hypothetical Earners, as Judged by a Probability Sample of 20 Respondents

	Earner ID									
Respondent ID	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
1	2,975	6,722	3,570	10,083	6,000	4,166	10,340	10,000	6,722	6,546
2	10,000	9,211	3,817	13,817	6,000	9,557	14,000	10,000	6,288	10,251
3	10,000	11,810	4,938	11,364	9,353	14,000	14,000	10,000	11,810	22,000
4	10,000	12,446	18,953	18,668	6,000	14,000	14,000	10,000	12,446	13,929
5	10,000	15,486	12,000	23,228	16,696	14,000	14,000	16,681	9,283	22,000
6	4,323	10,701	12,000	16,051	13,879	6,052	14,000	23,131	10,701	14,465
7	6,501	11,198	12,000	16,797	6,000	14,000	14,000	10,000	11,198	14,302
8	10,000	10,743	5,178	16,114	9,134	14,000	14,000	23,176	10,743	9,492
9	3,899	7,022	4,679	10,533	4,383	5,458	7,472	5,337	5,130	11,741
10	6,990	8,375	4,099	8,782	8,583	14,000	14,000	10,000	8,375	5,253

(continued)

TABLE 9 (continued)

	Earner ID									
Respondent ID	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
11	10,000	10,241	12,000	15,361	20,424	9,307	14,000	15,043	10,241	6,463
12	6,739	9,697	8,087	14,546	6,000	9,435	14,000	6,739	9,697	14,826
13	7,023	8,220	5,919	12,330	6,000	6,906	9,833	10,000	8,220	10,852
14	10,000	11,296	7,784	16,943	9,250	9,082	21,582	10,000	11,296	14,271
15	10,000	6,566	5,432	9,849	8,918	6,338	14,000	14,863	9,759	9,959
16	10,000	7,346	4,523	11,019	8,306	5,277	7,305	10,000	7,346	8,292
17	27,090	8,918	7,291	22,017	9,875	14,000	14,000	27,090	8,918	13,366
18	10,000	13,673	12,000	20,509	6,000	14,000	22,638	10,000	13,673	22,000
19	10,000	12,969	12,000	19,454	9,575	8,773	14,000	15,958	12,969	22,000
20	7,100	7,869	3,050	11,803	6,000	7,058	14,000	10,000	7,869	7,875

NOTE: Estimates are for the Deck 06 vignettes, which were randomly assigned to 20 of the 200 respondents. Just earnings amounts are based on random parameters estimation of the justice evaluation equation and the signature constant. Just earnings amounts are in 1974 dollars. The amount $10,000 in 1974 dollars is approximately equivalent to $38,000 in year 2005 dollars. Thus, the reader may apply a crude inflator of 3.8 to the figures.

amount is interpreted as based on need, reflecting the minimum amount a full-time employed person should earn, even if such a person had zero schooling (but not reflecting a tax or bonus associated with gender); the interpretation in the human capital literature would be as the just rental price of a unit of human capital.[35] The second component, estimated by the coefficient of schooling, provides an estimate of the just return to investment in an additional year of schooling. The third component, estimated by the exponential of the coefficient of the binary sex variable, measures the gender multiplier; the multiplier is applied to the earnings of females, so that subtracting one yields the tax (if negative) or bonus (if positive) on women's earnings, relative to the earnings of comparable men, in percentage points. The gender multiplier has a natural interpretation as the ratio of female-to-male earnings; a gender multiplier of .85 would indicate the view that the just earnings for a woman is 85 percent of the just earnings of a comparable man. A useful feature of this approach is that the statistical properties of the estimated components are known. If the underlying parameter estimates are unbiased and consistent, then the estimated components are unbiased if and only if they are linear transformations of the parameter estimates and, by Slutsky's theorem, are consistent even if they are nonlinear transformations of the parameter estimates. Thus, for example, in OLS estimation of the just reward functions, all three estimated components are consistent, but only the just rate of return to schooling component is unbiased.

Table 10 reports the three components for each of the 20 respondents, based on the OLS-based estimates of just earnings. Table 11 summarizes the distributions of three estimates of the three components: (a) based on OLS analysis of both the justice evaluation equation and the just reward equation, (b) based on OLS analysis of the justice evaluation equation and RP analysis of the just reward equation, and (c) based on RP analysis of both equations.

There is obviously wide variation across respondents in their ideas of justice. Given that all respondents saw the same vignettes, none of the variation can be attributed to sampling variability in the vignette sample. To illustrate with the OLS/OLS results, the just male base salary ranges from \$4,240 to \$26,726. Four of the estimated just rates of return to schooling are negative; the largest rate of return is .054, less than the estimates of .06 to .07 obtained around the same time

TABLE 10: Estimated Components of Observer-Specific Just Reward Functions

Respondent	*Just Base Salary for Men*	*Just Rate of Return to Schooling*	*Just Gender Multiplier*
1	4,240	0.0444	0.700
2	9,386	0.00268	0.815
3	16,901	−0.0138	0.670
4	7,384	0.0439	0.936
5	14,386	0.00277	1.043
6	6,762	0.0479	0.800
7	6,381	0.0543	0.757
8	11,435	0.0127	0.695
9	5,135	0.0202	0.848
10	6,427	0.0327	0.710
11	8,251	0.0188	1.144
12	6,808	0.0345	0.804
13	7,956	0.0103	0.827
14	8,926	0.0272	0.831
15	10,558	−0.0000324	0.767
16	11,188	−0.0304	1.024
17	26,726	−0.0440	1.001
18	8,845	0.0499	0.726
19	12,698	0.00848	0.874
20	7,342	0.0171	0.704

NOTE: Estimates are based on the ordinary least squares (OLS)−based analyses of Deck 06 vignettes, which were randomly assigned to 20 of the 200 respondents. The base salary/wage amounts are in 1974 dollars. The amount $10,000 in 1974 dollars is approximately equivalent to $38,000 in year 2005 dollars. Thus, the reader may apply a crude inflator of 3.8 to the figures. The gender multiplier is applied to women's earnings; subtracting 1 from the multiplier yields the tax (if negative) or bonus (if positive) on women's earnings, in percentage points.

in OLS analyses of data from the Panel Study of Income Dynamics and the National Longitudinal Surveys and considerably less than the estimates obtained when adjusting for endogeneity (Griliches 1977; Hausman and Taylor 1981). The gender multiplier ranges from the conventional .67 to 1.14—that is, from a "tax" on women's earnings of 33 percent to a "bonus" of 14 percent (four respondents assigned a bonus for women)—and the mean is .83; thus, while 80 percent of these respondents view a tax on women's earnings as just, the amount of the tax they favor appears to be smaller than that thought to have existed at the time of the survey.

