Appendices A–G for
Hard Choices, Easy Answers

A Roadmap of the Technical Appendices

This document provides the technical appendices for our book, *Hard Choices, Easy Answers* (2002). These supplemental materials give details of the statistical methodologies that we use in our research, in-depth discussions of the empirical analyses in each chapter of our book, and present estimation results that form the basis for the conclusions reached in each chapter.

These appendices serve as an electronic supplement to our book. As such, they will remain as published, and will continue to be available at www.pupress.princeton.edu/alvarez. Additional materials, including statistical software code for our statistical work and some replication datasets, can be found at http://hardchoices.caltech.edu. This website will evolve as we determine which extra materials are useful for readers of our book.

There are seven appendices, referenced A–G. The materials they contain are as follows:

Appendix A: Methodological Materials for Chapter 3. This appendix provides a basic primer for multivariate statistical models, and a basic derivation of binary and ordinal choice models.

Appendix B: Models for Heterogeneous Choices. This appendix follows directly from appendix A, as we present the basic derivations for the heteroskedastic models that are the primary statistical tool used in our research.

Appendix C: Methodological Materials for Chapter 5. Here are tables of model estimates for the abortion, euthanasia, and suicide results discussed in chapter 5.

Appendix D: Methodological Materials for Chapter 6. In this appendix we provide details about the racial attitudes analyses in chapter 6, including tables of parameter estimates.

Appendix E: Methodological Materials for Chapter 7. This appendix gives tables of parameter estimates for the Internal Revenue Service analysis.

Appendix F: Methodological Materials for Chapter 8. Here we discuss the ordered heteroskedastic logit model, and the aggregate model derived from it. We also present in this appendix model parameter estimates that form the basis for the secondary analyses discussed in chapter 8.

Appendix G: Methodological Materials for Chapter 9. This last appendix gives parameter estimates for the analysis discussed in chapter 9.

References. We conclude this document with a list of references cited in these appendices.

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APPENDIX A

Methodological Materials for Chapter 3

In this appendix we discuss the estimation of multivariate statistical models. We begin with a brief discussion of a common approach for estimating multivariate statistical models: multiple regression. Readers of chapter 3 of the printed book will recall that we use multiple regression in our analysis of "Who is informed about the IRS?" in that chapter. Multiple regression is particularly suited for a situation where the dependent variable (the variable one is attempting to explain) has an important property—it is continuous. In other words, it is measured by a variable that has meaningful, integer-type valuation. For the assumptions needed to insure that multiple regression estimation produces results with reliable statistical properties (the estimated impacts of independent variables are unbiased and efficient—statistical properties which loosely translate into the estimated impacts being the best guesses that provide the least uncertain estimates), the dependent variable must be something like our IRS information variables.

Continuous Dependent Variable Models

If the dependent variables are continuous or essentially continuous, then we can proceed using most statistical software packages (including many spreadsheet packages) to estimate something like the following:

$$Y_i = \alpha + \beta X_i + \varepsilon_i \tag{A.1}$$

where Y_i is the dependent variable we wish to explain and where X_i is the independent variable we are using to explain Y_i. In this equation α is a parameter we estimate called the "intercept" or "constant," and β is the "slope." Lastly, ε_i is the "error" term, or the part of the dependent variable which we do not explain by $\alpha + \beta X_i$. The addition of the error term to the statistical model allows us to partition the variation in Y across different individuals (i) into the part that we can explain (which we will call the "systemic component") and the part we cannot explain (which we will call the "error component").

When we undertake multiple regression on such a statistical model, we get numerical estimates for both parameters (α and β), which we can easily interpret. In the multiple regression setup, the slope parameter (β) is usually the most important estimated parameter and is understood as the impact we expect to see in Y_i, given a 1-unit change in X_i. So, for example, in our multiple regression results for the IRS "soft" information measure, we interpret the estimated impact of the income independent variable as showing that if we increase income by 1-unit, we will obtain a 2.4-unit increase in the respondent's soft information rank.

Multiple regression also provides an estimate of how certain we can be in our inferences about the impacts of the slope parameters: the estimated standard errors. The estimated standard errors can be used in one of two ways to gain understanding of our estimation certainty. The first way is to use the estimated standard errors to construct confidence intervals around the estimate of a particular slope parameter. To continue the example from the IRS soft information multiple regression, we have an estimated impact of 2.4 with a standard error of .7. We can construct a 95% confidence interval using this estimated standard error—roughly twice the standard error, which in this case ranges from 1 to 3.8. Thus, we are 95% confident that the impact of income in this case falls within this interval.

The second way in which the standard error can be used is to construct a precise statistical test for the statistical significance of a parameter. Usual practice is to infer that a parameter is statistically different from zero—from having no effect at all—if the estimated parameter is larger than roughly twice the estimate's standard error. So with our estimated impact of "soft" information of 2.4, we infer that this estimated impact is statistically different from zero when it is greater than approximately twice the size of the standard error (in this case 1.4).[1]

Binary Choice Models

In many situations, however, we do not have continuous dependent variables. In fact, virtually all of the survey questions we use in our analyses as dependent measures are not continuous. Since most of our dependent variables are not continuous we must use techniques that are more appropriate for non-continuous dependent variables. In the applications we examine in this book we have dependent variables which are either binary (yes or no, agree or disagree) or ordinal (agree strongly, agree weakly, disagree weakly, or disagree strongly).

Luckily, a special class of statistical models has been developed which are appropriate for binary or ordinal dependent variables—discrete choice models. While these statistical models have their roots in economic applications, they are now quite common in many social science applications.

The most basic of the discrete choice models is the binary choice model. Here we start with a model which is identical to that above:

$$Y_i = \alpha + \beta X_i + \varepsilon_i \tag{A.2}$$

where the variables and parameters are identical to those we discussed earlier. The problem is that we do not really observe Y_i, instead we observe a binary realization of the underlying continuous variable. For example, we commonly assume that while survey respondents may have attitudes which might be thought of as continuous, in the survey setting we ask them to provide only a binary indication of their underlying continuous attitude:

$$Y_i^* = 1 \quad \text{iff} \quad Y_i \geq \mu \tag{A.3}$$

$$Y_i^* = 0 \quad \text{iff} \quad Y_i < \mu \tag{A.4}$$

Thus, if we have asked our survey respondent to tell us whether she or he agrees or disagrees that women should have the right to an abortion only when the mother's life is in danger, our survey respondent would say "agree" if her underlying opinion was greater than some threshold we denote by μ (which we would then code in our dataset as a 1) or he would say "disagree" if his underlying opinion was less than his threshold μ (which we would then code in our dataset as a 0). Thus, given that we do not elicit from our survey respondents in these types of situations Y_i but instead we ask them Y_i^* we need a different statistical model than multiple regression.

The solution is quite simple, since we have two almost identical statistical distributions, the normal and the logistic, which we can employ in this situation to appropriately cope with the binary dependent variable. We need to assume for simplicity here that $\mu = 0$ and that the variance of $\varepsilon = 1$. We first write the probability that $Y_i^* = 1$ as:

$$\text{Prob}(Y_i^* = 1) = \text{Prob}(\alpha + \beta X_i \geq 0) \tag{A.5}$$

$$= \text{Prob}(\mu \geq -(\alpha + \beta X_i)) \tag{A.6}$$

$$= F(\alpha + \beta X_i) \tag{A.7}$$

where F is either the standard normal distribution (which we will later refer to as Φ) or a logistic distribution function. When we use the normal density, we have what is usually called the "probit" model; when we use the logistic, we have what is called the "logit" model. In practice the probit and logit binary choice models are for all purposes identical in the binary choice case.

Estimation of the probit or logit model is straightforward using today's powerful computers, also the probit and logit models are common in most statistical software packages. But there are important differences between the binary choice (and all discrete choice models) and the multiple regression approach. The most important of these differences is in how a researcher can interpret the probit or logit model estimates.

Recall our discussion above, where we pointed out that multiple regression estimates can easily be interpreted as the marginal change caused by a 1-unit variation in the independent variable upon the dependent variable. Unfortunately, all of the discrete choice models we use in this book are nonlinear statistical models, which means that the estimates cannot be interpreted in such a straightforward manner. As is easily seen in the binary choice model derivation above, the probability functions we employ in the probit or logit cases are not linear, so that the estimated impact of one independent variable on the explanatory variable is dependent upon the values of other independent variables and their estimated impact on the explanatory variable as well. This makes interpretation of discrete choice models quite complicated. Our practice throughout the book is to avoid discussion of model estimates as much as possible, and to report instead the model estimates in the chapter appendices posted here. We present in the empirical chapters printed in the book only our estimates of the impacts of each variable upon the dependent phenomenon under examination. In appendix B we discuss in much more detail how we obtain these estimated marginal impacts in our discrete choice models. But in the next section of this appendix we turn to a slightly more complicated type of non-continuous dependent variable model, one for ordinal dependent variables.

Ordinal Choice Models

Ordinal choice models differ from binary choice models. In fact, most survey response data are either binary or ordinal, depending on the choice options and the decision of the researcher whether to include "don't know"s in the response model. In any case, many of the survey questions we use as dependent variables in our analyses in this book are ordinal in nature: for example, questions asking respondents whether they "agree strongly," "agree weakly," "disagree weakly," or "disagree strongly." If we want to assume that these survey responses represent categories which come from some underlying one-dimensional scale, then the ordinal choice model is appropriate for the analysis of these survey responses.

We assume that there is a continuous underlying scale or attitude Y_i such that:

$$Y_i \sim F(y_i \mid \pi_i) \tag{A.8}$$

where the systemic component is:

$$\pi_i = F(X_i\beta) \tag{A.9}$$

Next we denote our threshold parameters by μ_j, where $j = 1,\ldots,m$ and $\mu_1 = -\infty$ and $\mu_m = \infty$. The threshold parameters are simply estimates of the breakpoints between ordinal responses, or the place where we would assume that a respondent would switch from one category of response to the next. We constrain the thresholds so that the probabilities are always positive:

$$\mu_{j-1} < \mu_j < \ldots < \mu_m \tag{A.10}$$

We know from the data which category y_i belongs to, so we can write that y_i belongs to category j if the following expression holds:

$$\mu_{j-1} < y_i \leq \mu_j \tag{A.11}$$

Next we assume that y_i is a series of j binary variables (instead of being coded as one ordinal variable) such that:

$$y_{ij} = \begin{cases} 1 & \text{if } \mu_{j-1} < y_i \leq \mu_j \\ 0 & \text{otherwise} \end{cases} \tag{A.12}$$

We next write the probability that y_i is in j as:

$$\begin{aligned} P(y_i = j) &= P(\mu_{j-1} < y_i \leq \mu_j) && \text{(A.13)} \\ &= F\left(\frac{\mu_j - \beta' X_i}{\sigma_i}\right) - F\left(\frac{\mu_{j-1} - \beta' X_i}{\sigma_i}\right) && \text{(A.14)} \end{aligned}$$

Here we assume, just as we did in the previous binary choice model derivation, that the error terms are homoskedastic or that they have identical variance, which we write as $\sigma_i = 1$.

