A NEW MODEL OF JUSTICE EVALUATIONS:
USING GRADED CHARACTERISTICS TO ESTIMATE JUST REWARDS

By
David Melamed

A Dissertation Submitted to the Faculty of The
Department of Sociology
In Partial Fulfillment of the Requirements
For The Degree of
Doctor of Philosophy

In the Graduate College
University of Arizona
2012
As members of the Dissertation Committee, we certify that we have read the dissertation prepared by David Melamed entitled “A New Model of Justice Evaluations: Using Graded Characteristics to Estimate Just Rewards” and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

____________________________________________ Date: March 26, 2012
Ronald L. Breiger

____________________________________________ Date: March 26, 2012
Erin Leahey

____________________________________________ Date: March 26, 2012
Linda D. Molm

Final approval and acceptance of the dissertation is contingent upon the candidate’s submission of the final copies of the dissertation to the Graduate College. I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

____________________________________________ Date: March 26, 2012
Dissertation Director: Linda D. Molm
STATEMENT BY AUTHOR

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SIGNED: David Melamed
ACKNOWLEDGEMENTS

This research was made possible by grants from the National Science Foundation (SES-1029068) and the Mathematical Sociology Section of the American Sociological Association. Various versions of this research have been presented at the annual meetings of the American Sociological Association (2009, 2010, & 2011) and the 22nd Annual Group Processes Conference. The proposal version of this document, which contained the same fundamental ideas without the empirical tests, won the Outstanding Dissertation-In-Progress Award from the Mathematical Sociology Section of the American Sociological Association. An earlier version of the justice and status chapters (Chapters 2 and 3) and a portion of the empirical analysis of chapter six won the Graduate Student Paper Award from the Mathematical Sociology Section of the American Sociological Association, and the Raymond V. Bowers award for Outstanding Graduate Student Paper in the Sociology Department at the University of Arizona (2010). The vignette analysis of the graded characteristics procedure was published in *Advances in Group Processes* (2011), and the formal models of just rewards and the analysis of the International Social Justice Project was published in *Social Science Research* (2012).

I thank Ronald L. Breiger (HDTRA1-10-1-0017) and Linda D. Molm (SES-0814317) for their support while I was working on this project. I thank Guillermina Jasso for sharing a sample vignette survey and I thank Joseph Berger, M. Hamit Fisek, Martha Foschi, Will Kalkhoff, Robert K. Shelly, Shane R. Thye, David G. Wagner, Murray Webster Jr., David Willer, Robb Willer and several anonymous reviewers for helpful feedback and comments on various parts of this project. I especially thank Ronald L. Breiger, Scott R. Eliason, and Erin Leahey for helpful comments and encouragement. I am also especially grateful to Linda D. Molm, whose encouragement, feedback and patience were vital to this dissertation. Finally, I thank Henry A. Walker, whose guidance, feedback and encouragement made this project possible.
TABLE OF CONTENTS

LIST OF TABLES…………………………………………………………………………7
LIST OF FIGURES………………………………………………………………………..9
LIST OF EQUATIONS………………………………………………………………….10
ABSTRACT………………………………………………………………………………12
1.    INTRODUCTION…………………………………………………………………..14
2.    DISTRIBUTIVE JUSTICE THEORIES…………………………………………….20
   2.1 Exchange Theory Tradition...............................................................20
   2.2 The Status-Value Tradition...............................................................24
   2.3 Expectation States Theories...............................................................26
   2.4 Reward Expectations and Just Rewards.............................................28
   2.5 Reward Expectations Theory............................................................30
   2.6 The Mathematics of Reward Expectations Theory.............................36
   2.7 Applying the Mathematics of Reward Expectations Theory to Just Rewards....40
   2.8 Conclusion.......................................................................................42
3.    STATUS CHARACTERISTICS THEORY AND GRADED STATUS
   CHARACTERISTICS...................................................................................44
   3.1 Status Characteristics Theory............................................................45
   3.2 Graded Status Characteristics............................................................49
   3.3 Graded Status Characteristics: Revised Path Function Equations..........51
4.    EXPERIMENTAL EVALUATION OF GRADED STATUS
   CHARACTERISTICS...................................................................................57
   4.1 Predictions.......................................................................................58
   4.2 Method..............................................................................................58
   4.3 Design and Subjects..........................................................................59
   4.4 Procedures........................................................................................60
   4.5 Manipulation.....................................................................................62
   4.6 Results..............................................................................................66
   4.7 Discussion........................................................................................74
5.    WITHIN-SUBJECTS FACTORIAL DESIGN SURVEY.................................77
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1</td>
<td>Predictions</td>
<td>80</td>
</tr>
<tr>
<td>5.2</td>
<td>Results</td>
<td>81</td>
</tr>
<tr>
<td>5.2.1</td>
<td>Graded Characteristics Results</td>
<td>82</td>
</tr>
<tr>
<td>5.2.2</td>
<td>Just Rewards Results</td>
<td>83</td>
</tr>
<tr>
<td>5.3</td>
<td>Discussion</td>
<td>87</td>
</tr>
<tr>
<td>6.</td>
<td>ANALYSIS OF THE INTERNATIONAL SOCIAL JUSTICE PROJECT</td>
<td>89</td>
</tr>
<tr>
<td>6.1</td>
<td>Assumptions</td>
<td>89</td>
</tr>
<tr>
<td>6.2</td>
<td>Data</td>
<td>91</td>
</tr>
<tr>
<td>6.3</td>
<td>Calculating Reward Expectation State Values</td>
<td>92</td>
</tr>
<tr>
<td>6.4</td>
<td>Analytic Strategy</td>
<td>95</td>
</tr>
<tr>
<td>6.5</td>
<td>Results</td>
<td>97</td>
</tr>
<tr>
<td>6.6</td>
<td>Discussion</td>
<td>103</td>
</tr>
<tr>
<td>7.</td>
<td>CONCLUSION</td>
<td>106</td>
</tr>
<tr>
<td></td>
<td>APPENDIX A: THE WITHIN-SUBJECTS FACTORIAL DESIGN SURVEY</td>
<td>115</td>
</tr>
<tr>
<td></td>
<td>APPENDIX B: LINEAR MIXED MODEL SELECTION</td>
<td>142</td>
</tr>
<tr>
<td></td>
<td>REFERENCES</td>
<td>152</td>
</tr>
</tbody>
</table>
LIST OF TABLES

Table 2.1: Estimates for $f(i)$ Drawn from Three Procedures...............................39

Table 4.1: Summary of the Phase I Scores Used to Manipulate Status.......................65

Table 4.2: Observed $P(S)$ Scores and Sample Sizes by Conditions........................66

Table 4.3: Summary of Four Regression Models Illustrating the Status Manipulation Check
and a Mediation Analysis.................................................................................68

Table 4.4: Summary of Results from Regressing $P(S)$ on Two Estimates of Expectation
Advantages........................................................................................................69

Table 4.5: Observed Cell Counts of Stay Responses and Trials Influence..................71

Table 4.6: Predicted Cell Counts and Chi-Squared Values for the Ordinal Comparison
Model...............................................................................................................72

Table 4.7: Predicted Cell Counts and Chi-Squared Values for the Graded Characteristics
Model...............................................................................................................73

Table 5.1: Descriptive Statistics for the Vignette Data........................................82

Table 5.2: Summary of LMMs Predicting the Expectation States Scale......................83

Table 5.3: Summary of LMMs Predicting Target’s Logged Just Rewards..................86

Table 5.4: Summary of LMMs Predicting Target’s Logged Just Rewards- Without Sex....87

Table 6.1: Means and (Standard Deviations) for Key Theoretical and Control Variables..98

Table 6.2: Summaries of Linear Mixed Models Predicting Logged Deserved Incomes......100

Table A.1.1: Summary of Targets’ Sex, Years of Schooling, Occupations, and Occupational
Prestige Scores.................................................................................................116

Table A.2.1: Summary of Linear Mixed Models Predicting the Expectation States Scale...142
LIST OF TABLES - Continued

Table A.2.2: Summary of Linear Mixed Models Predicting the Expectation States Scale…143
Table A.2.3: Summary of Linear Mixed Models Predicting Just Rewards (Vignette Data)...143
Table A.2.4: Summary of Linear Mixed Models Predicting Just Rewards (Vignette Data)...144
Table A.2.5: Summary of Linear Mixed Models Predicting Just Rewards (Vignette Data)...145
Table A.2.6: Summary of Linear Mixed Models predicting Just Rewards (ISJP). Results of Likelihood Ratio Chi-Squared Tests from Removing the Random Effects of Each Interaction Term……………………………………………………………………….147
Table A.2.7: Summary of Linear Mixed Models predicting Just Rewards (ISJP). Results of Likelihood Ratio Chi-Squared Tests from Removing the Random Effects of Each Main Effect Term……………………………………………………………………….148
Table A.2.8: Summary of Linear Mixed Models predicting Just Rewards (ISJP). Results of Likelihood Ratio Chi-Squared Tests from Removing the Fixed Effect of Each Interaction Term……………………………………………………………………….149
Table A.2.9: Summary of Linear Mixed Models Predicting Just Rewards (ISJP)……….150
Table A.2.10: Summary of Linear Mixed Models Predicting Just Rewards (ISJP)………151
LIST OF FIGURES

Figure 2.1: Graphic Representation of an RET Situation with one D and one C………32

Figure 3.1: Graphic Representation of $S^*$ with One Diffuse Status Characteristic………46

Figure 4.1: The Distribution that was used to Manipulate Contrast Sensitivity Ability….63
LIST OF EQUATIONS

Equation 2.1 .................................................................................................................. 35
Equation 2.2 .................................................................................................................. 36
Equation 2.3 .................................................................................................................. 36
Equation 2.4 .................................................................................................................. 37
Equation 2.5 .................................................................................................................. 38
Equation 2.6 .................................................................................................................. 38
Equation 2.7 .................................................................................................................. 38
Equation 2.8 .................................................................................................................. 38
Equation 2.9 .................................................................................................................. 38
Equation 2.10 ............................................................................................................... 39
Equation 2.11 ............................................................................................................... 40
Equation 2.12 ............................................................................................................... 41
Equation 3.1 .................................................................................................................. 53
Equation 3.2 .................................................................................................................. 54
Equation 3.3 .................................................................................................................. 54
Equation 3.4 .................................................................................................................. 54
Equation 3.5 .................................................................................................................. 54
Equation 3.6 .................................................................................................................. 54
Equation 3.7 .................................................................................................................. 55
<table>
<thead>
<tr>
<th>Equation</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.8</td>
<td>55</td>
</tr>
<tr>
<td>4.1</td>
<td>67</td>
</tr>
<tr>
<td>4.2</td>
<td>70</td>
</tr>
<tr>
<td>5.1</td>
<td>83</td>
</tr>
<tr>
<td>5.2</td>
<td>83</td>
</tr>
<tr>
<td>5.3</td>
<td>83</td>
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<td>5.4</td>
<td>84</td>
</tr>
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<td>5.5</td>
<td>84</td>
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<tr>
<td>5.6</td>
<td>84</td>
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<td>5.7</td>
<td>84</td>
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<tr>
<td>6.1</td>
<td>96</td>
</tr>
<tr>
<td>6.2</td>
<td>96</td>
</tr>
<tr>
<td>A.2.1</td>
<td>147</td>
</tr>
<tr>
<td>A.2.2</td>
<td>148</td>
</tr>
<tr>
<td>A.2.3</td>
<td>149</td>
</tr>
<tr>
<td>A.2.4</td>
<td>150</td>
</tr>
</tbody>
</table>
ABSTRACT

In this dissertation I examine the link between status and perceptions of just rewards. Specifically I focus on how an individual’s status-valued attributes shape their perceptions of just rewards, or the amount of a good that they deem fair. According to equity theorists, status-valued attributes constitute one ‘input’ that shapes perceptions of just rewards, but the precise nature of this relationship has been heretofore unspecified. Drawing from reward expectations theory, which is one of the equity theories, I develop a set of equations to estimate point predictions of just rewards based on individual’s status-valued attributes. The model quantifies the commonly held belief that individuals with the more positively evaluated states of status-valued attributes expect to receive relatively more rewards from a distribution of valued goods. The model borrows the quantification of reward expectations states from reward expectations theory, which requires reducing all status differences to two states of relatively high and relatively low. This is an unnecessary simplifying assumption that requires throwing away the relative magnitude of status-valued attributes. In the interest of increasing the precision and realism of the formal model of just rewards, I also extend the mathematics of reward expectations theory to account for status-valued attributes with more than two states (e.g., occupational prestige or education). This extension not only increases the precision of the formal model of just rewards, but is also applicable to all of the expectation states theories, which account for a large body of scholarship and have a broad domain of applicability. To evaluate these ideas I use a variety of quantitative methodologies, including an experiment, a vignette study and the analysis of secondary data from thirteen countries. Across these methods, I find support for both the formal model of just rewards
and the procedure for modeling status-valued attributes with more than two states. I conclude the dissertation with the implications of this research and future directions of the project.
1. INTRODUCTION

How does an individual determine how many rewards he or she deserves? How much income, for example, does an individual think is fair for her or him to earn? Social psychological justice theories not only explain how individuals determine their just rewards, but also how they react if their actual rewards are greater than or less than their perceived just rewards. If individuals are under-rewarded, they are likely to express anger; if individuals are over-rewarded, they are likely to express guilt (Homans 1961).

Empirical evidence shows that perceptions of just rewards, or the amount of a good that an individual deems fair, vary in systematic ways. Perceptions of just rewards have been shown to vary by context (Hegtvedt, Clay-Warner and Johnson 2003; Johnson et al. 2007) as well as by actor characteristics (Jasso and Webster 1997; Moore 1991; Stewart and Moore 1992; Wagner 1995). In terms of actor characteristics, many attributes that individuals possess shape their perceptions of just rewards, including their age, occupation, educational attainment, or even their race or sex (Homans 1961). Common to these attributes is that they are each status characteristics, or individual attributes with widely held cultural beliefs that attach greater value and competence to one category of the attribute than to another.

The finding that individual attributes shape perceptions of just rewards is applicable to reward allocations based on equity processes, or the belief that rewards should be commensurate with inputs. This applies to many situations (Hegtvedt and Markovsky 1995), including income from employment or the order of authorship on a scientific paper. Here equity is a distribution rule, or a principle that defines the relations between a dimension of
evaluation and the reward or outcome (Cook 1975; Cook and Hegtvedt 1983). The other dominant distribution rule is equality, which dictates that each individual receives the same amount of the reward to be distributed. In this dissertation, I focus on perceptions of just rewards that are based on an equity distribution rule.

Homans (1961), Adams (1963) and Berger, Zelditch, Anderson, and Cohen (1972) each developed equity theories explaining how individuals determine their just rewards. Each takes different components as inputs (i.e., effort or individual attributes), with different points of comparison (i.e., local or referential). Of these theories, reward expectations theory (Berger et al. 1972) is a formal equity theory that explains how status-valued attributes are related to reward allocations through an intervening cognitive construct referred to as reward expectation states, which refer to anticipations of rewards for self and others in task situations. For Berger and associates, status-valued attributes are inputs and the point of comparison does not come from the local situation, as with Homans and Adams, but rather from the broader cultural environment, where the status beliefs come from. These status beliefs shape expectations for rewards, which in turn condition reward allocations (Berger, Fisek, Norman and Wagner 1985).

Based on the logic of reward expectations theory, one can predict which individuals will think they deserve relatively more rewards and which individuals will think they deserve relatively few rewards, but the theory is silent with respect to the actual amount each individual should receive. This in unfortunate in light of the fact that reward expectations theory comes from a family of theories, known collectively as expectation states theory, that is quantified. Specifically, the mathematics of the expectation state theories allows one to
estimate a priori reward expectation state values, which quantify the presumed cognitive representations of status differences in an encounter.

In this dissertation, I use the mathematics of reward expectations theory to develop a formal mathematical model of just rewards. The model is based on the logic of equity theories and yields point predictions of just rewards based on the expected value of a good and salient status information. The model is the first to quantify the commonly held belief that individuals with the more positively evaluated states of status-valued attributes expect to receive relatively more rewards from a distribution of valued goods. I use reward expectation state values to generate two distinct formal models of just rewards.

However, the mathematics of expectation states theory relies on an “ordinal comparison hypothesis” (Balkwell 2001), which asserts that status characteristics have only two states, relatively high and relatively low. This assumption is warranted in many instances. The diffuse status characteristics of race or sex, for example, are two examples of binary status characteristics where one state (whites or men) is more positively valued than the other (non-whites or women) (Webster and Foschi 1988). Many other status characteristics (e.g., intelligence, education, occupational prestige), referred to as graded status characteristics (Fisek 2009; Foddy and Smithson 1996; Shelly 1998), have more than two states, but are dichotomized in terms of relatively high or low. The ordinal comparison hypothesis implies that estimates drawn from the expectation state theories will necessarily be discrete since status characteristics are categorical in this framework. Moreover, the ordinal comparison hypothesis requires that analysts throw away the magnitude of difference on graded status characteristics. This is both unrealistic and unnecessary; in society, many of the most important status characteristics are graded. To move beyond the ordinal
comparison hypothesis, I also develop a technique to incorporate gradations of status characteristics into the existing mathematical formulation of the expectation state theories. This technique is immediately relevant to the just rewards model, and is also useful to expectation state theories in general.

To evaluate the graded status characteristics procedure, I draw from practices developed throughout the development of status characteristics theory, which is another branch of the expectation states theories (Berger, Zelditch and Cohen 1966; Berger, Fisek, Norman, and Zelditch 1977). Status characteristics theory provides the dominant sociological account of social influence in small group interactions. The logic of status characteristics theory is closely related to the logic of reward expectations theory. Status characteristics theory argues that in collective task situations, when status characteristics, such as education or intelligence, differentiate individuals they will become salient and shape the development of performance expectation states for each individual in the setting. Subsequently, those individuals who have the positively evaluated states of status characteristics, and consequently higher or more positive performance expectation states, will be more influential over the group, participate more often, and be evaluated more positively for their contributions (Berger and Webster 2006). This theory is relevant here because it the proverbial ‘workhorse’ theory of expectation states theory. It has been tested numerous times (Berger, Cohen and Zelditch 1972; Berger et al. 1977; Correll and Ridgeway 2003; Kalkhoff and Thye 2006; Webster and Driskell 1978), each of its assumptions have also been evaluated with empirical evidence (Berger and Fisek 1970; Berger, Fisek and Freese 1976; Berger, Balkwell, Norman and Smith 1992; Freese and Cohen 1973; Moore 1968; Parcel and Cook 1977; Webster 1977), and there are standard procedures for
evaluating the theory (Berger et al. 1977). Related to the last point, there is a standard experimental setting for testing status characteristics theory (Berger 2007; Kalkhoff and Thye 2006), which makes comparisons across studies more reliable. Consequently, I use status characteristics theory, and its standard experimental setting, to evaluate the graded characteristics procedure that I develop herein. Provided the results support the use of the procedure, it then makes sense to apply my graded characteristics procedure to the formal model of just rewards.

The following chapters develop the formal mathematical models of just rewards, extend the mathematics of the expectation state theories to include graded status characteristics, and evaluate those developments with three empirical evaluations. Chapter two reviews the literature on equity processes, focusing on theoretical accounts of how individuals determine their just rewards. Chapter two also provides a detailed account of reward expectations theory since it is the theory that informs the development of the formal models of just rewards, which are developed after the exposition of reward expectations theory. Chapter three presents status characteristics theory and its mathematics. I then extend the math of status characteristics theory (and by extension reward expectations theory) to include the magnitude of difference separating individuals on graded status characteristics. In order to assess the validity of the graded characteristic procedures, chapter four describes an experimental investigation of the extent to which the procedure explains more influence behaviors than the traditional ordinal comparison hypothesis. This material is presented before any evaluations of the just rewards models because if it does not explain more variation or fit better than traditional models, then there is no need to apply the graded characteristics formulation to the formal model of just rewards. I find, however, that the
results from the experiment support the use of the procedure; consequently I apply it in chapters five and six. Chapters five and six present the results from two applications of the formal model of just rewards. The first evaluates data from a vignette survey that I conducted at the University of Arizona, and the second evaluates secondary data from the International Social Justice Project (Alwin, Klingel, and Merilynn 1993), which collected data from individuals in thirteen countries. Finally, chapter seven concludes with a discussion of the implications of this research for theories of justice and the expectation state theories.

Altogether, the results from the empirical studies show support for both the mathematical model of just rewards and the graded characteristics procedure. The just rewards models enable researchers to make quantitative estimates without having to rely on data to obtain estimates. This is a substantial advance in the area of distributive justice, but also more generally as typical “predictions” in quantitative sociology entail a non-zero coefficient. Likewise, the ability to estimate graded expectations will enable further application of the expectation state theories, an area within sociology that has steadily grown for over forty years.
2. DISTRIBUTIVE JUSTICE THEORIES

Distributive justice refers to the distribution of rewards within a group that corresponds to what is expected based on a normative principle (Hegtvedt and Johnson 2000). Theories of distributive justice explain: 1) how individuals determine their just rewards, or the amount of a good that they deem fair, and 2) how individuals react to justice evaluations of rewards, where justice evaluations are conceptualized as a comparison of actual rewards to just rewards. The focus of this project is on the first of these issues, but how individuals determine what is a just reward has consequences for the second of these issues. Consequently, below I review developments in distributive justice theory with an emphasis on the determination of just rewards, but I also note the implications of these developments for justice evaluations and subsequent reactions.

2.1 Exchange Theory Tradition

Although the philosophy of distributive justice can be traced back to at least Aristotle ([c. 350-23BC] 1998), Homans (1961) was the first social scientist to cast issues of distributive justice in terms of relative deprivation, making justice a distinct theoretical concern (Berger et al. 1972). Homans’ concern with justice is a product of the exchange relations that develop out of his behavioral account of interaction. Homans (1961: 53-55) develops a set of backward looking (Macy 1993) assumptions about exchange behavior that can be summarized as follows: 1) if past behavior has been rewarded in a particular situation, then the more similar the present situation, the more likely the rewarded behavior will be replicated. 2) The more often an individual’s activity rewards the activity of another, the more often the other will emit the activity. 3) The more another values one’s behavior, and
hence the more the reward, the more often an individual will emit the behavior. And, 4) the more often an activity has been recently rewarded, the less valuable the reward becomes through satiation. Together, these statements explain elementary exchange behavior. Evaluations of distributive justice, or “justice in the distribution of rewards and costs between persons” (74) follow from elementary exchanges in social life. An additional assumption is brought in to account for reactions to exchange behavior: 5) The more a person’s reward is disadvantaged relative to distributive justice, the more likely the person is to display the emotion we call anger. Although Homans does not identify the following as an assumption, the following, from Homans, should be called assumption 5b) The more a person’s reward is advantaged relative to distributive justice, the more likely the person is to display the emotion we call guilt (Homans 1961: 75-6).

Homans’ (1961) assumptions explain reactions to evaluations of distributive justice, or the second aspect of theories of distributive justice. Homans also presents an argument for how individuals determine distributive justice. The rule of distributive justice states that “a [man] in an exchange relation with another will expect the profits of each to be directly proportional to his investments, and when each is being rewarded by some third party, he will expect the third party to maintain this relation between the two of them. If the investments of two men, or two groups, are equal, their profits should be equal, and if their investments are unequal, the one with the greater investment should get the greater profit.” (244). For Homans, investments have a distinct theoretical status. They are a combination of all of the ascribed and achieved attributes that are deemed reward-relevant. Investments include race, sex, experience, effort, and so forth. As an example, when describing why a low status individual is selected as the “lunch boy” from a male work group, Homans notes: “his
menial job was in line with the other features of his status… his background characteristics [were] determined by the events of his past history, but they had the same effect as if they had been *his own fault*. Inasmuch as the other members of the group had more pay, seniority, skill, etc., than he, they were “better” than he was, they held higher status in the larger society, and so they did not, but he did, *deserve* the menial job” (236, italics added). Here, Homans is equating characteristics, or investments, across domains. The low status male gets paid the least because he is the youngest and the least experienced; this same person is the “lunch boy” for the same reasons.

In essence, Homans (1961) argues that in elementary exchange relations, people compare their investments (broadly defined), costs and profits to the investments, costs and profits of their exchange partners. If these factors are congruent across the individuals in the exchange relation, then distributive justice obtains. However, to the extent that they are incongruent, then distributive injustice obtains. The key point here is that the ratio of investments to costs be proportional across individuals in exchange relations; to the extent that the relationship between these factors is not proportional, just rewards are not met – one party is over-rewarded and another is under-rewarded.