Statistical tests of interrespondent parameter homogeneity reject the homogeneity hypothesis in all three sets of estimates. For example, the

TABLE 11: Summary Statistics of the Estimated Components of Observer-Specific Just Reward Functions

Summary Statistic	*Just Base Salary for Men*	*Just Rate of Return to Schooling*	*Just Gender Multiplier*
A. Based on ordinary least squares (OLS) estimates of justice evaluation equation and OLS estimates of just reward equation			
Mean	9,887	0.0169	0.834
Standard deviation	5,051	0.0264	0.133
Minimum	4,240	– 0.0440	0.670
Maximum	26,726	0.0543	1.144
B. Based on random parameters (RP) estimates of justice evaluation equation and OLS estimates of just reward equation			
Mean	10,114	0.0178	0.835
Standard deviation	6,339	0.0318	0.140
Minimum	2,826	– 0.0625	0.666
Maximum	31,777	0.0739	1.215
C. Based on RP estimates of justice evaluation equation and RP estimates of just reward equation			
Mean	9,150	0.0179	0.833
Standard deviation	2,757	0.0126	0.0527
Minimum	4,301	– 0.0075	0.757
Maximum	15,059	0.0453	0.963

NOTE: See notes to Table 10.

RP estimate of the just reward function yields a chi-squared statistic of 113.06, which, at 57 degrees of freedom, is significant beyond the .0001 level.

The three sets of respondent-specific estimates of the components of the just reward function (Tables 10 and 11, plus the OLS/RP and RP/RP estimates, not shown, which parallel the OLS/OLS estimates in Table 10) suggest an interesting negative relationship between the just male base salary and the rate of return to schooling. The estimated correlation is –.794 in the OLS/OLS estimates, –.857 in the RP/OLS estimates, and –.829 in the RP/RP estimates—the larger the base, the smaller the return to schooling. In distributive justice terms, the larger the need amount, the smaller the merit return; in human capital terms, the larger the just rental price of a unit of human capital, the smaller the return on investments in human capital.

Methodologically, the most interesting feature of these estimates concerns the similarities and differences among them. As can be seen in Table 11, the means of the respondent-specific estimates are very similar across estimation procedure; for example, the mean of the just rates of return to schooling ranges from .0169 to .0179, and the mean of the just gender multiplier ranges from .833 to .835. Even the mean of the just base salary ranges over a narrow interval, from $9,150 to $10,114. Moreover, the correlations (not shown) are high, although they exhibit different patterns across components of the just reward function. For example, while the correlations among the gender multiplier estimates are uniformly high (.943, .951, and .985), the correlations among the schooling estimates vary (.843, .933, and .940, with the OLS/OLS-RP/RP correlation the lower one). In general, however, as would be expected, the RP/RP estimates exhibit greater compression than the others. This is visible in all three components but is heightened in the base salary estimates.

Thus, the data unambiguously indicate that respondents have their own personal just reward function. What remains an open question is the magnitude of the cross-respondent differences, with the OLS-based estimates possibly accentuating their differences and the RP-based estimates possibly attenuating them.

What accounts for the interobserver variation in the components of the just reward function? The data contain three respondent characteristics that may be at work; these are sex, age/birth cohort, and schooling. Of these, sex and age/birth cohort are unambiguously exogenous; schooling, however, cannot be assumed exogenous. Thus, we estimate both ordinary least squares and two-stage/least squares (TSLS) versions of a simple model in which sex and schooling directly affect each of the three components of the just reward function, while age/birth cohort, although not influencing directly the components, may do so indirectly by affecting the amount of schooling obtained. The 20 respondents who rated the Deck 06 vignettes were born between 1896 and 1956; their mean age in 1974 was 45 years. Their schooling, in completed years, ranged from 8 to 19, with a mean of 13.2 years and a standard deviation of 3.04 years.

Table 12 reports three sets of estimates of the six equations, based on the three estimates of the components of the just reward function. Because the analyses are performed on only 20 respondents, the t ratios cannot be expected to reach statistical significance; we thus focus on the magnitudes of the coefficients. We again emphasize that our purpose is to illustrate the method; thus, the results should be interpreted as illustrating the kinds of questions that can be addressed rather than as providing estimates of the answers to the questions. The results in Table 12 combine expected and unexpected findings. First, respondent's sex and schooling explain more of the variation in the base salary/wage (16-17 percent) and in the gender multiplier (19-22 percent in the OLS/OLS- and RP/OLS-based estimates and 8 percent in the RP/RP-based estimates) than in the return to schooling (4-8 percent). Second, schooling makes the respondent more egalitarian; the more highly schooled favor a larger base salary/wage (TSLS coefficient), a lower return to schooling, and higher wages for women relative to comparable men. Third, women are less egalitarian than men; they favor a smaller base salary/wage, a higher return to schooling, and lower wages for women relative to comparable men (a tax on women about 2 to 8 percentage points larger than that imposed, ceteris paribus, by male respondents).

Note that in a large study, findings such as these would permit assessment of several perspectives, including the rational choice notion that individuals act in their own material self-interest, the Marxian notion that individuals must learn what is in their interest, and Jefferson's notion that (the right kind of) schooling nurtures the democratic spirit. The coefficients of schooling in the return-to-schooling equation and of sex in the gender-multiplier equation indicate that, in these data, people are not acting in their self-interest narrowly conceived; whether "consciousness raising" would alter the results, these data cannot say (but an interesting experimental design is suggested). Furthermore, among these respondents, the effect of schooling in all three equations supports Jefferson's hypothesis.

As a final look at Table 12, we examine differences across the three sets of estimates (Panels A, B, and C). With only a single exception, the signs of the estimated coefficients are the same across the three sets of estimates. And treating schooling as endogenous moves the coefficients in the same direction across all three sets of estimates. Thus, again, the direction of the effects is robust to differences in estimation procedure. The magnitudes of the effects, however, are sensitive to whether the justice evaluation equation (and thus just

TABLE 12: Determinants of the Estimated Components of Observer-Specific Just Reward Functions

Respondent Characteristic	*Just Male Base Salary* OLS	*Just Male Base Salary* TSLS	*Just Return to Schooling* OLS	*Just Return to Schooling* TSLS	*Just Gender Multiplier* OLS	*Just Gender Multiplier* TSLS
A. Dependent variable based on OLS estimates of justice evaluation equation and OLS estimates of just reward equation						
Sex (1 = female)	−2693.24	−2893.75	0.0138	0.0162	−0.0651	−0.0814
	(1.23)	(1.21)	(1.15)	(1.07)	(1.15)	(0.96)
Schooling (years)	−449.11	52.17	−0.000848	−0.00674	0.0165	0.0573
	(1.21)	(0.03)	(0.42)	(0.68)	(1.72)	(1.04)
Intercept	17161.60	10644.99	0.0212	0.0978	0.649	0.118
	(3.39)	(0.52)	(0.76)	(0.76)	(4.96)	(0.16)
R^2	0.158	—	0.0783	—	0.191	—
F ratio	1.59	0.78	0.72	0.65	2.01	0.80
B. Dependent variable based on RP estimates of justice evaluation equation and OLS estimates of just reward equation						
Sex (1 = female)	−3561.26	−3843.13	0.0161	0.0196	−0.0608	−0.0751
	(1.30)	(1.27)	(1.11)	(0.99)	(1.03)	(0.93)
Schooling (years)	−564.08	140.60	−0.000338	−0.00910	0.0196	0.0553
	(1.22)	(0.07)	(0.14)	(0.70)	(1.98)	(1.05)
Intercept	19340.62	10179.76	0.0143	0.128	0.606	0.142
	(3.06)	(0.39)	(0.42)	(0.75)	(4.47)	(0.21)
R^2	0.167	—	0.0674	—	0.218	—
F ratio	1.70	0.85	0.61	0.59	2.36	0.78
C. Dependent variable based on RP estimates of justice evaluation equation and RP estimates of just reward equation						
Sex (1 = female)	−1018.40	−1287.23	0.00474	0.00656	−0.0161	−0.0215
	(0.85)	(0.81)	(0.81)	(0.73)	(0.67)	(0.67)
Schooling (years)	−312.01	360.05	0.000228	−0.00431	0.00422	0.0178
	(1.54)	(0.35)	(0.23)	(0.73)	(1.04)	(0.85)
Intercept	13777.61	5040.76	0.0126	0.0715	0.6785	0.609
	(5.00)	(0.52)	(0.93)	(0.93)	(14.21)	(2.24)
R^2	0.163	—	0.0420	—	0.0785	—
F ratio	1.65	0.34	0.37	0.42	0.72	0.47