The likelihood for a given set of parameters is:

$$L = \prod_{i=1}^{n}\prod_{j=1}^{m}\left[F\left(\frac{\mu_j - \beta' X_i}{1}\right) - F\left(\frac{\mu_{j-1} - \beta' X_i}{1}\right)\right]^{y_{ij}} \tag{A.15}$$

We take logs to produce the log-likelihood function:

$$\ln L = \sum_{i=1}^{n} \sum_{j=1}^{m} y_{ij} \ln \left[F\left(\frac{\mu_j - \beta' X_i}{1} \right) - F\left(\frac{\mu_{j-1} - \beta' X_i}{1} \right) \right] \tag{A.16}$$

By substituting either the standard normal cumulative distribution for F or a logistic cumulative distribution, we can readily estimate this model. The ordinal choice model, typically implemented using the normal distribution, is usually called the "ordered probit" model. It is programmed in most common statistical packages and is relatively simple to estimate. The only problems arise infrequently when the estimated underlying thresholds do not have the necessary ordering; this happens either when the dependent variable has been miscoded (so that, for example, two response options are inadvertently switched) or when survey respondents see the response categories in a different ordering than did the designers of the survey. Lastly, the ordinal choice model is exactly like the binary choice model in that both are nonlinear models; in appendix B we discuss in more detail how we produce results from our estimation of the ordinal choice models to yield estimates which are easier to understand.

Notes

1.For more detailed discussion of hypothesis testing, please see Greene 1993: 125-36.

APPENDIX B

Models for Heterogeneous Choices

Heteroskedastic Choice Models

In the empirical chapters of the printed book we are interested in testing two different types of propositions about the beliefs of Americans on many different aspects of public policy. First, we want to know how different predispositions and values influence the beliefs which people have about public opinion. For example, we are critically concerned in our analysis of the beliefs of white Americans about affirmative action to find whether the predisposition commonly called modern racism has a strong influence on what particular beliefs are held by individuals. In other words, in the case of affirmative action, we want to determine how much influence modern racism has on whether individual citizens want to see minority set-aside programs in government contracts continued, or racial and ethnic criteria utilized in public university admissions.

But, second, we are also trying to understand the variability in responses on particular issues across respondents. That is, we have theoretical reasons to believe that some respondents have greater underlying and unobserved variability in their responses to survey questions about public policy than other respondents. As we discuss in the early chapters of the book, the differences across respondents in the underlying variance of their survey responses can be due to uncertainty, equivocation, or ambivalence. What we need is a methodological tool which allows us to test both for the direct effects of predispositions on policy beliefs as well as for these three different effects on the variance of the survey response.

For our work in the book we use as our methodological tool an inferential statistical model to test for the direct effects of predispositions and for the possibility of uncertain, ambivalent, or equivocal survey responses. One of the first wrinkles we need to discuss, however, is the fact that the data we have on the beliefs of survey respondents about public policy are discrete, not continuous. Thus, we cannot use statistical modeling tools like ordinary least squares (as presented in appendix A) to make inferences about how predispositions matter or what drives response variability.

Instead, we use two different types of discrete choice models in our empirical analyses. Which type of model we use is determined by whether we have discrete survey responses which are binary or ordinal, which we discuss in appendix A. Recall that binary response data are usually in the form of “agree” and “disagree” survey responses about public policy. For binary response data we use the binary probit model, which is the appropriate technique to use for such response data. On the other hand, ordinal response data are those in which individuals are asked to use some type of scale to give their opinion about a particular policy issue. For example, an ordinal survey response would be one where individuals are asked whether a minority set-aside program for government contracting should be totally eliminated, partially eliminated, kept the same, increased somewhat, or increased greatly. The assumption is that there is an implicit ordering of these responses ranging from total elimination to a great increase; the statistical model we use for ordinal responses like these assumes such an implicit ordering. Our statistical model for such data is the ordinal probit model, which is the appropriate technique to use for ordinal response data. [1]

If we were not concerned about the problem of unequal survey response variability across individuals in our surveys, it would be relatively simple for us to examine the effects of predispositions on public policy preferences using our survey response data. Both the binary and ordinal probit choice models are well understood and are easy to implement in virtually all major statistics packages. However, if the process that causes the unequal survey response variance is not accounted for in an empirical model of the particular survey question, the model is likely to produce incorrect results. Moreover, the underlying variance in a respondent’s answers yields direct information about the degree of certainty that a respondent has in his or her opinions. When there is the possibility that uncertainty, ambivalence or equivocation are operative for some individuals, then these three different sources of response variability must be included in models of issue preferences.

Yet, the problem of unequal variance across observations is familiar to every analyst of regression models as heteroskedasticity. In the least squares regression model, if the errors are heteroskedastic, the estimator is unbiased and consistent but is inefficient; and the typical estimate of the parameter covariance matrix is incorrect. Unfortunately, unequal variance is a worse problem for both binary and ordinal choice models. In the specific case of the probit model, for example, heteroskedasticity makes the maximum likelihood estimates inconsistent and the estimate of the covariance matrix of the model estimates is incorrect (Yatchew and Griliches 1985). The same result holds for the ordinal choice model, as we will see below, because both the binary and ordinal choice models are nonlinear statistical models. Unlike the case of linear models (where heteroskedasticity only leads to inefficiency), in nonlinear choice models we will have both inconsistent and inefficient coefficient estimates because the heteroskedasticity will affect both the coefficient estimates and the estimated variances of the parameters. Therefore, if heteroskedasticity is suspected in a probit model, it must be tested for and modeled if we expect to obtain consistent estimates.

We begin this appendix by developing the binary choice model with heteroskedasticity. Then we extend the ordinal choice model to also include heteroskedasticity. The two sections that follow present two other statistical models with heteroskedasticity: the ordinal choice model for aggregated response data, and the negative binomial model with heteroskedasticity. The appendix then concludes with a technical summary of how to produce estimated marginal effects for these non-linear statistical models—estimates of the effects of each independent variable that are easier to understand and discuss than the actual parameter estimates.

Heteroskedastic Binary Choice Models

We begin by presenting our model for binary choices with heteroskedasticity, and then we present our model of ordinal choices with heteroskedasticity. In maximum likelihood terms, the idea behind modeling dichotomous choice is to specify the systematic component of some probability (π_i) of individual *i* adopting the choice (y_i). In conventional probit and logit estimations, the analyst assumes that the π_i were generated by a homogeneous process, or that the data are identically and independently distributed. This permits the analyst to write the likelihood function in a relatively simple form:

$$\log L(\pi|y) = \sum_{i=1}^{N} y_i \log \pi_i + (1 - y_i) * \log(1 - \pi_i) \qquad \text{(B.1)}$$

(where π_i is reparameterized as a function, usually the normal distribution [Φ] of a set of explanatory variables). Our argument is that preferences for public policy choices are *not* identically distributed and that the process of generating responses to policy choices is heterogeneous: some respondents will be more uncertain, more ambivalent, or more equivocal than other respondents and this will cause them to have a wider underlying distribution of choices. This means that the standard probit (equation B.1) will yield inconsistent estimates (see Greene 1993: 649-50).

We can address this source of inconsistency by modeling the heterogeneity. A plausible choice for the functional form of the heterogeneity is a variation of Harvey's "multiplicative heteroskedasticity" approach (1976):

$$y_i^* = X_i\beta + \varepsilon_i \qquad \text{(B.2)}$$

$$\text{var}(\varepsilon_i) = [exp(Z_i\gamma)]^2$$

where y_i^* is a binary response to the policy question, X_i and Z_i are matrices of independent variables, ε_i is an error term, and β and γ are coefficient vectors to estimate. The first equation is a model of choice, in which a person's policy beliefs are a linear combination of interests leading the respondent to opt for a particular choice. (In this equation, we will also add sets of control variables which allow us to obtain accurate estimates about the effects of the core beliefs and predispositions on preferences and to test alternative hypotheses about what determines particular policy preferences.) The second equation is a model for the error variance, where we introduce variables accounting for alternative explanations (the multiplicative heteroskedasticity idea). This means that the systematic component now describes an identically distributed process for π_i^*:

$$\pi_i^* = g(\frac{X_i\beta}{e^{Z_i\gamma}}) \tag{B.3}$$

where $g()$ is an appropriate link function bounded between zero and one such as the probit function ($\Phi()$). The only identifying assumption in this model is that the variance equation cannot have a constant.

This leads to a log-likelihood function very similar to the usual probit log-likelihood:

$$\log L = \sum_{i=1}^{n} \left(y_i \log \Phi\left(\frac{X_i\beta}{\exp^{Z_i\gamma}}\right) + (1-y_i)\log\left[1-\Phi\left(\frac{X_i\beta}{\exp^{Z_i\gamma}}\right)\right]\right) \tag{B.4}$$

The significant difference between the likelihood above and the conventional probit is the inclusion of the variance model in the denominator in equation B.4.

Since in the log-likelihood of equation B.4 we have the term $\frac{X_i\beta}{\exp^{Z_i\gamma}}$ it is easy to gain an intuition for why it is important that heteroskedasticity in discrete choice models must be explicitly dealt with. Given that we have the systemic component of the choice function $X_i\beta$ divided by the variance function $\exp^{Z_i\gamma}$ we clearly have a nonlinear model. That is, the estimated effect of each component of the choice function (each β) is conditional on the elements of the denominator of this fraction ($\exp^{Z_i\gamma}$). If the denominator takes a different value for each individual, then the parameters of the choice function will be incorrectly estimated unless this individual variation is taken into account in the estimation of the model parameters.

This can also be seen in the derivatives of the log-likelihood function given in equation B.4 for the two sets of coefficients. First, the derivative of the log-likelihood function with respect to β is:

$$\frac{\partial \log L}{\partial \beta} = \sum_{i=1}^{n}\left[\frac{\phi_i(y_i-\Phi_i)}{\Phi_i(1-\Phi_i)}\right]\exp^{-Z_i\gamma}X_i \tag{B.5}$$

And the derivative of the log-likelihood function with respect to γ is:

$$\frac{\partial \log L}{\partial \beta} \quad = \quad \sum_{i=1}^{n} \left[\frac{\phi_i (y_i - \Phi_i)}{\Phi_i (1 - \Phi_i)} \right] \exp^{-Z_i \gamma} Z_i (-X_i \beta) \tag{B.6}$$

Thus, from the derivatives in equation B.5, it is easy to see that the estimates of β depend on the variance function. This implies that if there is heteroskedasticity in the data which is ignored, then the coefficient estimates are biased.

Fortunately our prediction of heterogenous responses to public policy questions can be formulated as a statistical test; so we test for the presence of heteroskedasticity in our models of public policy preferences using a simple likelihood ratio test (Davidson and MacKinnon 1984; Engle 1984).[2] This test compares an unrestricted model (with a fully specified variance model, equation B.4) to a restricted model (in which homoskedasticity is assumed, equation B.1). The null hypothesis is that the error variances are homoskedastic (i.e., that $\gamma = 0$), indicating that an ordinary probit will suffice. The alternative is that at least one γ is not zero. Let L_0 be the log likelihood for the restricted (homoskedastic) probit, L_H be the log likelihood for the unrestricted (heteroskedastic) probit, and k be the number of γ_i coefficients in the variance portion of the model. Then the likelihood ratio

$$LR = 2 \times (L_H - L_0) \tag{B.7}$$

is distributed as a χ^2 with k degrees of freedom.[3] If we cannot reject the null hypothesis that the error variances are homoskedastic (i.e., that $\gamma = 0$), then an ordinary probit will suffice.[4]

Heteroskedastic Ordinal Choice Models

The likelihood function for our ordinal heteroskedastic probit model is also relatively easy to derive. In fact, the ordinal heteroskedastic choice model is a simple extension of the binary heteroskedastic choice model derived in the previous section. We begin by assuming that there is a continuous underlying process Y_i such that:

$$Y_i \sim F(y_i \mid \pi_i) \tag{B.8}$$

where the systemic component is:

$$\pi_i = F(X_i \beta) \tag{B.9}$$

Next we denote our threshold parameters by μ_j, where $j = 1, \ldots, m$ and $\mu_1 = -\infty$ and $\mu_m = \infty$. We constrain the thresholds so that the probabilities are always positive:

$$\mu_{j-1} < \mu_j < \ldots < \mu_m \tag{B.10}$$

We know from the data which category y_i belongs to, so we can write that y_i belongs to category j if the following expression holds:

$$\mu_{j-1} < y_i \leq \mu_j \tag{B.11}$$

To make the exposition easier, we assume that y_i is a series of j binary variables (instead of being coded as one ordinal variable) such that:

$$y_{ij} = \begin{cases} 1 & \text{if } \mu_{j-1} < y_i \leq \mu_j \\ 0 & \text{otherwise} \end{cases} \tag{B.12}$$

We next write the probability that y_i is in j as:

$$P(y_i = j) = P(\mu_{j-1} < y_i \leq \mu_j) \tag{B.13}$$

$$= F\left(\frac{\mu_j - \beta' X_i}{\sigma_i}\right) - F\left(\frac{\mu_{j-1} - \beta' X_i}{\sigma_i}\right) \tag{B.14}$$

Usual derivations of this likelihood at this point assume that $\sigma_i = 1$. As we argue in the text, we wish to assume that choice is heterogeneous, so we assume instead that

$$\sigma_i = \exp(\gamma' Z_i) \tag{B.15}$$

where Z_i are variables which we believe measure the heterogeneity in choices across individuals and γ are coefficients.