Adams (1963; 1965) distinguishes between the antecedents and the consequences of justice evaluations, and these are parallel to the determination of just rewards and reactions to justice evaluations. Although the focus and framing of the 1963 paper plays up the role of cognitive dissonance, and the 1965 paper plays up the role of exchange processes, the logic of the arguments are quite similar. In terms of the antecedents, Adams’ formulation (both 1963 and 1965) is strikingly similar to Homans (1961). Aside from formalizing the comparison process, it is with respect to the consequences that Adams makes his
contribution. Adams (1965) defines equity as follows: \( \frac{O_p}{I_p} = \frac{O_a}{I_a} \), where \( p \) refers to a person, \( a \) refers to an alter, \( O \) refers to outcomes and \( I \) refers to inputs. Here ‘inputs’ are equivalent to Homans’ ‘investments.’ Thus the comparison process is defined precisely, although precise measurement can never be assured. Nonetheless, Adams uses this definition of equity to develop a taxonomy of ways in which individuals might react to inequity.

While Homans (1961) noted that under-rewarded individuals would feel anger and that over-rewarded individuals would feel guilt, Adams’ (1965) taxonomy went much further. If inequity exists then an individual may engage in six different strategies for yielding equity. First, the individual may alter her inputs. If the person is over-rewarded, she may try harder to increase inputs; if the person is under-rewarded, she may try less to decrease inputs. Second, the individual may alter her outcomes. In the case of under-rewarded wages from employment, for example, she might seek a raise or a new title (conferring status as an outcome). Third, the individual may cognitively distort her inputs and outcomes. In the case of either under- or over-reward, reweighting the inputs or evaluating outcomes by different criteria can bring about equity. Fourth, the individual may “leave the field” by quitting a job with unjust pay, or ceasing a unilateral relationship. Fifth, the individual may alter some aspect of the comparison other. In this case, the individual may try to get the other to leave the field or possibly the individual will cognitively distort the inputs and outcomes of the other. Finally, the individual may change the comparison other when they are in an exchange relationship with a third party. A graduate assistant may perceive inequity of pay when comparing salaries with a professor (both of whom are paid by the university or college). If
that assistant changes the comparison other to another graduate student then equity may be restored.

2.2 The Status-Value Tradition

In response to Homans’ and Adams’ exchange-theoretic approaches, Berger, Zeldtich, Anderson and Cohen (1972) developed the status value theory of distributive justice. Berger and colleagues pointed out that the theories of Homans and Adams accounted for equity processes only in a local situation of action where a person compares her inputs or investments and outcomes to specific others in exchange relations. That is, Homans and Adams do not allow for referential comparisons, which enable individuals to have a more general frame of reference from which to evaluate outcomes. Put differently, both Homans’ and Adams’ formulations allow for collective states of injustice in which both parties are referentially rewarded unjustly. Suppose two mechanics are paid as follows: Mechanic 1 makes $12.00 per hour and has three years of experience and Mechanic 2 makes $13.00 per hour and has five years of experience. Depending on how one weights experience, a state of equity is likely to exist within Homans’ or Adams’ framework. However, if the average hourly wage for a mechanic is $25.00 per hour, then both Mechanics are underpaid. If the comparison is local, then equity exists; if the comparison is referential, then both Mechanics are underpaid. Hence Berger and colleagues argue that a stable frame of reference is required for theories of distributive justice. Within the theory, these frames of reference are called referential structures, or socially validated beliefs that are held in common by actors (Berger, Ridgeway and Zelditch 2002).

In formulating the status value theory, Berger et al. (1972) begin by distinguishing between the consummatory value and the status value of goods. They argue, albeit
incorrectly, that Homans and Adams focus exclusively on the consummatory value of goods.\footnote{Adams (1965) argues that a new job title is one way to increase outcomes. There is no consummatory value to a title, it is a matter of status value.} Although many goods obtained in exchange are for consumption, many are not and the accumulation of status-valued goods that confer worth, esteem or honor has received substantial attention from social scientists (e.g., Thye 2000). Hence Berger et al. (1972: 128) define outcomes as goal objects: any object, tangible or intangible, that an actor might want, or that might satisfy some need.

The theory is a set of five assumptions or propositions relating status value to a situation of balance or equity. Assumption 1 addresses the spread of status value: if an element \((e_1)\) is related to another element that has status value \((e_2)\), then \(e_1\) acquires the same status value as \(e_2\). For example, a painting that was recently sold at a garage sale turned out to be an original Jackson Pollack painting. Because it was a Pollack, the painting purchased at the garage sale was deemed a classic work of art. Assumption two addresses the spread of relevance: if \(e_1\) is similar to \(e_2\) and \(e_2\) is relevant to \(e_3\), then \(e_1\) will become relevant to \(e_3\) or any element similar to \(e_3\). This assumption says that, for example, because Jackson Pollack \((e_2)\) is a famous artist \((e_3)\), then other similar artists, such as Janet Sobel \((e_1)\), should also be a famous artist \((e_3)\). Assumption 3 states that the situation is stable if it is balanced (i.e., equity exists with respect to the status-value of elements in the situation). Assumption 4 is a basic cognitive dissonance assumption: if the situation is imbalanced with respect to status-valued elements, then it produces tension (see also Homans 1961). Assumption 5 addressed the resolution of dissonance: if there is imbalance, then there will be pressure to change the situation towards a state of balance.
Subsequent developments of the status value theory have been made within a theoretical research program known as the expectation states tradition. The expectation states tradition encompasses several theories that share a similar logical structure and several key theoretical concepts. A key development in this tradition came in 1977 when Berger, Fisek, Norman and Zelditch published *Status Characteristics and Social Interaction: An Expectation States Approach*. In this book, they develop the key concepts and assumptions that lay the groundwork for all of the theories in this tradition. Later reformulations of the status value theory are cast in terms of the developments made in the 1977 book. As a consequence of these developments, Berger and colleagues now refer to the status value theory as reward expectations theory. Before describing the advances in reward expectations theory, however, I provide a general introduction to the expectation states theories since I draw from two of them to inform the developments in this chapter and the next one.

### 2.3 Expectation States Theories

Common to the expectation states theories are the idea that status organizing processes are a key process to understanding small group inequalities. The theories argue that the possession of status-valued elements or behaviors shape the formation of expectation states, or cognitive anticipations and evaluations of competence and worth, which in turn create hierarchies of prestige, honor and deference. Although there are several expectation states theories, I restrict the discussion here to reward expectations theory and status characteristics theory.

Within the expectation states tradition, status characteristics may be either specific or diffuse (Berger et al. 1977; see below for formal definitions of specific and diffuse status characteristics). Diffuse characteristics, such as intelligence or sex, are assumed to be relevant
to many tasks, while specific characteristics, such as math or gardening abilities, are only assumed to be relevant to related tasks. Status characteristics theory is restricted in scope to task and collectively oriented groups. Task orientation entails that it is important for the group members to succeed at the task that they are working on. The tasks should also have clear states of success and failure, meaning that it will evident whether or not the group succeeds at their task. Collective orientation implies that it is necessary and legitimate for the group members to take each others’ opinions into consideration. Status characteristics theory argues that differences in specific or diffuse status characteristics lead to differences in performance expectation states, or anticipations of ability for self and other(s), and that these expectations result in a self-fulfilling prophecy such that those individuals with the more positively evaluated states of the status characteristics will be more influential, will participate more often, and will be more positively evaluated for their contributions (Berger et al. 1977).

Reward expectations theory (Berger et al. 1985, 1998a), which was a revised formulation of the status value theory of distributive justice, was presented after status characteristics theory as one auxiliary proposition to the core propositions that constitute status characteristics theory (see the proposition set of reward expectations theory below and the proposition set of status characteristics theory in chapter three). This theory argues that differences in status characteristics lead to different reward expectation states, or anticipations of allocations for rewards, and that reward allocative behaviors are a direct function of reward expectations. Although the distributive justice literature distinguishes between allocations made by recipients and third-party allocators (e.g., Hegtvedt and Markovsky 1995), reward expectations theory assumes that these allocations should be equal because the status hierarchy, and hence reward expectations, arises from a consensual process. Reward
expectations theory is not as limited in scope as status characteristics theory. Specifically, reward expectations theory is not restricted to collective situations, but is instead limited to situations where individuals are working on a unitary task and known reward levels exist.

In addition to logical arguments, Berger et al. (1977) introduced a graphic representation that visually represents the elements found in status characteristics theory’s logical core. By extension, the graphic representation has been applied to all of the other expectation state theories, including reward expectations theory. Once a graphic representation has been identified for a particular status situation, functions of path lengths from the representation can be used to estimate the expectation state values for the individuals in the situation. In the case of status characteristics theory, the graphic representation may be used to estimate performance expectation states; in the case of reward expectations theory, the graphic representation may be used to estimate reward expectation states. Berger and colleagues use experimental data to estimate the path functions, while Balkwell (1991a) and Fisek, Norman and Nelson-Kilger (1992) subsequently developed theoretically derived values for the path function equations.

2.4 Reward Expectations and Just Rewards

As stated in the previous chapter, the main objective of this research is to develop a formal mathematical model of just rewards based on an equity distribution rule, or a principle that defines the relations between a dimension of evaluation (e.g., a status characteristic) and the distribution of rewards or outcomes (Cook 1975; Cook and Hegtvedt 1983). Although scholars typically recognize that equity is the appropriate distribution rule in

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2 For reward expectations theory, see Hysom (2009); for power and prestige theory, see Fisek, Berger and Norman (1991); for status legitimation theory, see Berger, Ridgeway, Fisek and Norman (1998b).
most settings (Hegtvedt and Markovsky 1995), they lack the formal tools to obtain a priori estimates of just rewards based on equity processes. Consequently, what is often done in applications of distributive justice theories is to assume that the just reward is an equal share (e.g., Markovsky 1985), or, alternatively, some scholars will use statistical techniques (e.g., OLS regression) to estimate the weights associated with various reward-relevant characteristics (e.g., Jasso and Rossi 1977; Jasso and Webster 1999). Assuming equality as a just reward is a simplifying assumption when there is no alternative (e.g., when data are not available to estimate predicted just rewards based on equity). Although estimating just rewards from data is more accurate than using the mean reward, this procedure is still problematic because: 1) it is post hoc to collect the data and then use the data to determine which factors are associated with just rewards, and 2) if data are not available on just rewards, and hence weights cannot be estimated for extant factors, then estimates of just rewards cannot be obtained. Consequently, the aim of this project is to develop a means of estimating just rewards which does not require regression weights to be estimated from data. Specifically, I develop a formal mathematical model of just rewards that is premised on equity processes.

To develop the formal model, I borrow extensively from reward expectations theory (RET; Berger et al. 1985; 1998a) because the theory is already mathematized. That is, RET yields a priori numerical estimates of reward expectations based on individuals’ status-valued attributes. Put differently, reward expectation values should be a transformed quantification of just rewards. Hence I do not make use of the full theory in explaining reward allocative

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3 It is theoretically possible to use regression weights from a published study in conjunction with data on status-valued attributes to generate predictions of just rewards. However, there is presently no way to know how much bias would be introduced by doing so because the regression coefficients have a sampling variability around them.
behaviors; rather, I use the ability to mathematically define reward expectations to generate a mathematical model of just rewards. Below I describe RET in detail. I then describe the mathematics of the theory, and describe how I apply RET and its math to the problem of estimating or predicting just rewards.

2.5 Reward Expectations Theory

Reward expectations theory explains how individuals’ status-valued attributes and performances affect the development of a consensual hierarchy of reward expectations, and how that hierarchy is related to reward allocative behaviors. Although the theory accounts for rewards based on performance outputs, in addition to status-valued attributes, I focus only on attributes because the empirical applications only use attributes (though see Berger et al. 1985; 1998a). The theory applies to situations in which a group of individuals is working on a single unitary task, and where there is an ability that is instrumental to completing the task. The theory is also restricted to situations in which clearly defined reward levels exist (Berger et al. 1998a: 127-8).

RET is concerned with two types of status characteristics, specific and diffuse. Formally, a characteristic is a specific status characteristic (denoted C) if and only if: (1) The states are differentially evaluated, and (2) the states are associated with specific performance expectation states, having the same evaluations as the state of the characteristic. Athletic ability and mathematical skill are examples of specific status characteristics. Some specific status characteristics are also instrumental task characteristics (denoted C*). The states of C* reflect an ability (or inability) to perform well at the task on which group members are

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4 The models developed herein could be applied to predict actual allocative behaviors. Further research will be required to evaluate the models when allocations are the outcome. I focus on perceptions of just rewards in this dissertation.
working. Mathematical ability is a specific status characteristic but it is presumed to be an
instrumental task characteristic if the group’s task requires mathematical skill.

Formally a characteristic is a diffuse status characteristic (denoted D) if and only if it
satisfies conditions (1) and (2) of a specific status characteristic, and also satisfies a third
condition: (3) to each state of the characteristic there corresponds a distinct general
expectation state, having the same evaluation as the state of the characteristic (Berger et al.
1977: 94). Race, sex, age, and education are diffuse status characteristics in most Western
societies because there are cultural beliefs that attach more competence and worth to whites
(Lovaglia et al. 1998), men (Ridgeway 1991), older individuals (Freese and Cohen 1973), and
more highly educated individuals (Ridgeway, Johnson and Diekema 1994).

Goal objects (denoted G), or any object that an individual might want or that might
satisfy some need (Berger et al. 1972), are the outcome in RET. That is, status differences
produce differences in reward expectations, which in turn should be behaviorally related to
distributions of goal objects. Money, baseball cards, diamonds, etc. may each function as
goal objects in different situations.

RET describes the status organizing processes through which specific and diffuse
characteristics affect reward expectations. The theory includes a set of integrated
propositions, scope restrictions, and rules for constructing graphic representations of
situations in which status organizing processes unfold. Graphic representations of
interaction contain points (elements) and lines (relations) that symbolize relations between
status-bearing elements (see Berger et al. 1977 and Figure 2.1). Elements of status situations
include actors (p, q, etc.), states of diffuse and specific characteristics (D+, D-, C+, and C-),
reward expectations ($R^+$ and $R^-$ for relatively high and relatively low reward expectations), and states of goal objects ($G^+$ and $G^-$ for more or fewer goals objects respectively).

In general, graphic representations entail three types of relations. Possession relations connect actors ($p$, $o$) to states of characteristics they possess. Relevance relations (or bonds) connect status-bearing elements (e.g., states of characteristics, goal outcome states, etc.). Specifically, element $e_i$ is relevant to element $e_j$ if and only if when $p$ possesses $e_i$, $p$ expects to possess or is expected to possess $e_j$ (Berger et al. 1977: 98). A special relation, the dimensionality relation, connects differentially evaluated states of characteristics that actors actually possess in a given situation (Berger et al. 1977: 99).

![Figure 2.1](image)

Figure 2.1. Graphic Representation of an RET situation with one D and one C.

- = Possession Relation
- - = Dimensionality Relation
----- = Relevance Relation

The lines connecting $p$ and $o$ to states of D and C in Figure 2.1 below are possession relations. The lines connecting states of D to R and C to $\rho$ are relevance (expected possession) relations and the two states of D and the two states of C are connected by
dimensionality relations. By convention, possession and relevance relations are positive and the dimensionality relation is negative.

A set of six logically related propositions explain how status characteristics are related to reward allocations of goal objects (Berger et al. 1998a: 130-137). Assumption 1 (salience completion process) is as follows:

1. If status characteristics provide a basis for discrimination between interactants, the states of these characteristics become salient in the reward situation.

The salience completion assumption describes the activation of status elements (e.g., Cs and Ds). RET’s second assumption describes how culturally-conditioned expectations for rewards are activated. Once salient, Cs and Ds are linked to reward expectations (denoted R) through referential structures if and only if the characteristics have referential structures linking states of the characteristics to reward levels. Referential structures define relations between dimensions of evaluation and expectations for goal objects. Two kinds of referential structures are relevant here. *Ability referential structures* link actors’ abilities to reward expectations in task situations such that individuals that are more able are expected to contribute more to the task and to receive more goal objects from the distribution. *Categorical referential structures* link actors’ states of diffuse status characteristics to reward expectations in task situations such that individuals with higher states of socially valued diffuse status characteristics are expected to contribute more to the task of the group and to receive more goal objects or rewards from the group distribution. Ability referential structures are activated in task situations when states of specific status characteristics that are associated

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5 I thank Joseph Berger for helping to compile the propositions.
with reward expectations become salient. Categorical referential structures are activated in
task situations when states of diffuse status characteristics that are associated with reward
expectations become salient (Berger et al. 1985: 227). In a situation with an activated
categorical referential structure organized around education, for example, the actors have a
“set of anticipations and moral expectancies” that rewards will be consistent with levels of
educational attainment (Berger et al. 1998a: 130). Assumption 2 (activation of referential
structures) is as follows:

2. If the specific or diffuse status characteristics that are salient are referentially
   associated with states of reward levels, this association also becomes salient in the
   situation.

The next assumption describes how people behave as if they use non-relevant
characteristics. Assumption 3 (burden of proof) applies to salient characteristics that do not
have referential structures linking states of the characteristics to reward levels. For such
characteristics that are connected to actors but are not connected to reward expectations by
paths of length 6 or fewer (paths longer than 6 have effects near zero and are therefore not
included into the calculations 6), then:

3. a. If the salient element is a diffuse characteristic, the associated state of the
generalized expectation state for rewards (Λ) will be activated and will become
relevant to reward expectations.

---

6 This is a simplifying assumption (Berger et al. 1977: 131).
b. If the salient element is a specific characteristic, the associated state of the specific expectation state for rewards (ρ) will be activated and will become relevant to reward expectations.

The burden of proof assumption states that characteristics that are irrelevant to the task the group is working on, and hence are irrelevant to R, become linked to goal object outcomes despite this irrelevance. Because the salient status element discriminates between the interactants, it forms a dimension along which inequalities in expectations and allocations can form. The fourth assumption describes how this status structure is altered by changing interactants and tasks. Assumption 4 (structure completion) is as follows:

4. A given status structure developed through (1), (2) and (3) is stable even as interactants and tasks in the situation change provided that the actor remains in the situation.

RET’s fifth assumption (aggregation) explains how the salient status elements in assumptions 1-4 are combined into aggregate reward expectations. This assumption has two parts that describe procedures for calculating aggregate reward expectations.

5. a. If an actor, p, is connected to goal object states by paths of like sign, and strengths $f(i) \ldots f(n)$ (i for initial path and n for the final path, with each path length having a different strength), then these paths are combined to yield separate subsets of positively and negatively evaluated status information. Equation 2.1 represents the positive subset and equation 2.2 represents the negative subset.
\[ e^+_p = \left[ 1 - (1 - f(i)) \ldots (1 - f(n)) \right] \] (2.1)

\[ e^-_p = -\left[ 1 - (1 - f(i)) \ldots (1 - f(n)) \right] \] (2.2)

b. The positive and negative subsets are then combined by adding the value of the negative subset to the value of the positive subset to yield a value of aggregated reward expectations, \( e \), for \( p \). That is,

\[ e_p = e^+_p + e^-_p \] (2.3)

Finally, RET argues that reward allocations are a direct function of the aggregated reward expectations in the situation. Since the theory assumes consensus of reward expectations, the allocation should be constant for any allocator. Assumption 6 (basic reward expectation assumption) of RET is as follows:

6. Reward allocative behaviors will be a direct continuous function of the aggregated reward expectation states.

These six propositions or assumptions constitute the formal theory. However, the graphic representation of the theory is the foundation for calculating reward expectation state values, which, as argued above, quantify reward expectations. Consequently, below I describe the mathematics of RET in more detail.

2.6 The Mathematics of Reward Expectations Theory

Graphic representations are used to calculate reward expectation state values. In figure 2.1, \( P \) is connected to the positive state of expectations for goal objects by a path of length three (\( P - D^{(+) - R^{(+) - G^{(+)}} \)) that stems from the diffuse status characteristic. \( P \) is also
connected to the positive state of expectations for goal objects by a four-path \( (P - C^+ - \rho^+ - R^+ - G^+) \) that stems from the specific status characteristic. P is also connected to the negative state of expectations for goal objects by a four-path \( (P - D^+ - D^- - R^- - G^-) \) and a five-path \( (P - C^+ - C^- - \rho^- - R^- - G^-) \), both of which go through the dimensionality bond. Through symmetry, the opposite is true for O, who is connected to \( G^- \) by a three-path and a four-path, and to \( G^+ \) by a four-path and a five-path through the dimensionality bond. The overall valence of a path is determined as the algebraic product of the valences of the paths connecting an actor to an outcome state, multiplied by the sign of the outcome state. Thus, P’s paths all have positive valences (i.e., two positive paths to a positive outcome and two negative paths to a negative outcome), while O’s paths all have negative valences. The sign of a path dictates its effect on the actor’s expectation state. Having determined the length and valence of the paths in Figure 2.1, below I review the path function equations needed to estimate the subsets of positive and negative status information.

Presently there are three procedures for calculating the weights of each of the path segments in graphic representations (i.e., \( f(i) \ldots f(n) \)). Berger et al. (1977) estimated these values from experimental data. Balkwell (1991a) and Fisek, Norman and Nelson-Kilger (1992) have provided theoretically derived functions. Both Balkwell’s and Fisek et al.’s derivations are reasonable mappings of mathematical formalizations of theoretical constructs. All three formalizations return estimates that are consistent with existing experimental data. Consequently, I review all three estimating procedures.

Balkwell (1991a), Berger et al. (1977) and Fisek et al. (1992) began with the idea that the two terms, \( i \) and \( k \), define a monotonic function such that:
Berger et al. (1977:138-161) analyzed data from twelve experiments and evaluated the fit of several values of \( k \) and found that \( k = 3 \) produced the best fit to the experimental data (144). Consequently the general formula for estimating \( f(i) \) values in their formulation is:

\[
f(i) = 1 - \left[ 1 - f(i+1) \right]^k
\]  

(2.4)

From (2.4) Balkwell deduces that for all permissible values of \( i \) and for any positive integer \( n \):

\[
\frac{\log[1 - f(i)]}{\log[1 - f(i+n)]} = k^n
\]  

(2.6)

Next, Balkwell (1991a) makes use of Berger et al.’s (1977: 117) observation that paths of length one are not possible and that paths longer than six are not effective. Balkwell reasons that \( f(i) \) is near its upper limit when \( i = 1 \), and that \( f(i) \) is near its lower limit when \( i = 7 \), since subsets of expectation state values should fall within \((0, 1)\) and this is within the range of observable \( f(i) \) values. He interprets “near” to be the small constant .005; therefore \( f(1) = .995 \) and \( f(7) = .005 \). Then he substitutes these values into (2.6) and solves for \( k \), which yields \( k \approx 3.192 \). Thus all of the relevant \( f(i) \) values may now be obtained. For example, \( f(6) = 1 - (1 - .005)^{3.192} = .016 \). More generally, \( f(i) \) values may be obtained from:

\[
f(i) = 1 - (1 - f(i+1))^{3.192}
\]  

(2.7)

By induction, Fisek et al. (1992: 291) show that when \( i = 0 \) equation (2.4) becomes:

\[
f(n) = 1 - \left[ 1 - f(0) \right]^{k^n}
\]  

(2.8)

By substituting \( e^d \) for \( 1 - f(0) \) they find:
In (2.9), $e$ refers to the mathematical constant ($2.178$), $k$ is the same theoretical constant as in (4), and $d$ is the point at which the graph of $y = f(n)$ crosses the $y$-axis (i.e., it defines $f(0)$). Next, the authors argue that expectation states theory suggests a function with two local maxima as $i$ increases from two to six. To ensure that this occurs, the authors set the third derivative of (2.9) to be equal to zero and solve the subsequent system of equations. The result is a new function for estimating $f(i)$ values:

$$f(n) = 1 - e^{dk^n}$$  \hspace{1cm} (2.9)$$

Next, the authors argue that expectation states theory suggests a function with two local maxima as $i$ increases from two to six. To ensure that this occurs, the authors set the third derivative of (2.9) to be equal to zero and solve the subsequent system of equations. The result is a new function for estimating $f(i)$ values:

$$f(i) = 1 - e^{-2.618^2i}$$  \hspace{1cm} (2.10)$$

Table 2.1. Estimates for $f(i)$ Drawn from Three Procedures.

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$f(2)$</td>
<td>.810</td>
<td>.826</td>
<td>.632</td>
</tr>
<tr>
<td>$f(3)$</td>
<td>.406</td>
<td>.442</td>
<td>.317</td>
</tr>
<tr>
<td>$f(4)$</td>
<td>.150</td>
<td>.177</td>
<td>.136</td>
</tr>
<tr>
<td>$f(5)$</td>
<td>.050</td>
<td>.063</td>
<td>.054</td>
</tr>
<tr>
<td>$f(6)$</td>
<td>.016</td>
<td>.021</td>
<td>.021</td>
</tr>
</tbody>
</table>

Table 2.1 presents estimates of all $f(i)$ values for two- through six- paths. Using the values in Table 2.1, estimates of P’s reward expectation state value from Figure 2.1 may now be obtained. Recall, P has a positive three-path, two positive four-paths, and a positive five-path. Using Berger et al.’s (1977) estimates, the positive subset is as follows:

$$e^p = \{1 - [1 - .442] \times [1 - .177] \times [1 - .177] \times [1 - .063]\} = .646,$$

and since P has no negative

---

*Recall, paths longer than 6 are not effective (i.e., near zero).*
status information (i.e., no negative paths), P’s negative subset is zero (i.e., \( e_p^- = 0 \)). Therefore, P’s reward expectation state value is +.646. Through symmetry, O’s reward expectation state value is -.646.