NOTE: The base salary is in 1974 dollars. In the two-stage least squares specifications, the excluded exogenous variable is year of birth. Absolute values of t ratios appear in parentheses under the corresponding estimates. Sample size is 20 respondents. OLS = ordinary least squares; TSLS = two-stage least squares; RP = random parameters.

earnings) was estimated via OLS or RP and whether the just earnings function was estimated via OLS or RP.

6.6. THE OBSERVER-SPECIFIC JUST REWARD DISTRIBUTIONS

As is visible in the just reward matrix, each observer generates his or her own just reward distribution for the rewardees. These observer-specific just reward distributions may differ in many particulars, including their mean and several measures of inequality. Table 13 reports, for each of the 20 respondents, six parameters of the respondent-specific just earnings distributions shown in Table 8—the mean, standard deviation, minimum, maximum, Gini's ratio, and Plato's ratio (the ratio of the maximum to the minimum). The four quantities in dollar amounts are in 1974 dollars (as before, the reader may apply a crude inflator of 3.8 to obtain amounts in approximate year 2005 dollars); Gini's and Plato's ratios are scale free. As shown, Respondent 01's just earnings distribution for the 10 vignettes has a mean of $6,701, a minimum of $3,414, and a maximum of $10,702; the value of Gini's ratio is .219, while that for Plato's ratio is 3.1344. In contrast, Respondent 17's just earnings distribution has the largest mean ($17,270), one of the largest minimum earnings ($6,767), the largest maximum ($31,450), the largest Gini's ratio (.3027), and the third largest Plato's ratio (4.6479).

Before proceeding, it may be useful to place the estimated quantities in context. Plato (*Laws*, Book V) has the Athenian Stranger argue that the minimum "lot" or allowance should be set at something decent and dignified and that the householder may acquire up to four times the value of the lot—for a total of five times the value of the lot. Any excess must be handed over to the state. Thus, for Plato, who might be thought of as an early sociologist, the maximum allowable value (consistent with achieving peace and harmony) of the ratio of maximum to minimum is 5. It is most interesting that only 1 of the 20 values of Plato's ratio estimated for these respondents exceeds 5 (Respondent 06), and it exceeds 5 only trivially.

To provide a context for the values of Gini's ratio reported in Table 13, we briefly review some values estimated in the United States. It is widely believed that inequality varies considerably across type of good (e.g., larger for wealth than for earnings), across type

TABLE 13: Parameters of Observer-Specific Just Reward Distributions

Respondent	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*	*Gini's Ratio*	*Plato's Ratio*
1	6,701	2,474	3,414	10,702	0.219	3.134
2	9,397	3,369	3,659	14,619	0.206	3.996
3	12,356	4,454	4,637	22,000	0.196	4.744
4	13,212	4,045	6,000	19,365	0.175	3.228
5	15,910	5,029	9,965	25,529	0.184	2.562
6	12,253	5,043	4,457	22,439	0.236	5.035
7	11,736	3,544	6,000	17,467	0.175	2.911
8	11,995	4,680	5,340	22,472	0.213	4.208
9	6,562	2,686	3,849	11,641	0.228	3.024
10	8,770	3,187	4,261	14,000	0.207	3.286
11	11,670	3,384	7,204	18,323	0.170	2.543
12	10,032	3,407	6,000	14,901	0.198	2.484
13	8,495	2,105	6,000	11,980	0.147	1.997
14	12,108	4,238	7,805	21,524	0.190	2.758
15	9,723	3,181	5,208	15,180	0.192	2.915
16	7,860	1,878	4,847	10,048	0.142	2.073
17	17,270	9,604	6,767	31,450	0.303	4.648
18	15,152	6,032	6,000	23,350	0.235	3.892
19	13,804	4,314	8,758	22,000	0.181	2.512
20	8,165	2,909	3,315	14,000	0.201	4.223

NOTE: Just earnings is based on ordinary least squares (OLS) estimate of justice evaluation equation. Estimates are based on the subsample of respondents who received the Deck 06 vignettes. Each respondent's just reward distribution appears as a row vector in the just reward matrix shown in Table 8. Plato's ratio is defined as the ratio of the maximum to the minimum amount; figures shown are calculated on the unrounded just earnings amounts. All earnings amounts are in 1974 dollars; Gini's ratio and Plato's ratio are scale free.

of unit (e.g., larger for all workers than for full-time employed workers and larger for families than for workers), and across geopolitical entities; that inequality declined over about 150 years, until about the late 1960s or mid-1970s, increasing steadily since then (Jones and Weinberg 2000; Karoly and Burtless 1995). Kearl, Pope, and Wimmer (1980) estimate that Gini's ratio for real estate wealth in Utah in 1850 was .69, while in the United States as a whole, it was .86. Levy (1987:95) estimates values of Gini's ratio in 1969 of .38 and .31 for the earnings of men in the service and goods-producing sectors, respectively; the corresponding values of Gini's ratio for the earnings of men who were employed full-time are .26 and .24. Levy (1987:14) also reports a time series of Gini's ratio for family income; the estimated inequality declines from .378 in 1949 to .349 in 1969, then climbs to .385 in 1984. Values of Gini's ratio for 1974, reported by Levy (1987:14,16), are .356 for family income and .444 for the income of unrelated individuals. Historical tables prepared by the Census Bureau (Jones and Weinberg 2000) provide a time series (1967-2001) of Gini's ratio for individual earnings among full-time, year-round workers (Table IE-2) and for household income (Table IE-6). According to these estimates, Gini's ratio in 1974 was approximately .326 for individuals and .395 for households; in 1967, these measures were .34 and .399, respectively; and in 2001, they were .409 and .466, respectively.