We now write the likelihood for a given set of parameters as:

$$L = \prod_{i=1}^{n} \prod_{j=1}^{m} \left[F\left(\frac{\mu_j - \beta' X_i}{\sigma_i}\right) - F\left(\frac{\mu_{j-1} - \beta' X_i}{\sigma_i}\right) \right]^{y_{ij}} \tag{B.16}$$

We take logs to produce the log-likelihood function:

$$\ln L = \sum_{i=1}^{n} \sum_{j=1}^{m} y_{ij} \ln \left[F\left(\frac{\mu_j - \beta' X_i}{\sigma_i}\right) - F\left(\frac{\mu_{j-1} - \beta' X_i}{\sigma_i}\right) \right] \tag{B.17}$$

where we assume that F represents the standard cumulative normal distribution.

The first derivatives of the model are easy to present (Alvarez and Brehm 1998; Greene 1997). Using the same notation, except referencing one of the ordinal categories as k from the set j and noting that f gives the normal density ϕ, we obtain the following derivative:

$$\frac{\partial \ln L_i}{\partial \beta} = \frac{f[(\mu_{j-1,k} - \beta' X_i)/\sigma_i] - f[(\mu_{j,k} - \beta' X_i)/\sigma_i]}{F[(\mu_{j,k} - \beta' X_i)/\sigma_i] - F[(\mu_{j-1,k} - \beta' X_i)/\sigma_i]} X_i/\sigma_i \tag{B.18}$$

Define:

$$f_{j,k} = f[(\mu_{j,k} - \beta' X_i)/\sigma_i] \tag{B.19}$$

and

$$F_{j,k} = F[(\mu_{j,k} - \beta' X_i)/\sigma_i] \tag{B.20}$$

This allows us to easily write the remaining first derivatives:

$$\frac{\partial \ln L_i}{\partial \mu_{j,k}} = [f_{j,k}/(F_{j,k} - F_{j-1,k})]/\sigma_i \tag{B.21}$$

$$\frac{\partial \ln L_i}{\partial \mu_{j-1,k}} = -[f_{j-1,k}/(F_{j,k} - F_{j-1,k})]/\sigma_i \tag{B.22}$$

$$\frac{\partial \ln L_i}{\partial \gamma} = -([1/(F_{j,k} - F_{j-1,k})]/\sigma_i)[(\mu_{j,k} - \beta' X_i) - (\mu_{j-1,k} - \beta' X_i) f_{j-1,k}]Z_i \tag{B.23}$$

Aggregate Heteroskedastic Ordinal Choice Models

The next step is to extend the heteroskedastic ordered choice model to aggregates. The dependent variable now measures the number of people who respond in each of the three or four categories. If we make the strong assumption that each observation within an aggregate is uncorrelated with any other and generated by the same process (i.e., distributed independently and identically), then the extension is simple:

$$\begin{aligned} N(y_i = 1) &= \binom{\sum N_i}{N_1} P(y_i = 1)^{N_1} \\ N(y_i = 2) &= \binom{\sum N_i}{N_2} P(y_i = 2)^{N_2} \\ &\vdots \end{aligned} \tag{B.24}$$

$$N(y_i=4) \quad = \quad \binom{\sum N_i}{N_4} P(y_i=4)^{N_4} \tag{B.25}$$

where N_i represents the observed number who respond in category i.[5]

Substituting in the formula for the probabilities of each choice (B.14), we have:

$$\begin{aligned} N(y_i=1) &= \binom{\sum N_i}{N_1} F\left(\frac{-X_i\beta}{\exp(Z_i\gamma)^2}\right)^{N_1} \\ N(y_i=2) &= \binom{\sum N_i}{N_1} \left[F\left(\frac{\mu_1-X_i\beta}{\exp(Z_i\gamma)^2}\right) - F\left(\frac{-X_i\beta}{\exp(Z_i\gamma)^2}\right)\right]^{N_2} \\ &\vdots \end{aligned} \tag{B.26}$$

$$N(y_i=4) \quad = \quad \binom{\sum N_i}{N_1} \left[1-F\left(\frac{\mu_3-X_i\beta}{\exp(Z_i\gamma)^2}\right)\right]^{N_4} \tag{B.27}$$

What is important to notice is that, as a consequence of the strong independent and identical distribution assumption above, the parameters of interest, β and γ, refer to exactly the same thing across the two levels of analysis: the effect of a unit change upon the probability of individual choice and the variability of individual choice, respectively. In (B.27) we explicitly use aggregate information to draw inferences about individual choice.

Heterogeneous Negative Binomial Models

Our inferential method for estimating the determinants of variance in the heterogeneous negative binomial model that follows is similiar to our heterogenous discrete choice models. The two parameters in the negative binomial model are the mean event count rate (λ_i) and the dispersion (α). The event count rate must be greater than or equal to zero, while the dispersion must be greater than one.

We begin by assuming that each dependent variable ($Y_i = 0,1,2,3,\ldots$ and i indexes respondents) has the following distribution:[6]

$$Y_i \sim f_{nb}(y_i|\lambda_i,\alpha) \tag{B.28}$$

where $E(Y_i)=\lambda_i$. This produces a probability distribution for $P(Y_i=y_i|\lambda_i,\alpha_i)$:

$$P(y_i|\lambda_i,\alpha_i) = \prod_{i=1}^{N} \frac{\Gamma(1/\alpha_i+Y_i)}{\Gamma(Y_i+1)\Gamma(1/\alpha_i)} \left(\frac{1}{1+\alpha_i\lambda_i}\right)^{1/\alpha_i} \left(1-\frac{1}{1+\alpha_i\lambda_i}\right)^{Y} \tag{B.29}$$

The log-likelihood for the negative binomial model is given by:

$$\ln L(\lambda,\alpha|Y) = \sum_{i=1}^{N} \frac{\Gamma(1/\alpha_i + Y_i)}{\Gamma(Y_i+1)\Gamma(1/\alpha_i)} (\frac{1}{1+\alpha_i\lambda_i})^{1/\alpha_i} (1 - \frac{1}{1+\alpha_i\lambda_i})^{Y} \tag{B.30}$$

Now we reparameterize the event count rate to be a function of the explanatory variables in the choice component of the model (X) and coefficients (β):

$$\lambda_i = \exp(X_i\beta) \tag{B.31}$$

and similarly for the variance model variables (Z) and coefficients (γ):

$$\alpha_i = \exp(Z_i\gamma) \tag{B.32}$$

So after parameterizing for the rate (λ) and dispersion (α), this produces a log-likelihood function slightly different from the standard one presented above:

$$\begin{aligned} \ln L(\beta,\gamma|Y_i,X_i,Z_i) \quad = \quad & \sum_{i=1}^{N} \ln\Gamma(1/\exp(Z_i\gamma)+Y_i) - \ln\Gamma(Y_i+1) - \ln\Gamma(1/\exp(Z_i\gamma)) \\ & - \ln\Gamma(1/\exp(Z_i\gamma)) - \ln((1+\exp(X_i\beta))/\exp(Z_i\gamma)) \\ & + Y_i \ln(\exp(X_i\beta)/(1+\exp(X_i\beta))) \end{aligned} \tag{B.33}$$

Again, we simply will estimate the choice function parameters using this log-likelihood function (i.e., the β parameters) in the choice function and we parameterize the error variance as in our ordinal heteroskedastic choice model with a set of variables measuring the potential sources of heterogeneity (the Z_i variables) and their associated parameters (the γ parameters).

Estimation of Heteroskedastic Choice Models

These heteroskedastic choice models are widely used in this book. Fortunately, they are also relatively easy statistical models to estimate. In the previous sections, we presented all of the information needed to program both heteroskedastic choice models in any type of statistical software package which can perform maximum likelihood analysis, like GAUSS. Armed with the log likelihood and the first derivatives, it is relatively simple to program either model in GAUSS; also, the heteroskedastic choice models do not take an extremely long time to reach convergence.

We have used GAUSS, SHAZAM, and STATA to maximize our log-likelihood functions for the heteroskedastic choice models presented in this book. Also, LIMDEP can estimate both models without programming the log-likelihood function, making it a very simple and effective way to estimate this class of discrete choice models; we also use LIMDEP to estimate the models we present in this book. The most recent release of STATA has included a command to estimate heteroskedastic binary probit models. Computer code using each of these statistical software packages is available from the authors at http://hardchoices.caltech.edu.

In our work with the heteroskedastic choice models we have experienced no unusual problems in the actual estimation of the models. For example, the ordinal heteroskedastic probit models we use in chapter 6 (on attitudes about race and affirmative action) converge rapidly and in just thirty to thirty-five iterations. The only problem which researchers must be aware of when using these models is one which is actually more an aspect of the ordinal choice model in general; in some cases the maximum-likelihood estimation of any ordinal choice model (with or without heteroskedasticity) might produce estimates of the underlying thresholds which are not strictly ordered. If this occurs, the estimation routine is likely either to not converge or to produce estimates which are clearly incorrect. But we have not encountered this problem in any of the applications which we report in the book.

Interpretation of Heteroskedastic Choice Models

The primary problem with using these heteroskedastic discrete choice models is that the estimates can be difficult to interpret. Since both the binary and the ordinal heteroskedastic choice models are highly nonlinear, that means that any particular coefficient estimate depends on both the other coefficient estimates and the values of the independent variables. The coefficient estimates themselves can only reveal the sign of the estimates relationship and whether it is statistically different from zero.

Thus, we largely refrain from presenting coefficient estimates in the text of the book. Instead we present the coefficient estimates in the appendices posted here; we also provide discussion in these same appendices of how we code variables, how we generate many of the scales used in our analysis, and some general discussion of the fit of each particular model. Readers who are interested in the details of model estimation can examine the results directly for themselves in the appropriate appendices.

When we present results from our heteroskedastic discrete choice models in the printed chapters of the book we present secondary analyses. That is, we use the coefficient estimates we obtain to produce results which we can more easily interpret and discuss in the context of each chapter. To produce our secondary estimates we rely upon three different approaches.

First, we often make use of the *estimated marginal effects* of variables in the choice function of the model. Once we have coefficient estimates in hand, it is relatively easy to compute the estimated marginal effects of each right-hand side variable. These marginal effect estimates are simply the estimates of the change in probability of choice which we expect conditioned on a change in the value of the particular independent variable. In other words, the marginal effect estimates for the effects of variables in the choice function of our heteroskedastic discrete choice models are simply the partial derivatives of the probability of a certain choice being made with respect to a change in one of the independent variables.