2.7 Applying the Mathematics of Reward Expectations Theory to Just Rewards\(^8\)

Reward expectation state values (RESV) are an \textit{a priori} measure of reward anticipations on the basis of salient status elements. To the extent that equity is an operational distribution rule, RESVs should be perfectly correlated with perceptions of just rewards, and reward allocations should follow from these expectations. Here, I am concerned with estimating perceptions of just rewards rather than the subsequent behaviors. Thus formally defining estimates of just rewards based on equity simply requires that those individuals with higher valued states of reward-relevant characteristics receive more than those individuals with lower valued states of those same characteristics, and that rewards be proportional to inputs or investments (Homans 1961; Adams 1965). Fortunately, the mathematics of reward expectations theory does just that. Equation 2.11, then, defines a model of just rewards based on equity processes. In equation 2.11, \( \bar{x} \) refers to the mean or expected value of the valued good, and \( r_i \) refers to an individual’s reward expectation state value.

\[
\text{Just Reward} = \bar{x} + (1 + r_i)
\]  

(2.11)

Equation 2.11 models the phenomenon that higher status people expect and are expected by others to receive relatively more rewards than lower status people, which is precisely what equity theories predict (e.g., Berger et al. 1972). As a first approximation

---

equation 2.11 seems reasonable. The question remains, however, about the relationship between the just reward function (2.11) and the distribution of the valued good. If the good in question is normally distributed, equation 2.11 is probably a good approximation of that distribution since the distribution of just rewards will be symmetrical, but the fit between these two distributions is an empirical rather than a theoretical question. If, however, the distribution of the good takes on another functional form, equation 2.11 may not adequately represent the distribution of just rewards. Incomes, for example, are notoriously right-skewed and are typically represented with a log-normal distribution. Thus we want the distribution of just rewards to follow a similar functional form. Equation 2.12 produces a log-normal distribution of just rewards and is preferred when the actual good is log-normally distributed. In equation 2.12 $e$ refers to the mathematical constant ($2.718\ldots$). Exponentiating the reward expectation state value has the effect that relatively low status individuals are predicted to have just rewards closer to the mean than would be predicted using equation 2.11; likewise, high status individuals are predicted to have just rewards further from the mean than would be predicted using equation 2.11.$^9$

$$Just\ Reward = \bar{x} \times e^x$$  \hspace{1cm} (2.12)

The just reward functions presented in equations 2.11 and 2.12 are contingent on reward allocations based on an equity distribution rule. That is, the models only apply to reward allocative situations where inputs are deemed important for the attainment of the goods. Most task groups, such as a construction team, are instances where the just rewards model would apply.

$^9$ Other approximations are certainly possible and researchers should attempt several specifications of just rewards. The important point here is that the just reward distribution can be generated using the mean of the valued good and some function of reward expectation state values.
2.8 Conclusion

The formal models of just rewards developed above are the first models to make \textit{a priori} estimates of just rewards without requiring estimated weights from empirical data (e.g., regression coefficients). That is, simply based on the expected value of a good and the recipients’ salient attributes, the models presented above make point predictions of just rewards based on an equity distribution rule.

Although the RESVs are beneficial with respect to predicting just rewards, there remains a problematic assumption about the way that the processing of status is transformed into the mathematics of reward expectations theory. Specifically, the “ordinal comparison hypothesis” (Balkwell 2001) assumes that all status differences are processed in terms of relatively high and relatively low. Consequently all information on magnitudes of status differences is lost in applications of RET. This is unfortunate, particularly since empirical evidence suggests that gradations of status differences explain more variation in behaviors than the ordinal comparison hypothesis (Driskell and Mullen 1990; Foddy and Smithson 1996; Shelly 1998), and neurological evidence shows that status processes are processed in the same part of the brain as continuous numerical comparisons (Chiao et al. 2009).

Presently, there is no \textit{a priori} method to include the information on graded status characteristics, or status characteristics with more than two ordered states, into estimates of RESVs. Fisek (2009) has developed a procedure for modeling small and large differences on graded status characteristics using the theory of status cue gestalts (Fisek, Berger and Norman 2005), but there is no principled way to determine what constitutes “small” and “large” differences and the resulting procedure still yields categorical or discrete predictions. In the interest of increasing the precision and accuracy of estimates of RESVs, which will in
turn increase the precision and accuracy of predictions of just rewards, in the next chapter I
extend the mathematics of the expectation state theories to include graded status
characteristics. I do so in the context of status characteristics theory rather than reward
expectations theory because status characteristics theory is easily the dominant expectation
state theory, and there are standard procedures and measures for empirically evaluating it.
3. STATUS CHARACTERISTICS THEORY AND GRADED STATUS CHARACTERISTICS

This chapter reviews status characteristics theory (SCT), revises theoretical assumptions to be consistent with the incorporation of graded status characteristics, reviews the extant literature on graded status characteristics, and then extends the mathematics of SCT to include graded status characteristics. There are two main reasons for focusing on SCT as opposed to reward expectations theory. First, SCT is the ‘workhorse’ theory for tests and refinements of the expectation states theories. Validations of the theoretical assumptions of the expectation states theories have taken place in the context of SCT (e.g., Berger, Balkwell, Norman and Smith 1992; Moore 1968), and none of the other expectation states theories have been empirically validated more than SCT (Berger and Webster 2006). Second, there is a standardized experimental setting for tests of SCT, making comparisons and generalizations across studies more meaningful. Moreover, I use the standard experimental setting in the next chapter to evaluate the procedure for incorporating graded status characteristics into the expectation state theories because there are standard ways of evaluating predictions from SCT.

There are two main reasons for improving upon the “ordinal comparison hypothesis” (Balkwell 2001). First, this simplifying assumption results is some of the most important status distinctions, such as differences in intelligence, occupational prestige or educational attainment, being reduced to relatively high and relatively low. Consider a

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situation, for example, in which a physician worked with a lawyer at a collective task. The theory would make the same predictions as for a situation in which a physician worked with a line cook. In both of these situations the physician is higher in occupational prestige (Bose and Rossi 1983), but one would think that the physician is much less likely to defer to a line cook than to a lawyer. Second, this assumption implies that estimates of status differences will always be categorical or discrete. This is particularly problematic for the formal models of just rewards that were developed in the preceding chapter. The predicted values from the model will be categorical, making the distribution of just rewards quite unrealistic. Specifically, there can only be one more predicted value than there are salient status characteristics. If there are three salient status characteristics, for example, then one may be high status on all three, high status on two, high status on only one, or low status on all three.

3.1 Status Characteristics Theory

SCT describes how specific and diffuse status characteristics become associated with performance expectation states, and how those expectations shape interactions in small groups. Unlike RET, SCT is restricted to collective task situations (Berger et al. 1977; Kalkhoff and Thye 2006). RET is not restricted to collective situations because reward allocative situations are necessarily mixed-motive situations. On the one hand, individuals want to defer to high status people because they are (supposedly) the most competent people in the group. On the other hand, individuals want to maximize individual outcomes or rewards. SCT, on the contrary, describes status-organizing processes when groups are working on a unitary task, and the successful completion of that task benefits all members equally.
While RET links individuals to reward expectations and subsequent reward allocative behaviors, SCT links individuals to performance expectations and subsequent ‘power and prestige’ behaviors, such as participation rates, opportunities to perform, evaluations of performances, and social influence. Despite these differences, the logic of how status shapes interactions is quite similar, because RET was originally introduced as a single proposition that was to be used in conjunction with the five propositions of SCT (Berger et al. 1985). Further, the graphic representation of both theories is also similar. Given the similarities across the theories, I will not review SCT in as much detail as RET. Rather, I will focus on the differences between the theories’ assumptions and how they need to be modified to account for graded status characteristics.

![Figure 3.1. Graphic Representation of S* with One Diffuse Status Characteristic.](image)

Figure 3.1 presents a graphic representation for a status structure of two individuals. In Figure 3.1, $p$ has the positively evaluated state of a diffuse status characteristic, and through symmetry, $o$ has the negatively evaluated state. Graphic representations of SCT situations have the same relations (i.e., possession, dimensionality, and relevance) as representations of RET. For RET, the paths in the graphs end at goal object allocations; for SCT, the graphs end at states of task performances or task outcomes ($T^+$ and $T^-$ for more
or less successful outcomes, respectively). The other elements in the graphic representation will be discussed in the context of the assumptions or propositions of SCT.

SCT explains how status characteristics are related to observable differences in power and prestige behaviors for any situation that satisfies its scope restrictions. The theory consists of five propositions or assumptions (Berger et al. 1977: 107-131). Assumption 1 (salience completion process) is as follows:

1. If status characteristics provide a basis for discrimination between interactants, the states of these characteristics become salient in the situation.²

SCT does not have a referential structures assumption; rather it moves right to the burden of proof assumption. RET’s burden of proof assumption makes explicit the relation between non-relevant characteristics and either generalized or specific expectation states for rewards. SCT’s burden of proof assumption links non-relevant characteristics to either generalized or specific performance expectation states, as follows:

2. a. Salient non-relevant diffuse status characteristics activate associated states of generalized expectation states (Γ), which become relevant to the positively correlated state of the instrumental task characteristic (C*). In turn, the state of the instrumental task characteristic will become relevant to a positively correlated outcome of the task at hand (T) (see Figure 3.1).

b. Salient non-relevant specific status characteristics activate associated states of specific expectation states (τ), which become relevant to the positively correlated

² Note that the only change to this proposition from chapter two is the omission of the word “reward.” Also, if elements are on paths in the graphic representation that link actors to task outcome states they will also become salient.
state of abstract task ability (ϒ). In turn, the state of abstract task ability will become relevant to a positively correlated outcome of the task at hand (T).

Assumption two applies only to effective paths, or paths that are shorter than seven path segments removed from the task outcome (Berger et al. 1977; Balkwell 1991a). It should be noted here that SCT’s burden of proof assumption is parallel to RET’s burden of proof assumption, except that here I use the term ‘correlated with’ to denote that the status-organizing processes may operate in the context of continuous dimensions. Assumption three (structure completion) does not change from RET to SCT:

3. A given status structure developed through (1) and (2) is stable even as interactants and tasks in the situation change provided that the actor remains in the situation.

SCT’s fourth assumption (formation of performance expectations) describes how status differences lead to varying anticipations for performance for self and other(s) in the situation. This assumption parallels RET’s fifth assumption (formation of reward expectations) as follows:

4. a. If an actor, p, is connected to task outcome states by paths of like sign, and strengths f(1)...f(n), then these paths are combined to yield separate subsets of positively and negatively evaluated status information (see equations 2.1 and 2.2).

b. The positive and negative subsets are then combined by adding the value of the negative subset to the value of the positive subset to yield a value of aggregated performance expectation states (see equation 2.3).
SCT’s final assumption (basic expectation assumption) argues that actors’ standings on power and prestige are a direct function of the aggregated expectations they have for themselves and others in the situation. For two actors, \( p \) and \( o \), \( p \) will have higher prestige and greater power and influence than \( o \) if expectations are higher for \( p \) than \( o \). Formally,

5. For \( p \) and \( o \) who have formed aggregated expectations for self and other, \( p \)'s power and prestige position relative to \( o \) will be a direct function of \( p \)'s expectation advantage over \( o \) (i.e., \( e_p - e_o \)).

Together these five integrated assumptions constitute SCT. As mentioned, however, SCT and its applications have heretofore treated all status differences as binary differences of relatively high and relatively low. To increase the accuracy and precision of the theory and measurement, and to extend the scope of its applications, below I extend the mathematics of the expectation states theories to include graded status characteristics. First, however, I review the extant literature on graded status characteristics.

3.2 Graded Status Characteristics

A few studies have addressed graded status characteristics within the SCT research program (Foddy and Smithson 1996; Shelly 1998; Fisek 2009). Foddy and Smithson (1996) randomly assigned scores on a continuously distributed (fictitious) characteristic to subjects in the standardized experimental setting that is used for tests of SCT (see Berger et al. 1977). The procedure enabled Foddy and Smithson to compare models that use finely graded differences in ability with models that use categorical distinctions of the ability (e.g., high and low). They found that models with graded measures explained more variation in influence than those with simple dichotomous measures. Foddy and Smithson (1996:151) concluded:
“These results are sufficient to warrant considerations about including graded ability levels and differences in degrees of ability into the SCT framework.”

Fisek (2009) recently introduced a method for incorporating graded status characteristics into SCT research. Drawing from the theory of status cues (Fisek, Berger and Norman 2005), he argued that status cue gestalts, or the entirety of information that can be used to infer states of a status characteristic, can be collapsed into two categories—strong and weak. Strong cue gestalts emerge when an actor actually possesses the relevant status element; weak cue gestalts occur when an actor is expected to possess a particular status element. Fisek theorizes that subtle distinctions between strong and weak cue gestalts produce cognitive differences for actors in collective task situations. He models small differences on graded characteristics (those producing weak cue gestalts) differently than obvious status distinctions (those producing strong cue gestalts). Specifically, Fisek argues that paths linking states of characteristics that generate weak cue gestalts to other elements of status situations are one path segment longer (see discussion of paths in graphic representations in Chapter 2 and below) than are those that generate strong cue gestalts. Fisek’s modeling procedure represents an advance over the standard model but his conceptualization still treats differences on graded characteristics as categorical rather than continuous. Further, it is unclear what constitutes the threshold at which a weak cue gestalt becomes a strong cue gestalt. The method I propose takes full advantage of quantitative differences on graded characteristics and incorporates such differences into the existing mathematical structure of SCT. I do so in the context of the path function equations that were reviewed in the previous chapter (i.e., eqs. 2.5, 2.7, and 2.10).
3.3 Graded Status Characteristics: Revised Path Function Equations

Given the value (i.e., positive or negative) of a status characteristic, the most important aspect of it is its relevance. The more relevant to task completion or expectations for goal objects a characteristic is, the more it affects the expectation state values; that is, as it stands now the calculation of expectation state values are completely contingent on relevance. A characteristic’s relevance is determined by the cultural context and is subsequently modeled as such by the researcher. Sex, for example, becomes relevant to task outcomes that are not explicitly associated with any state of sex by a four path (i.e., $P - D(+) - \Gamma(+) - C^*(+) - T(+)\)) and a five path (i.e., $P - D(+) - D(+) - \Gamma(-) - C^*(-) - T(-)\)) through the burden of proof process. Where the task is associated with a state of sex (e.g., a mechanical task, which is masculine), sex is directly relevant to task outcomes by a three path (i.e., $P - D(+) - C^*(+) - T(+)\)) and a four path (i.e., $P - D(+) - D(-) - C^*(-) - T(-)\)) without having to model the burden of proof process. When the characteristic is not explicitly relevant to the group task, the paths connecting actors to outcomes are longer than when the characteristic is explicitly relevant to the group task. When solved using the Balkwell (1991a), Berger et al. (1977), or Fisek et al. (1992) functions for path lengths, longer path lengths produce smaller or weaker expectation state values, and shorter path lengths produce larger or stronger expectation state values. This observation provides an opportunity to incorporate graded status characteristics into the existing structure by weighting path lengths.

A large status difference on a graded status characteristic should have more of an effect than the traditional ordinal comparison hypothesis would suggest. Consider two situations (S1 and S2) where two actors ($p$ and $o$) are working on a collective mathematics task. Assume that the only salient status characteristic in S1 and S2 is mathematics ability as
measured by the graduate record examination (GRE). In S1, \( p \) has a GRE score of 800 and \( o \) has a GRE score of 400. In S2, \( p \) has a GRE score of 600 and \( o \) has a GRE score of 580. The ordinal comparison hypothesis predicts the same outcome in both S1 and S2. To be sure, \( p \) should be more influential in both situations, but in S1, \( p \) is much more competent than \( o \) and is expected to contribute much more than \( o \) to success at the task. In S2, \( p \)'s score suggests greater competence than \( o \) but the difference is only 20 points compared to 400 points in S1. An adequate technique for modeling graded status characteristics will yield different values for \( p \)'s expectation advantage over \( o \) in S1 and S2. Further, an adequate technique will allow an actor’s expectation state value to change based on the relative distance between actors in a situation.

To capitalize on the information contained in graded status characteristics, I propose weighting two path segments from the current formulation by a quantitative weight that is a function of the distance between \( p \) and \( o \) on the graded status characteristic. Weighting two path segments has the effect that very large graded status differences can have more of an effect on the expectation state values than they would under the ordinal comparison hypothesis, and very small graded status differences can have less of an effect on the expectation state values than they would under the ordinal comparison hypothesis. Consider S1 and S2 from above. Mathematics ability is relevant to states of task completion by a two-path and a three-path. For the two-path, I propose that the calculation of the path function take on a value somewhere between \( f(1) \) and \( f(3) \) depending on the distance between \( p \) and \( o \) on the graded status characteristic. Likewise, for the three-path I am proposing making the calculation of the path function take on a value somewhere between \( f(2) \) and \( f(4) \). The idea that the cultural context informs the initial relevance of a status characteristic is maintained,
but the expectation state values may now take on a continuous range of values around that level of relevance, or more precisely around the $f(\delta)$ values for a given path length.

In developing the weight, I begin by assuming a functional form on the graded characteristic. For exemplary purposes I use the normal distribution due its familiarity, but the actual functional form may be specified by the user. Using the normal distribution enables one to transform values on the graded characteristics into standard normal scores. Then differences between the value of $p$'s score and $o$'s score can be translated into the area under the standard normal curve. That is, values of graded characteristics for $p$ and $o$ can be translated into the probability of observing that difference if we assume that graded characteristics follow a normal distribution. In turn, the probability (or area) can be used as a path weight.

Let $Z_p$ and $Z_o$ indicate z-scores for $p$ and $o$ on a graded status characteristic. Multiplying each of these values by the cumulative distribution function (CDF) for the standard normal curve, and then subtracting those two values yields the graded characteristic weight:

$$\Phi(Z_p - Z_o)$$  \hspace{1cm} (3.1)

In equation 3.1, $\Phi$ refers to the CDF. Equation 3.1 has a lower bound of zero and an upper bound of one, but the weight should affect two path lengths; thus I double the weight to increase the upper bound to two. By adding the weight to the Balkwell (1991a), Berger et al. (1977) and Fisek et al. (1992) path function equations, I am incorporating the graded status information. Equations 3.2, 3.3 and 3.4 do so in the context of the Balkwell, Berger et al. and Fisek et al. path function equations, respectively:
\[ f(i_g) = 1 - \left\{ 1 - \left[ f(i + 2) + (\phi[Z_p] - \phi[Z_o]) \ast f(i) \right] \right\}^{3.192} \]  
(3.2)

\[ f(i_g) = 1 - \left\{ 1 - \left[ f(i + 2) + (\phi[Z_p] - \phi[Z_o]) \ast f(i) \right] \right\}^3 \]  
(3.3)

\[ f(i_g) = 1 - e^{-2.618 \left\{ 3 - \left(4 + 2 - 2\ast \phi[Z_p] - \phi[Z_o]) \right) \right\} \]  
(3.4)

Where \( f(i_g) \) refers to the function of a path length for a graded characteristic. This formalization of graded characteristics can be used in conjunction with any number of graded or ungraded characteristics; Equations 2.1 through 2.3 still maintain their generality with this formalization.

To be explicit, I will work through an example of using equation 3.2 to produce expectation state values based on graded status characteristics. In the example above, \( p \) has a GRE score of 800 and \( o \) has a GRE score of 400. Assuming a mean of 500 and a standard deviation of 100, \( p \) has a \( z \)-score of 3 and \( o \) has a \( z \)-score of -1. Substituting these values into equation 3.1 yields a graded status characteristic weight of .84. Mathematics ability, in this example, is initially relevant to the task outcome by a two-path and a three-path. Using the Balkwell (1991a) equation, we obtain:

\[ f(2_g) = 1 - \left\{ 1 - [(4) + (.84) \ast f(2)] \right\}^{3.192} \]  
(3.5)

And since \( f(4) \) is .1504 and \( f(2) \) is .8099 (see Table 2.1) we can solve equation 3.5 to produce an estimate of the strength of the path connecting \( p \) to the positive state of the task outcome:

\[ f(2_g) = 1 - \left\{ 1 - [(0.1504) + (.84) \ast (0.8099)] \right\}^{3.192} = .9966 \]  
(3.6)

For the strength of the path connecting \( p \) to the negative state of the task outcome (a three-path through the dimensionality bond), we obtain:
\[ f(3_g) = 1 - \{1 - [(0.0498) + (0.84) \times (0.4056)]\}^{3.192} = 0.7941 \quad (3.7) \]

Combining equations 3.6 and 3.7 using equation 2.1 provides \( p \)'s positive subset of status information:

\[ e_p^+ = \{1 - [1 - 0.9966] \times [1 - 0.7941]\} = 0.9993 \quad (3.8) \]

And because \( p \) has no negative status information in this example, \( p \)'s expectation state value based on the graded status characteristic of mathematics ability is 0.9993. Conversely, \( o \)'s expectation state value is -0.9993. Under the ordinal comparison hypothesis, \( p \)'s expectation state value would only be 0.887. Using the Berger et al. (1977) equation with the weight yields a value of 0.9996; under the ordinal comparison hypothesis, the value would be 0.9023. Using the Fisek et al. (1992) path functions yields an expectation state value based on graded status information of 0.93; under the ordinal comparison hypothesis, \( p \)'s expectation state value would be 0.7489. Thus the graded characteristics weights in equations 3.2, 3.3 and 3.4 produce larger expectation state values than the estimates under the ordinal comparison hypothesis when the actors are greatly separated on a graded status characteristic. In contrast, \( p \)'s expectation state value in S2 from above (where \( p \) has a GRE score of 600 and \( o \) has a GRE score of 580) is 0.6025 using the Balkwell estimates with the weight, 0.6391 using the Berger et al. estimates with the weight, and 0.4428 using the Fisek et al. estimates with the weight. These values are less than their corresponding expectation state values under the ordinal comparison hypothesis.

In summary, I began this chapter with a description of the logic of SCT, amending the burden of proof assumption to be consistent with graded status characteristics. I then reviewed prior research on graded status characteristics within the expectation states
tradition. Finally, I detailed one means of including graded status characteristics into the existing mathematical structure of the expectation state theories. In the next chapter, I describe an experiment designed to evaluate predictions drawn using the graded characteristics procedure. Results suggest that these estimates explain more and fit the data better than estimates drawn using the ordinal comparison hypothesis. Consequently, I apply the graded characteristics procedure to the formal model of just rewards in chapter five, which elaborates two empirical investigations of the model of just rewards.
4. EXPERIMENTAL EVALUATION OF GRADED STATUS CHARACTERISTICS

The preceding chapter reviewed status characteristics theory (SCT) and extended its mathematics to include the additional information contained in graded status characteristics. In this chapter, I present the results from an experiment that was designed to evaluate the graded characteristics procedure. Specifically, I conducted an experiment using the standard experimental setting for tests of SCT with the goal of comparing estimates drawn using the ordinal comparison hypothesis to estimates drawn using my procedure. To the extent that the estimates based on my graded characteristics procedure fit the experimental data better and explain more variation in social influence, I am justified in applying the graded characteristics procedure to the formal model of just rewards that was developed in chapter two.

In terms of research methodology, experiments are the gold standard for evaluating causal relations (Campbell and Stanley 1963) and testing social theory (Cohen 1989; Molm 1997; Willer and Walker 2009). At the other end of the quantitative methodology spectrum is the observational study, offering little control but the ability to “look like” some population. Experiments are well suited for evaluating the validity of knowledge claims (Cohen 1989), while observational studies are well suited for evaluating the extent to which a relationship stemming from some knowledge claim may be found to exist in some population.

In light of the above, I designed the experiment described below to establish the validity and accuracy of the graded characteristics procedure. The experiment manipulates one graded status characteristic and can be used to make theoretical inferences about the
utility of the estimation procedure. The experiment reported in this chapter is similar to many experimental tests of SCT. Before describing the methods, procedures and results, I present the predictions which the experiment is intended to evaluate.

4.1 Predictions

Expectation states are the cognitive realization of status differences between participants in a collective task group. That is, SCT argues that status differences produce differences in relative performance expectations, and subsequently power and prestige behaviors are predicted to be a direct continuous function of performance expectation states. Several experimental studies have supported this logic (see Berger and Webster 2006 for a review). The theoretical and mathematical innovations in the previous chapter increase the precision of estimates of expectation states by modeling graded status characteristics. As such, models based on the more precise measure of expectation states should better reflect the data generating mechanism of power and prestige behaviors. I therefore predict that expectation state estimates based on the graded characteristics procedure will completely mediate the relationship between the status manipulation and the influence outcome. They will also better represent the data generating mechanism of power and prestige behaviors than will expectation state estimates based on the ordinal comparison hypothesis. Of course, the previous statement applies to graded status characteristics and not discrete ones.