Two additional parameters of the just earnings distributions may be calculated from the figures reported in Tables 8, 9, and 13. These are the minimum relative earnings and the maximum relative earnings, defined, respectively, as the minimum and maximum divided by the mean. The relative minimum ranges from 0 to 1, and the relative maximum ranges from 1 to infinity. Both the relative minimum and the relative maximum play prominent parts in real-world discussions of salary and wage schedules. It is not uncommon, for example, to hear, in salary negotiations, that the relative minimum should not be allowed to become smaller than some specified figure (such as one third) or that the relative maximum should not exceed some specified quantity (such as two). Of course, the ratio of the relative maximum to the relative minimum is identically equal to Plato's ratio.

Table 14 reports two sets of summary statistics for four parameters: Gini's and Plato's ratios and the relative minimum and maximum; the underlying just earnings amounts in the two sets are based, respectively, on OLS estimation and RP estimation of the justice evaluation equation (see Tables 8 and 9). For each parameter, the two estimates shown are remarkably similar; of course, this is not unexpected, given the correlation between the two estimates of just earnings (.985, as reported above). As shown, the obtained values of Gini's ratio range from .14 (lower than any Gini's ratio calculated on any heterogeneous real-world group) to .30 (also lower than the values calculated by Levy 1987 and the Census Bureau for full-time employed workers, families, and households in 1974). The values of Plato's ratio range from under 2 to slightly over 5, suggesting that the respondents agree with Plato. The relative minimum ranges from .34 to .71, and the relative

TABLE 14: Summary Statistics for Four Measures of Inequality in the Respondent-Specific Just Earnings Distributions

Summary Statistic	*Gini's Ratio*	*Plato's Ratio*	*Relative Minimum*	*Relative Maximum*
A. Just earnings based on ordinary least squares (OLS) estimate of justice evaluation equation				
Mean	0.200	3.309	0.515	1.616
Standard deviation	0.0352	0.910	0.103	0.157
Minimum	0.142	1.997	0.364	1.278
Maximum	0.303	5.035	0.706	1.874
B. Just earnings based on random parameters (RP) estimate of justice evaluation equation				
Mean	0.201	3.328	0.509	1.618
Standard deviation	0.0315	0.867	0.100	0.155
Minimum	0.151	2.083	0.345	1.388
Maximum	0.280	5.350	0.694	1.891

NOTE: All quantities are scale free. The relative minimum (maximum) is defined as the ratio of the minimum (maximum) to the mean of the just earnings distribution.

maximum ranges from 1.28 to 1.89, suggesting that these respondents are more egalitarian than real-world employers. Taken together, these results indicate that the distributions of earnings thought just by these respondents are more egalitarian than the actual distribution of earnings. To visualize the respondents' egalitarianism, we show in Figure 2 the Lorenz curves for each of the 20 just earnings distributions. These Lorenz curves appear to be considerably tighter than most Lorenz curves depicted in the literature.

Although generally egalitarian, the respondents nonetheless exhibit variation in their egalitarianism. To explore interrespondent differences, we again estimate simple models in which gender and schooling are specified as direct determinants of each of the four measures highlighted in Table 14. As before, we report both models in which the parameters of the just reward distribution are calculated from just earnings amounts based on the OLS estimate of the justice evaluation equation and also models based on the RP estimate. The estimates, reported in Table 15, indicate an interesting pattern of results. First, gender and schooling appear to influence Plato's ratio and the relative

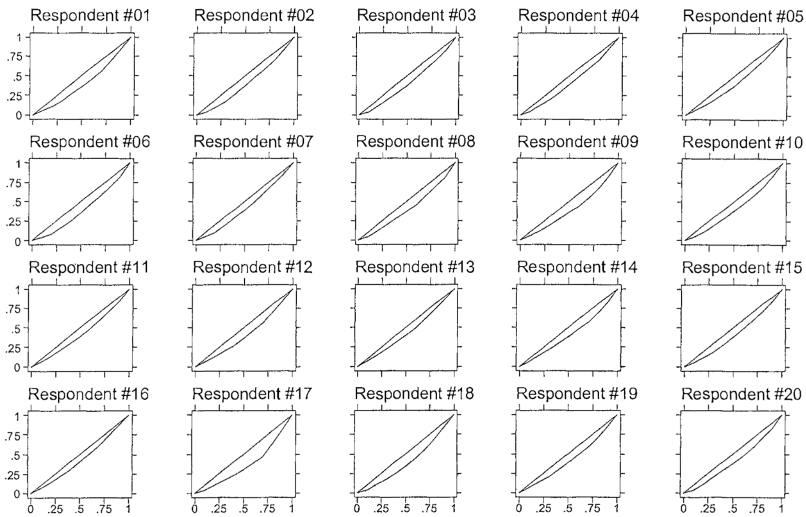


Figure 2: Lorenz Curves of Respondents' Just Reward Distributions

minimum earnings but not the relative maximum earnings or Gini's ratio. Second, 15 of the 16 sex coefficients (including all of the TSLS coefficients) indicate that women are less egalitarian than men, consistent with the results obtained in the specifications of the components of the just reward functions (Table 12). Third, all the schooling coefficients indicate that schooling increases egalitarianism—smaller values of Gini's and Plato's ratios, higher relative minimum earnings, and lower relative maximum earnings—again in accord with the findings reported in Table 12 on the just reward functions and providing additional evidence in support of Jefferson's hypothesis, at least among these respondents.

6.7. STARTING A SENSITIVITY ANALYSIS

All results in this illustration of a normative-judgment (Type III) equation rest on the justice evaluation function, which, jointly with the factorial survey method, enables estimation of the true just reward and hence the just reward function, the just reward distribution, and the principles of justice. But what if the form of the justice evaluation

TABLE 15: Determinants of the Amount of Inequality Regarded as Just

	Gini's Ratio		*Plato's Ratio*		*Relative Minimum*		*Relative Maximum*	
	OLS	*TSLS*	*OLS*	*TSLS*	*OLS*	*TSLS*	*OLS*	*TSLS*
A. Dependent variable based on ordinary least squares estimate of justice evaluation equation								
Sex	0.00176	0.00292	0.473	0.511	−0.0764	−0.0776	−0.00369	0.00148
	(0.11)	(0.17)	(1.27)	(1.24)	(1.84)	(1.80)	(0.05)	(0.02)
Education	−0.00188	−0.0048	−0.134	−0.231	0.0174	0.0204	−0.0112	−0.0241
	(0.68)	(0.42)	(2.12)	(0.86)	(2.48)	(0.72)	(0.91)	(0.47)
Constant	0.224	0.262	4.836	6.102	0.324	0.284	1.765	1.933
	(5.90)	(1.75)	(5.63)	(1.74)	(3.38)	(0.77)	(10.51)	(2.92)
R^2	0.0264	—	0.254	—	0.346	—	0.0469	—
F	0.23	0.09	2.89	0.93	2.82	1.66	0.42	0.12

TABLE 15: (continued)