For the binary choice model with heteroskedasticity, we write the marginal effects as:

$$\frac{\partial P(Y=1)}{\partial X_i} = \left[\frac{\phi X_i \beta}{\exp^{Z_i \gamma}}\right] \frac{\beta}{\exp^{Z_i \gamma}} \tag{B.34}$$

The expression given in equation B.34 holds for each particular independent variable (that is, each X) and the respective coefficient estimate (the corresponding estimated value of β).

We write the marginal effect estimates for the ordinal choice model with heteroskedasticity in a very similar way:

$$\frac{\partial P(k)}{\partial X_i} = [f(\mu_{j-1} - X_i\beta)/\exp(Z_i\gamma) - f(\mu_j - X_i\beta)/\exp(Z_i\gamma)]\beta/\exp(Z_i\gamma) \tag{B.35}$$

Since we present the marginal of each right-hand side variable on the probabilities of choosing the low (L) and high (H) categories, these expressions are given as:

$$\frac{\partial P(L)}{\partial X_i} = -\frac{\phi(X_i\beta)}{\exp(\gamma' Z_i)} \frac{\beta}{\exp(\gamma' Z_i)} \tag{B.36}$$

and

$$\frac{\partial P(H)}{\partial X_i} = \frac{\phi(\mu_4 - X_i\beta)}{\exp(\gamma' Z_i)} \frac{\beta}{\exp(\gamma' Z_i)} \tag{B.37}$$

The second way we present our secondary analyses is by using *differencing*.[7] We use the differencing approach primarily for our presentation of the effects of the variables in the variance function. The essence of the differencing approach begins with the estimated values of the coefficients in the variance function (γ) and with the sample distribution information of each variable in the variance function (the mean, the standard deviation, and the sample minimum and maximum of each variance function variable). We set all of the variables in the variance function to their mean values; multiplying each of these mean values by the coefficient estimates, and then summing these products gives us an estimate of the magnitude of the error variance. Thus, we begin with the estimated magnitude of the error variance at the sample means of the variables in the variance function.

Then we start with one of the variables in the variance function. We change the value of this one variable by some predetermined amount (either by one standard deviation or by changing the value to the sample minimum or maximum). We then recompute the magnitude of the error variance at this second value of the particular variable; the difference between this estimated error variance and the first gives us an estimate of the effect of the particular variable in the variance function on the error variance. We repeat this procedure for all of the variables in the error variance function.

This differencing procedure also can be used to present the estimated effect of each variable in the choice function. All this involves is the identical approach to that which we just discussed; we set all of the choice function variables to their sample means and there we compute the probability of a particular policy choice. We then vary one of the choice function variables by some predetermined amount (by one standard deviation, or by changing it to the sample minimum or maximum), and then we recompute the probability of policy choice. The difference between these two probability estimates gives us an estimate of the effect of the particular choice function variable on the probability that a representative individual might make a certain policy choice.

The third approach we use for presenting estimated effects of variables in both the choice and variance function is a *graphical approach*. Here, we just generalize the differencing approach for both the choice and variance function variables. For example, if we were interested in measuring the impact of a particular variable from the choice function we would begin by setting all of the variables (but not the variable of interest) to their sample mean values. We would set the variable of interest to the sample minimum value, and we could compute the probability of policy choice. Then, we would increase the variable of interest by some small amount, and again recompute the probability of policy choice. We would continue to increase the variable of interest by incremental amounts, each time recomputing the probability of policy choice, until we reached the sample maximum value for the variable of interest. Last, we would graph each of these probability estimates for each value of the variable of interest.

The graphical approach also works for the variance function estimates. The only important difference is that for each value of the variable of interest from the variance function we would compute the magnitude of the error variance, holding the other variables in the variance function at their sample means. We would compute the magnitude of error variance for each incremental value of the variable of interest; again, we would graph these two sets of points for presentation purposes.

Notes

1.For both binary and ordinal response data another widely used statistical model is called the logit binary or categorical choice model (these are sometimes called the logistic choice models in the literature). This is essentially identical to the probit model; the only major distinction between the two models is that the former assumes that the response data have slightly different statistical distributions (the logistic rather than the normal). The logit function can be substituted here for a similar model (Dubin and Zeng 1991; Gerber and Lupia 1993). Another interesting application of the heteroskedastic probit model is given by Knapp and Seaks (1992).

2.There are two other tests for heteroskedasticity in the binary choice framework—the Lagrange multiplier and Wald test statistics. We use the likelihood ratio test here since it is most familiar to political scientists, since we have a theoretical specification for the variance function and since we have a strong interest in estimating the parameters in γ. Also, they are asymptotically equivalent tests (Engle 1984).

3.Davidson and MacKinnon (1984) demonstrate through Monte Carlo simulations that this LR test falsely rejects the null in less than 1 percent of the replications at the $p < .01$ level, with only five hundred observations in each replication. With the greater number of observations in our sample, Davidson and MacKinnon's findings suggest even greater power in our application of the LR test.

4.All tests for heteroskedasticity are sensitive to model misspecification (Davidson and MacKinnon 1984). In fact, an alternative approach to heteroskedasticity is to regard it as a problem of misspecified functional form, and to incorporate a series of interactive terms into the model. For testing our model, though, the variance function is of intrinsic interest, and is a function of understandable parameters. Estimating the variance function, moreover, is a direct test of our argument.

5.Assuming that observations are independently and identically distributed is very clearly a strong assumption. This implies, for example, that the beliefs about racial policies in one congressional district in a state are uncorrelated with those same beliefs in the adjacent district. Our next task is to determine how sensitive this empirical model is to this assumption. Then we will have to weaken this assumption, and to develop an alternative estimation model which does not require that observations be independently and identically distributed.

6.This follows the explication in Long (1997).

7.This is similar to the *first difference* approach discussed by King (1989).

APPENDIX C

Methodological Materials for Chapter 5

TABLE C.1. Heteroskedastic Probit Estimates of Attitudes toward Abortion Policy, 1982 General Social Survey

	Mothers' Health	*Rape*	*Birth Defect*	*Too Poor*	*No More Kids*	*Single*	*Any Reason*
Percent Yes	90.4	83.9	82.1	49.0	45.8	45.5	38.5
Choice Model							
Constant	2.55	1.92	2.02	0.02	0.03	0.11	−0.07
	(0.46)	(0.40)	(0.40)	(0.01)	(0.08)	(0.09)	(0.13)
Black	−0.51	−0.47	−0.54	−0.09	−0.11	−0.23	−0.15
	(0.14)	(0.13)	(0.15)	(0.06)	(0.06)	(0.10)	(0.09)
Male	−0.08	−0.20	−0.21	−0.04	−0.02	−0.06	−0.13
	(0.11)	(0.09)	(0.11)	(0.04)	(0.03)	(0.05)	(0.07)
Catholic	−0.52	−0.15	−0.33	0.01	0.02	−0.03	0.05
	(0.13)	(0.10)	(0.12)	(0.04)	(0.04)	(0.04)	(0.07)
Religious intensity	−0.39	−0.17	−0.51	−0.17	−0.13	−0.18	−0.22
	(0.20)	(0.14)	(0.19)	(0.10)	(0.69)	(0.09)	(0.12)
Attend church	−1.04	−0.99	−0.91	−0.35	−0.43	−0.47	−0.79
	(0.25)	(0.23)	(0.24)	(0.17)	(0.17)	(0.20)	(0.26)
Know what ERA means	−0.18	−0.14	0.01	0.10	0.09	0.09	0.12
	(0.17)	(0.15)	(0.16)	(0.08)	(0.07)	(0.08)	(0.10)
Support ERA	0.33	0.12	0.40	0.22	0.31	0.31	0.51
	(0.17)	(0.14)	(0.18)	(0.12)	(0.13)	(0.13)	(0.17)
Variance Model							
Pro count	−0.14	−0.19	−0.06	−0.25	−0.26	−0.34	−0.22
	(0.07)	(0.09)	(0.08)	(0.22)	(0.18)	(0.17)	(0.15)
Con count	0.17	0.20	0.37	−0.50	−0.58	−0.41	−0.48
	(0.09)	(0.12)	(0.12)	(0.19)	(0.17)	(0.16)	(0.14)
Pro count × con count	−0.44	−0.03	−0.09	0.19	0.25	0.21	0.22
	(0.04)	(0.05)	(0.05)	(0.11)	(0.09)	(0.08)	(0.08)
Importance	0.51	0.17	−0.14	−0.16	−0.18	−0.24	−0.30
	(0.15)	(0.15)	(0.16)	(0.31)	(0.26)	(0.25)	(0.25)
Information	0.37	−0.13	0.05	−0.32	−0.28	−0.28	0.68
	(0.13)	(0.14)	(0.14)	(0.29)	(0.25)	(0.24)	(0.23)
Firmness of opinion	−0.37	−0.58	−0.61	0.60	0.47	1.81	0.63
	(0.16)	(0.17)	(0.16)	(0.58)	(0.43)	(0.67)	(0.38)
Heteroskedasticity Test							
Likelihood ratio test ($\chi^2_{df=6}$)	47.4†	46.7†	41.2†	12.5	19.9†	27.2†	25.9†
N	1312	1302	1294	1291	1289	1293	1295
Goodness of fit ($\chi^2_{df=13}$)	126.12†	173.66†	181.29†	142.30†	182.86†	193.54†	180.86†

Note: Standard errors are in parentheses below coefficients. † indicates a χ^2 significant at the $p \leq .01$ level.

TABLE C.2. Heteroskedastic Probit Estimates of Attitudes toward Abortion, 1985 General Social Survey

Variable	*Mothers' Health*	*Rape*	*Birth Defect*	*Too Poor*	*No More Kids*	*Single*	*Any Reason*
Choice Model							
Constant	1.25*	0.64*	0.77*	0.08	−0.25	−0.11	−0.29
	(0.39)	(0.23)	(0.23)	(0.12)	(0.22)	(0.21)	(0.35)
Feminism	1.26*	0.61*	0.67*	0.62*	1.41*	1.35*	2.04*
	(0.53)	(0.27)	(0.28)	(0.26)	(0.54)	(0.51)	(0.67)
Fear of God	−0.48*	−0.12	−0.12	−0.19*	−0.19	−0.32*	−0.36
	(0.27)	(0.11)	(0.11)	(0.11)	(0.16)	(0.19)	(0.27)
Black	−0.08	−0.07	−0.17	−0.11	−0.11	−0.23	−0.07
	(0.15)	(0.09)	(0.11)	(0.09)	(0.14)	(0.15)	(0.22)
Male	0.25*	0.05	0.04	0.09	0.21*	0.13	0.17
	(0.12)	(0.06)	(0.06)	(0.06)	(0.11)	(0.10)	(0.16)
Catholic	−0.21*	−0.18*	−0.19*	−0.18*	−0.32*	−0.33*	−0.53*
	(0.10)	(0.08)	(0.07)	(0.09)	(0.15)	(0.16)	(0.24)
Religious intensity	−0.68*	−0.44*	−0.59*	−0.47*	−0.84*	−0.83*	−1.56*
	(0.24)	(0.17)	(0.19)	(0.24)	(0.39)	(0.39)	(0.62)
Variance Model							
Education	−0.91*	−0.87*	−0.80*	−0.95	−0.10	0.24	1.26*
	(0.30)	(0.35)	(0.35)	(0.65)	(0.56)	(0.57)	(0.51)
$1 - \lvert \text{Feminism} - \text{Fear of God} \rvert$	0.53*	0.00	0.08	0.07	0.14	−0.06	0.28
	(0.31)	(0.34)	(0.26)	(0.40)	(0.34)	(0.37)	(0.34)
Mean Log-Likelihood	−0.30	−0.45	−0.46	−0.64	−0.62	−0.63	−0.61
N	1219	1219	1219	1219	1219	1219	1219

Note: Standard errors are in parentheses below coefficients. * indicates a $p \leq .05$ level of statistical significance, two-tailed test.