4.2 Method

A single factor experimental design is well suited to evaluate the graded characteristics estimation procedure. The experiment was run in a computer mediated version of the standardized experimental setting (SES) for testing SCT (Berger et al. 1977: 43-48; Kalkhoff and Thye 2006). In general the SES requires that four conditions are met:
(1) The SES requires that the participants do not meet, so that a status hierarchy may be “created.” That is, it is important that non-manipulated characteristics, such as ethnicity and beauty, are not salient to the participants in order to ensure that the manipulated characteristic is the only factor driving the observed inequalities. (2) The SES requires a set of standard instructions for ensuring the initial conditions of the theory are met (e.g., that the participants are both task and collectively oriented). (3) The SES requires the use of a non-veridical binary choice task that is used to manipulate relative status between the participant and their purported partner. And, (4) the SES also requires the use of a standard measure of social influence- the number of trials in which the participant behaviorally rejects influence attempts from their partner.

4.3 Design and Subjects

The experiment was a single factor design with six conditions. The SES uses a binary choice task to manipulate the status of participants relative to their partners. Hence, six different levels of relative status constituted the status manipulation. In two of the conditions, the participant \( P \) and the partner \( O \) were differentiated as much as possible. In the remaining four conditions, \( P \) and \( O \) were differentiated as little as possible, at both ends of the distribution of the manipulation (see below). One-hundred-twenty undergraduate students were randomly assigned to the six conditions.\(^1\)

\(^1\) Seventeen cases were excluded for one of the following reasons: 1) Failure to recall the number of trials used to manipulate status (i.e., a manipulation check); 2) Disbelief in the deception in the experiment (the task or the simulated partners); or, 3) Blatant lack of collective orientation. The latter two reasons were discerned during a post-experiment interview. Excluded cases were re-ran in random order yielding the desired twenty cases per condition. The incorrect condition number entered when running one of the re-dos; consequently there are 21 cases in condition one and nineteen cases in condition three.
Sex was not controlled by design as both female and male participants were randomly assigned across conditions.²

4.4 Procedures

Participants were escorted to isolated rooms and were informed that they would be working with a partner over a computer network in a two-phase experiment. In reality they did not work with a partner; the computer program simulated the behavior of a fictitious partner. Participants did not meet or see each other to avoid non-manipulated status characteristics, such as beauty (Webster and Driskell 1983) from becoming salient. They were told that they would be working at an individual task in the first phase and that they would then work over a computer network with a partner on a collective task. After this initial introduction to the study the remainder of the session was computer mediated.

The instructions addressed three important aspects of the experiment. First, participants were informed that they would be paid for their performance in the experiment. Specifically, they were told that the minimum they could earn was $6.00. They were told that they could earn an additional $.25 for each trial that they got correct in phase two and $.25 for each trial that their partner got correct in phase two. The earnings were used to motivate participants to be both task and collectively oriented; making the amount they earned contingent on their performance should increase task orientation and making them dependent on their partner should increase collective orientation. Research has shown that subtle protocol variations, such as performance-based pay, can lead to systematic changes in

² There were 32 males and 105 females. Of the 17 cases that were re-ran, 5 of them were males and 12 of them were females; given the marginals, this is within sampling variability, indicating that sex does not have an effect on having to redo a case ($\chi^2_{(1)} = .4, p = .53$). Among the 120 cases that are analyzed, men were not systematically assigned to any of the conditions ($\chi^2_{(5)} = 1.7, p = .89$). Moreover, in the regression models reported below a dummy variable for sex is not significant (results available from the author upon request).
SCT results (Kalkhoff and Thye 2006). This change was made to the SES in order to maximize task and collective orientation, and may be why fewer of the cases had to be re-run than normal (for a similar protocol, see Ridgeway and Correll 2006).

Second, the instructions introduced the task for the experiment, contrast sensitivity. Contrast sensitivity was described as a relatively new ability that is not associated with other abilities such as mathematical or verbal skills. Participants were shown two rectangular images, each composed of smaller black and white areas, and were asked to select which of the two images contained the most white area. They were told that “the difference in the amount of white area is sometimes quite small,” and that they would therefore “probably find that some of the pictures … are very difficult [to judge].” Participants were then told that people with high contrast sensitivity consistently choose more correct answers than people with low or average contrast sensitivity, and that people with high levels of contrast sensitivity may not be aware of how it is that they choose the correct answer. Nonetheless, they were informed that there is a correct answer to each trial and that the test in phase one, which was designed for student populations, is designed to measure the presence of contrast sensitivity ability. In reality, contrast sensitivity is not an actual ability and there is no correct answer (Moore 1968).

Third, the instructions were used to create the initial conditions of SCT. The instructions described the team portion of the experiment as a “critical choice” situation in which taking others’ opinions into consideration leads to an increased likelihood of making a correct decision. It was stressed to the participants that they work as a team because “exchanging information with others often leads to more correct decisions than an
individual could make working alone.” This portion of the instructions was intended to increase participants’ collective orientation.

Phase one of the experiment consisted of a practice trial with on-screen instructions followed by twenty-five trials of contrast sensitivity problems. On each trial, participants were asked which of two images contained the most white area. Participants were given ten seconds to decide, after which they were unable to make a choice for that trial. After phase one, the participant’s and partner’s (fictitious) scores were reported to the participant constituting the experimental manipulation.

Phase two of the experiment also consisted of twenty-five trials of contrast sensitivity problems. In phase two participants were given ten seconds to make their initial opinions as to which of two images contained the most white area. Then they were shown their partner’s initial opinion, given ten more seconds to study the images, and were asked for their final opinions. Once the ten seconds were up, the participants were no longer eligible to make a choice for that trial. On twenty predetermined trials the partner’s initial decision was different from the participant’s initial decision; that is, participants did not really interact with another person, they interacted with a simulated partner so that the partner’s behavior could be controlled. The proportion of trials that the participant rejects this influence attempt from the partner is the main outcome; that is, the proportion of twenty trials that the participant stays with her own initial opinion (referred to as P(S) for proportion of stay responses) is a continuous measure of social influence. After phase two, participants completed a brief questionnaire and then they were debriefed.

4.5 Manipulation
The participant’s score and the simulated partner’s score in phase one were used to manipulate status. Traditionally the scores are reported with a rule-of-thumb interpretation that induces thinking about contrast sensitivity as if it is a discrete ability with states that are poor, average, and superior (e.g., Berger and Fisek 1970: 295). For example, if twenty trials are used to manipulate status, participants might be told that a score of zero to ten represents a poor performance and a relative lack of ability, a score of eleven to fifteen represents an average performance, and a score of sixteen or more represents a superior performance. Given that I want to evaluate the extent to which participants make use of more finely graded distinctions than the above mentioned three categories, the phase one scores were reported as integer scores from the distribution of contrast sensitivity ability. Figure 4.1 visually represents the distribution that was used for the manipulation.

![Figure 4.1: The Distribution that was used to Manipulate Contrast Sensitivity Ability.](image)

There are three important aspects of the distribution of contrast sensitivity scores. First, it induces thinking about contrast sensitivity as a continuously distributed ability rather than a discrete ability with three ordered states. Second, the distribution visually represents that the ability is centered about fourteen. Third, the distribution visually represents that the standard deviation is three, indicating that as scores move farther away from fourteen they
become less likely. Again, I do not assume that the participants consciously processed this distributional information; I just assume that behavior will unfold as if they did.

Manipulating subjects’ relative contrast sensitivity in phase one and then measuring influence using the same characteristic in phase two serves a distinct purpose. Once contrast sensitivity is manipulated, it is the only salient status characteristic since the participants did not meet or even see one another before the study. In this case, contrast sensitivity is the most relevant characteristic to solving contrast sensitivity problems (i.e., it is the “instrumental task characteristic”). This is analogous to math ability being the only salient characteristic in a group that is working on a linear algebra problem, except that I can manipulate contrast sensitivity ability. Since it is the most relevant characteristic, the effect sizes of status on social influence should be the largest, allowing the graded characteristics procedure the most variation to explain.

Only two screens varied across conditions in the experiment. The first showed the participant her score and her partner’s score in raw form beneath the distribution that is presented in figure 4.1. The second screen converted the raw scores into percentiles (based on the distributional information in the figure) and informed the participant that both her score and her partner’s score were relatively rare levels of performance.

The specific values that were used to manipulate status were selected to create a strong manipulation. Table 4.1 presents the phase one scores that were used to manipulate status. The first two conditions created a very large status difference between the participant and their partner. In the very high status condition, the participant was told that she got 23 out of 25 trials correct in phase one, and she was told that her partner got 5 out of 25 trials correct. In the very low status condition, the scores and corresponding percentiles were
reversed, telling the participant she got 5 correct while the partner got 23 correct. The scores, 23 and 5, correspond to plus and minus three standard deviations, respectively. The other four conditions induced relatively small status differences between the participant and her partner at both ends of the distribution of contrast sensitivity ability. In the high status, small difference conditions the participant was told that she got either 9 or 23 correct and that her partner got either 5 or 19 correct, respectively. In the low status, small difference conditions the participant was told that she got either 5 or 19 correct and that her partner got either 9 or 23 correct, respectively. In all four of the small difference conditions, four trials separated the scores of the participant from the partner.

Table 4.1: Summary of the Phase I Scores used to Manipulate Status

<table>
<thead>
<tr>
<th>Condition</th>
<th>P's Phase I Score</th>
<th>O's Phase I Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1- High Status, Large Difference</td>
<td>23</td>
<td>5</td>
</tr>
<tr>
<td>2- Low Status, Large Difference</td>
<td>5</td>
<td>23</td>
</tr>
<tr>
<td>3- High Status, Small Difference, High End</td>
<td>23</td>
<td>19</td>
</tr>
<tr>
<td>4- High Status, Small Difference, Low End</td>
<td>9</td>
<td>5</td>
</tr>
<tr>
<td>5- Low Status, Small Difference, High End</td>
<td>19</td>
<td>23</td>
</tr>
<tr>
<td>6- Low Status, Small Difference, Low End</td>
<td>5</td>
<td>9</td>
</tr>
</tbody>
</table>

I used contrast sensitivity because its states could be manipulated. A real-world example of this process might entail occupational prestige. Conditions 1 and 2 are analogous to a physician working with a short order cook, where the physician holds an extremely high state of occupational prestige and a short order cook holds an extremely low state of occupational prestige. Conditions 3 and 5 are analogous to a physician working with a lawyer, and conditions 4 and 6 are analogous to a short order cook working with a welder. In
both of the latter sets of occupations subtle differences in occupational prestige differentiate
the individuals (Bose and Rossi 1983).

4.6 Results

Table 4.2 presents the observed P(S) values for the six conditions in the experiment. The results reflect the expected status differences. The mean P(S) values for the three high
status conditions (1, 3 and 4) are higher than the mean P(S) values in the low status
conditions (2, 5 and 6). The P(S) in the very high status condition is substantially higher than
any other condition. Likewise, the P(S) in the very low status condition is substantially lower
than any other condition. The P(S) values for the two high status small difference conditions
(3 and 4) are relatively close to each other, but quite a bit smaller than the very high status
condition. Likewise, the P(S) values for the two low status small difference conditions (5 and
6) are relatively close to each other, but quite a bit larger than the very low status condition.

Table 4.2: Observed P(S) Scores and Sample Sizes by Conditions

<table>
<thead>
<tr>
<th>Condition</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed P(S)</td>
<td>.765</td>
<td>.250</td>
<td>.661</td>
<td>.599</td>
<td>.307</td>
<td>.440</td>
</tr>
<tr>
<td>N</td>
<td>21</td>
<td>20</td>
<td>19</td>
<td>20</td>
<td>20</td>
<td>20</td>
</tr>
</tbody>
</table>

To assess whether the graded characteristics estimates of performance expectation
states mediate the relationship between the status manipulation and the P(S), I estimated a
conventional mediation model (Baron and Kenny 1986), which entails that three conditions
must be satisfied: (1) status differences must significantly account for variation in
expectation state values, (2) variation in expectation state values must account for variation in power and prestige behaviors, and (3) when the expectation state values are added to the model, a previously significant relationship between status differences and power and prestige behaviors should become nonsignificant (with zero association representing the best case).

Table 4.3 present the results from four conventional linear probability models, which were estimated using the Balkwell (1991a) version of the graded characteristics path function equations to obtain the estimates of performance expectation states (i.e., equation 3.3). The form of the models is as follows:

\[ P(s) = m + q(e_p - e_o) \]  

(4.1)

In the above model, \( m \) is an intercept term that captures the baseline propensity to reject influence, \( q \) is a slope term that captures setting and other systematic effects, and \( e_p - e_o \) refers to \( P \)'s expectation advantage over \( O \) (see chapter two). The first model in Table 4.3 shows that the manipulation had the intended effect since the \( P(S) \) scores are significantly related to the manipulation. Model two shows support for the first step of the mediation analysis: the manipulation explains variation in the theoretical construct. Model three shows support for the second step of the mediation analysis: the estimates of graded performance expectation states are significantly related to the \( P(S) \) values. And model four shows that the estimates of graded performance expectation state values indeed mediate the relationship between the manipulation and the \( P(S) \) values since the coefficient for the manipulation is indistinguishable from zero. What is more, the estimates of performance expectation states

---

3 Substantively similar results are obtained if the Berger et al. (1977) or the Fisek et al. (1992) \( f(\theta) \) values are used; the selection of Balkwell's estimates is arbitrary.
that are based on the ordinal comparison hypothesis *do not mediate this relationship*, as the manipulation is still significant ($\beta_1 = .009, \sigma^2_{\beta_1} = .003, p < .001$). This evidence suggests that the graded characteristics version of the performance expectation states is a better representation of the theoretical construct “expectation states.”

Table 4.3: Summary of Four Regression Models Illustrating the Status Manipulation Check and a Mediation Analysis.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P(s)</td>
<td>Graded Expectations</td>
<td>P(s)</td>
<td>P(s)</td>
</tr>
<tr>
<td>Constant</td>
<td>.503***</td>
<td>-.005</td>
<td>.503***</td>
<td>.504***</td>
</tr>
<tr>
<td></td>
<td>(.019)</td>
<td>(.032)</td>
<td>(.018)</td>
<td>(.018)</td>
</tr>
<tr>
<td>Contrast Sensitivity Scores</td>
<td>.016***</td>
<td>.118***</td>
<td></td>
<td>-.003</td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td>(.003)</td>
<td></td>
<td>(.006)</td>
</tr>
<tr>
<td>Graded Expectation States</td>
<td></td>
<td></td>
<td>.136***</td>
<td>.158***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.013)</td>
<td>(.052)</td>
</tr>
</tbody>
</table>

R-Squared: .427 .934 .469 .469

*Note: **p < .01, ***p < .001.*

To assess the prediction that the aggregate expectation state values based on the graded characteristics estimation procedure will better capture the data generating mechanism of status based influence than the traditional aggregate expectation state values, I estimated two more traditional linear probability models. The closed form solution to $m$ and $q$ may be obtained using the least squares estimator (OLS regression); however, I estimated these two versions of equation 4.1 using maximum likelihood estimation (Eliason 1993). I used maximum likelihood estimation to obtain the log-likelihood in order to calculate the Bayesian Information Criterion (BIC) (Raftery 1985). The BIC represents global model fit, where smaller values indicate better fit.
The first model used the expectation advantages calculated from the ordinal comparison hypothesis version of Balkwell’s (1991a) \( f(i) \) estimates. The second model used expectation advantages calculated using Balkwell’s equation with the graded characteristics weight. A summary of these regression models is presented in Table 4.4. Of note in Table 4.4 are the R-Squared values and the BIC statistics for each model. The model with the expectation advantage calculated using the graded characteristics procedure explains an additional 5 percentage points of the variation in P(S) scores than the ordinal comparison hypothesis model.\(^4\) Furthermore, the BIC statistic is smaller for the graded characteristics regression model, indicating that the graded characteristics model is the preferred model from Table 4.4.

<table>
<thead>
<tr>
<th></th>
<th>Ordinal Comparison Hypothesis</th>
<th>Graded Status Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>M (( \beta_0 ))</td>
<td>.505***</td>
<td>.504***</td>
</tr>
<tr>
<td>(Std. Error)</td>
<td>(.019)</td>
<td>(.018)</td>
</tr>
<tr>
<td>Q (( \beta_1 ))</td>
<td>.097***</td>
<td>.120***</td>
</tr>
<tr>
<td>(Std. Error)</td>
<td>(.011)</td>
<td>(.012)</td>
</tr>
<tr>
<td>R-Squared</td>
<td>.416</td>
<td>.466</td>
</tr>
<tr>
<td>BIC</td>
<td>-27.0</td>
<td>-37.8</td>
</tr>
</tbody>
</table>

*Note:*** \( p < .001 \)

It would be useful, and supportive, to identify that the model based on the graded characteristics procedure explains significantly more than the model based on the ordinal

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\(^4\) The effect size (\( \beta_i \)) is larger in the graded characteristics model than in the ordinal comparison hypothesis model; indeed this is mathematically related to the larger R-squared value as the larger effect size indicates a smaller within groups sum of squares and a larger between groups sum of squares.
comparison hypothesis. In a traditional sense, the two regression models are not nested, nor can they be viewed as components of a comprehensive model. Consequently I turned to an “artificial” test of nested models (Davidson and MacKinnon 1981; Weakliem 1992). The logic of the artificial test of nested models is this: if the residuals from a null model (i.e., the regression model using the ordinal comparison hypothesis estimates) are predicted by the difference in predicted values between the alternative model (i.e., the graded characteristics model) and null model, then the alternative model is the preferred model because it explains variation that is left over after estimating the first model (the null model). That is, if the null model captures the data generating mechanism, then there should be no structure for the alternative model to explain in the residuals after parceling out the effect of the null model.

Here is the artificial nested model that I estimated:

\[ e_o = \beta_1 (\hat{y}_g - \hat{y}_o) + \beta_2 (x_o) + e \]  

(4.2)

Where \( e_o \) refers to the residuals from the regression model using the ordinal comparison hypothesis estimates of the expectation advantage, \( \hat{y}_g \) and \( \hat{y}_o \) refers to the predicted values from the graded and ordinal comparison versions of the regression models, respectively, \( x_o \) refers to the expectation advantages calculated using the ordinal comparison procedure, and \( e \) refers to an error term. The results of the artificial nested model suggests that the graded characteristics model is the preferred model as it explains a significant amount \((\beta_1 = 1.31, \sigma^2_{\beta_1} = .382, t_{(110)} = 3.44, p < .001)\) of the variation in P(S) after parceling out the effects of the ordinal comparison hypothesis model. Thus not only does the explained variance and the

---

5Including the original covariate ensures that the standard error of \( \beta_1 \) has an asymptotic standard normal distribution under the null hypothesis (Weakliem 1992: 152-3).
BIC statistic indicate the graded characteristics model is the preferred model, but also the artificial test of nested models suggests that the graded characteristics model is a significantly better model with respect to the data generating mechanism.\(^6\)

The question of model fit is still relevant to addressing the hypothesis that the expectation state estimates based on the graded characteristics procedure will better represent the data generating mechanism of power and prestige behaviors than will expectation state estimates based on the ordinal comparison hypothesis. To assess overall model fit, I estimated two chi-squared tests (e.g., Balkwell 1991b). Specifically, Table 4.5 presents the cell counts for trials in which the participants stayed with their initial opinions and for trials in which the participants deferred to their partners. This information is cross-classified by conditions.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Stay Response</th>
<th>Defer to Partner</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (23 – 5)</td>
<td>311</td>
<td>96</td>
</tr>
<tr>
<td>2 (5 – 23)</td>
<td>97</td>
<td>286</td>
</tr>
<tr>
<td>3 (23 – 19)</td>
<td>246</td>
<td>125</td>
</tr>
<tr>
<td>4 (9 – 5)</td>
<td>251</td>
<td>142</td>
</tr>
<tr>
<td>5 (19 – 23)</td>
<td>109</td>
<td>277</td>
</tr>
<tr>
<td>6 (5 – 9)</td>
<td>172</td>
<td>220</td>
</tr>
</tbody>
</table>

To generate the expected cell counts under the models, I estimated the predicted probabilities of both potential outcomes- a stay response and its complement, a trial where

\(^6\) Reversing the artificial nested model test does not have the same effect; that is, the ordinal comparison hypothesis model does not explain any of the variation left over after estimating the graded characteristics model.
the participant was influenced. I then multiplied both of those probabilities by the total number of trials in each condition generating a theoretical model of predicted counts. I did this for the model using the ordinal comparison aggregate expectations and for the model using the graded aggregate expectations. Table 4.6 presents the predicted cell counts and the chi-squared components for the ordinal comparison model. The results suggest that the theoretical model does not fit the data ($\chi^2_{(10)} = 52.26, p < .001$). Table 4.7 presents the predicted cell counts and the chi-squared components for the graded characteristics model. Again, the results suggest that the theoretical model does not fit the data ($\chi^2_{(10)} = 22.13, p < .014$). Although neither of the models fits the data, the chi-squared value for the graded characteristics theoretical model is substantially smaller than the chi-squared value for the ordinal comparison hypothesis model.

### Table 4.6: Predicted Cell Counts and Chi-Squared Values for the Ordinal Comparison Model

<table>
<thead>
<tr>
<th>Condition</th>
<th>Trials Influenced</th>
<th>Trials Not Influenced</th>
<th>Chi-Squared Components</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (23,5)</td>
<td>131.46</td>
<td>275.54</td>
<td>-35.46</td>
</tr>
<tr>
<td>2 (5,23)</td>
<td>255.46</td>
<td>127.54</td>
<td>30.54</td>
</tr>
<tr>
<td>3 (23,19)</td>
<td>119.83</td>
<td>251.17</td>
<td>5.17</td>
</tr>
<tr>
<td>4 (9,5)</td>
<td>126.94</td>
<td>266.06</td>
<td>15.06</td>
</tr>
<tr>
<td>5 (19,23)</td>
<td>257.46</td>
<td>128.54</td>
<td>19.54</td>
</tr>
<tr>
<td>6 (5,9)</td>
<td>261.46</td>
<td>130.54</td>
<td>-41.46</td>
</tr>
<tr>
<td><strong>Chi-Squared</strong></td>
<td><strong>52.26</strong></td>
<td><strong>52.26</strong></td>
<td><strong>52.26</strong></td>
</tr>
</tbody>
</table>
Table 4.7: Predicted Cell Counts and Chi-Squared Values for the Graded Characteristics Model

<table>
<thead>
<tr>
<th>Condition</th>
<th>Trials Influenced</th>
<th>Trials Not Influenced</th>
<th>Residuals</th>
<th>Chi-Squared</th>
<th>Components</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (23,5)</td>
<td>103.79</td>
<td>303.22</td>
<td>-7.79</td>
<td>7.79</td>
<td>.58</td>
</tr>
<tr>
<td>2 (5,23)</td>
<td>282.27</td>
<td>100.73</td>
<td>3.73</td>
<td>-3.73</td>
<td>.05</td>
</tr>
<tr>
<td>3 (23,19)</td>
<td>131.33</td>
<td>239.67</td>
<td>-6.33</td>
<td>6.33</td>
<td>.31</td>
</tr>
<tr>
<td>4 (9,5)</td>
<td>139.12</td>
<td>253.88</td>
<td>2.88</td>
<td>-2.88</td>
<td>.06</td>
</tr>
<tr>
<td>5 (19,23)</td>
<td>246.27</td>
<td>139.73</td>
<td>30.73</td>
<td>-30.73</td>
<td>3.84</td>
</tr>
<tr>
<td>6 (5,9)</td>
<td>250.10</td>
<td>141.90</td>
<td>-30.10</td>
<td>30.10</td>
<td>3.62</td>
</tr>
<tr>
<td>CHI-Squared</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>22.13</td>
</tr>
</tbody>
</table>

As in the linear regression case, the chi-squared models are not nested in one-another and there is no comprehensive model that both of them could be nested in. There are, however, significance tests for comparing non-nested models for contingency tables (Weakliem 1992). Specifically, the C test (Weakliem 1992: 161) is well suited to my particular problem of not being able to discern between estimates drawn from the graded and ordinal comparison hypotheses. The C test requires three steps: 1) Estimate the predicted cell counts under both models, and let \( f \) refer to the cell counts under the ordinal comparison hypothesis and let \( g \) refer to the cell counts under the graded characteristics procedure; 2) define a variable \( h = g - f \), and then regress \( y - f \) on \( h \) using \( 1/f \) as a weight (where \( y \) refers to the
observed cell counts); and, 3) divide the coefficient for $h$ by its standard error to obtain the $C$-test statistic. The results of the $C$ test suggest that the cell counts drawn from the graded characteristics model are a significantly better approximation of the observed cell counts than the cell counts drawn from the ordinal comparison hypothesis ($C = 3.82, p = .003$). At the same time, the cell counts drawn from the ordinal comparison hypothesis are not a better approximation of the observed cell counts than the cell counts drawn from the graded characteristics procedure ($C = -.44, p = .670$). This result offers support for the hypothesis that estimates drawn from the graded characteristics procedure better reflect the data generating mechanism of power and prestige behaviors than estimates drawn from the ordinal comparison hypothesis; indeed, the graded characteristics procedure explains significantly more of the observed behaviors than the ordinal comparison hypothesis.