	Gini's Ratio		*Plato's Ratio*		*Relative Minimum*		*Relative Maximum*	
	OLS	*TSLS*	*OLS*	*TSLS*	*OLS*	*TSLS*	*OLS*	*TSLS*
B. Dependent variable based on random parameters (RP) estimate of justice evaluation equation								
Sex	0.00356	0.00574	0.610	0.670	−0.0836	−0.0869	0.00429	0.0144
	(0.24)	(0.33)	(1.73)	(1.57)	(2.18)	(2.09)	(0.06)	(0.17)
Education	−0.00153	−0.00699	−0.110	−0.258	0.0145	0.0227	−0.00512	−0.0303
	(0.61)	(0.62)	(1.84)	(0.92)	(2.24)	(0.84)	(0.41)	(0.55)
Constant	0.219	0.290	4.470	6.403	0.359	0.252	1.683	2.011
	(6.43)	(1.97)	(5.48)	(1.76)	(4.05)	(0.71)	(9.97)	(2.79)
R^2	0.0238	—	0.259	—	0.350	—	0.0100	—
F	0.21	0.21	2.97	1.37	4.58	2.24	0.09	0.15

NOTE: Respondent-specific values of Gini's ratio, Plato's ratio, the relative minimum, and the relative maximum are calculated from the (unrounded) respondent-specific just reward distributions in Table 8 (just rewards based on OLS estimate of the justice evaluation equation) and Table 9 (just rewards based on RP estimate of the justice evaluation equation). Respondent's schooling is measured in years of completed schooling; respondent's sex is a binary variable, with 1 = female. In the two-stage least squares specifications, the excluded exogenous variable is year of birth. Absolute values of *t* ratios appear in parentheses under the corresponding estimates. Sample size is 20 respondents. OLS = ordinary least squares; TSLS = two-stage least squares.

function is incorrect? Despite the growing strength of its foundation, as indicated by the eight properties discussed above, it is useful to periodically revisit this question. In the context of the analysis reported here, the main question concerns the effects of functional form on the estimated true just reward. Our strategy is to build a set of alternate specifications, representing different constellations of properties, and then repeat the analysis. Such an undertaking is outside the scope of this article, but we do present the first step for one alternate family of specifications.

To choose the alternate specification, we begin by choosing two properties for it: additivity and loss aversion. Given the remarkable property of the logarithmic ratio form that it is the limit of the difference between two power functions divided by the power, as the power goes to zero from the right (Jasso 1996), we choose for the first test case the following family:

$$J = \theta(A^k - C^k), \tag{23}$$

where k is positive and lies on the unit interval (to ensure satisfying loss aversion). This function satisfies all the properties satisfied by the log-ratio form except scale invariance and, ignoring its behavior at the limit, the unification of the difference and ratio perspectives. Its members include the well-known square root function.

As a starter set, we selected four values of the exponent k: 1/2, 1/5, 1/10, and 1/100. We next regressed, separately for each respondent, the expressed justice evaluation on the corresponding power of A (e.g., the square root of A). These regressions yielded estimates of the signature constant, which we then used to estimate the true just reward with the correct member of the family of estimation formulas:

$$\hat{C} = [A^k - (J/\hat{\theta})]^{\frac{1}{k}}, \tag{24}$$

Table 16 reports the summary characteristics for the estimated true just rewards, based on the log-ratio specification and four power function specifications. The expected convergence toward the values obtained from the log-ratio specification is vivid. As the exponent in the power functions approaches zero, all measures approach their log-ratio-based counterparts. At k equal .01, the two sets of estimated just rewards are almost indistinguishable. Graphs of each of the power function–based just earnings on the log-ratio-based amounts,

TABLE 16: Descriptive Characteristics of Estimates of the True Just Reward, Assuming Different Functional Forms for the Justice Evaluation Function

Functional Form	*Mean*	*Standard Deviation*	*Minimum*	*Median*	*Maximum*
A. Logarithmic ratio: $J = \theta \ln\left(\frac{A}{C}\right)$					
	11,158	5,042	3,315	10,000	31,450
B. Difference between two power functions: $J = \theta(A^k - C^k)$					
$k = 1/2$	11,633	4,178	3,050	11,360	22,000
$k = 1/5$	11,277	4,449	3,323	10,319	25,483
$k = 1/10$	11,199	4,683	3,329	10,182	27,952
$k = 1/100$	11,160	4,999	3,317	10,000	31,038

NOTE: Estimates are for the Deck 06 vignettes, which were randomly assigned to 20 of the 200 respondents. Just earnings amounts are based on ordinary least squares (OLS) estimates of the justice evaluation equation and the signature constant. Just earnings amounts are in 1974 dollars. The amount \$10,000 in 1974 dollars is approximately equivalent to \$38,000 in year 2005 dollars. Thus, the reader may apply a crude inflator of 3.8 to the figures.

not shown, depict vividly the convergence; by $k = 1/100$, the graph is a straight diagonal line.

Correlations between the estimated just rewards based on the log-ratio form and each of the other four sets of estimated just rewards are high and increase rapidly as k goes to zero. At $k = 1/2$, the correlation is .925; by $k = 1/5$, the correlation is .985; and by $k = 1/10$, the correlation is .996. At $k = 1/100$, the correlation rounds to 1.

A full sensitivity analysis would incorporate many more functional forms and would repeat all the analyses reported in the preceding sections. By delineating the existence and magnitude of discrepancies, it would provide a useful empirical adjunct to the theoretical foundation for the justice evaluation function.

7. REMARK CONTRASTING THE TWO ILLUSTRATIONS

We note briefly that our illustration of a normative-judgment equation is somewhat more elaborate than our illustration of a positive-belief equation due to complexities associated with studying justice. In principle, the two illustrations could have been exactly parallel, the one estimating a positive-belief (Type II) equation and the other estimating a normative-judgment (Type III) equation, both followed by determinants (Type IV) equations.

The positive-belief illustration conformed closely to the protocol. The marital happiness equation was estimated separately for each respondent. Next, determinants of the belief components were assessed.

Had the normative-judgment illustration proceeded along the same path, the analysis would have been limited to estimation of the just earnings equations, separately for each respondent, followed by assessment of the determinants of the judgment components in the just earnings equation. However, the illustration, following standard practice in the study of justice, included several additional steps. First, the just earnings amounts were not directly measured (paralleling measurement of marital happiness) but instead, to avoid pitfalls associated with disclosure mechanisms, were themselves estimated (as noted above, by first estimating justice evaluation equations and then solving algebraically for the implicit just earnings). Second, the just earnings are of immediate interest and were reported in the just earnings matrix, unlike the marital happiness ratings, which, perhaps because of their nonfundamental nature, are not themselves of sufficient immediate interest to warrant reporting in a matrix. Third, the just earnings give rise to the just reward distributions, which figure prominently in the literature and whose parameters, such as inequality, also become of interest, whereas the marital happiness ratings, again possibly because of their nonfundamental nature, do not give rise to a distribution whose shape and parameters are of major interest. Finally, in the justice illustration, there are two sets of judgment components whose determinants are to be assessed—parameters of the just earnings function and parameters of the just earnings distribution—whereas in the marital happiness illustration, there is a single set of belief components whose determinants are to be assessed.