TABLE C.3. Heteroskedastic Probit Coefficients, Attitudes toward Euthanasia and Suicide, 1985 General Social Survey

Coefficient	*Euthanasia*	*Incurable*	*Bankrupt*	*Dishonored*	*Tired of Life*
Choice Model					
Constant	0.74	1.78	−1.86	−2.04	−0.96
	(0.41)	(0.99)	(0.90)	(0.97)	(0.95)
Fundamentalist	−0.13	−0.73	−0.64	−0.59	−0.78
	(0.09)	(0.38)	(0.41)	(0.43)	(0.51)
Attend church	−0.60	−1.95	−1.98	−2.48	−2.98
	(0.32)	(0.99)	(0.82)	(1.01)	(1.16)
Religious intensity	−0.12	−0.74	0.26	0.56	0.27
	(0.12)	(0.48)	(0.56)	(0.64)	(0.68)
Good world	0.03	0.30	1.08	1.31	−0.27
	(0.14)	(0.38)	(0.88)	(0.95)	(1.05)
Normlessness	−0.01	0.45	0.40	0.87	0.98
	(0.08)	(0.31)	(0.37)	(0.40)	(0.43)
Fear of God	−0.08	−0.09	−1.26	−1.29	−0.82
	(0.10)	(0.26)	(0.67)	(0.61)	(0.42)
Variance Model					
1 − |Good World − Normlessness|	−0.15	0.07	−0.06	0.19	0.27
	(0.39)	(0.32)	(0.23)	(0.25)	(0.23)
1 − |Good World − Fear of God|	0.04	0.19	−0.04	−0.19	−0.04
	(0.47)	(0.38)	(0.25)	(0.25)	(0.24)
1 − |Normlessness − Fear of God|	0.16	0.48	0.49	0.48	0.50
	(0.32)	(0.28)	(0.22)	(0.22)	(0.23)
Education	−0.98	−0.11	0.85	0.93	1.10
	(0.47)	(0.49)	(0.29)	(0.32)	(0.31)
Mean Log-Likelihood	−0.58	−0.58	−0.25	−0.25	−0.34

Note: Standard errors are in parentheses below coefficients.

APPENDIX D

Methodological Materials for Chapter 6

Data and Variable Coding

Operationalization of the Dependent Variables

All of the dependent variables we use in chapter 6 in the printed book were coded so that the high response (for binary choices this is 1, for the ordinal choices this is 3 or 4, depending on the question) indicates an affirmative choice and the low response indicates a negative choice. For example, on the Contracts question, we coded the affirmative response (1) as the respondent favoring federal set-asides for minorities, while the negative response (0) was reserved for respondents who did not favor set-asides. We begin by discussing the racial policy questions, binary and ordinal, followed by the opinions about blacks questions.

Binary Racial Policy Questions

The first question in these set of analyses was Contracts. Here, respondents were asked the following question: “(Many people/Many blacks) (believe/are demanding) that there should be a law to make sure that a certain number of federal contracts go to black contractors. What do you think about such a law—is it a good idea or a bad idea?” We coded three dummy variables to control for the different wordings of this question. If a respondent had the “Many people believe” stem, we coded Dummy1 = 0 and Dummy2 = 0; if they had the “Many blacks believe” stem, we coded Dummy1 = 1 and Dummy2 = 0; if they had the “Many people are demanding” stem, we coded Dummy1 = 0 and Dummy2 = 1; last, if they had the “Many blacks are demanding” stem, we coded Dummy1 = 1 and Dummy2 = 1. We also include Dummy3, which is the interaction between Dummy1 and Dummy2, to control for possible interactive effects of the question wordings.

Next, we analyzed Taxes. Respondents were asked to give their opinion on: “(Some people have said/Both the President and Congress, including both Democrats and Republicans, have decided) that taxes need to be raised to take care of pressing national needs. How do you feel—would you be willing to have your taxes raised a little in order to improve (education in public schools/educational opportunities for minorities)?" Again, we used three dummy variables to control for the different possible wordings of this question. Respondents who were asked "Some people have said/education in public schools" were given a coding of Dummy1 = 0 and Dummy2 = 0; if the respondent was asked "Some people have said/educational opportunities for minorities"), we coded Dummy1 = 0 and Dummy2 = 1; respondents who were asked "Both the President and Congress, including both Democrats and Republicans, have decided/education in public schools" were scored Dummy1 = 1 and Dummy2 = 0; respondents who were asked "Both the President and Congress, including both Democrats and Republicans, have decided/educational opportunities for minorities" were scored Dummy1 = 1 and Dummy2 = 1. We again include an interaction between Dummy1 and Dummy2 (which we give below in our tables of results as Dummy3), to control for possible interactive effects in the question wordings.

The variable Housing, measuring binary opinions on open housing laws, actually had three different versions: one was neutrally worded, the second invoked the idea of property rights, and the third led respondents to think about open housing in the context of the role of government. The three wordings were:

1. (Neutral, Dummy1 = 0, Dummy2 = 0): Suppose there were a community-wide vote on a general housing issue and that there were two possible laws to vote on. One law says that homeowners can decide for themselves who to sell their houses to, even if they prefer *not* to sell to blacks. The other law says that homeowners cannot refuse to sell to someone because of their race or color. Which law would you vote for?
2. (Property rights, Dummy1 = 1, Dummy2 = 0): Some people believe that homeowners should be free to decide for themselves who to sell their house to, even if they prefer not to sell it to blacks. For example, some people might say it isn't that they don't want to sell to blacks; it's just that they don't want to be told what to do with their own property. In other words, they feel that because it's their property, they should have the right to sell to anyone they want to. How do you feel about this? Do you think homeowners should be able to decide for themselves who to sell their houses to, even if they prefer not to sell to blacks, or do you think homeowners should not be allowed to refuse to sell to someone because of their race or color?
3. (Role of government, Dummy1 = 0, Dummy2 = 1): Some people believe that the government should

make an active effort to see that blacks can live anywhere they choose, including white neighborhoods. Others believe that this is not the government's business and it should stay out of this. How do you feel? (Is this an area the government should stay out of or should the government make an active effort to see that blacks can live anywhere they can afford to—including white neighborhoods?)

Both the property rights and role of government frames introduce a rationale for opposing rights of equal access to housing for blacks. The property rights frame invokes one of the traditional values embedded in the modern racism concept and so advocates of this concept might expect the sign on the coefficient to be negative and sizable. (It is.) We do not see the same relationship to the role of government frame, although it introduces government intrusion, and a potential reactance effect. The dummy term for the role of government is also negative and sizable. (The coefficient on the role of government dummy is larger than the equivalent for property rights, although the two are statistically indistinguishable).

Next, we have a binary indicator for opinions on preferences for black university admissions (Universities). This question had two different formats:

1. (Preference, Dummy1 = 0): Some people say that because of past discrimination, qualified blacks should be given preference in university admissions. Others say that this is wrong because it discriminates against whites. How do you feel—are you in favor of or opposed to giving qualified blacks preference in admission to colleges and universities?
2. (Extra effort, Dummy1 = 1): Some people say that because of past discrimination, an extra effort should be made to make sure that qualified blacks are considered for university admission. Others say that this extra effort is wrong because it discriminates against whites. How do you feel—are you in favor of or opposed to making an extra effort to make sure qualified blacks are considered for admission to colleges and universities?

The preference frame reflects a stronger policy than simply making an extra effort. Hence, we expected the sign on Dummy1 to be positive, and it was both positive and statistically significant.

The last two binary racial policy dependent variables involve questions about the provision of jobs. Job Quotas was asked with three slightly different versions: "(Blank/There are some large companies where blacks are underrepresented/There are some large companies with employment policies that discriminate against blacks.) Do you think (that/these) large companies should be required to give a certain number of jobs to blacks, or should the government stay out of this?" We included two variables in our model to control for the different wordings: respondents who received no stem (Blank) were coded Dummy1 = 0 and Dummy2 = 0; those who received the "blacks underrepresented" stem were coded Dummy1 = 1 and Dummy2 = 0; those who got the "companies discriminate" stem were coded Dummy1 = 0 and Dummy2 = 1.

The second question relating to jobs for blacks we called Jobs. This question had two slightly different versions: "Some people feel that the government in Washington should (increase spending for programs to help blacks get more jobs/do more to make sure that blacks are not discriminated against in getting jobs). Others feel that blacks should take care of their own problems. How do you feel?" We used one variable to control for these different versions; if a respondent was asked the "increase spending" stem, we coded Dummy1 = 1, while if they received the "do more" stem, we coded Dummy1 = 0.

Ordinal Racial Policy Questions

Our analysis of the ordinal racial policy questions begins with a question about anti-discrimination laws which we call Discrimination. This question had three different versions, where respondents were asked if they strongly favored, somewhat favored, somewhat opposed, or strongly opposed the following statement: "How about laws protecting people—many of whom are (blacks/Asian Americans/women) from discrimination in hiring and promotion?" We created two variables to control for the different versions of this question. If a respondent received the frame blacks, we coded these two variables Dummy1 = 1 and Dummy2 = 0; if they received the frame Asian Americans, we coded these two variables Dummy1 = 0 and Dummy2 = 1; if they received the frame women we coded these variables Dummy1 = 0 and Dummy2 = 0.

Next, we used two different questions to probe respondent preferences regarding open housing laws. The first of these dependent variables is Housing, which is based on a simple question: "How do you feel about blacks buying houses in white suburbs?" Respondents were asked the extent to which they agreed (strongly, somewhat) or opposed (strongly, somewhat) with that question. The second version of this question we called White Suburbs, which involved a more complicated multi-version wording of a similar question. This question also asked the extent of a respondent's support for or opposition to "(programs set up by religious and business groups that/government subsidizing housing to/the goverment putting its weight behind programs to) encourage blacks to buy homes in white suburbs." Here we used two variables to control for the question wording. If the respondents were given the first stem, we coded the two variables Dummy1 = 1 and Dummy2 = 0; if they got the second stem, these two variables were coded Dummy1 = 0 and Dummy2 = 1; if they received the third stem, both variables were coded zero.

The last two questions in this series did not involve any question-wording experiments; both of these questions attempted to assess respondents' opinions about the extent of federal government involvement in private life to combat racial discrimination. The first question we called Interference, and respondents were asked how strongly they agreed or disagreed with the statement "The government in Washington tries to do too many things that should be left up to individuals and private businesses." The second question we called Overboard, and again respondents were asked how strongly they agreed or disagreed with the statement "This country sometimes goes overboard in its efforts to fight racism these days."

Opinions about Blacks

Respondents to the mailback survey were asked to say whether each of the following statements is definitely or probably true or false.

- *Students:* The average black child in American does as well in school as the average white child.
- *Knives:* Poor black children are more likely to carry knives and other dangerous weapons to school than poor white children are.
- *Advantage:* When they have the chance to improve their economic position, most blacks make good use of such opportunities.
- *Employers:* Nowadays, when the average employer must decide between two equally qualified applicants, he is more likely to choose the black rather than the white applicant.
- *Fair trial:* In most American courts, a white person has a better chance to get a fair trial than a black person does.
- *Racist:* White people are more likely to be racists than blacks are.

Specification of the Variance Function

The specification of the variance function reflects our desire to test two competing explanations for differences across Americans in the variation of their racial policy beliefs. As we argued above, variation in policy beliefs may reflect fundamental uncertainty about the policy choice under discussion. In other words, people may simply lack information about the policy choices and what they might imply, and that uncertainty will be reflected in the variance function of the heteroskedastic probit model (Alvarez and Franklin 1994;

Franklin 1991).