4.7 Discussion

The results of the experiment reported in this chapter suggest that estimates of performance expectations based on the graded characteristics procedure explain more variation and fit the data better than the estimates of performance expectations that are based on the ordinal comparison hypothesis. This suggests that when gradations of status differences can be assumed to be salient, better theoretical models and predictions can be deduced by using the procedures developed in the previous chapter. School settings are one applied area where the graded characteristics formulation may be useful. It is often the case that grade point averages or test scores are salient and operate as a basis of inequality in task groups. Applied research within the expectation states tradition has shown that “status

---

7 I estimated the weighted regression two ways: I first ran the model in Stata 11 using $1/f$ as an analytic weight. To check this, I then imported the information into R and solved this equation: $b = (X'WX)^{-1}X'WY$ (Neter et al. 1996: 409), where $X$ is a vector of $h$ values (i.e., there was no intercept), $Y$ refers to $y - \bar{y}$, and $W$ is a diagonal matrix with values $1/f$ on the diagonal. The results were exactly the same.
interventions” can ameliorate the interactional inequalities that arise from status-organizing processes (Cohen 1982; Cohen and Lotan 1995), and the ability to better estimate the amount of status disadvantage low status individuals face may prove useful.

The results from the chi-squared goodness-of-fit were surprising in the sense that neither the ordinal comparison hypothesis model nor the graded characteristics model fit the experimental data. If I ignore condition 6 in the experiment, the graded characteristics model fits the data, but the ordinal comparison model does not. However, the data from condition 6 contains an important aspect of status organizing processes: condition 6 created a power and prestige order where the participant was very low in status, but the partner was only marginally better than the participant. Why would we expect someone who is bad at a task to be influenced by someone else who is almost as bad at that task? In this condition we observed a higher proportion of stay responses than expected under the model. Perhaps the higher \( P(S) \) than expected is driven by the same self-bias that drives the constant term \( (m) \). The constant is typically estimated to be .6 (Kakhhoff and Thye 2006), which indicates that participants stay with their own initial choice 10% more than chance would predict. Having an incompetent partner may lead participants – even low status participants – to a more pronounced manifestation of this same self-bias.

Having shown the utility of the graded characteristics procedure, I apply it in the next two chapters. In chapter five, I describe data from a within-subjects factorial design survey that I conducted at the University of Arizona. I use the graded characteristics procedure to predict respondent-reported expectations for targets, or fictitious individuals the respondents evaluated, and I also apply the graded characteristics procedure to the formal model of just rewards to predict the respondents’ evaluations of targets’ just rewards.
based on their attributes. Chapter six applies the graded characteristics procedure and the formal model of just rewards to predict respondents’ evaluations of their own just rewards using secondary data from thirteen countries.
5. WITHIN-SUBJECTS FACTORIAL DESIGN SURVEY

The results in the previous chapter demonstrate that, under highly controlled circumstances, with one manipulated graded status characteristic, the graded characteristics estimation procedure better reflects the data generating mechanism of power and prestige behaviors than the ordinal comparison hypothesis model. In terms of graded status characteristics, the next logical step is to evaluate the adequacy of the model when more than one characteristic is varying. To do so, I administered a within-subjects factorial design survey of the type pioneered and used extensively in the Rossi-Jasso program of studies of justice processes (Jasso and Rossi 1977; Jasso and Webster 1999; Rossi 1979). Data from this survey can evaluate the graded characteristics procedure by predicting respondents’ expectations for others, and also evaluate the formal mathematical model of just rewards by predicting respondents’ evaluations of the just rewards of others.

The survey asked respondents to evaluate vignettes that described fictitious individuals, or targets (Appendix A contains the survey instrument and Table A.1.1 presents a summary of the targets’ attributes). The vignettes varied the targets’ sex, education, and occupation. Targets were described as males or females, who had completed a specific number of years of schooling (from seven to sixteen years), completed a degree (or not when years of education were fewer than 12),¹ and who worked at a given occupation (seventeen occupations were sampled from the frame). After reading each target’s description, respondents were asked the seven most reliable questions from Zeller and Warnecke’s scale for estimating expectation states (Zeller and Warnecke 1973: 96-97). The

¹ Degree is not manipulated by design, but is a consequence of years of schooling.
Zeller and Warnecke items were tailored to the instrument by asking respondents how the
target would do “compared to others” rather than “compared to you.” This modification
was made to decouple the items from a relational context: rather than comparing the targets
to self, I wanted the respondents to compare the targets to a generalized other. This makes
comparisons across respondents more reliable and avoids occupational prestige dominating
the evaluations of expectations since all of the participants are students. The questionnaire
items are listed as the first seven questions pertaining to each target in Appendix A. Finally,
respondents were asked how much each target should earn on an annual basis; that is, this
question provides a direct indicator of the just reward for each target. The analysis of this
indicator constitutes the first empirical evaluation of the just rewards model.

Following Jasso and Rossi, the first step in constructing the survey instrument was to
generate the set of characteristics by which targets are described, and to establish the levels
of those characteristics. The set consisting of all possible combinations of levels of the
characteristics is referred to as a vignette and the sample of actors and characteristics drawn
from the vignette is referred to as a deck (Jasso and Webster 1999: 369). Considering the
large number of actor-attribute combinations (a total of 2,200, i.e., 2 sexes x 10 years of
schooling x 110 occupations), each respondent evaluated only one deck of twenty targets.
Impossible combinations of variables (e.g., a doctor with only 12 years of schooling) are then
deleted from the deck. Due to the random nature of targets’ years of schooling and
occupational prestige scores (i.e., I might randomly draw a high occupational prestige score
but an education that does not warrant that occupation), I added two additional targets to
make up for the low probability of observing targets simultaneously high on education and
occupational prestige and to ensure that targets represented the full range of education and
occupational prestige. These last two targets were a female and a male physician giving me a total of 22 targets. Occupational prestige and educational attainment were randomly ordered within target sexes. I balanced target sex by presenting respondents with the male targets interspersed with female targets. The data collection method inhibited full counter-balancing for order effects (see below).

Male and female targets had a range of 7 to 20 years of schooling with a mean of 12. The ranges of occupational prestige for male and female targets were not identical (the female distribution has a lower bound, but only due to the random assignment of occupations to sexes), but the means are roughly equal (50.23 for males and 49.36 for females). Following Jasso and Webster (1999), I used the Bose and Rossi (1983) scale of occupational prestige which has a range of 100 and a mean of 50. The standard deviation for the Bose and Rossi scale is 22.72.

The survey instructions indicated to the respondents that all of the targets were 35 years old, and had been working in their occupations since the completion of their education. Further, the instructions told the participants that, in the US, the average age is 35, the average educational attainment is 12 years of schooling, and the average income is $35,000. This information was provided for two reasons: (1) It provided a baseline, or anchor (Markovsky 1988), from which to generate expectations. That is, the participants knew that the targets had worked full-time for some years in their occupation and it gave them a reference point from which to compare the target’s educational achievements. (2)

---

2 I assume that education has a standard deviation of 2.74. I base this assumption on the actual dispersion of the years of educational attainment variable from the 1990 to 2006 file of the General Social Survey (Davis and Smith 1974-2006).

3 Author’s calculations based on results presented in Bose and Rossi.

4 Although the point estimates of income, age, and education are not exact, they are approximate and were only intended to orient the participants expectations about these attributes.
The information was used as a manipulation check at the end of the survey. Participants were asked open-ended questions about how old the average American is and how many years of schooling the average American completes. For participants who answered these questions correctly, I am more confident that age was not operating as a status characteristic since all of the targets were of average age and participants’ baseline expectations about average education were the same.5

I used a combination of an online and a pen-and-paper survey to collect data from 253 unpaid undergraduate students during the summer and fall of 2010. For the online survey, participants were provided with a link to an online consent document. From that page, once participants had consented to participate, they followed another link to the survey page where they downloaded the survey. Participants then filled out and emailed the completed survey to me. For the pen-and-paper survey, I administered the survey to one large undergraduate sociology course. A total of twelve subjects (4.7%) could not identify the mean age of the population or the average years of schooling completed and their data have been removed from the analyses pertaining to the expectation states. In addition to the twelve subjects removed based on the age and education manipulation checks, one subject (.4%) was removed from the just rewards analyses because that subject could not identify the mean income that was reported in the beginning of the study. For the expectation state analysis there was a total eligible sample of 5,302 targets nested in the 241 participants, and for the just rewards analysis there was a total eligible sample of 5,280 nested in 240 participants.

5.1 Predictions

5The complexity of occupational prestige scales prohibited a manipulation check for this characteristic.
As with the experimental data, I predict that expectation state estimates based on the graded characteristics procedure will better represent the data generating mechanism of expectation states than will expectation state estimates based on the ordinal comparison hypothesis.

In terms of the just rewards model, I predict that the equity-based mathematical model of just rewards will reflect the data generating mechanism of just rewards. More precisely, I expect it to perform as well as a baseline model that estimates the effects of the targets’ attributes (i.e., sex, education and occupational prestige). Because the baseline model uses regression procedures to estimate the weights associated with these factors, it would be a substantial finding to demonstrate that just rewards can be predicted without having to estimate regression weights from the data. Further, I expect the model of just rewards based on the graded characteristics procedure to fit better than the model of just rewards based on the ordinal comparison hypothesis.

5.2 Results

Table 5.1 presents the descriptive statistics for the vignette data. The respondent sample was 64% female with an average age of 21.58. The seven item expectation state scale, which was highly reliable ($\alpha = .94$), has a mean of 38.83 (the minimum is seven and the maximum is 49). The respondents reported that the targets deserved to earn $44,150 per year, which reflects the common finding that just rewards are more than actual rewards (the subjects were told that the average income is $35,000). There were missing data for two of

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the targets’ expectation state estimates, and for twelve of the targets’ just rewards. In the
corresponding results reported below, list wise deletion was used to account for missing data.

Table 5.1: Descriptive Statistics for the Vignette Data

<table>
<thead>
<tr>
<th></th>
<th>Mean (Standard Deviation)</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Target Level</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expectation State Estimates</td>
<td>38.83 (10.06)</td>
<td>5,300</td>
</tr>
<tr>
<td>Just Rewards</td>
<td>$44,149.48 ($27,609.57)</td>
<td>5268</td>
</tr>
<tr>
<td><strong>Subject Level</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>.64</td>
<td>241</td>
</tr>
<tr>
<td>Age</td>
<td>21.58 (2.82)</td>
<td>241</td>
</tr>
</tbody>
</table>

5.2.1 Graded Characteristics Results.

To evaluate the prediction that the expectation state values based on the graded
classifications estimation procedure fits better than the ordinal comparison hypothesis
estimates, I estimated three linear mixed models (LMM). The derivation of all of the LMMs
presented in this chapter and the next one are reported in Appendix B. All of the LMMs
have the expectation states scale as an outcome. The first model is a baseline model that
simply accounts for the nesting of targets in respondents. The other two models have
random intercepts and different versions of the expectation state estimates (graded and
ordinal comparison hypothesis) as predictors. Equation 5.1 represents the baseline model
and equations 5.2 and 5.3 represent the models with the expectation state estimates.
\[(ESV)_r = \beta_{0r} + \varepsilon_r \]  

(5.1)

Where, \( \beta_{0r} = \gamma_{00} + \mu_{0r} \)

\[(ESV)_r = \beta_{0r} + \beta_i(OrdinalESV)_r + \varepsilon_r \]  

(5.2)

Where, \( \beta_{0r} = \gamma_{00} + \mu_{0r} \)

\[(ESV)_r = \beta_{0r} + \beta_i(GradedESV)_r + \varepsilon_r \]  

(5.3)

Where, \( \beta_{0r} = \gamma_{00} + \mu_{0r} \)

As illustrated in Table 5.2, the model represented in equation 5.3, which uses the graded characteristics procedure to generate estimates of expectation states, explains 26.5% of the variation in respondents’ expectations for the targets. The model that uses the ordinal comparison hypothesis to generate estimates explains only 13.6% of the variation in expectations. Similarly, the BIC statistic suggests that the model with the graded characteristics estimates of expectations is the preferred model of the models presented in Table 5.2. Based on this information, I conclude that the graded characteristics estimates fit the data better than the ordinal comparison estimates.

<table>
<thead>
<tr>
<th></th>
<th>Residual</th>
<th>R-Squared</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Intercept (5.1)</td>
<td>85.17</td>
<td></td>
<td>39008.9</td>
</tr>
<tr>
<td>Ordinal ESV (5.2)</td>
<td>73.55</td>
<td>.136</td>
<td>38272.4</td>
</tr>
<tr>
<td>Graded ESV (5.3)</td>
<td>62.63</td>
<td>.265</td>
<td>37459.5</td>
</tr>
</tbody>
</table>

*Note:*** p < .001

5.2.2 Just Rewards Results

In terms of the formal just rewards models presented in chapter two, I evaluate the model presented in equation 2.12 (i.e., \( just \ rewarding = \bar{x} \times e^\gamma \)) because incomes are notoriously
right-skewed, indicating that the distribution of just rewards in this study should follow the same distribution (see Chapter 2). To evaluate the model, I begin by taking the natural logarithm of just rewards. Consequently, the just rewards model ‘unravels’ and I am able to directly estimate the effect associated with the reward expectation state values. Specifically I estimated four LMMs from the vignette data. The first is a baseline model that accounts for nesting (e.q., 5.4), the second is a formal model of just rewards with the reward expectation state values calculated using estimates drawn from the ordinal comparison hypothesis (e.q., 5.5)\(^8\), the third is a formal model of just rewards with the reward expectation state values calculated using estimates drawn from the graded characteristics procedure (e.q., 5.6), and the fourth model estimates the effects of the targets’ sex, occupation and education after accounting for nesting (e.q., 5.7).

\[
\ln(\text{Just Rewards})_{tr} = \beta_{0r} + \varepsilon_{tr} \quad (5.4)
\]

Where, \( \beta_{0r} = \gamma_{00} + \mu_{0r} \)

\[
\ln(\text{Just Rewards})_{tr} = \beta_{0r}(\bar{x}) + \beta_1(\text{OrdinalRESV}) + \varepsilon_{tr} \quad (5.5)
\]

Where, \( \beta_{0r} = \gamma_{00} + \mu_{0r} \)

\[
\ln(\text{Just Rewards})_{tr} = \beta_{0r}(\bar{x}) + \beta_1(\text{GradedRESV}) + \varepsilon_{tr} \quad (5.6)
\]

Where, \( \beta_{0r} = \gamma_{00} + \mu_{0r} \)

\[
\ln(\text{Just Rewards})_{tr} = \beta_{0r}(\bar{x}) + \beta_1(\text{Male}) + \beta_2(\text{Education}) + \beta_3(\text{Occupation}) + \varepsilon_{tr} \quad (5.7)
\]

Where, \( \beta_{0r} = \gamma_{00} + \mu_{0r} \)

\(^7\) See chapter six for a detailed interpretation of the linear mixed model coefficients for the formal models of just rewards.

\(^8\) The estimates were obtained using Balkwell’s (1991a) path function equations.
Table 5.3 presents a summary of the four LMMs that I estimated to evaluate the just rewards model. The random intercept only model was estimated as a point of comparison, to evaluate the amount of explained variance after accounting for the nesting in the data. The other models show the explained variance and Bayesian Information Criterion for equations 5.4-5.7. Two results warrant discussion. First, the formal model of just rewards that uses the graded characteristics procedure estimates of reward expectation state values fits the data better than the formal model that uses the ordinal comparison estimates of the reward expectation state values. Indeed the graded characteristics version of the formal model explains more than twice the variance of the ordinal comparison version of the model, and the BIC statistic is substantially lower (i.e., the difference is 595.9). Once again the results of the vignette study show that the graded characteristics procedure better represents the theoretical construct “expectation states” than the ordinal comparison hypothesis. Here, however, I am measuring reward expectation states rather than performance expectation states. This shows that the graded characteristics procedure is robust across operationalizations of expectations.

Second, the results indicate that the formal models of just rewards do substantially worse by the data than the model that simply estimates the effects of the reward-relevant characteristics (e.g., sex, education and occupation). In fact, the model that estimates the effects of the reward-relevant characteristics explains 43.9% of the variation in just rewards, while the formal models based on the ordinal comparison hypothesis and the graded characteristics procedure explains 9.1% and 19.3%, respectively. That is, the best fitting formal model explains less than half of the variation explained by the model that estimates the effects of the reward-relevant characteristics.
The relatively poor performance of the formal model of just rewards prompted me to do some investigating as to why the model did not perform better. Of the three characteristics that are treated as being reward-relevant (i.e., sex, education and occupational prestige), sex has been the recent subject of debate about whether or not it still functions as a status characteristic. Jasso and Webster (1999), for example, found no sex differences in reported just earnings for targets in a similar vignette-type study. Consequently, I re-estimated the reward expectation state values treating only education and occupational prestige as reward-relevant characteristics. I did so using both the ordinal comparison hypothesis and my graded characteristics procedure. Results from these models are reported in Table 5.4. The results suggest that removing sex from the calculation of the reward expectation state values increases global model fit and explained variance, but the explained variance and overall model fit are still worse than the model that estimates the effects of occupation and education. The model that estimates the effects of education and occupation, without sex, is also reported in Table 5.4. Results of this model indicates that the explained variance does not increase and the BIC decreases slightly (specifically it decreases as a function of the sample size since sex explained no variance and the parameter was removed). For the model based on the ordinal comparison hypothesis, the explained variance increases 6.7%, and the explained variance increases 4.7% for the model using the
graded characteristics procedure. Thus the model based on the graded characteristics procedure explains 55% as much variation as the empirical model (i.e., the model that estimates the effects of sex, education, and occupational prestige), and it does so with only one term - the reward expectation state value.

Table 5.4: Summary of LMMs predicting Target’s Logged Just Rewards- Without Sex

<table>
<thead>
<tr>
<th></th>
<th>Residual</th>
<th>R-Squared</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Intercept</td>
<td>.221</td>
<td></td>
<td>7226.6</td>
</tr>
<tr>
<td>Ordinal RESV without Sex</td>
<td>.186</td>
<td>.158</td>
<td>6365.2</td>
</tr>
<tr>
<td>Graded RESV without Sex</td>
<td>.168</td>
<td>.240</td>
<td>5861.7</td>
</tr>
<tr>
<td>Education and Occupation</td>
<td>.124</td>
<td>.439</td>
<td>4327.7</td>
</tr>
</tbody>
</table>

Note: ***p < .001

5.3 Discussion

The results of the vignette study have supported the logic of the graded characteristics estimation procedure. Using it to predict the expectation states scale leads to more explained variance and better model fit than traditional estimates based on the ordinal comparison hypothesis. This finding extends to the estimates of reward expectation state values that were used in the formal model of just rewards. Here too the estimates of expectation states – expectations of rewards, rather than performance – explain more variation and have a better fit to the data. This is consistent with the experimental results reported in the previous chapter, and constitutes further support for the use of the graded characteristics procedure.

Unfortunately, the results of the formal mathematical model of just rewards are not as clean and clear as I would have liked. The results do suggest that the models explain some of the processes giving rise to the data, but in both cases (equations 5.5 and 5.6) there is at least 80% of the variation in just rewards left to explain. In a post hoc analysis I found that
removing sex from the computation of the reward expectation state values leads to increased
model fit and explained variation. This finding is interesting and certainly suggests that
further research is required with respect to sex as a status characteristic. On the one hand,
this research, as well as research reported by Jasso and Webster (1999), suggests that sex may
no longer be a reward-relevant characteristic. However, sex still operates as a status
characteristic (Ridgeway 1997; Ridgeway 2011; Rashotte and Webster 2005), which indicates
a curious puzzle: why doesn’t sex operate as a reward-relevant characteristic if sex itself is
still a status characteristic? This inconsistency implies one of three interpretations: 1) that the
logic of reward expectations theory is incorrect, 2) that the student populations on which the
results are based are different in a systematic way, or 3) that research suggesting that sex is
still operating as a status characteristic is flawed. Clearly, further research is required to
delineate this inconsistency.

In summary, on the one hand, the vignette allowed me to estimate the effects of
three reward-relevant characteristics on perceptions of just rewards, showing that the graded
characteristics procedure indeed works when multiple graded status characteristics are
salient. On the other hand, the vignette study suffers from a limited sample (Arizona
undergraduates) and the outcomes refer to fictitious targets. The sample is problematic
because it is not representative of any population (including Arizona undergraduates). The
fact that the outcome refers to the participants’ evaluations of the targets’ incomes may have
been influenced by the anchor that was provided to them (Markovsky 1988), and anchors
have generally been shown to affect evaluational survey responses (Groves et al. 2004). To
overcome both of these limitations, in the next chapter I turn to the analysis of survey data
with representative samples from 13 countries.
6. ANALYSIS OF THE INTERNATIONAL SOCIAL JUSTICE PROJECT

The preceding two chapters evaluated the graded characteristics procedure in a highly controlled laboratory setting, and then applied the graded characteristics procedure to an expectation states scale and to the formal model of just rewards using a vignette-type survey, respectively. The former study has extremely high internal validity, as experiments are noted for, and the latter study also has relatively high internal validity. Here, I want to cast a wide net and apply the graded characteristics procedure and the formal model of just rewards as generally as possible. To do so, I use secondary data from 10,000 respondents in thirteen different countries. This survey, therefore, has very high external validity, with representative samples from the thirteen countries. Below I describe the additional assumptions required to apply the formal model of just rewards to survey respondents. I then describe my strategy for operationalizing and evaluating the just reward model. Next I describe the data and results. Finally I conclude with implications and a discussion of these results.

6.1 Assumptions

Moving beyond the initial conditions of reward expectations theory and applying the formal model of just rewards more broadly requires an additional assumption. Presently, the aim is to apply the just rewards model to individual responses about evaluations of incomes. In this case, the model no longer applies to a small group working on a unitary task, as is customary within the expectation states tradition (e.g., Hysom 2009; Webster and Rashotte 2011).

2010). Rather, I assume that the model applies to an individual actor who is comparing self to a generalized other.

Several studies have documented that status beliefs affect task performance and evaluations in individual task-oriented settings (e.g., Lovaglia et al. 1998; Steel and Aronson 1995). In these “individual evaluative settings,” individuals need only to compare their abilities and performances with others for status processes to operate (Correll 2004; Erickson 1998; Thebaud 2010). That is, they do not need to be interacting in a group on a collective task for status processes to operate. Given the effects of individual evaluative settings, it is reasonable to assume that status processes affect evaluations of incomes since perceptions of just rewards are fundamentally about comparison processes within task-oriented settings, such as places of employment.

For my purposes, individual evaluative settings are a natural extension of reward expectations theory since they have already been used to extend status characteristics theory to explain other individual phenomena (e.g., Correll 2001). A parallel argument can also be made using the self-evaluation hypothesis (Della Fave 1980). The self-evaluation hypothesis suggests that individuals internalize a sense of self-worth that is consistent with their position in society such that advantaged individuals have a superior sense of self and disadvantaged individuals have an inferior sense of self. Based on self-concepts, then, individuals come to view their relative advantage as the way things ‘ought’ to be. When individuals assess their incomes, they consider what is just for them to earn. If they think of themselves as ‘inferior,’ then they deserve relatively little, but if they think of themselves as ‘superior,’ then they deserve relatively more (Sutphin and Simpson 2009). To the extent that status beliefs factor
into perceptions of inferiority and superiority, the just rewards models presented in the previous chapter quantify these beliefs.

Assuming that a respondent evaluating his or her just rewards induces an individual evaluative setting allows equation 2.12 (i.e., $\text{just reward} = \bar{x} \times e^r$) to apply broadly. Specifically, I assume that the respondents compare themselves with a generalized other. As a simplifying assumption, I assume the generalized other for each country is average on several reward-relevant characteristics. This is a first approximation of the generalized other, and further research is required to validate this assumption. But for now, it enables me to evaluate equation 2.12 with respect to an average comparison other. I now turn to a description of the data and how I instantiate and evaluate the just rewards model.