These differences serve to underscore the flexibility and adaptability of Rossi's factorial survey method.

8. CONCLUDING NOTE

We have presented a framework, based on Rossi's factorial survey method, for estimating positive-belief (Type II) and normative-judgment (Type III) equations and for studying the components of beliefs and judgments and their determinants (via Type IV equations) and consequences (via Type V equations). The framework highlights two kinds of two-equation systems: first, the multiequation system formed by a Type II or Type III equation combined with a Type IV equation and, second, the multiequation system formed by a Type II or Type III equation combined with a Type V equation. The first system (a Type II or Type III equation combined with a Type IV equation) is always a multilevel system; the second system (a Type II or Type III equation combined with Type V equation) may, but need not, be a multilevel system. Moreover, we distinguished between multilevel systems linked by a parameter (slope or intercept) of the Type II or Type III equation and systems linked by a function of one or more of these parameters.

We described procedures for collecting factorial survey data and an array of procedures for estimating the Types II to V equations. These estimation procedures include estimation of a single Type II or Type III equation; estimation of Type II or Type III equations in a set of respondents via OLS, GLS-SUR, and RP approaches and embodying differing restrictions on error structure and parameter homogeneity, together with tests of these restrictions; and multilevel estimation of the two kinds of systems generated in the framework.

To illustrate the framework, we investigated both a positive-belief equation—describing adolescents' views concerning determination of marital happiness—and a normative-judgment equation—describing judgments of the justice of earnings. In each case, we reported respondent-specific estimates of several components of the beliefs and judgments and estimated the effects of respondent characteristics on the components.

The justice illustration brought to light several additional multilevel complexities that can be accommodated within the framework, including (a) a case in which a preparatory Level 1 equation must be estimated before the Level 1 equation in the multilevel model of interest (because it yields estimates needed to obtain measures of the response variable in the Level 1 equation of interest) and (b) a case in which the link between the Level 1 and Level 2 equations in the multilevel model is even more elaborate than a simple function of the parameters of the Level 1 equation—namely, the response variables in the Level 2 equation are parameters of the distribution formed by the response variable in the Level 1 equation.[36]

The empirical results, though only illustrative, serve to highlight the wide range of questions that may be addressed and quantities that may be estimated by Rossi's method. For example, as shown, Rossi's method enables estimation of the perceived ceteris paribus effect of a couple's offspring configuration on their marital happiness, the just earnings return to schooling investment, and the amount of inequality thought just for the earnings distribution. Similarly, the illustrations show that Rossi's method can be used to study the effects of gender, position in the offspring configuration, and parental divorce on the certitude with which adolescents hold their views of the determination of marital happiness. Factorial survey analysis can thus be used to assess the extent to which belief formation may be among the mechanisms involved in a wide range of phenomena, such as inheritance of the propensity to divorce and the tendency of girls to marry at earlier ages than boys, ceteris paribus.

The analysis of judgments on the justice of earnings showed that Rossi's method makes it possible to isolate respondent-specific components of such judgments—the just male base salary, the just rate of return to schooling, and the just gender multiplier embodied in respondent-specific just earnings functions and the amount of inequality embodied in respondent-specific just earnings distributions—and to investigate their determinants. Factorial survey analyses can be used to assess a wide variety of behaviors and outcomes, such as the magnitude of egalitarianism among respondents and the effects of gender, schooling, and other factors on egalitarianism.

An important set of topics for future research pertains to features of the design and analysis protocols in factorial surveys. These include the choice of estimation procedure and the link to the growing set of multilevel procedures. Rich cross-fertilization can be anticipated. For example, some of the questions and models generated in factorial surveys, for which explicit multilevel tools are not currently available, may stimulate development of new multilevel tools. Conversely, the expanding set of multilevel procedures will contribute to development of best-practice protocols in factorial survey analysis.

Substantively, further research using Rossi's factorial survey method, especially longitudinal research, would make possible quantitative assessment of the precise effects of age, experience, and other factors on the components of beliefs/judgments, as well as the effects of the components of beliefs/judgments on many important behaviors and outcomes at different points in the life course.

APPENDIX

TABLE A.1: Sample Vignettes: Married Couples

	Wife	*Husband*
Age	35	37
Education	Finished college	Finished college
Employment	Works full-time	Works full-time
Annual earnings	$35,000	$25,000
Siblings	One younger sister	One older sister
They have two children, a twin boy and girl, who are 13 years old.		

	Wife	*Husband*
Age	30	30
Education	Finished college	Finished college
Employment	Works full-time	Works part-time
Annual earnings	$25,000	$15,000
Siblings	One older brother	One younger brother
They have two sons, ages 9 and 10 years old.		

TABLE A.2: Sample Vignettes: Immigrant Visa Applicants

A man, 35 years of age, who finished eighth grade,
scored 35 in the English test, comes from a European country
whose nationals obtained 5 percent of all immigrant visas
in the last five years, has a job offer,
and does not have a U.S. citizen sibling.

A woman, 65 years of age, who finished college,
scored 55 in the English test, comes from a Latin American country
whose nationals obtained 8 percent of all immigrant visas
in the last five years, does not have a job offer,
and does not have a U.S. citizen sibling.

TABLE A.3: Sample Vignettes: Adolescents

A boy, who is 14 years old,
who is in the eighth grade, and works after school.
He has no brothers and one older sister.
He smokes 2 cigarettes daily and exercises frequently.
His parents both work full-time; each earns $20,000 a year.

A girl, who is 12 years old,
who is in the ninth grade, and does not work.
She has no brothers and one younger sister.
She does not smoke and exercises occasionally.
Her father died; her mother works full-time
and earns $25,000 a year.

TABLE A.4: Sample Vignettes: Chief Executive Officers

1. *Perceptions Substudy*

The CEO is 45 years old,
a woman who completed 20 years of school,
receiving a doctoral diploma.
She was a CEO elsewhere for 11 years.
The firm, headquartered in the United States,
is in the manufacturing sector.
The firm has a market value of $50 billion.

2. *Justice Substudy*

The CEO is 45 years old,
a woman who completed 20 years of school,
receiving a doctoral diploma.
She was a CEO elsewhere for 11 years.
The firm, headquartered in the United States,
is in the manufacturing sector.
The firm has a market value of $50 billion.
The proposed total compensation for the CEO
for the first year is $1 million.

TABLE A.5: Sample Rating Tasks: Marital Cohesiveness

1. *Judgments of Marital Happiness*
This packet contains short descriptions of forty married couples. We would like to know what you think about how happily or unhappily married each couple is. Let negative numbers denote unhappiness, and positive numbers happiness, with zero used to denote a couple who is neither happily nor unhappily married. Further, let −100 denote the extreme of marital unhappiness, and let +100 denote the extreme of marital happiness. Please choose the number between −100 and +100 which best fits your judgment about each couple. Of course, you may choose any real number (for example, decimals and fractions as well as whole numbers) to represent a judgment.
2. *Predictions of Divorce*
This packet contains short descriptions of forty married couples. We would like to know what you think about the probability that each couple will get a divorce. Let zero denote the case where you think there is absolutely no chance that this couple will divorce; let 100 denote the case where you think that this couple will without doubt divorce; let 50 denote "fifty-fifty" chance that the couple will divorce. Please choose the number between 0 and 100 which best fits your judgment about each couple. Of course, you may choose any real number (for example, decimals and fractions as well as whole numbers) to represent a judgment.