To control for the effect of uncertainty, we include in the specification of the variance function a variable which measures what we call chronic information. This is a simple political information measure, based on the earlier measures advocated by Zaller (1992). We use an additive scale which measures whether the respondent correctly knew the number of Supreme Court members and the maximum number of presidential terms. This variable is coded to range from 0 to 1, where 1 indicates correct answers to both factual political information questions. We expect the estimated coefficient to be negative, which implies that with increased political information the amount of variance in policy choices diminishes.

The 1991 survey data also include three factual items which are race-related: the percentage of poor who are black, the percent arrested who are black, and the percentage of black males who are unemployed. We used responses to these three questions to develop a domain-specific racial information measure. Although the mechanics of the difference are far from clear, chronic information measures regularly outperform domain-specific information measures (Zaller 1992).

The rival explanation for variability in attitudes toward racial policy is ambivalence induced by core beliefs underlying racial attitudes. We set two criteria in order to identify ambivalence. The first is that additional information should not reduce, and may in fact heighten, the response variability. The second criterion is that response variability should increase as core beliefs and values conflict. Prior research instructs us to attend to one particular source of conflict, between egalitarianism and individualism. To the extent that racial policies achieve egalitarianism by rejecting individualism, we should expect to see greater response variability among individuals who prize both egalitarianism and individualism.

To test for the core belief conflict, we include the absolute values of the differences of levels of egalitarianism and individualism.[1] To get an intuition for what this operationalization means, recall that each of these core value scales is coded so that the minimum score is 0 and the maximum is 1. Thus, when we use the absolute value of the differences, when a respondent's level of egalitarianism and individualism are in conflict (i.e., both are highly prized values), then we get a measure of zero. When the respondent's level of egalitarianism differs from the level of individualism then the values are not in conflict, and we get a positive value for the conflict term. In this particular case, we expect that if the conflict of the two values structures response variability, then this can only occur when both values are in agreement. Hence, if ambivalence is the appropriate characterization, we expect the coefficient on this measure to be negative and significant.

A second way in which these scales might influence variability in racial attitudes is via a kind of measurement effect. Sniderman and colleagues (Sniderman and Piazza 1993; Sniderman and Hagen 1985; Sniderman and Tetlock 1986) have argued that researchers should not hold that opposition to racial policy is an indication of racism, since opposition to racial policy might be grounded in non-racial objections. This is tantamount to holding that racists are relatively fixed in their opposition to racial policy, but that non-racists might be quite variable in attitudes about racial policy. We estimate a second set of heteroskedastic probit models which include the two primary racial core values, modern racism and antiblack stereotyping, in the variance function. Our expectation is that people who are more racist on these scales will have lower variance, hence that the sign of the direct effects of modern racism and antiblack stereotyping should be negative. [2]

Notes

1.It is conceivable that conflict among the other scales might also lead to greater response variability. An earlier version of this paper, in fact, included all possible combinations of scales in a similar test. None of the results summarized in the tables vary significantly with the results of the fully saturated test. We prefer the simpler test of conflict between egalitarianism and individualism as it is one based upon the standing literature. We can think of no similarly motivated reason to expect conflict among any other pair of values.

2.We also include ideology in the variance function, in order to control for a similar effect such that liberals may be more variable in their opinions about racial policy than conservatives. As the reader will note below, this effect did not materialize. We explored another variation of this model wherein we scaled ideological self-placement to reflect extremism (i.e., extreme liberals and extreme conservatives score at the maximum, moderates at the minimum), and there was again no effect of ideology on variance.

Heteroskedastic probit results

TABLE D.1. Attitudes about Racial Policy: Binary Probit Models

Linear Variance Specification

Independent Variables	*Contracts*	*Taxes*	*Housing*	*Universities*	*Job Quotas*	*Jobs*
Choice Model						
Constant	0.98**	1.2**	1.6**	1.6**	0.92**	3.8**
	0.49	0.46	0.63	0.68	0.39	1.1
Dummy1	−0.07	−0.16**	−0.51**	1.6**	−0.06	−0.07
	0.09	0.09	0.20	0.50	0.07	0.10
Dummy2	0.07	−0.41**	−0.44**		0.43**	
	0.08	0.16	0.18		0.15	
Dummy3	−0.09	0.14				
	0.12	0.11				
Modern racism	−1.3**	−0.90**	−0.83**	−2.7**	−1.1**	−2.5**
	0.59	0.33	0.34	0.88	0.41	0.73
Individualism	−0.66**	0.09	0.07	−0.86**	−0.22	−1.3**
	0.34	0.19	0.20	0.49	0.19	0.52
Antiblack	−0.27	−0.003	−0.16	0.05	−0.27	−0.39
	0.25	0.16	0.19	0.35	0.24	0.31
Authoritarianism	0.12	0.31*	−0.50**	−0.02	−0.16	0.58*
	0.20	0.20	0.26	0.40	0.19	0.36
Anti-Semitism	0.64**	−0.28*	−0.32**	0.30	−0.14	−0.72**
	0.31	0.18	0.19	0.33	0.15	0.34
Egalitarianism	−0.68**	−0.58*	−0.34**	−0.95**	−0.72**	−1.8**
	0.32	0.25	0.21	0.43	0.28	0.57
Ideology	−0.02	−0.05**	−0.03*	−0.05*	−0.006	−0.09**
	0.02	0.02	0.02	0.04	0.02	0.04
Financial status	−0.02	−0.06**	−0.07*	−0.12*	−0.05	−0.23**
	0.05	0.03	0.04	0.08	0.05	0.09
Variance Model						
Race information	−0.19	−0.08	0.38	0.31	0.09	−0.08
	0.25	0.26	0.33	0.24	0.22	0.27
Chronic information	−0.60**	−0.58**	−0.82**	−0.16	−0.57**	−0.33*
	0.24	0.26	0.28	0.21	0.21	0.23
Modern racism	−0.31	−0.81**	0.21	0.65**	−0.03	−0.19
	0.40	0.34	0.31	0.29	0.37	0.28
Antiblack	1.02**	0.91**	0.54*	0.33	0.02	0.75**
	0.51	0.38	0.41	0.34	0.43	0.32
Ideological strength	−0.15**	−0.03	0.05	−0.10*	−0.10*	−0.02
	0.08	0.08	0.09	0.07	0.07	0.08
Financial status	0.02	0.01	−0.18**	0.04	0.05	0.13**
	0.10	0.09	0.09	0.07	0.09	0.08
Sample size	1353	1362	1360	1360	1359	1249
Model χ^2	229.7**	205.4**	201.9**	374.5**	259.5**	326.3**
Heterogeneity test	20.2**	14.8**	13.5**	14.0**	−13.44**	12.25
Percentage correct	71.2%	68.1%	65.9%	72.5%	73.0%	70.6%

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE D.2. Attitudes about Racial Policy: Binary Probit Models

Interactive Variance Specification

Independent Variables	*Contracts*	*Taxes*	*Housing*	*Universities*	*Job Quotas*	*Jobs*
Choice Model						
Constant	0.54**	0.74**	0.87**	0.67**	0.99**	2.8**
	0.23	0.27	0.31	0.28	0.36	0.73
Dummy1	−0.06	−0.09**	−0.29**	0.78**	−0.06	−0.06
	0.05	0.05	0.10	0.20	0.08	0.09
Dummy2	0.05	−0.26**	−0.26**		0.46**	
	0.05	0.09	0.09		0.14	
Dummy3	−0.05	0.08				
	0.07	0.07				
Modern racism	−0.79**	−0.51**	−0.46**	−1.3**	−1.1**	−1.7**
	0.27	0.18	0.16	0.34	0.35	0.44
Individualism	−0.41**	0.17*	0.07	−0.31*	−0.21	−0.87**
	0.17	0.12	0.11	0.21	0.21	0.36
Antiblack	0.00	−0.05	−0.08	0.04	−0.29*	−0.49**
	0.11	0.11	0.11	0.18	0.19	0.25
Authoritarianism	0.04	0.20*	−0.31**	0.02	−0.17	0.41*
	0.12	0.13	0.15	0.20	0.21	0.27
Anti-Semitism	0.40**	−0.26**	−0.19**	0.19	−0.16	−0.50**
	0.16	0.13	0.11	0.16	0.16	0.23
Egalitarianism	−0.29**	−0.51**	−0.15*	−0.40**	−0.84**	−1.3**
	0.18	0.18	0.11	0.18	0.35	0.36
Ideology	−0.02*	−0.03**	−0.02*	−0.03**	−0.00	−0.07**
	0.01	0.01	0.01	0.02	0.02	0.03
Financial status	−0.01	−0.04**	−0.03*	−0.05*	−0.06	−0.17**
	0.03	0.02	0.02	0.04	0.05	0.06
Variance Model						
Race information	−0.19	0.09	0.48*	0.31*	0.07	−0.06
	0.25	0.28	0.33	0.24	0.22	0.27
Chronic information	−0.68**	−0.61**	−0.84**	−0.17	−0.58**	−0.40**
	0.23	0.25	0.28	0.22	0.21	0.22
$1- \mid \text{EG} - \text{IN} \mid$	−0.31	−0.93**	−0.29	−0.50**	0.17	−0.15
	0.35	0.33	0.33	0.27	0.30	0.25
Ideological strength	−0.14**	−0.06	0.02	−0.07	−0.10*	−0.00
	0.08	0.09	0.09	0.06	0.07	0.08
Financial status	0.005	0.05	−0.19**	0.02	0.05	0.14**
	0.10	0.09	0.08	0.07	0.08	0.07
Sample size	1353	1362	1360	1360	1359	1249
Model χ^2	226.3**	204.5**	199.6**	369.7**	259.5**	321.9**
Heterogeneity test	16.8**	13.9**	11.2	9.1	13.8**	7.8
Percentage correct	71.6%	67.5%	65.6%	71.3%	73.3%	70.9%

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE D.3. Attitudes about Racial Policy: Ordinal Probit Models

Linear Variance Specification

Independent Variables	*Discrimination*	*Housing*	*White Suburbs*	*Interference*	*Overboard*
Choice Model					
Constant	2.5**	3.6**	2.7**	3.6**	4.3**
	0.49	0.52	0.51	0.59	0.57
Dummy1	−0.37**		0.42**		
	0.09		0.11		
Dummy2	−0.47**		−0.03		
	0.11		0.10		
Modern racism	−0.89**	−0.55**	−1.7**	−1.4**	−2.0**
	0.20	0.13	0.33	0.28	0.28
Individualism	0.31*	0.17	0.04	−1.3**	−0.48**
	0.21	0.16	0.28	0.36	0.24
Antiblack	−0.32**	−0.60**	0.20	0.30	−0.86**
	0.19	0.15	0.25	0.25	0.21
Authoritarianism	0.30*	−0.30**	0.20	−0.28	−0.49**
	0.20	0.18	0.25	0.28	0.23
Anti-Semitism	−0.47**	−0.84**	−0.37*	−0.65**	−0.54**
	0.19	0.19	0.23	0.25	0.18
Egalitarianism	−0.76**	−0.11	−1.4**	−0.62**	−0.57**
	0.20	0.12	0.30	0.21	0.18
Ideology	−0.07**	−0.04**	−0.06**	−0.09**	−0.06**
	0.02	0.01	0.03	0.03	0.02
Financial status	−0.06**	−0.09**	−0.13**	−0.10**	−0.09**
	0.03	0.03	0.05	0.05	0.04
Variance Model					
Race information	−0.15	0.17*	0.11	−0.07	−0.04
	−0.13	0.13	0.11	0.10	0.11
Chronic information	−0.17**	−0.25**	0.03	−0.12	−0.30**
	0.10	0.10	0.10	0.10	0.09
Modern racism	0.09	−0.18	0.27**	−0.02	0.01
	0.15	0.15	0.14	0.13	0.10
Antiblack	0.13	0.04	−0.11	0.28**	0.25**
	0.21	0.17	0.17	0.15	0.14
Ideological strength	0.02	−0.05*	0.07**	0.06**	0.03
	0.04	0.03	0.04	0.03	0.03
Financial status	−0.08**	−0.05*	−0.03	0.09**	0.05**
	0.04	0.04	0.03	0.03	0.03
μ_1	0.51**	0.58**	0.94**	1.6**	1.3**
	0.10	0.11	0.17	0.23	0.16
μ_2	1.4**	1.6**	2.4**	3.2**	2.6**
	0.26	0.26	0.40	0.44	0.31
Sample size	1360	1354	1208	1361	1363
Model χ^2	233.2**	230.7**	264.0**	193.5**	426.8**
Heterogeneity test	9.1	4.7	10.4	17.1**	18.3
Percentage correct	51.7%	44.4%	43.0%	47.5%	44.9%