6.2 Data

To evaluate the just rewards function provided in equation 2.12 in multiple cultural contexts, I fit the model to data from the International Social Justice Project (ISJP; Alwin, Klingel and Merilynn 1993). The ISJP sampled individuals 18 years or older in thirteen nations. Sampling strategies varied by nation but were designed to yield national probability samples. The response rates ranged from 51% to 91% with an average of 72% across all nations. The data file contains information on Bulgaria, Czechoslovakia, East and West Germany, Estonia, Great Britain, Hungary, Japan, the Netherlands, Poland, Russia, Slovenia, and the United States.

The ISJP selected nations on the grounds of comparing transitioning states to more stable, post-industrial states in terms of general senses of social justice (Alwin et al. 1993; Alwin, Gornev and Khakhulina 1995; Kluegel, Mason and Wegener 1995). The breakup of the Soviet Union in 1991 led to governments in transition for several Eastern Europe states.
Bulgaria, Czechoslovakia, East Germany, Estonia, Hungary, Poland, Slovenia and Russia were all sampled to investigate the differences in perceptions of social justice in transitioning states. At the other end of the spectrum, Britain, Japan, the Netherlands, the United States and West Germany were selected as the more stable post-industrial nations.

These data are ideal for my purposes for at least three reasons. First, they allow me to calculate reward expectation values based on several graded and ungraded status characteristics (see below). Second, the fact that there is information on thirteen nations allows me to test the theoretical process and robustness of the model in many cultural environments. Finally, the data contains several reward-relevant characteristics allowing me to estimate a baseline model on which to base comparisons.

The main outcome of interest asked respondents how much income they thought they deserved from their job or business. Consequently I restricted my sample to respondents who were in the labor force. The ISJP also has information on several status characteristics. I assume that race, education, sex, occupational prestige and age operate as status characteristics in these data. I also generated a variable representing the respondents’ number of children to include in the baseline model (see below), which is not a status characteristic, but is an attribute that shapes perceptions of just rewards based primarily on need.

6.3 Calculating Reward Expectation State Values

In terms of the status characteristics that contribute to the just rewards model, the ISJP contains information on several diffuse status characteristics that are relevant to reward
expectations. Specifically, five diffuse characteristics (race, sex, education, age and occupational prestige) are combined to calculate aggregate reward expectation state values. Race, age and sex are included because they are (typically) visible status markers that can safely be assumed to be salient in most social situations, and they are associated with referential beliefs about rewards. Ridgeway (2007: 322) notes, for example, that sex is a background identity that primes gender stereotypes simply as a result of categorization based on sex. Race and age also operate in a similar manner, evoking stereotypes simply on the basis of categorization (Cuddy, Norton and Fiske 2005; Fiske 2000; Ridgeway 1997). Race was included for countries in which the data were available (Britain, Bulgaria, Estonia, Russia, Slovenia, and the United States). Education and occupational prestige, as two of the most important human capital factors (Becker 1993), are also assumed to be a part of the just reward calculus. Information for the respondents’ occupational prestige was not collected in Estonia or Russia, but data from these countries were retained since they include all of the other status characteristics.

The inclusion of age, race, sex, education and occupational prestige into the calculation of aggregate reward expectation state values does not necessarily capture all of the status inputs in the formation of just rewards; rather, they are the only inputs which I can be reasonably sure will be salient for the respondents as they make their income evaluations, and for which the data file contains information. Other diffuse status characteristics, such as beauty (Webster and Driskell 1983), may factor into perceptions of just rewards depending on situational factors, but data limitations restrict the calculation of the reward expectation values to the above five diffuse status characteristics.
Based on the above described criteria for status characteristics, I calculated aggregate reward expectation state values in two ways. The first assumes the ordinal comparison hypothesis in calculating the values and the second uses the technique for estimating expectation state values with graded status characteristics. For both sets of estimates, the calculations were estimated within each country. Respondents’ aggregate reward expectation state values assuming the ordinal comparison hypothesis were estimated based on how many positively evaluated characteristics they had. Specifically, I used Balkwell’s (1991a) estimates for path functions in estimating the values. The Berger et al. (1977) and the Fisek et al. (1992) estimates produce substantively similar results; the selection of the Balkwell estimates simply reduces the number of models to present and describe. Respondents with three positively evaluated and two negatively evaluated states of status characteristics, for example, received reward expectation state values of .126 (see Fisek et al. 1992; Whitmeyer 2003; or, chapter two).

In applying the graded characteristics procedure, race and sex were left as dichotomous two-state status characteristics. The respondents’ values on education, age and occupational prestige were translated into \( z \)-scores. Then the \( z \)-scores were translated into areas under distributions using cumulative distribution functions. The mean for education, age and occupational prestige were also translated into points on the cumulative distributions. To calculate the weight, I integrated over the area between the respondents’ values and the mean for each variable. The weights were then included into equation 3.3 (i.e., Balkwell’s graded path function equation), and separate positive and negative subsets were

\[ \text{Equation 3.3} \]

---

3 More specifically the values for age and occupational prestige scores were translated into \( z \) scores based on the cumulative distribution function for the standard unit normal distribution. The values for education were translated into \( z \) scores based on the cumulative mass function or the discrete cumulative function since it was measured with seven ordered categories.
estimated (see equations 2.1 and 2.2). If the respondent’s value was above the mean for the characteristic, that characteristic was included in the positive subset, and if the respondent’s value was below the mean for the characteristic it was included in the negative subset. Finally the subsets were combined to obtain an estimate of aggregate reward expectation state values (e.g., equation 2.3). This procedure produces a distribution of reward expectation states values that varies continuously between negative one and positive one. Both the ungraded and graded estimates of the reward expectation state values were separately entered into equation 2.12 to produce two distributions of just rewards for each of the thirteen countries.

### 6.4 Analytic Strategy

To evaluate the just rewards model, I compare it to a model that estimates the effects of several reward-relevant characteristics; I refer to this model as the “empirical model” because the dependent variable is used to obtain the weights associated with the reward-relevant characteristics. The empirical model contains all of the status characteristics discussed above (i.e., age, education, occupational prestige, race and sex). The empirical model also contains an indicator for the respondent’s number of children, which assesses the respondent’s need for resources because the more children they have, the more resources they need to provide for their family (Jasso and Rossi 1977). In an analysis of just rewards using the ISJP, Jasso and Wegener (1999) argue that all reward-relevant effects may vary by sex. Consequently, I estimated the empirical model with all relevant sex-by-covariate

---

4 Along similar lines, I also included an indicator for being single. Preliminary analyses indicated that being single, and a single-by-sex interaction effect added nothing to the model- indeed the BIC statistic increased with these parameters in the model. Consequently, I removed these terms from the empirical model.
interactions. Empirical evidence was then used to determine the final model specification (see Appendix B).

The just rewards models based on equation 2.12 require modification before parameters can be estimated from the data. As with the vignette data, I take the natural logarithm of the just rewards, which ‘unravels’ the model, enabling me to estimate two parameters from the data. Equation 6.1 illustrates the effect of taking the natural logarithm of equation 2.12 and equation 6.2 shows the resulting linear mixed model that may be estimated with the ISJP data. In equation 6.2, \( \varepsilon \) refers to a vector of errors, \( i \) indexes individuals, and \( j \) indexes countries. For purposes of comparability, all models are estimated on the natural log of the just reward.

\[
\ln(\text{Just Reward})_{ij} = \ln(\bar{x}_j) + r_{ij} \tag{6.1}
\]

\[
\ln(\text{Just Reward})_{ij} = \beta_{0j} \ln(\bar{x}_j) + \beta_{1j} r_{ij} + \varepsilon_{ij} \tag{6.2}
\]

Where, \( \beta_{0j} = \gamma_{00} + \mu_{0j} \)

And, \( \beta_{1j} = \gamma_{10} + \mu_{1j} \)

The fixed-effect regression parameters from the empirical model have a straightforward interpretation: for a unit change in \( X \), there is a corresponding \( \beta \) change in logged just rewards. The regression parameters in equation 6.2 do not have the same interpretation because the distribution of just rewards was derived from the model developed in equation 2.12. Rather, the coefficients capture the extent to which the theoretically derived distribution represents the observed distribution of just rewards. The estimated intercept term in equation 6.2, when exponentiated, refers to a scaling parameter
that centers the derived distribution of just rewards about the center of the empirically observed distribution. Likewise, the estimated slope term, when exponentiated, is a systematic variability parameter that models the dispersion of the derived distribution of just rewards as a function of the dispersion of the observed distribution of just rewards.⁵

Empirically estimated weights are required in both the empirical model and the just rewards model of equation 2.12. In the empirical model, one must use the dependent variable vector to estimate regression coefficients that indicate the relationship of each variable to the outcome. In the just rewards model, one needs to know where each respondent stands with respect to the distribution of the independent variables in order to estimate the reward expectation state values. Then, one can estimate the extent to which the derived just rewards distribution adequately reflects the central tendency and systematic variability of the observed distribution of just rewards.

6.5 Results

Table 6.1 presents the sample sizes, means and standard deviations for the relevant variables for each country, as well as overall. The total sample size is 10,291 respondents. The largest contributor to the sample is Russia with 1,135 respondents and the smallest contributor is Hungary with 518 respondents. The average age of all of the respondents is 39.6. Education was measured on a seven point scale.⁶ Bulgaria has the highest average education and Slovenia has the lowest. The Netherlands has the highest average education and Slovenia has the lowest.

---

⁵ If the estimated intercept were .2 and the estimated slope were .5, for example, then this would indicate that the center of the distribution of just rewards is 1.22 (i.e., exp(.2)) times the mean income, and the spread of the distribution of just rewards is best represented by 1.65 (i.e., exp(.5)) times each respondent’s reward expectation state value.

⁶ The response categories for education were as follows: 1) Less than general, 2) General, 3) General and basic vocational training, 4) Medium vocational and medium formal, 5) Secondary formal, 6) Lower tertiary, and 7) Higher tertiary.
<table>
<thead>
<tr>
<th>Country</th>
<th>N</th>
<th>Age</th>
<th>Education¹</th>
<th>Occupational Prestige</th>
<th>Male²</th>
<th># of Children</th>
<th>Deserved Income</th>
<th>Observed Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>Britain</td>
<td>697</td>
<td>38.82</td>
<td>4.17</td>
<td>42.00</td>
<td>.51</td>
<td>.86</td>
<td>14,757</td>
<td>11,528</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(12.67)</td>
<td></td>
<td>(1.05)</td>
<td>(22,874)</td>
<td>(8,418)</td>
</tr>
<tr>
<td>Bulgaria</td>
<td>836</td>
<td>41.14</td>
<td>5.28</td>
<td>41.45</td>
<td>.53</td>
<td>1.06</td>
<td>5,674</td>
<td>643</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(11.11)</td>
<td></td>
<td>(.91)</td>
<td>(66,049)</td>
<td>(287)</td>
</tr>
<tr>
<td>Czech</td>
<td>706</td>
<td>38.90</td>
<td>4.19</td>
<td>41.20</td>
<td>.54</td>
<td>1.24</td>
<td>5,719</td>
<td>2,884</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(10.39)</td>
<td></td>
<td>(1.02)</td>
<td>(38,413)</td>
<td>(1,393)</td>
</tr>
<tr>
<td>East Germany</td>
<td>618</td>
<td>39.11</td>
<td>4.17</td>
<td>42.64</td>
<td>.51</td>
<td>.96</td>
<td>2,177</td>
<td>1,261</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(10.84)</td>
<td></td>
<td>(.96)</td>
<td>(1,123)</td>
<td>(647)</td>
</tr>
<tr>
<td>West Germany</td>
<td>892</td>
<td>39.94</td>
<td>4.20</td>
<td>44.65</td>
<td>.63</td>
<td>.72</td>
<td>3,385</td>
<td>2,713</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(11.40)</td>
<td></td>
<td>(.94)</td>
<td>(4,249)</td>
<td>(1,694)</td>
</tr>
<tr>
<td>Estonia</td>
<td>662</td>
<td>40.19</td>
<td>4.55</td>
<td>.48</td>
<td>1.06</td>
<td>28,877</td>
<td>8,223</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(12.49)</td>
<td></td>
<td>(1.07)</td>
<td>(61,144)</td>
<td>(5,714)</td>
</tr>
<tr>
<td>Hungary</td>
<td>518</td>
<td>38.97</td>
<td>4.14</td>
<td>37.83</td>
<td>.57</td>
<td>1.09</td>
<td>19,425</td>
<td>11,280</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(10.48)</td>
<td></td>
<td>(.97)</td>
<td>(12,812)</td>
<td>(7,251)</td>
</tr>
<tr>
<td>Japan</td>
<td>533</td>
<td>45.90</td>
<td>4.99</td>
<td>42.45</td>
<td>.57</td>
<td>1.40</td>
<td>532</td>
<td>412</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(13.72)</td>
<td></td>
<td>(1.09)</td>
<td>(589)</td>
<td>(328)</td>
</tr>
<tr>
<td>Netherlands</td>
<td>1,086</td>
<td>38.59</td>
<td>4.70</td>
<td>46.74</td>
<td>.65</td>
<td>1.20</td>
<td>2,842</td>
<td>2,448</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(9.48)</td>
<td></td>
<td>(1.20)</td>
<td>(1,197)</td>
<td>(1,168)</td>
</tr>
<tr>
<td>Poland</td>
<td>818</td>
<td>39.90</td>
<td>3.76</td>
<td>40.69</td>
<td>.55</td>
<td>1.32</td>
<td>2,768</td>
<td>1,514</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(11.59)</td>
<td></td>
<td>(1.20)</td>
<td>(1,260)</td>
<td>(1,207)</td>
</tr>
<tr>
<td>Russia</td>
<td>1,135</td>
<td>38.82</td>
<td>4.67</td>
<td>.52</td>
<td>1.01</td>
<td>1,174</td>
<td>564</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(11.50)</td>
<td></td>
<td>(.89)</td>
<td>(1,027)</td>
<td>(458)</td>
</tr>
<tr>
<td>Slovenia</td>
<td>849</td>
<td>37.33</td>
<td>3.46</td>
<td>39.09</td>
<td>.48</td>
<td>1.29</td>
<td>16,235</td>
<td>8,458</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(10.37)</td>
<td></td>
<td>(.98)</td>
<td>(62,852)</td>
<td>(5,862)</td>
</tr>
<tr>
<td>United States</td>
<td>941</td>
<td>39.32</td>
<td>4.91</td>
<td>46.54</td>
<td>.51</td>
<td>.87</td>
<td>34,564</td>
<td>28,426</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(11.84)</td>
<td></td>
<td>(1.12)</td>
<td>(33,091)</td>
<td>(32,050)</td>
</tr>
<tr>
<td>Overall</td>
<td>10,291</td>
<td>39.57</td>
<td>4.37</td>
<td>42.43</td>
<td>.54</td>
<td>1.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(11.46)</td>
<td></td>
<td>(1.06)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: ¹ Measured with seven ordered categories. ² Male = 1.
occupational prestige and Hungary has the lowest. The proportion male in the data varies from .48 in Slovenia to .65 in the Netherlands. The overall proportion male is .54 across the thirteen countries. The average number of children per respondent is just above one (1.07). The means and standard deviations for deserved incomes and actual incomes are also reported, but the metric varies across countries: both actual and deserved incomes were measured in varying units across the countries (i.e., dollars in the United States and pounds in Britain). To account for the varying metric between countries, deserved incomes were translated into $z$-scores before they were logged. Unsurprisingly reported incomes are consistently less than deserved incomes. Race is not reported in Table 6.1; Britain has 95% majority members, Bulgaria has 87% majority members, Estonia has 60% majority members, Russia has 93% majority members, Slovenia and the United States have 86% majority members.

Table 6.2 presents three linear mixed models predicting logged deserved incomes. The first model is the empirical baseline model. The specification of this model was somewhat theoretically derived and somewhat empirically derived (See Appendix B for the derivation of this model); I refer to it as the “empirical” model because all of the net effects are simply estimated weights, as opposed to the equity model where the coefficients represent scale and systematic variability. The “full” empirical model began with estimates of the main effects of education, occupational prestige, sex, race, age, and number of children. Following Jasso and Wegener’s (1999) analysis of the ISJP, I also included interaction effects
Table 6.2: Summaries of Linear Mixed Models Predicting Logged Deserved Incomes

<table>
<thead>
<tr>
<th>Factor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>.029***</td>
<td>(.006)</td>
<td></td>
</tr>
<tr>
<td>Occupational Prestige</td>
<td>.003***</td>
<td>(.001)</td>
<td></td>
</tr>
<tr>
<td>Female (=1)</td>
<td>-.106***</td>
<td>(.027)</td>
<td></td>
</tr>
<tr>
<td>Racial Majority Member</td>
<td>-.028**</td>
<td>(.009)</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>.002***</td>
<td>(.0004)</td>
<td></td>
</tr>
<tr>
<td>Number of Children</td>
<td>.027***</td>
<td>(.003)</td>
<td></td>
</tr>
<tr>
<td>Female x # of Children</td>
<td>-.029***</td>
<td>(.004)</td>
<td></td>
</tr>
<tr>
<td>Constant(^1)</td>
<td>.819***</td>
<td>(.048)</td>
<td>.129***</td>
</tr>
<tr>
<td>Ordinal RESV(^2)</td>
<td></td>
<td></td>
<td>.179***</td>
</tr>
<tr>
<td>Graded RESV(^2)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>-4062.3</td>
<td>-2817.6</td>
<td>-3632.6</td>
</tr>
<tr>
<td>R-Squared</td>
<td>.31</td>
<td>.17</td>
<td>.26</td>
</tr>
</tbody>
</table>

Note: \(^1\)For models 2 and 3, this parameter scales the logged mean in each country. \(^2\)Refers to Reward Expectation State Values. **p < .01; ***p < .001.
with sex and all of the other covariates. Jasso and Wegener (1999) do this in the context of OLS regression, which requires estimating 26 models (13 countries with separate estimates for males and females). I estimated only one model, with all of the sex-by-covariate interactions in a linear mixed model framework (e.g., Littell et al. 2006).

The full model had a random intercept and all of the slopes, including the interaction effects, had random effects. I then systematically removed the random effect of each of the sex-by-covariate interaction terms one at a time. Likelihood ratio chi-squared tests suggested that none of these random effects were warranted by the data. Next I conducted another set of likelihood ratio chi-squared tests to determine which random main effects to leave in the model. This set of tests indicated that age, sex, occupational prestige, and education have different effects on deserved incomes across the countries, and therefore warrant random effects. Lastly, I estimated a set of likelihood ratio chi-squared tests to determine if the sex-by-covariate interaction effects were warranted by the data. The results indicated that the only interaction effect that could be discerned from sampling variability was the sex-by-number-of-children interaction term; all of the other interaction terms were therefore dropped from the model. This model, therefore, uses 68 degrees of freedom in predicting deserved incomes (i.e., 13 intercepts, 13 effects of age, education, occupational prestige, and sex, plus fixed effects for number of children, race and sex-by-number-of-children). A summary of this model (Model 1) is reported in Table 6.2. Model 1 does reasonably well by the data, explaining 31% of the variance in logged deserved incomes. Indeed all of the main effects, as well as the sex-by-number-of-children interaction effect, are significant. One counterintuitive finding from model 1 is that being a racial majority member has a negative effect on deserved incomes (see the discussion below).

Jasso and Wegener (1999) do this in the context of OLS regression, which requires estimating 26 models (13 countries with separate estimates for males and females). I estimated only one model, with all of the sex-by-covariate interactions in a linear mixed model framework (e.g., Littell et al. 2006).
Model 2 in Table 6.2 presents the results of the just rewards model from equation 6.2 with the reward expectation state values based on the ordinal comparison hypothesis. This model has random intercepts for the logged means within each country and random slopes for the expectation state values. Likelihood ratio chi-squared tests indicated that the intercept and slope terms should have random effects (See Appendix B). This 26 parameter model (i.e., 13 intercepts and 13 slopes) explains 17% of the variance in logged incomes. Exponentiating the fixed-effect intercept term yields 1.14 (i.e., exp(.129)), which indicates that, on average, respondents report deserving to earn 1.14 times the mean income in their country. Exponentiating the fixed-effect slope term yields 1.20, which indicates that, on average, the reward expectation state values need to be multiplied by 1.2 to best represent the systematic variability in the distribution of just rewards.

Model 3 in Table 6.2 contains reward expectation state values that use the graded status characteristics procedure. This model also has random intercepts and random slopes. This 26 parameter model explains 26% of the variation in just rewards, which is almost as much explained variation as the empirical model. It is no coincidence that the fixed-effect intercept is the same as in model 2 (within rounding error); both intercept terms simply scale the theoretically derived distributions to have the same central tendency as the observed distribution of just rewards. More meaningfully, the effect size for the graded reward expectation state values is larger than the effect size for the ordinal expectation state values. The effect size, coupled with a larger explained variance, indicates that model 3 better reflects the data generating mechanism of just rewards than model 2.

Although the coefficients for the logged means are technically slopes rather than intercepts, I refer to them as intercepts because the logged mean is a constant within each country; the coefficient simply scales the logged mean in each country.
Between the two formal models of just rewards (model 2 and model 3) the model with graded reward expectation state values is clearly preferred. Comparing across all of the statistical models of just rewards, the best-fitting model appears to be the empirical model: it explains the most variation and has the smallest BIC statistic. However, this model uses 68 degrees of freedom to explain 31% of the variation in just rewards. Model 3 uses only 26 degrees of freedom, which is 38% of the degrees of freedom used by the empirical model (i.e., 26/68). At the same time, model 3 explains 26% of the variation in just rewards, which is 84% of the variation explained by the empirical model. That is, on only 38% of the degrees of freedom, Model 3 explains 84% of the variation explained by the empirical model. Moreover, the just rewards model that uses the graded characteristics procedure can produce predictions of just rewards without reference to the dependent variable, which is a desirable property to the extent that prediction is a goal of science.

6.6 Discussion

In general, the results from all three empirical investigations support both the graded characteristics technique and the just rewards model that is based on a norm of equity. The results from the ISJP are powerful, especially in light of the assumptions. In particular, the assumption that participants are comparing themselves to a generalized other that is average on reward relevant characteristics is a relatively strong assumption to make. The logic of this assumption is similar to Della Fave’s (1980) argument about the legitimation of inequality. He argues that the structure of the larger society, including the dimensions on which the society is stratified, “becomes incorporated within the inner consciousness of the individual”
Della Fave asserts that through repeated interactions, people develop a conception of self that is consistent with how they think others view them.

Although Della Fave (1980) cites some status characteristics research, he draws primarily from the classic theorists that undergird SCT (e.g., Mead 1934). In this sense Della Fave’s argument is looser than that of SCT in two senses: (1) the logic is looser in the sense that he does not develop logically related propositions, and relatedly (2) he is describing an “armchair” process whereby large-scale inequality is maintained on a daily basis. Both SCT and Della Fave assert that inequality is perpetuated through a set of consensual processes. For SCT, consensual status beliefs lead to relatively low status actors being less influential in collective task groups; in turn this perpetuates status beliefs throughout the broader culture (Ridgeway 1991). For Della Fave, over repeated interactions that yield a sense of powerlessness, individuals internalize that powerlessness and come to endorse the very system that disadvantages them.

The analysis of the ISJP is in the same vein as Della Fave’s argument. The respondents were not in a task group, a scope restriction of Reward Expectations Theory (RET; Berger et al. 1998a), but I was able to use the formalisms of RET to quantify the internalization process that Della Fave describes. To the extent that race, sex, education, occupation, and age are dimensions of stratification, as research suggests that they are, then the reward expectation state values capture the extent to which the respondents have developed senses of self consistent with their location in some broader social space.

It is also interesting to think about the fact that the formal model of just rewards actually explains more with the ISJP than with the controlled vignette study from the previous chapter. The formal model explains 26% of the variation in just rewards when
using the ISJP data, but only 19.3% of the variation when using the vignette data. There are several potential explanations for this finding. First, the ISJP was fielded in 1991 and 1992, while the vignette survey was fielded in 2010. Given that status beliefs come from the broader cultural environment, it may be the case that shifting cultural meanings of the reward-relevant characteristics produced this difference. Sex, for example, is significantly related to just rewards in the ISJP data, but not in the vignette data. This may reflect a broader trend which suggests that younger populations, like the vignette sample, do not view sex as a status characteristic, while the population writ large does still view sex as a status characteristic. A related point is that the ISJP sample is older and more experienced than the college student sample. Another possible reason for the difference in the performance of the formal model of just rewards has to do with self versus other evaluations. In the ISJP, respondents were evaluating their own just rewards. In the vignette study, respondents were evaluating the just rewards of fictitious others. Respondents may weight achieved attributes more when they actually have to work for them (as in the ISJP sample) than when they are simply assigned in a questionnaire (as in the vignette study). Contrary to this interpretation, however, sex is related to just rewards in the ISJP sample, but not in the vignette sample, which indicates that the ascribed versus achieved status distinction may not be useful in determining the relative performance of the formal model of just rewards. A final point to consider is the number of characteristics that are varying. There were five status characteristics varying in the ISJP, but only three in the vignette study. This discussion implies that there are potentially too many differences between the two studies to conclusively determine what is driving the difference in the relative performance of the formal model of just rewards.
7. CONCLUSION

This research set out to develop an *a priori* means to estimate just rewards in the context of social psychological theories of distributive justice. Previously, researchers either had to assume an equal share as the just share because they lacked the data or tools to estimate just shares based on equity processes, or researchers used regression-type analyses of the factors that are significantly related to self-reported just rewards (e.g., the baseline model reported in chapter six). As argued in chapter two, both of these means of determining just rewards have flaws. The former uses an incorrect normative assumption (i.e., equality) because equity processes are known to operate in most settings (Hegtvedt and Markovsky 1995), while the latter is necessarily post hoc and estimates are not transferable from one study to the next.