TABLE A.6: Sample Rating Tasks: Healthiness

1. *Predicting Life Expectancy*
This packet contains brief descriptions of forty persons. We would like to know what you think about how long each person will live. Please write the number of years that represents your best judgment about each person's life expectancy. Of course, you may choose any real number (for example, decimals and fractions as well as whole numbers) to represent a judgment.
2. *Perceptions of General Healthiness*
This packet contains brief descriptions of forty persons and married couples. We would like to know what you think about how healthy or unhealthy each person is. We will use negative numbers to represent poor health and positive numbers to represent good health. Let −100 denote a person who is in extremely poor health; let zero denote a person who is neither healthy nor unhealthy; let +100 denote a person who is in extremely good health. Please choose the number between −100 and +100 that best describes your judgment about the healthiness of each person. Of course, you may choose any real number (for example, decimals and fractions as well as whole numbers) to represent a judgment.

TABLE A.7: Sample Rating Tasks: Scholastic Achievement

1. *Predicting High School Grade Point Average*

This package contains brief descriptions of forty boys and girls who are in your grade in school. We would like to know what you think about what their grades will be in high school, and in particular, what their grade point average will be when they graduate from high school. Let the numbers between zero and 100 denote the average of all courses taken in high school. Please choose the number between zero and 100 which best fits your judgment about each student. Of course, you may choose any real number (for example, decimals and fractions as well as whole numbers) to represent a judgment.

2. *Predicting Highest Degree*

This packet contains brief descriptions of forty students in your grade in school. We would like to know what you think about how much education they will ultimately acquire. Please write in the name of the highest degree which you think each student will receive.

TABLE A.8: Sample Rating Tasks: Perceptions of CEO Compensation

Chief executive officers (CEOs) and their firms differ in a lot of ways. We have made up descriptions of different kinds of CEOs and firms. The firms' market value is expressed in U.S. dollars (note that a billion corresponds to what in Europe is called a milliard). All the CEOs are newly hired at the firms. Some have been a CEO before at other firms. We would like to know what you think is that CEO's total compensation for the first year. This total compensation amount includes salary, signing bonus (if any), value of restricted stock, savings and thrift plans, and other benefits, but excludes stock options. The total compensation amount is expressed in U.S. dollars.

When you read each description of a CEO, please write the dollar amount which best represents what you think is that CEO's total compensation for the first year.

You may read the descriptions in any order.

You may change any of the amounts.

Your responses are completely confidential.

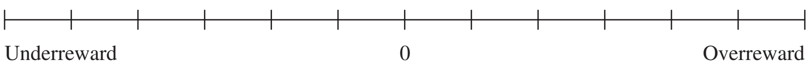
Thank you very much for your participation.

TABLE A.9: Sample Rating Tasks: Justice of CEO Compensation

Chief executive officers (CEOs) and their firms differ in a lot of ways. We have made up descriptions of different kinds of CEOs and firms. The firms' market value is expressed in U.S. dollars (note that a billion corresponds to what in Europe is called a milliard). All the CEOs are newly hired at the firms. Some have been a CEO before at other firms. Each CEO has been randomly assigned a hypothetical total compensation for the first year. This total compensation amount includes salary, signing bonus (if any), value of restricted stock, savings and thrift plans, and other benefits, but excludes stock options. The total compensation amount is expressed in U.S. dollars. We would like to know what you think about whether each CEO is fairly or unfairly paid, and, if you think that a CEO is unfairly paid, whether you think the CEO is paid too much or too little.

We would like you to use numbers to represent your judgments. Let zero represent the point of perfect justice. Let negative numbers represent degrees of underreward, and positive numbers represent degrees of overreward. The greater the degree of underpayment, the larger the absolute value of the negative number you choose (for example, if two CEOs receive ratings of −68 and −23, the CEO receiving the −68 is viewed as more underpaid than the CEO receiving the −23). Similarly, the greater the degree of overpayment, the larger the positive number (for example, a CEO receiving a rating of +200 is viewed as more overpaid than a CEO receiving a rating of +75). In other words, mild degrees of underreward and of overreward are represented by numbers relatively close to zero; larger degrees of underreward and of overreward are represented by numbers farther away from zero.

The justice evaluation scale may be visualized as follows:



When you read each description of a CEO, please write the number that best matches your judgment about the fairness or unfairness of that CEO's compensation. There is no limit to the range of numbers that you may use. For example, some respondents like to map their personal scale to the numbers from −100 to +100; others prefer to use smaller regions, and still others, larger regions. Of course, you may choose any real number (for example, decimals and fractions as well as whole numbers) to represent a judgment.

You may read the descriptions in any order.

You may change any of your ratings.

Your responses are completely confidential.

Thank you very much for your participation.

NOTES

1. Note also that positive-belief equations provide a tool for assessing the aggregate state of knowledge among experts.

2. Thus, we distinguish between views of *what is* and views of *what ought to be* and, for simplicity, refer to the former as positive beliefs and to the latter as normative judgments.

3. Following Rossi and Anderson (1982:53, 56), we interpret the respondent-specific R^2 as a measure of certitude. We hope to tap the quality of being “more sure” or “less sure” that a given model—that is, a given set of explanatory regressors together with their associated coefficients—is the correct one, descriptively in the positive-belief case and prescriptively in the normative-judgments case. Goodness-of-fit measures would appear to be natural indicators of the quality we seek to tap. However, both definition and measurement of the notion of the respondent’s certitude raise new issues, especially at the extremes, which we leave for future research to address. To illustrate, consider the case where a respondent in a just earnings vignette study is very sure that all workers should have the same earnings and, accordingly, assigns all vignettes the same earnings amount; in this case, the total sum of squares will be zero, and R^2 will be undefined. Future work might also assess other candidates for a measure of certitude, such as the error variance.

4. Of course, the extent to which individuals ponder, ceteris paribus, effects may differ across substantive domains and by personal or demographic characteristics. For example, casual observation suggests the ubiquity of ceteris paribus thinking with respect to medical outcomes, with great interest centering on the effect on life expectancy of making this or that change to one’s diet or exercise behavior.

5. The aim of this article is to provide an introduction to the factorial survey method, and thus no attempt is made to summarize all the recent developments in applications of the method to particular substantive domains. For example, in the study of justice, factorial survey methods are now used to estimate such phenomena as whether a respondent regards a given thing (earnings, say) as a good or a bad and whether a respondent judges the inequality embodied in the vignettes to be larger or smaller than his or her idea of the just inequality; procedures associated with such developments will not be discussed here.

6. This unitary goal implies that many of the decisions are joint. For example, if it is important to increase the number of characteristics in the vignettes, and hence the number of explanatory regressors in the Type II or Type III equation, then the number of vignettes presented to each respondent must also be increased.