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE D.4. Attitudes about Racial Policy: Ordinal Probit Models

Independent Variables	Interactive Variance Specification				
	Discrimination	*Housing*	*White Suburbs*	*Interference*	*Overboard*
Choice Model					
Constant	2.2**	3.6**	2.1**	2.9**	3.6**
	0.34	0.50	0.35	0.41	0.40
Dummy1	−0.32**		0.37**		
	0.07		0.09		
Dummy2	−0.40**		−0.03		
	0.08		0.08		
Modern racism	−0.79**	−0.61**	−1.5**	−1.1**	−1.7**
	0.15	0.14	0.22	0.21	0.20
Individualism	0.30**	0.16	0.12	−1.0**	−0.37**
	0.18	0.19	0.22	0.28	0.19
Antiblack	−0.32**	−0.66**	0.16	0.30*	−0.74**
	0.16	0.16	0.20	0.21	0.18
Authoritarianism	0.26*	−0.38**	0.17	−0.22	−0.41**
	0.17	0.21	0.21	0.24	0.20
Anti-Semitism	−0.39**	−1.0**	−0.28*	−0.51**	−0.44**
	0.15	0.18	0.18	0.20	0.15
Egalitarianism	−0.67**	−0.09	−1.1**	−0.47**	−0.46**
	0.14	0.14	0.21	0.18	0.15
Ideology	−0.06**	−0.05**	−0.05**	−0.07**	−0.05**
	0.02	0.02	0.02	0.02	0.02
Financial status	−0.05**	−0.11**	−0.11**	−0.09**	−0.08**
	0.03	0.03	0.04	0.04	0.03
Variance Model					
Race information	−0.16	0.17*	0.14*	−0.09	−0.05
	0.13	0.12	0.11	0.10	0.11
Chronic information	−0.17**	−0.26**	0.03	−0.15*	−0.31**
	0.10	0.10	0.10	0.10	0.08
$1-\mid EG - IN \mid$	−0.07	0.21**	−0.23**	−0.09	−0.09
	0.12	0.11	0.12	0.11	0.10
Ideological strength	0.02	−0.06**	0.07**	0.06**	0.03
	0.04	0.03	0.04	0.03	0.03
Financial status	−0.07**	−0.05*	−0.04*	0.09**	0.05**
	0.04	0.03	0.03	0.03	0.03
μ_1	0.43**	0.68**	0.76**	1.3**	1.1**
	0.06	0.10	0.10	0.03	0.11
μ_2	1.2**	1.9**	2.0**	2.6**	2.2**
	0.15	0.22	0.24	0.30	0.20
Sample size	1360	1354	1208	1361	1363
Model χ^2	233.5**	232.0**	263.7**	190.9**	424.4**
Heterogeneity test	8.3	16.4**	10.1	14.4**	16.0
Percentage correct	51.4%	57.1%	43.0%	47.6%	45.2%

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE D.5. Attitudes about Blacks: Ordinal Probit Models

	Linear Variance Specification					
Independent Variables	*Students*	*Knives*	*Advantage*	*Employers*	*Fair Trial*	*Racist*
Choice Model						
Constant	0.51**	2.8**	3.5**	2.7**	3.6**	0.97**
	0.30	0.57	0.73	0.55	0.70	0.27
Modern racism	−0.04	−0.53**	−0.85**	−1.2**	−1.1**	−0.62**
	0.20	0.22	0.25	0.30	0.30	0.18
Individualism	0.13	0.39	−0.03	−0.23	−0.42	−0.31*
	0.32	0.30	0.30	0.33	0.34	0.22
Antiblack	−0.58**	−1.5**	−1.4**	0.16	0.07	−0.30**
	0.29	0.32	0.35	0.26	0.31	0.18
Authoritarianism	0.94**	0.62**	0.67**	−0.21	−0.93**	0.24*
	0.33	0.29	0.32	0.30	0.39	0.19
Anti-Semitism	0.12	−1.0**	−0.46**	0.22	0.08	0.48**
	0.25	0.30	0.25	0.24	0.28	0.15
Egalitarianism	−0.64**	0.29	−0.42**	−0.24	0.03	−0.04
	0.27	0.23	0.22	0.25	0.27	0.15
Ideology	0.05*	−0.03*	−0.03	−0.02	−0.08	−0.02
	0.03	0.02	0.03	0.03	0.03	0.02
Financial status	0.14**	−0.07*	−0.00	−0.04	−0.01	−0.03
	0.06	0.05	0.05	0.05	0.06	0.03
Variance Model						
Race information	0.13	−0.23**	0.02	−0.18*	0.04	0.04
	0.13	0.13	0.14	0.14	0.13	0.14
Chronic information	0.01	−0.11	−0.34**	−0.22**	−0.15	−0.18*
	0.11	0.11	0.13	0.11	0.12	0.13
Modern racism	0.01	0.18	−0.03	0.20*	0.34**	−0.22*
	0.13	0.15	0.16	0.15	0.16	0.16
Antiblack	0.13	0.19	0.22	0.04	0.13	−0.02
	0.04	0.17	0.20	0.17	0.20	0.20
Ideological strength	−0.01	−0.05	0.09**	0.09	0.03	−0.00
	0.04	0.04	0.04	0.04	0.04	0.04
Financial status	0.01	−0.03	−0.03	−0.00	0.00	−0.04
	0.03	0.04	0.04	0.04	0.04	0.04
μ_1	1.8**	1.7**	1.8**	1.4**	1.6**	0.87**
	0.31	0.31	0.39	0.24	0.28	0.17
μ_2	3.3**	3.3**	3.8**	3.4**	3.5**	1.7**
	0.58	0.56	0.73	0.56	0.58	0.32
Sample size	814	813	815	813	816	814
Model χ^2	40.3**	117.1**	116.7**	64.9**	87.2**	51.5
Heterogeneity test	2.0	11.5	15.5**	14.5**	10.3	5.0
Percentage correct	51.6%	52.6%	61.8%	52.8%	45.6%	43.6%

Note: Data from mail-back survey. Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE D.6. Attitudes about Blacks: Ordinal Probit Models

	Interactive Variance Specification					
Independent Variables	*Students*	*Knives*	*Advantage*	*Employers*	*Fair Trial*	*Racist*
Choice Model						
Constant	0.46*	2.2**	3.1**	2.2**	2.6**	1.1**
	0.28	0.37	0.47	0.36	0.39	0.27
Modern racism	−0.04	−0.44**	−0.78**	−1.0**	−0.85**	−0.74**
	0.19	0.17	0.19	0.22	0.20	0.19
Individualism	0.13	0.35*	−0.01	−0.15	−0.26	−0.33*
	0.31	0.25	0.27	0.27	0.25	0.25
Antiblack	−0.57**	−1.3**	−1.3**	0.13	0.03	−0.35**
	0.27	0.24	0.27	0.22	0.22	0.20
Authoritarianism	0.90**	0.51**	0.59**	−0.13	−0.67**	−0.27*
	0.31	0.24	0.26	0.25	0.28	0.21
Anti-Semitism	0.13	−0.76**	−0.38**	0.19	0.08	0.58**
	0.24	0.20	0.21	0.20	0.21	0.21
Egalitarianism	−0.60**	0.23	−0.40**	−0.18	0.05	−0.06
	0.23	0.18	0.20	0.20	0.20	0.18
Ideology	0.04*	−0.03*	−0.02	−0.01	−0.06**	−0.03*
	0.02	0.02	0.02	0.02	0.02	0.02
Financial status	−0.13**	−0.05	−0.00	−0.04	0.01	−0.04
	0.05	0.04	0.04	0.04	0.04	0.04
Variance Model						
Race information	0.13	−0.25**	−0.00	−0.17*	0.03	0.04
	0.12	0.12	0.14	0.14	0.13	0.13
Chronic information	−0.03	−0.15*	−0.38**	−0.23**	−0.18*	−0.16*
	0.11	0.11	0.12	0.11	0.12	0.13
$\mid$ EG − IN $\mid$	−0.11	0.05	0.04	−0.14	−0.10	0.03
	0.14	0.15	0.13	0.13	0.12	0.15
Ideological strength	−0.02	−0.05	0.09**	0.10**	0.04	−0.00
	0.04	0.04	0.03	0.04	0.04	0.04
Financial status	0.01	0.03	−0.03	−0.00	0.00	−0.04
	0.03	0.04	0.04	0.04	0.04	0.04
μ_1	1.6**	1.4**	1.6**	1.1**	1.2**	1.0**
	0.19	0.17	0.21	0.15	0.14	0.14
μ_2	3.1**	2.7**	3.4**	2.8**	2.6**	2.0**
	0.35	0.32	0.40	0.34	0.31	0.27
Sample size	814	813	815	813	816	814
Model χ^2	40.5**	113.8**	115.6**	63.6**	80.7**	49.3**
Heterogeneity test	2.1	8.2	14.4**	13.2**	3.7	2.8
Percentage correct	51.8%	52.3%	62.0%	52.8%	44.7%	44.0%

Note: Data from mail-back survey. Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

APPENDIX E

Methodological Materials for Chapter 7

TABLE E.1. Heteroskedastic Probit Estimates, IRS Taxpayer Opinion Survey

	Accurate	*Equitable*	*Honesty*	*Integrity*
Choice Model				
Constant	0.18∗	−0.14	0.21∗	−0.07
	(0.08)	(0.08)	(0.09)	(0.07)
Responsiveness	0.50∗	0.68∗	0.22	0.66∗
	(0.19)	(0.25)	(0.13)	(0.23)
Fairness	0.02	0.22∗	0.07	0.18∗
	(0.05)	(0.11)	(0.08)	(0.09)
Honesty	0.32∗	0.55∗	0.53∗	0.66∗
	(0.14)	(0.22)	(0.19)	(0.22)
Male	−0.03	0.01	−0.07	0.00
	(0.03)	(0.03)	(0.04)	(0.03)
White	−0.10∗	−0.03	−0.02	−0.07
	(0.05)	(0.04)	(0.05)	(0.05)
IRS contact	−0.09∗	−0.08	0.00	−0.04
	(0.04)	(0.04)	(0.04)	(0.04)
Audit	−0.03	−0.05	0.09	0.03
	(0.04)	(0.06)	(0.06)	(0.05)
μ_1	0.14∗	0.20∗	0.18∗	0.22∗
	(0.05)	(0.07)	(0.06)	(0.08)
μ_2	0.32∗	0.42∗	0.39∗	0.48∗
	(0.11)	(0.15)	(0.12)	(0.15)
μ_3	0.53∗	0.65∗	0.67∗	0.88∗
	(0.18)	(0.22)	(0.21)	(0.27)
μ_4	0.79∗	0.96∗	0.96∗	1.19∗
	(0.27)	(0.32)	(0.30)	(0.36)
Variance Model				
Soft information	−0.14	0.42∗	0.02	−0.10
	(0.14)	(0.15)	(0.13)	(0.12)
Education	−0.25	−0.34∗	−0.13	−0.45∗
	(0.17)	(0.17)	(0.17)	(0.15)
Fairness vs. responsiveness	−0.12	0.28	0.00	0.06
	(0.27)	(0.24)	(0.24)	(0.26)
Fairness vs. honesty	0.18	−0.12	−0.41	0.21
	(0.25)	(0.26)	(0.23)	(0.21)
Responsiveness vs. honesty	−1.34∗	−1.11∗	−0.68∗	−1.10∗
	(0.35)	(0.32)	(0.29)	(0.28)
Log-Likelihood	−935.4	−962.8	−945.5	−844.9
Percentage correct	33.5%	34.3%	32.7%	40.8%
PRE	11.5%	21.6%	12.2%	6.9%
Heterogeneity test	27.0∗	26.2∗	12.4∗	28.9∗
N	606	601	578	586

Note: * indicates an estimate statistically significant at the $p \leq .05$ level, two-tailed test.