Fortunately, reward expectations theory (Berger et al. 1998a) provided a valuable foundation for the development of a formal mathematical model of just rewards. Indeed, RET is a quantified theory that may generate reward expectation state values, which are argued to be a direct continuous function of reward allocative behaviors. For my purposes, reward expectation state values are a quantification of just rewards. The only thing that was left for me to do was to find a function that defined how the reward expectation state values are transferrable to just rewards. Chapter two developed two such functions.

However, one simplifying assumption of the expectation states theories hindered my ability to make precise point estimates of just rewards. Specifically, the “ordinal comparison hypothesis” (Balkwell 2001) is a simplifying assumption that treats all status differences as two-state differences of relatively high and relatively low. Expectation state theorists are
surprised at how far this assumption has carried them (Hamit Fisek, personal correspondence), but for my purposes, the assumption simply would not suffice. In the application to the International Social Justice Project, for example, there were five reward-relevant characteristics. Under the ordinal comparison hypothesis the reward expectation state values could only take on six possible values (i.e., high on all five, high on four, high on three, high on two, high on one, or low on all five); indeed there is only one more value of reward expectation states than there are salient reward-relevant characteristics. When applying this to the International Social Justice Project, the resulting distribution of just rewards could not be argued to reflect the actual data, which has a much smoother, continuous distribution.

In the interest of being able to generate a continuous distribution of just rewards, I therefore generalized the mathematics of the expectation state theories to include graded status characteristics. This was developed in chapter three, where I demonstrate how to maintain the conception of relevance, which dictates the strength of a salient status-valued element, and also include the magnitude of difference on a graded status characteristic. The resulting set of equations is completely general in two senses. First, any number of graded and ungraded status characteristics may be combined to generate aggregate estimates of reward or performance expectations. Second, it does not matter what distribution the graded characteristic follows. Continuously distributed status characteristics, such as intelligence, GPA or education, may be modeled with the normal distribution or even the gamma distribution. Ordinally distributed status characteristics may be modeled using the discrete cumulative function, also known as the cumulative mass function.
Ironically, the graded characteristics procedure developed herein is arguably a more important development for sociological social psychology and the study of group processes than the formal mathematical model of just rewards, and it was developed as a by-product of the model of just rewards. I say this because status characteristics theory, and even power and prestige theory (another expectation state theory—see Fisek, Berger and Norman 2005), are more influential theories within social psychology, and the graded characteristics procedure is applicable to all of the expectation state theories. To be sure, I only know of one empirical test of reward expectations theory (Hysom 2009), while SCT and power and prestige theory have been tested numerous times (for SCT, see Berger and Webster 2006 for a review; for power and prestige theory, see Webster and Rashotte 2010 for a recent example).

The first empirical investigation of this dissertation was the experimental investigation of the graded characteristics procedure. This experiment showed that estimates of performance expectations that are drawn from the graded characteristics procedure are a better representation of “expectation states” than are the estimates of performance expectations that are drawn from the conventional ordinal hypothesis mathematics of the theory. Indeed the graded version of the expectation states values completely mediated the relationship between the experimental manipulation and the subjects’ proportion of stay responses, while the ordinal comparison version of the expectation state values does not mediate this relationship. Further, the evidence showed that the graded characteristics estimates of expectations explain more variance in influence behaviors and fit better than the conventional estimates.
After experimentally validating the graded characteristics procedure, I used it to predict respondents’ expectations for fictitious targets using vignette-type data that I collected. In this case, the targets varied on three characteristics (i.e., sex, education, and occupational prestige), which enabled me to discern if the graded characteristics procedure worked in conjunction with status characteristics theory’s assumption of organized subsets (e.g., Berger et al. 1992). It is possible that people can process the magnitude of difference on one characteristic, but if more than one characteristic is differentiating them, this may be too much to process. Contrary to this concern, the results from the vignette study showed that estimates of the participants’ expectations for the targets that were based on the graded characteristics procedure again explain more variance and fit the data better than the conventional estimates.

I also used the vignette data for the first empirical evaluation of the formal mathematical model of just rewards. Specifically, participants determined a just reward for each target, and I was able to estimate the just reward based on their salient attributes. On the one hand, this was a success because the formal model explained about 20% of the variance in just rewards without having to estimate the weights associated with the reward relevant characteristics. On the other hand, the success was limited because the formal model explained less than half of the variance explained by a model that did estimate the effects of the reward-relevant characteristics. This result prompted some sensitivity analyses revealing that sex did not operate as a reward-relevant characteristic in these undergraduate student data. Removing sex from the computations of the reward expectation state values did increase the overall fit of the models and the explained variance, but it is still troubling
that the formal model only explained about three-fifths of the variation as the baseline model.

The previous two empirical investigations – both of which are variants of experiments – have quite high internal validity, meaning that alternative or competing explanations for differences in varied factors are minimized. Experiments are ideal for testing theory, or models that are developed from theory, as in the present case. However, evaluating the extent to which that theory or theoretical model explains behaviors or attitudes in natural settings requires methods with more external validity. In this connection, the final empirical investigation applied both the formal model of just rewards and the graded characteristics procedure to secondary data from thirteen different countries. Specifically, I used data from the International Social Justice Project (ISJP), which after selecting out cases for various reasons (i.e., not being in the labor force, etc.) had information on over 10,000 respondents. That is, the ISJP enabled me to cast a wide net and achieve a high level of external validity.

Applying reward expectations theory to data from a representative random sample is tricky. On the one hand, reward expectations theory is a small group theory that may explain perceptions of just rewards and subsequent reward allocative behaviors in small groups. On the other hand, reward expectations theory explicitly recognizes that perceptions of just rewards are shaped by referential structures, which by definition do not come from the local situation of action. Making use of this latter point, I made the assumption that survey respondents were comparing themselves with a generalized other that is average on the salient reward-relevant characteristics. Consistent with this assumption, Berger et al. (1998a: 126) point out that referential structures are generalized beliefs about generalized others.
This assumption enabled me to estimate reward expectation state values, and consequently point estimates of just rewards, for the over 10,000 respondents in the ISJP.

Results from the analysis of the ISJP were parallel to, but better than, the results from the vignette data. Again, the estimates of reward expectation state values that were based on the graded characteristics procedure explained more variation and fit the data better than the estimates based on the ordinal comparison hypothesis. With respect to the formal model of just rewards, though, the results from the ISJP were substantially better than the results from the vignette study. Here there were five status characteristics varying, while there were only three in the vignette data. Still, the formal models explained proportionately more variation with the ISJP than with the vignette data. Indeed the formal model with estimates of reward expectation state values based on the ordinal comparison hypothesis explains 55% as much variation as the baseline model (i.e., the model that estimates the effects of the five reward-relevant characteristics), while the formal model with estimates of reward expectation state values based on my graded characteristics procedure explains 84% as much variation as the baseline model.

The results from the ISJP, then, are quite impressive. In thirteen different cultural contexts, simply based on the logic of reward expectations theory, the formal model of just rewards predicts just rewards with almost as much accuracy as a linear mixed model that estimates the effects of age, education, occupational prestige, sex and race. This is done only knowing the mean income in each country, and where the respondents stand on the distribution of the independent variable. That is, there is no need to determine the effect size or coefficient for the independent variables; rather, the logic and mathematics of reward
expectations theory determines the weights through the notion of the relevance of the characteristics to the valued goal objects (i.e., income).

A few results from the empirical investigations warrant follow up research. For example, systematic research on the role of sex as a status characteristic is warranted (see also Ridgeway 2011). Ridgeway and colleagues (2011; Ridgeway and Smith-Lovin 1999) have argued that sex persists as a dimension of stratification, citing unequal pay, and other less objective evidence (e.g., influence behaviors). At the same time, research by Jasso and Webster (1999) and the results of the vignette study that was reported herein suggests that sex is not a reward-relevant characteristic. The results from the vignette studies may driven by cohort effects (i.e., college student populations are, on average, younger than the population at large) or there may be slippage in the population between just rewards for females and actual rewards for females (i.e., despite thinking that women should earn as much as men, employers still do not actually pay women as much). Another possibility is that respondents do not treat sex as reward-relevant because they are being asked about fictitious individuals (i.e., a sort of social desirability bias in the responses). When respondents evaluate the fairness of their own incomes, sex is significantly related to just rewards (see Jasso and Wegener 1999; and chapter 6). This anomaly leads me to believe that the apparent paradox is driven by the younger samples in the vignette studies, but further research is required to evaluate this conjecture.

Further research is also warranted on the role of status-organizing processes in countries other the US and Turkey. The results from the ISJP suggest that the factors that were taken to be reward-relevant characteristics (i.e., race, sex, age, education and occupational prestige) are fairly robust across the thirteen different countries, but the
statistical models invariably suggested that the effects should be random, which indicates that the effects are different across the countries. Further comparative and in-depth study is required to understand the cultural contexts giving rise the observed differences in the effects of the reward-relevant characteristics. A related point is that the formal model of just rewards assumes homogeneous equity effects across all of the thirteen countries. This, again, is perhaps an unrealistic assumption. The countries in the ISJP were purposively selected to compare post-communist countries to post-industrial countries. Preference for equity over equality as a distribution rule is likely affected by the cultural heritage of this legacy. In this vein, Fisek and Hysom (2008) developed a framework for estimating what they call “equity sensitivity,” which captures the extent to which people use an equity distribution rule as opposed to an equality distribution rule. Future research on comparative justice processes can easily generalize Fisek and Hysom’s procedure to the country-level (rather than the individual-level) in order to determine the effect of a country’s legacy as either post-communist or post-industrial.

Related to the graded status characteristics procedure, there are also a few points that warrant further research. First, research should be done on the sensitivity of the procedure to the assumed functional form of the graded status characteristic. In the analyses reported herein, only the standard unit normal distribution and the cumulative mass function were used. Based on “arm-chair” theorizing about how low status people process status information, I decided that the Gumbel distribution would be a good approximation of how status is processed, and used this distribution to fit the experimental data. Results from this exercise suggest that the model fits the data, while none of the other models reported herein accomplished this. This exercise suggests two things: 1) the graded characteristics procedure
is sensitive to which functional form is being used, and 2) status may be processed
differently than it is presented, and this process effect likely varies by relative status. Both of
these points warrant further attention, and the latter of them is currently being researched.

A second point pertaining to the graded characteristics procedure is that it opens up
Status Characteristics Theory to more adequately deal with multiple actor situations. Under
the ordinal comparison hypothesis, dyadically it is possible to determine which of two actors
is relatively high in status and which is low. When three actors are interacting, and hence
three states of a quantitative characteristic may be salient, it is less straightforward to
determine expectation state values and expectation standings among the group members.
However, having the procedures to determine the magnitude of status difference between
each pair of interactants will enable predictions that account for the distribution of status in
the entire group, rather than on any two individuals from the group. Further theorizing and
research will be required to determine the mechanics of such predictions, but the graded
characteristics procedure is a significant first step in this direction.

Moving forward, it is clear that the effects of reward-relevant characteristics vary
across populations, regions and cultures. However, presently there is no way to weight a
status characteristic in the calculation of reward expectation state values. This simplifying
assumption will need to be improved upon for the formal model to perform better
empirically. Also, it is a consistent finding that perceptions of just rewards are greater than
actual rewards, and this finding also needs to be incorporated into the formal model of just
rewards. Despite these shortcomings, though, the formal model of just rewards presented in
this dissertation is a good first approximation, and the graded characteristics procedure
developed herein also appears to show much promise.
APPENDIX A: THE WITHIN-SUBJECTS FACTORIAL DESIGN SURVEY

The main portion of the survey instrument was provided by Guillermina Jasso. An early introduction to factorial surveys is found in Rossi (1979), a good technical description of the factorial survey methodology may be found in Jasso (2006) and results based on a variant of this particular survey may be found in Jasso (2007). This vignette survey manipulates the education, sex and occupational prestige of fictitious targets, or persons that are abstractly described based on their attributes. The educational sample space of the vignette is seven to sixteen years of schooling. The occupational prestige sample space of the vignette is all occupations found in the Bose and Rossi (1983: 327-8) occupational prestige scale (there are 110 occupations listed in Bose and Rossi). The sex sample space of the vignette is males and females. Thus the total sample space for the vignette is 2,220 combinations of education, occupation and sex, minus the impossible combinations such as a physician with only eight years of schooling, etc. Based on this total sample space, Jasso (e.g., 2007) generated a random sample of twenty targets. I then added two targets to Jasso’s original twenty – a male and a female physician. As noted in chapter five, I added these targets to account for the low probability of randomly drawing a high occupational prestige from the vignette sample space and simultaneously randomly drawing a high enough number of years of schooling to warrant that occupation. Table A1.1 presents the sex, years of schooling, occupation and the occupational prestige score for each of the 22 targets found in the survey instrument. The actual survey that was administered follows table A1.1. The pen-and-paper version of the survey was exactly as below, while the online version had highlighted text boxes where the respondents entered their answers (see chapter five). The
online version was secured so that the only place the participants could edit the document was where they provided their responses.

Table A1.1: Summary of Targets’ Sex, Years of Schooling, Occupations and Occupational Prestige Scores.

<table>
<thead>
<tr>
<th>Target</th>
<th>Sex</th>
<th>Years of Schooling</th>
<th>Occupation</th>
<th>Occupational Prestige Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Female</td>
<td>12</td>
<td>Office Secretary</td>
<td>51.3</td>
</tr>
<tr>
<td>2</td>
<td>Female</td>
<td>16</td>
<td>Registered Nurse</td>
<td>56.4</td>
</tr>
<tr>
<td>3</td>
<td>Female</td>
<td>14</td>
<td>Shoe Repairperson</td>
<td>26</td>
</tr>
<tr>
<td>4</td>
<td>Female</td>
<td>20</td>
<td>Physician</td>
<td>95.8</td>
</tr>
<tr>
<td>5</td>
<td>Female</td>
<td>16</td>
<td>Registered Nurse</td>
<td>56.4</td>
</tr>
<tr>
<td>6</td>
<td>Female</td>
<td>12</td>
<td>Box Packer</td>
<td>15.1</td>
</tr>
<tr>
<td>7</td>
<td>Male</td>
<td>12</td>
<td>Assembly Line Worker</td>
<td>28.3</td>
</tr>
<tr>
<td>8</td>
<td>Male</td>
<td>15</td>
<td>Tool Machinist</td>
<td>48.4</td>
</tr>
<tr>
<td>9</td>
<td>Male</td>
<td>12</td>
<td>Warehouse Supervisor</td>
<td>54.2</td>
</tr>
<tr>
<td>10</td>
<td>Male</td>
<td>16</td>
<td>Carpenter</td>
<td>53.5</td>
</tr>
<tr>
<td>11</td>
<td>Male</td>
<td>8</td>
<td>Insurance Agent</td>
<td>62.5</td>
</tr>
<tr>
<td>12</td>
<td>Male</td>
<td>7</td>
<td>Phone Operator Supervisor</td>
<td>60.3</td>
</tr>
<tr>
<td>13</td>
<td>Male</td>
<td>13</td>
<td>Manager of a Supermarket</td>
<td>57.1</td>
</tr>
<tr>
<td>14</td>
<td>Male</td>
<td>16</td>
<td>Truck Driver</td>
<td>40.1</td>
</tr>
<tr>
<td>15</td>
<td>Male</td>
<td>15</td>
<td>Typist</td>
<td>44.9</td>
</tr>
<tr>
<td>16</td>
<td>Male</td>
<td>20</td>
<td>Physician</td>
<td>95.8</td>
</tr>
<tr>
<td>17</td>
<td>Male</td>
<td>16</td>
<td>Hospital Aide</td>
<td>29.5</td>
</tr>
<tr>
<td>18</td>
<td>Female</td>
<td>14</td>
<td>Manager of a Supermarket</td>
<td>57.1</td>
</tr>
<tr>
<td>19</td>
<td>Female</td>
<td>10</td>
<td>Coal Miner</td>
<td>24</td>
</tr>
<tr>
<td>20</td>
<td>Female</td>
<td>7</td>
<td>File Clerk</td>
<td>34</td>
</tr>
<tr>
<td>21</td>
<td>Female</td>
<td>15</td>
<td>Metal Container Maker</td>
<td>31.1</td>
</tr>
<tr>
<td>22</td>
<td>Female</td>
<td>14</td>
<td>Metal Container Maker</td>
<td>31.1</td>
</tr>
</tbody>
</table>

*Note: Prestige scores come from Bose and Rossi (1983: 327-8).*
SURVEY OF JUDGMENTS

To the Respondent:

People and their jobs differ in a lot of ways. Our study asks you to evaluate descriptions of different kinds of people and jobs. All the persons described work full-time; and all have worked continuously and full-time since finishing school. For each person we ask you to evaluate, we want to know what you think about these people in general. Then, after you report your general evaluations, we assign each person a randomly assigned hypothetical earnings amount. We would like to know what you think about whether each person is fairly or unfairly paid, and, if you think that a person is unfairly paid, whether you think the person 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 fairness. Let negative numbers represent degrees of underreward or being paid too little, and positive numbers represent degrees of overreward or being paid too much. The greater the degree of underpayment, the larger the absolute value of the negative number you choose (for example, if two persons receive ratings of -68 and -23, the person receiving the -68 is viewed as more underpaid than the person receiving the -23). Similarly, the greater the degree of overpayment, the larger the positive number (for example, a person receiving a rating of +90 is viewed as more overpaid than a person receiving a rating of +35). 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:

-100 ------------------------------- 0 ------------------------------- +100
Under-Reward Fair Over-Reward

When you read each description of a person, please write the number that best matches your judgment about the fairness or unfairness of that person's earnings. We only ask that you use values between -100 and +100. If you prefer to use a smaller region, that is OK too. Of course, you may choose any real number (for example, decimals and fractions as well as whole numbers) to represent a judgment.

Lastly, we will ask you how much you think the hypothetical person should make per year. Keep in mind, in the United States, the average American is about 35 years old, completes about 12 years of schooling, and earns about $35,000 per year. Of course, this is just an average and includes all sorts of people who do all sorts of work. You may base your decision for how much they deserve on whatever criteria you wish.

Your responses are completely confidential.

Thank you very much for your participation.
you will see a description of a person and some of their characteristics. This will look something like the following:

“A MAN 35 YEARS OLD,
WHO COMPLETED 12 YEARS OF SCHOOLING,
GRADUATING FROM HIGH SCHOOL.
HE IS A SALESPERSON.”

We ask that you use this information to evaluate the person described in quotes. YOU DO NOT NEED TO FILL IN THE HIGHLIGHTED TEXT BOXES ON THIS PAGE. We will ask a series of questions that will look like this:

“How much do you think that you would like this person?

Very Little 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Much

To answer the question, just enter the number that corresponds to your answer choice into the highlighted text box. For example, if you think you would like this person very much, enter a ‘9’ into the text box. If you think you would not like this person, but that you would like them more than “Very Little” you could enter a ‘2’ or a ‘3’ into the highlighted text box. If you think you would be indifferent towards this person, you could enter a ‘5’ into the highlighted text box.

After a series of questions like the one detailed above, we will provide you with an annual income for this person, and then ask for your justice evaluation of that income. For example,

“This person earns $35,000 per year. What is your rating?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward                                    Fair                                    Over-Reward

You should write in a value, as detailed on the previous page, in the highlighted text box. Recall, negative numbers indicate that you think the person is underrewarded and positive numbers indicate that you think the person is overrewarded. Lastly, we will ask you how much you think the person should earn per year. This question will look like this:

“How much should this person earn?

Again, just enter your answer into the highlighted text box.

We will ask these questions about a series of individuals.
A WOMAN 35 YEARS OLD, WHO COMPLETED 12 YEARS OF SCHOOLING, GRADUATING FROM HIGH SCHOOL. SHE IS AN OFFICE SECRETARY.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARS $25,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A WOMAN 35 YEARS OLD,
WHO COMPLETED 16 YEARS OF SCHOOLING,
GRADUATING FROM COLLEGE WITH A B.A. DEGREE.
SHE IS A REGISTERED NURSE.

How well do you expect this person to do in situations in general?

Very Poorly  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Much More Worthy

Is this person superior or inferior to others?

Inferior  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Superior

Is this person better or worse than others?

Worse  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Better

How able is this person to do things?

Unable  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Able

THIS PERSON EARS $25,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward                                     Fair                                     Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A woman 35 years old, who completed 14 years of schooling, finishing 2 years of college. She is a shoe repairperson.

How well do you expect this person to do in situations in general?
   Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?
   Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?
   Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?
   Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?
   Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?
   Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?
   Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

This person earns $30,000 per year. What is your rating?
   -100 ------------------------------- 0 ------------------------------- +100
   Under-Reward Fair Over-Reward

How much should this person earn?
A WOMAN 35 YEARS OLD, 
WHO COMPLETED 20 YEARS OF SCHOOLING, 
GRADUATING FROM COLLEGE WITH AN M.D. DEGREE. 
SHE IS A PHYSICIAN.

How well do you expect this person to do in situations in general?  

Very Poorly 1 2 3 4 5 6 7 8 9 Very Well

In terms of things that count in this world, how does this person compare to others? 

Much Worse 1 2 3 4 5 6 7 8 9 Much Better

How intelligent do you think this person is compared to others? 

Much Less Intelligent 1 2 3 4 5 6 7 8 9 Much More Intelligent

How worthy is this person, compared to others? 

Much Less Worthy 1 2 3 4 5 6 7 8 9 Much More Worthy

Is this person superior or inferior to others? 

Inferior 1 2 3 4 5 6 7 8 9 Superior

Is this person better or worse than others? 

Worse 1 2 3 4 5 6 7 8 9 Better

How able is this person to do things? 

Unable 1 2 3 4 5 6 7 8 9 Able

THIS PERSON EARS $70,000 PER YEAR. WHAT IS YOUR RATING?  

-100 --------------------------------------------------------------- 0 --------------------------------------------------------------- +100 

Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A WOMAN 35 YEARS OLD,  
WHO COMPLETED 16 YEARS OF SCHOOLING,  
GRADUATING FROM COLLEGE WITH A B.A. DEGREE.  
SHE IS A REGISTERED NURSE.

How well do you expect this person to do in situations in general?  
**Very Poorly** 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?  
**Much Worse** 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?  
**Much Less Intelligent** 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?  
**Much Less Worthy** 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?  
**Inferior** 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?  
**Worse** 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?  
**Unable** 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

**THIS PERSON EARS $70,000 PER YEAR. WHAT IS YOUR RATING?**  
-100 ----------------------------------------- 0 ----------------------------------------- +100  
Under-Reward Fair Over-Reward

**HOW MUCH SHOULD THIS PERSON EARN?**
A WOMAN 35 YEARS OLD, WHO COMPLETED 12 YEARS OF SCHOOL, GRADUATING FROM HIGH SCHOOL. SHE IS A BOX PACKER

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARN $15,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD,
WHO COMPLETED 12 YEARS OF SCHOOLING,
GRADUATING FROM HIGH SCHOOL.
HE IS AN ASSEMBLY LINE WORKER.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARS $35,000 PER YEAR. WHAT IS YOUR RATING?

-100 ---------------------- 0 ---------------------- +100
Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD,
WHO COMPLETED 15 YEARS OF SCHOOL,
FINISHING 3 YEARS OF COLLEGE.
HE IS A TOOL MACHINIST.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARNS $35,000 PER YEAR. WHAT IS YOUR RATING?

-100 ------------------------------- 0 ------------------------------- +100
Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD,
WHO COMPLETED 12 YEARS OF SCHOOL,
GRADUATING FROM HIGH SCHOOL.
HE IS A WAREHOUSE SUPERVISOR.

How well do you expect this person to do in situations in general?

Very Poorly 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Superior

Is this person better or worse than others?

Worse 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Better

How able is this person to do things?

Unable 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Able

THIS PERSON EARS $25,000 PER YEAR. WHAT IS YOUR RATING?

-100 ------------------------------- 0 ------------------------------- +100
Under-Reward                         Fair                         Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD,  
WHO COMPLETED 16 YEARS OF SCHOOL,  
GRADUATING FROM COLLEGE WITH A B.A. DEGREE.  
HE IS A CARPENTER.

How well do you expect this person to do in situations in general?  