7. We say “corresponding to” because one variable may be represented by more than one regressor.

8. A quantitative characteristic is a characteristic of which there can be “more” and “less” or “higher” and “lower”; examples include wealth and beauty. A qualitative characteristic has no inherent ordering; examples include race and sex.

9. As recently as five years ago, it was customary to take into account computational memory constraints in deciding how many levels of characteristics to include in the vignettes, as vignette generation in a fully crossed design quickly reaches millions of vignettes. However, as desktop computational memory exceeds one gigabyte and beyond, such considerations recede into historical memory. Of course, it is also possible to generate the samples of vignettes without first generating the complete fully crossed population via special computer programs, such as Weber and Rossi’s (1988) Vig-Write, which select each characteristic randomly.

10. It is useful to consider this conceptual step, even if the actual vignette generation bypasses generation of the full population.

11. The substantive context determines whether particular combinations are logically impossible and must be deleted. In some substantive contexts, there are no logically impossible combinations. For example, in the factorial survey analysis of the desirability as immigrants of visa applicants, there was no need to remove any of the fictitious applicants, as all combinations were perfectly plausible (Jasso 1988).

12. Again, this step may be accomplished via restrictions in the samples drawn or the vignettes generated.

13. Moreover, having multiple respondents per deck permits controlling for deck effects if, say, some respondents see some "treatments" more often than others.

14. STATA-based routines for computerized generation of vignettes will be posted on the author's Web site.

15. Categorical outcome variables have been less commonly used than quantitative outcome variables in factorial survey research. Berk and Rossi's (1977) pioneering use of a categorical outcome variable—sentence for a convicted offender—constitutes the textbook case.

16. S. S. Stevens (1975) and his associates developed many forms of scaling techniques for subjective judgments, including magnitude estimation and its inverse, magnitude production, as well as ratio estimation and its inverse, ratio production. For a brief description of these scaling methods, see J. C. Stevens (1968:124).

17. When a respondent rates all vignettes, the values of the regressors are fully under the investigator's control, and thus the regressor variables are nonstochastic. If a respondent does not rate all vignettes but the unrated vignettes are due to chance—a missing vignette, say, or two sheets of paper stuck together—the regressor variables remain nonstochastic. Note also that the assumption of independently distributed errors may not be unreasonable in the case of respondent-specific equations.

18. As is well known, there are several approaches to computing adjusted measures of goodness of fit when the number of parameters estimated is large relative to the number of observations (Greene 2003:34-36). Goldberger (1991:178) notes that "it may well be preferable" to report R^2 together with the sample size (n) and the number of parameters estimated (k) and "let readers decide how to allow for n and k."

19. Note that as survey rounds accumulate in the large longitudinal surveys, such as the Panel Study of Income Dynamics or the National Longitudinal Studies of Labor Market Experience, it will become possible to estimate a wide range of respondent-specific equations, addressing the question of whether individuals have unique slopes (e.g., individual-specific rates of return to schooling). Problems of micronumerosity will then become common, and experience gained from vignette analysis (such as the costliness of qualitative variables) may prove helpful.

20. Note that in some substantive contexts, the belief and the behavioral consequence may influence each other; that is, the "consequence" may also be a determinant of the belief. For example, the belief that smoking has a particular effect on healthiness may not only influence smoking behavior but may also reflect smoking behavior, via processes of rationalization, say. Thus, the Type IV and Type V equations may form a system.

21. Sometimes, an individual-level consequence S cannot be observed, but an aggregate pattern can. For example, in the immigrant visa study (Jasso 1988), factorial survey analysis detected deep and pervasive differences among the policy makers, and thus it was possible to predict—accurately—that, despite all the commonalities expressed publicly, the policy makers would not agree on a point system for the selection of immigrants and would not recommend it.

22. In the spirit of Goldberger (1991:178), we report all the information required for calculation of alternative measures of goodness of fit in the adolescents' equations. The values of R^2 are reported in Table 1. The number of parameters estimated is 16. The number of observations in each equation is 40, except for Respondent 6's equation, for which the number of observations is 39.

23. Table 3 extends the summary tables used in previous research in two ways, by increasing the number of models from three to four and the associated tests from three to five and by incorporating generalized least squares (GLS) as well as ordinary least squares (OLS) estimates.

24. The GLS estimates reported in Table 3 are obtained using the two-step GLS estimator. We also used the iterated estimator to obtain maximum likelihood estimation (MLE) estimates. These do not differ appreciably from the two-step-based estimates in Table 3. In particular, all five tests dictate rejection of homogeneity at the .0001 level of significance.

25. A further question, which we leave to future work, pertains to discerning subsets of respondents who may be described by the same equation.

26. Of course, a purist would argue that, except for the child's sex, age, and being first born, the exogeneity of the adolescent's background characteristics is open to question. For example, a child's temperament (which may shape his or her views of the production of marital happiness) may prompt the parents to move to a farm or to get a divorce or to have more children or to stop having children.

27. Of course, the Type II equation can be respecified and reestimated, with a variable representing the husband's earnings minus the wife's earnings, in which case the dependent variable in the Type IV equation would be a β. Note that if indeed there is respondent agreement on the husband's earnings, as some of the statistical tests indicate, then our analysis is equivalent to an analysis of the determinants of the effect of the wife's earnings.

28. The values of R^2 indicate that the basic set of characteristics explains almost two thirds of the variation in the husband-wife slope coefficient differential. Inclusion of the first-born binary variable increases R^2 by 6 to 8 percentage points.

29. Of course, offspring gender may not be exogenous but may be correlated with attributes that predispose to or reflect marital cohesiveness, as discussed in Norberg (2004) and Jasso (1985).

30. In the world beyond vignettes, the observers and rewardees may be real persons. If the observers and rewardees are the *same* persons—that is, if every person forms an idea of the just reward for every person—then the matrix is square, and the main diagonal yields a third just reward distribution—namely, the *reflexive just reward distribution*.

31. Note the criticality of a randomly attached actual reward to avoid error-regressor correlation, which would bias the estimate. See Jasso and Webster (1999) for further discussion and a second indirect procedure designed to ensure orthogonality.

32. Substantive considerations guide specification of the pertinent statistical models, which in this case differ from the usual Models 1, 2a, 2b, and 3, as shown in Jasso (1990:403-5) and briefly described below.

33. Pertinent discussion includes Mundlak (1978a, 1978b) and DiPrete and Forristal (1994).

34. In general, the exponential of the intercept is interpreted as the just base wage. If the equation includes rewardee sex, then the exponential of the intercept is interpreted as the just base wage for the sex coded zero.

35. Lucid discussion of the human capital perspective on earnings functions is found in Mincer (1958, 1974) and Griliches (1977).

36. To wit, (a) it is necessary to estimate the justice evaluation equation to obtain estimates of the true just reward, the response variable in the Level 1 just reward equation, and (b) not only do the just reward equation's intercept and slope and/or functions thereof become response variables in a Level 2 equation, but so also do parameters of the distribution of the just rewards, such as measures of inequality.

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