Very Poorly  1  ---  2  ---  3  ---  4  ---  5  ---  6  ---  7  ---  8  ---  9  Very Well

In terms of things that count in this world, how does this person compare to others?  

Much Worse  1  ---  2  ---  3  ---  4  ---  5  ---  6  ---  7  ---  8  ---  9  Much Better

How intelligent do you think this person is compared to others?  

Much Less Intelligent  1  ---  2  ---  3  ---  4  ---  5  ---  6  ---  7  ---  8  ---  9  Much More Intelligent

How worthy is this person, compared to others?  

Much Less Worthy  1  ---  2  ---  3  ---  4  ---  5  ---  6  ---  7  ---  8  ---  9  Much More Worthy

Is this person superior or inferior to others?  

Inferior  1  ---  2  ---  3  ---  4  ---  5  ---  6  ---  7  ---  8  ---  9  Superior

Is this person better or worse than others?  

Worse  1  ---  2  ---  3  ---  4  ---  5  ---  6  ---  7  ---  8  ---  9  Better

How able is this person to do things?  

Unable  1  ---  2  ---  3  ---  4  ---  5  ---  6  ---  7  ---  8  ---  9  Able

THIS PERSON EARNS $75,000 PER YEAR. WHAT IS YOUR RATING?  

-100 ----------------------------------------- 0 ----------------------------------------- +100  
Under-Reward                             Fair                             Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD,
WHO COMPLETED 8 YEARS OF SCHOOL,
GRADUATING FROM GRADE SCHOOL.
HE IS AN INSURANCE AGENT.

How well do you expect this person to do in situations in general?

Very Poorly 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Superior

Is this person better or worse than others?

Worse 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Better

How able is this person to do things?

Unable 1 -- 2 -- 3 -- 4 -- 5 -- 6 -- 7 -- 8 -- 9 Able

THIS PERSON EARS $55,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD, 
WHO COMPLETED 7 YEARS OF SCHOOL, 
FINISHING THE SEVENTH GRADE. 
HE IS A SUPERVISOR OF TELEPHONE OPERATORS.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARN$ 45,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward                                     Fair                                     Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD, WHO COMPLETED 13 YEARS OF SCHOOL, FINISHING 1 YEAR OF COLLEGE. HE IS A MANAGER OF A SUPERMARKET.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARS $20,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD,
WHO COMPLETED 16 YEARS OF SCHOOL,
GRADUATING COLLEGE WITH A B.A. DEGREE.
HE IS A TRUCK DRIVER.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARN $45,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD,
WHO COMPLETED 15 YEARS OF SCHOOL,
FINISHING 3 YEARS OF COLLEGE.
HE IS A TYPIST.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARS $45,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A MAN 35 YEARS OLD, WHO COMPLETED 20 YEARS OF SCHOOL, GRADUATING COLLEGE WITH AN M.D. DEGREE. HE IS A PHYSICIAN.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON Earns $45,000 Per Year. What Is Your Rating?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward Fair Over-Reward

How Much Should This Person Earn?
A MAN 35 YEARS OLD,  
WHO COMPLETED 16 YEARS OF SCHOOL,  
GRADUATING COLLEGE WITH A B.A. DEGREE.  
HE IS A HOSPITAL AIDE.

How well do you expect this person to do in situations in general?  

Very Poorly  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Very Well

In terms of things that count in this world, how does this person compare to others?  

Much Worse  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Much Better

How intelligent do you think this person is compared to others?  

Much Less Intelligent  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Much More Intelligent

How worthy is this person, compared to others?  

Much Less Worthy  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Much More Worthy

Is this person superior or inferior to others?  

Inferior  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Superior

Is this person better or worse than others?  

Worse  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Better

How able is this person to do things?  

Unable  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Able

THIS PERSON EARN $55,000 PER YEAR. WHAT IS YOUR RATING?  

-100 --------------------------------------------------------------- 0 --------------------------------------------------------------- +100  
Under-Reward  Fair  Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A WOMAN 35 YEARS OLD, 
WHO COMPLETED 14 YEARS OF SCHOOL, 
FINISHING 2 YEARS OF COLLEGE. 
SHE IS A MANAGER OF A SUPERMARKET.

How well do you expect this person to do in situations in general?  
Very Poorly  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Very Well

In terms of things that count in this world, how does this person compare to others?  
Much Worse  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Much Better

How intelligent do you think this person is compared to others?  
Much Less Intelligent  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Much More Intelligent

How worthy is this person, compared to others?  
Much Less Worthy  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Much More Worthy

Is this person superior or inferior to others?  
Inferior  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Superior

Is this person better or worse than others?  
Worse  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Better

How able is this person to do things?  
Unable  1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9  Able

THIS PERSON EARS $40,000 PER YEAR. WHAT IS YOUR RATING?  
-100 ----------------------------------------- 0 ----------------------------------------- +100  
Under-Reward  Fair  Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A woman 35 years old, who completed 10 years of schooling, finishing the tenth grade. She is a coal miner.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

This person earns $100,000 per year. What is your rating?

-100 ----------------------------------------- 0 ----------------------------------------- +100

Under-Reward Fair Over-Reward

How much should this person earn?
A woman 35 years old, who completed 7 years of schooling, finishing the seventh grade. She is a file clerk.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

This person earns $55,000 per year. What is your rating?

-100 ------------------------------ 0 ---------------------------------- +100
Under-Reward Fair Over-Reward

How much should this person earn?
A WOMAN 35 YEARS OLD, WHO COMPLETED 15 YEARS OF SCHOOL, FINISHING THREE YEARS OF COLLEGE. SHE IS A METAL CONTAINER MAKER.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARN$ $70,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100
Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
A WOMAN 35 YEARS OLD,
WHO COMPLETED 14 YEARS OF SCHOOL,
FINISHING TWO YEARS OF COLLEGE.
SHE IS A METAL CONTAINER MAKER.

How well do you expect this person to do in situations in general?

Very Poorly 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Very Well

In terms of things that count in this world, how does this person compare to others?

Much Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much Better

How intelligent do you think this person is compared to others?

Much Less Intelligent 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Intelligent

How worthy is this person, compared to others?

Much Less Worthy 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Much More Worthy

Is this person superior or inferior to others?

Inferior 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Superior

Is this person better or worse than others?

Worse 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Better

How able is this person to do things?

Unable 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9 Able

THIS PERSON EARN $25,000 PER YEAR. WHAT IS YOUR RATING?

-100 ----------------------------------------- 0 ----------------------------------------- +100

Under-Reward Fair Over-Reward

HOW MUCH SHOULD THIS PERSON EARN?
Finally, we would like some basic information about you.

How old are you?

What is your current year in school (freshman, sophomore, etc.)?

What is your current Grade Point Average (if you are unsure, your best guess is OK)?

What is your gender?

At the beginning of the survey, we gave you some basic information about people in the United States.

On average, how old is the typical American?

On average, how many years of schooling does a typical American complete?

On average, how much does a typical American earn?
APPENDIX B: LINEAR MIXED MODEL SELECTION

This appendix presents a series of tests of nested models which are used to determine the preferred models that are presented in chapters five and six. For each set of models presented, the expectation states scale models on the vignette data (equations 5.2 and 5.3), the just rewards models on the vignette data (equations 5.6, 5.7 and 5.8), and the just rewards models on the ISJP, I present a series of nested model tests to determine what terms to include in the model. By way of convention, the first model presented is a null model, and subsequent models are nested in the null. The preferred model in each table is highlighted in gray.

Table A.2.1: Summary of Linear Mixed Models predicting the Expectation States Scale.

<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Model</td>
<td>39513.8</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RI</td>
<td>38992.5</td>
<td>241</td>
<td>521.3</td>
<td>240</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>OCH</td>
<td>38250.4</td>
<td>242</td>
<td>742.1</td>
<td>1</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>OCH and RS</td>
<td>38245.0</td>
<td>482</td>
<td>5.4</td>
<td>240</td>
<td>.999</td>
</tr>
</tbody>
</table>

Note: RI = Random Intercept; OCH = Ordinal Comparison Hypothesis Estimates of Expectation States; RS = Random Slope.

Table A.2.1 presents the specification of Equation 5.2. The second model presented in Table A.2.1 is the baseline model in Table 5.2, which is represented in Equation 5.1. This model simply estimates a random intercept in order to account for the nesting in the data. The third model presented includes the main effect of the ordinal comparison hypothesis estimates of the expectation state values. Constraining the effect of this term leads to a loss of statistical information; consequently I move forward by allowing the expectation state
values to have random slopes. The results of this model (the last model in Table A.2.1) indicate that random slopes on the expectation state values are not warranted by the data.

Table A.2.2: Summary of Linear Mixed Models predicting the Expectation States Scale.

<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Model</td>
<td>39513.8</td>
<td>1</td>
<td></td>
<td>240</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>RI</td>
<td>38992.5</td>
<td>241</td>
<td>521.3</td>
<td>240</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Graded</td>
<td>37437.6</td>
<td>242</td>
<td>1554.9</td>
<td>1</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Graded and RS</td>
<td>37292.5</td>
<td>282</td>
<td>145.1</td>
<td>240</td>
<td>.999</td>
</tr>
</tbody>
</table>

Note: RI = Random Intercept; Graded = Graded Characteristics Estimates of Expectation States; RS = Random Slope.

In terms of the graded characteristics version of the expectation state values, Table A.2.2 presents the model derivation of equation 5.3. Again, the main effect of the estimates of the expectation state values is adding significantly to the model, but allowing the expectation state values to have random effects is not warranted by the data.

Table A.2.3: Summary of Linear Mixed Models predicting Just Rewards (Vignette Data).

<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>RI Only</td>
<td>7210.2</td>
<td>243</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OCH</td>
<td>6728.1</td>
<td>244</td>
<td>482.1</td>
<td>1</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>OCH and RS</td>
<td>6728.1</td>
<td>486</td>
<td>0</td>
<td>242</td>
<td>.999</td>
</tr>
</tbody>
</table>

Note: RI = Random Intercept; OCH = Ordinal Comparison Hypothesis Estimates of Expectation States; RS = Random Slope.
Table A.2.3 presents a series of models of the respondents’ evaluations of the targets’ just rewards from the vignette data. The first model presented is the baseline model, which only estimates a random intercept to account for the nesting in the data (i.e., eq. 5.4). The second model adds a term for the ordinal comparison hypothesis estimates of the target’s reward expectation state values. Adding the term for the reward expectation state values indeed explains a significant amount of information. This model is reflected in equation 5.5. Adding a random effect on the reward expectation state values does not explain any additional statistical information (model 3 in Table A.2.3).

Table A.2.4: Summary of Linear Mixed Models predicting Just Rewards (Vignette Data).

<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>RI Only</td>
<td>7210.2</td>
<td>243</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Graded</td>
<td>6132.3</td>
<td>244</td>
<td>1077.9</td>
<td>1</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Graded and RS</td>
<td>6129.3</td>
<td>486</td>
<td>3</td>
<td>242</td>
<td>.999</td>
</tr>
</tbody>
</table>

Note: RI = Random Intercept; Graded = Graded Characteristics Estimates of Expectation States; RS = Random Slope.

Table A.2.4 represents the graded characteristics version of the just rewards models estimated on the vignette data. The preferred model from Table A.2.4 is the second model, which is the model represented in equation 5.6. This model has the same specification as the model using the ordinal comparison hypothesis estimates of the reward expectation state values: There is a random intercept and a main effect of the expectation state values, but no random effect on the expectation state values.

---

1 This model does not include an intercept but rather a coefficient for the logged mean on incomes, which due to scaling, the estimated coefficient plays the same role as an intercept.
Table A.2.5: Summary of Linear Mixed Models predicting Just Rewards (Vignette Data).

<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>RI Only</td>
<td>7210.2</td>
<td>243</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E, O, and S</td>
<td>4300.2</td>
<td>246</td>
<td>3040.9</td>
<td>3</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>E, O, and S with RSs</td>
<td>4299.8</td>
<td>972</td>
<td>0.4</td>
<td>726</td>
<td>.999</td>
</tr>
</tbody>
</table>

Note: RI = Random Intercept; E = Target’s Education; O = Target’s Occupational Prestige; S = Target’s Sex; RS = Random Slope.

The derivation of the final model of just rewards using the vignette data is presented in Table A.2.5. The initial model simply accounts for nesting by including a random intercept term. Since the formal models treat the targets’ education, sex and occupational prestige as status characteristics, the second model in Table A.2.5 estimates the effects of each of these target attributes. Specifically, the main effects of these attributes are included in the second model, and the likelihood-ratio chi-squared test indicates that these terms explain a substantial amount of the statistical information in the respondent’s evaluations of the just rewards for the targets. Including random slopes on all of the targets’ attributes does explain any additional information (model 3 in Table A.2.5), nor does adding a random slope to any one of them (results not shown). Consequently, the second model from Table A.2.5 is the preferred model and is the model represented in equation 5.7.

Turning to the analysis of the International Social Justice Project, I begin with the specification of the baseline or empirical model. The baseline model takes just rewards to be a function of education, occupational prestige, age, race, sex and number of children. The first five attributes are the same attributes that are treated as status characteristics, and
number of children is included to assess the respondents’ need for material resources. Jasso and Wegener (1999) argued that the effects of each of these attributes should vary by sex; consequently they estimated 26 OLS regression models, with models for men and women estimated separately for each country. There is a clear problem with this approach: they are increasing the likelihood of a type II error with each additional model, and with 26 models they are almost certainly falsely rejecting at least one null hypothesis. There are two related problems with the Jasso and Wegener (1999) approach. First, estimating separate models for men and women is unparsimonious; one can simply estimate interaction effects between sex and all of the other covariates. This cuts the number of models from 26 to 13. Second, estimating separate models for each of the countries is similarly unparsimonious.

Fortunately there are two simple solutions to this problem. First, within a fixed-effects framework one can estimate the main effects of each of the attributes and the sex-by-other-attribute interactions, then include a series of dummy variables for country identification, and finally interact the country dummy variables with each of the main effects. This entails estimating only one model that does the same thing as Jasso and Wegener’s (1999) 26 models. This model has 156 parameters (i.e., 6 main effects + 5 interaction effects + a constant = 12 terms * 13 different countries = 156 parameters). An alternative to this model, the one that I prefer, is a linear mixed model with respondents nested in countries. The reason I prefer it is that the specification of the model is made simpler by the assumption that the random effects are multivariate normally distributed (Verbeke and Molenberghs 2009).

---

2 Along similar lines, I also included an indicator for being single. Preliminary analyses indicated that being single, and a single-by-sex interaction effect added nothing to the model—indeed the BIC statistic increased with these parameters in the model. Consequently, I removed these terms from the empirical model.
Equation A.2.1 illustrates the linear mixed model that I began with. In equation A.2.1
$i$ indexes individuals and $j$ indexes countries, and $E$ refers to education, $O$ refers to
occupational prestige, $A$ refers to age, $F$ refers to a female dummy variable, $R$ refers to a
racial majority member dummy variable and $C$ refers to the respondents’ number of
children. Thus there is a constant with a random effect, and 6 main effects and 5 interaction
effects (all with sex) all with random slopes across the countries. This is the second single
model analog to Jasso and Wegener’s (1999) 26 OLS models.

\[
\ln(\text{Just Rewards}_{ij}) = \beta_{0j} + \beta_{ij}(E_y) + \beta_{2j}(O_y) + \beta_{3j}(A_y) + \beta_{4j}(F_y) + \beta_{5j}(R_y) + \\
\beta_{6j}(C_y) + \beta_{7j}(F_y \times E_y) + \beta_{8j}(F_y \times O_y) + \beta_{9j}(F_y \times A_y) + \\
\beta_{10j}(F_y \times R_y) + \beta_{11j}(F_y \times C_y) + \varepsilon_{ij} \tag{A.2.1}
\]

Table A.2.6: Summary of Linear Mixed Models predicting Just Rewards (ISJP). Results of
Likelihood Ratio Chi-Squared Tests from Removing the Random Effects of Each
Interaction Term.

<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Model</td>
<td>-4148.4</td>
<td>156</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No F*E RS</td>
<td>-4148.0</td>
<td>144</td>
<td>0.4</td>
<td>12</td>
<td>.999</td>
</tr>
<tr>
<td>No F*O RS</td>
<td>-4146.3</td>
<td>144</td>
<td>2.1</td>
<td>12</td>
<td>.999</td>
</tr>
<tr>
<td>No F*A RS</td>
<td>-4135.4</td>
<td>144</td>
<td>13.0</td>
<td>12</td>
<td>.369</td>
</tr>
<tr>
<td>No F*R RS</td>
<td>-4145.8</td>
<td>144</td>
<td>2.6</td>
<td>12</td>
<td>.998</td>
</tr>
<tr>
<td>No F*C RS</td>
<td>-4134.8</td>
<td>144</td>
<td>13.6</td>
<td>12</td>
<td>.327</td>
</tr>
<tr>
<td>No Interaction RSs</td>
<td>-4112.7</td>
<td>96</td>
<td>35.7</td>
<td>60</td>
<td>.995</td>
</tr>
</tbody>
</table>

Note: $F =$ Female; $E =$ Education; $O =$ Occupational Prestige; $A =$ Age; $R =$ Race; $C =$ # of
Children; RS = Random Slope.

To begin paring down the model presented in equation A.2.1, I first systematically
removed the random effects of each of the interaction terms. The results from this are presented in Table A.2.6. The data indicates that none of the interaction effects require random slopes.

Table A.2.7: Summary of Linear Mixed Models predicting Just Rewards (ISJP). Results of Likelihood Ratio Chi-Squared Tests from Removing the Random Effects of Each Main Effect Term.

<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Model</td>
<td>-4112.7</td>
<td>96</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No E RS</td>
<td>-4034.4</td>
<td>84</td>
<td>78.3</td>
<td>12</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>No O RS</td>
<td>-4049.1</td>
<td>84</td>
<td>63.6</td>
<td>12</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>No A RS</td>
<td>-4081.6</td>
<td>84</td>
<td>31.1</td>
<td>12</td>
<td>.002</td>
</tr>
<tr>
<td>No F RS</td>
<td>-3777.6</td>
<td>84</td>
<td>335.1</td>
<td>12</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>No R RS</td>
<td>-4109.2</td>
<td>84</td>
<td>3.5</td>
<td>12</td>
<td>.991</td>
</tr>
<tr>
<td>No C RS</td>
<td>-4094.1</td>
<td>84</td>
<td>18.6</td>
<td>12</td>
<td>.099</td>
</tr>
<tr>
<td>No R or C RS</td>
<td>-4090.1</td>
<td>72</td>
<td>22.6</td>
<td>24</td>
<td>.544</td>
</tr>
</tbody>
</table>

Note: F = Female; E = Education; O = Occupational Prestige; A = Age; R = Race; C = # of Children; RS = Random Slope.

\[
\ln(\text{Just Rewards}_{ij}) = \beta_{0} + \beta_{1j}(E_{ij}) + \beta_{2j}(O_{ij}) + \beta_{3j}(A_{ij}) + \beta_{4j}(F_{ij}) + \beta_{5j}(R_{ij}) + \\
\beta_{6j}(C_{ij}) + \beta_{7}(F_{ij} \times E_{ij}) + \beta_{8}(F_{ij} \times O_{ij}) + \beta_{9}(F_{ij} \times A_{ij}) + \\
\beta_{10}(F_{ij} \times R_{ij}) + \beta_{11}(F_{ij} \times C_{ij}) + \epsilon_{ij} \quad (A.2.2)
\]

The next step in specifying the baseline or empirical model was to systematically remove the random effects of the main effect terms. These results are presented in Table A.2.7. The full model in A.2.7 is presented in equation A.2.2, and is the same as A.2.1 except that the random effects on the interaction terms have been constrained (see Table A.2.6).

The sixth and seventh models in Table A.2.7 show that removing the random effect of race
and number of children, respectively, does not result in a loss of statistical information. The final model shows that constraining the random effect of both race and number of children does not result in a loss of statistical information. This model is presented in equation A.2.3.

\[
\ln(\text{Just Rewards}_{ij}) = \beta_0 + \beta_{ij}(E_y) + \beta_{ij}(O_y) + \beta_{ij}(A_y) + \beta_{ij}(F_y) + \beta_{ij}(R_y) + \\
\beta_{ij}(C_y) + \beta_{ij}(F_y \times E_y) + \beta_{ij}(F_y \times O_y) + \beta_{ij}(F_y \times A_y) + \\
\beta_{ij}(F_y \times R_y) + \beta_{ij}(F_y \times C_y) + \epsilon_{ij}
\]  

(A.2.3)

Table A.2.8: Summary of Linear Mixed Models predicting Just Rewards (ISJP). Results of Likelihood Ratio Chi-Squared Tests from Removing the Fixed Effect of Each Interaction Term.

<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Model</td>
<td>-4090.1</td>
<td>72</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No F*E FE</td>
<td>-4089.0</td>
<td>71</td>
<td>1.1</td>
<td>1</td>
<td>.294</td>
</tr>
<tr>
<td>No F*O FE</td>
<td>-4089.3</td>
<td>71</td>
<td>0.8</td>
<td>1</td>
<td>.371</td>
</tr>
<tr>
<td>No F*A FE</td>
<td>-4088.8</td>
<td>71</td>
<td>1.3</td>
<td>1</td>
<td>.254</td>
</tr>
<tr>
<td>No F*R FE</td>
<td>-4090.0</td>
<td>71</td>
<td>0.1</td>
<td>1</td>
<td>.752</td>
</tr>
<tr>
<td>No F*C FE</td>
<td>-4040.1</td>
<td>71</td>
<td>50.0</td>
<td>1</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Only the F*C FE</td>
<td>-4087.7</td>
<td>68</td>
<td>2.4</td>
<td>4</td>
<td>.663</td>
</tr>
</tbody>
</table>

Note: F = Female; E = Education; O = Occupational Prestige; A = Age; R = Race; C = # of Children; FE = Fixed Effect.

Table A.2.8 begins with the model from equation A.2.3 as the full model and then systematically removes the fixed effect of each of the interaction terms. The results of Table A.2.8 show that the only interaction term that is warranted by the data is the female-by-number-of-children interaction term. The sixth model in Table A.2.8 shows that constraining this interaction leads to a loss of statistical information, and the seventh model in Table A.2.8 shows that constraining all of the other interaction terms does not lead to a
loss of statistical information. The final linear mixed model, therefore, is presented in equation A.2.4.

\[
\ln(Just \ Rewards)_{ij} = \beta_{0j} + \beta_{1j}(E_{ij}) + \beta_{2j}(O_{ij}) + \beta_{3j}(A_{ij}) + \beta_{4j}(F_{ij}) + \beta_{5j}(R_{ij}) + \\
\beta_{6j}(C_{ij}) + \beta_{7j}(F_{ij} \times C_{ij}) + \varepsilon_{ij}
\]  

(A.2.4)

In terms of the formal models of just rewards, both the Ordinal Comparison Hypothesis and the Graded Status Characteristics versions of the models have the same specification. The derivation of these models are presented in Tables A.2.9 and A.2.10, respectively. In both cases the models have random intercepts and random slopes on the reward expectation state values.

<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Model</td>
<td>-1336.4</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RI</td>
<td>-1345.1</td>
<td>13</td>
<td>8.7</td>
<td>12</td>
<td>.728</td>
</tr>
<tr>
<td>OCH</td>
<td>-2285.3</td>
<td>14</td>
<td>940.2</td>
<td>1</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>OCH and RS</td>
<td>-2830.4</td>
<td>26</td>
<td>545.1</td>
<td>12</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

Note: RI = Random Intercept; OCH = Ordinal Comparison Hypothesis Estimates of Expectation States; RS = Random Slope.
<table>
<thead>
<tr>
<th>Model Specification</th>
<th>-2 Log Likelihood</th>
<th># of Parameters</th>
<th>Chi-Squared</th>
<th>Degrees of Freedom</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Model</td>
<td>-1336.4</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RI</td>
<td>-1345.1</td>
<td>13</td>
<td>8.7</td>
<td>12</td>
<td>.728</td>
</tr>
<tr>
<td>Graded</td>
<td>-3042.2</td>
<td>14</td>
<td>1697.1</td>
<td>1</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Graded and RS</td>
<td>-3645.4</td>
<td>26</td>
<td>603.2</td>
<td>12</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

*Note:* RI = Random Intercept; Graded = Graded Characteristics Estimates of Expectation States; RS = Random Slope.
REFERENCES


Davis, James Allan and Smith, Tom W.: General Social Surveys, 1972-2006. [machine-readable data file]. Principal Investigator, James A. Davis; Director and Co-Principal Investigator, Tom W. Smith; Co-Principal Investigator, Peter V. Marsden, NORC ed. Chicago: National Opinion Research Center, producer, 2005; Storrs, CT: The Roper Center for Public Opinion Research, University of Connecticut, distributor. 1 data file (51,020 logical records) and 1 codebook (2,552 pp).