TABLE E.2. Heteroskedastic Ordered Probit Estimates, IRS Taxpayer Opinion Survey

	Knowledgeable	*Check Own*	*Reasonable*	*Snooping*
Choice Model				
Constant	0.22∗	0.13	−0.07	0.96∗
	(0.08)	(0.10)	(0.06)	(0.31)
Responsiveness	0.53∗	0.66∗	0.84∗	−0.28
	(0.17)	(0.25)	(0.26)	(0.15)
Fairness	−0.03	0.14	0.21∗	−0.16
	(0.06)	(0.11)	(0.09)	(0.10)
Honesty	0.13	0.59∗	0.31∗	0.01
	(0.10)	(0.24)	(0.13)	(0.13)
Male	0.00	0.00	−0.02	0.02
	(0.03)	(0.04)	(0.03)	(0.04)
White	−0.11∗	−0.12	−0.11∗	0.00
	(0.05)	(0.07)	(0.05)	(0.06)
IRS contact	−0.07∗	−0.05	−0.07∗	−0.12∗
	(0.04)	(0.05)	(0.03)	(0.05)
Audit	−0.05	−0.09	−0.04	0.02
	(0.04)	(0.08)	(0.04)	(0.07)
μ_1	0.19∗	0.21∗	0.14∗	0.27∗
	(0.06)	(0.08)	(0.05)	(0.09)
μ_2	0.36∗	0.48∗	0.35∗	0.51∗
	(0.11)	(0.16)	(0.11)	(0.16)
μ_3	0.55∗	0.82∗	0.65∗	0.87∗
	(0.17)	(0.27)	(0.19)	(0.27)
μ_4	0.77∗	1.18∗	0.96∗	1.17∗
	(0.23)	(0.39)	(0.28)	(0.36)
Variance Model				
Soft information	−0.02	0.16	−0.18	0.06
	(0.13)	(0.12)	(0.14)	(0.14)
Education	−0.32∗	−0.06	−0.48∗	−0.50∗
	(0.15)	(0.16)	(0.16)	(0.18)
Fairness vs. responsiveness	−0.15	−0.09	−0.33	−0.38
	(0.23)	(0.27)	(0.25)	(0.24)
Fairness vs. honesty	−0.12	0.40	0.27	0.18
	(0.22)	(0.25)	(0.24)	(0.23)
Responsiveness vs. honesty	−0.97∗	−1.17∗	−0.90∗	−0.28
	(0.27)	(0.31)	(0.28)	(0.31)
Log-Likelihood	−988.2	−889.0	−900.1	−1007.2
Percentage correct	31.6%	51.7%	40.1%	31.3%
PRE	16.0%	33.4%	15.2%	5.6%
Heterogeneity test	17.2∗	16.2∗	24.2∗	11.2∗
N	598	559	606	601

Note: * indicates an estimate statistically significant at the $p \leq .05$ level, two-tailed test.

APPENDIX F

Methodological Materials for Chapter 8

Model Derivation

The likelihood function for our ordered heteroskedastic logit model is relatively easy to derive, as it follows closely the derivations for the probit model we used in other chapters in the printed book. We begin by assuming that there is a continuous underlying process Y_i such that:

$$Y_i \sim F(y_i \mid \pi_i) \tag{F.1}$$

where the systemic component is:

$$\pi_i = F(X_i \beta) \tag{F.2}$$

Next we denote our threshold parameters by μ_j, where $j = 1, \ldots, m$ and $\mu_1 = -\infty$ and $\mu_m = \infty$. We constrain the thresholds so that the probabilities are always positive:

$$\mu_{j-1} < \mu_j < \ldots < \mu_m \tag{F.3}$$

We know from the data which category y_i belongs to, so we can write that y_i belongs to category j if the following expression holds:

$$\mu_{j-1} < y_i \leq \mu_j \tag{F.4}$$

To make the exposition easier, we assume that y_i is a series of j binary variables (instead of being coded as one ordinal variable) such that:

$$y_{ij} = \begin{cases} 1 & \text{if } \mu_{j-1} < y_i \leq \mu_j \\ 0 & \text{otherwise} \end{cases} \tag{F.5}$$

We next write the probability that y_i is in j as:

$$P(y_i = j) = P(\mu_{j-1} < y_i \leq \mu_j) \tag{F.6}$$

$$= F\left(\frac{\mu_j - X_i\beta}{\sigma_i^2}\right) - F\left(\frac{\mu_{j-1} - X_i\beta}{\sigma_i^2}\right) \tag{F.7}$$

Usual derivations of this likelihood at this point assume that $\sigma_i = 1$. As we argue in the printed book, we wish to assume that choice is heterogeneous, so we assume instead that

$$\sigma_i^2 = \exp(Z_i\gamma)^2 \tag{F.8}$$

where Z_i are variables which we believe measure the heterogeneity in choices across individuals, and γ are coefficients.

We now write the likelihood for a given set of parameters as:

$$L = \prod_{i=1}^{n}\prod_{j=1}^{m}\left[F\left(\frac{\mu_j - X_i\beta}{\sigma_i^2}\right) - F\left(\frac{\mu_{j-1} - X_i\beta}{\sigma_i^2}\right)\right]^{y_{ij}} \tag{F.9}$$

We take logs to produce the log-likelihood function:

$$\ln L = \sum_{i=1}^{n}\sum_{j=1}^{m} y_{ij} \ln\left[F\left(\frac{\mu_j - X_i\beta}{\sigma_i^2}\right) - F\left(\frac{\mu_{j-1} - X_i\beta}{\sigma_i^2}\right)\right] \tag{F.10}$$

where we assume that F represents the logistic distribution.

The extension to aggregates begins from

$$L = \prod_{i=1}^{n}\prod_{j=1}^{m}\begin{pmatrix}\sum N_i \\ N_1\end{pmatrix}\left[F\left(\frac{\mu_j - X_i\beta}{\sigma_i^2}\right) - F\left(\frac{\mu_{j-1} - X_i\beta}{\sigma_i^2}\right)\right]^{N_{ij}} \tag{F.11}$$

where i indexes each of the aggregates (states or congressional districts), and N_{ij} denotes the number of respondents in aggregate i who respond to category j.

Since the combinatoric term $\begin{pmatrix}\sum N_i \\ N_1\end{pmatrix}$ will not vary with the choice of β or γ, it can be dropped from the function to be maximized. The log-likelihood is then

$$\ln L = \sum_{i=1}^{n}\sum_{j=1}^{m} N_{ij} \ln\left[F\left(\frac{\mu_j - X_i\beta}{\sigma_i^2}\right) - F\left(\frac{\mu_{j-1} - X_i\beta}{\sigma_i^2}\right)\right] \tag{F.12}$$

These log-likelihood functions are easy to program in GAUSS, and they quickly converge to produce the results we present in the book. GAUSS code to implement these models is available from the authors. (LIMDEP has routines to estimate the individual level ordered logit and probit models with heteroskedasticity).

As we noted in the book, it is also possible to assume that F represents the normal distribution. That produces an ordered heteroskedastic probit model. We have replicated all of the results presented in the book using an ordered heteroskedastic probit model, and the results are identical to those presented here. We slightly prefer the logit results since the logit models converge more quickly than the probit models and since in practice the logit distribution is marginally easier to use and to program.

Estimation Results

TABLE F.1. Preferential Hiring

	Individual	*Congressional*
Choice Model		
Constant	−2.9∗∗	−0.61
	1.1	0.52
Racial resentment	3.2∗∗	0.43∗
	1.0	0.34
Economic individualism	−0.33∗	0.16
	0.23	0.16
Egalitarianism	0.45	0.07
	0.60	0.14
Spending preferences	1.2∗∗	0.43
	0.62	0.37
Liberal-conservative placement	−0.11	0.07
	0.17	0.08
Party ID	0.13	−0.01
	0.12	0.03
τ_2	1.0∗∗	0.10∗
	0.36	0.08
τ_3	2.0∗∗	0.19∗∗
	0.70	0.15
Variance Model		
Chronic information	−0.60∗∗	−1.0∗∗
	0.22	0.49
Racial resentment vs. egalitarianism	0.40	−1.4∗∗
	0.37	0.83
Racial resentment vs. individualism	−0.11	−0.12
	0.29	0.52
Egalitarianism vs. individualism	0.02	−0.98∗
	0.24	0.77
N	694	93
Mean Log-Likelihood	−0.806	−11.279
Heterogeneity test	7.10	11.98∗

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE F.2. Quotas

	Individual	*Congressional*
Choice Model		
Constant	−3.3∗∗	−0.41∗
	1.2	0.32
Racial resentment	4.1∗∗	0.46∗
	1.2	0.35
Economic individualism	−0.04	0.03
	0.22	0.08
Egalitarianism	1.3∗∗	0.30
	0.70	0.29
Spending preferences	1.3∗∗	0.05
	0.70	0.16
Liberal-conservative placement	0.14	−0.01
	0.17	0.07
Party ID	−0.22∗	−0.00
	0.13	0.04
τ_2	1.5∗∗	0.15∗
	0.48	0.11
τ_3	2.9∗∗	0.30∗
	0.93	0.225
Variance Model		
Chronic information	−0.28∗	−1.6∗∗
	0.19	0.48
Racial resentment vs. egalitarianism	0.15	−0.33
	0.29	0.76
Racial resentment vs. individualism	0.62∗∗	−0.57
	0.26	0.65
Egalitarianism vs. individualism	−0.34∗	−0.30
	0.22	0.79
N	679	93
Mean Log-Likelihood	−1.04	−14.051
Heterogeneity test	7.31	12.03∗

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE F.3. Hiring Preferences

	Individual	*Congressional*
Choice Model		
Constant	−1.5∗∗	−1.8
	.71	1.8
Racial resentment	0.34∗∗	0.98
	0.19	0.90
Economic individualism	−0.11	−0.28
	0.13	0.34
Egalitarianism	1.1∗∗	1.8
	0.63	2.0
Spending preferences	0.35∗	−0.45
	0.23	0.59
Liberal-conservative placement	−0.02	−0.27
	0.04	0.290
Party ID	−0.16∗	0.06
	0.10	0.21
τ_2	0.41∗∗	0.50
	0.17	0.46
τ_3	0.70∗∗	0.87
	0.29	0.80
Variance Model		
Chronic information	−0.41∗∗	−0.38∗
	0.15	0.30
Racial resentment vs. egalitarianism	−0.50	−0.13
	0.41	0.94
Racial resentment vs. individualism	−0.26	0.68
	0.29	0.76
Egalitarianism vs. individualism	−0.49∗∗	−1.4∗∗
	0.26	0.55
N	1055	181
Mean Log-Likelihood	−0.819	−5.70
Heterogeneity test	13.41∗	8.91

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE F.4. Affirmative Action

	Individual	*Congressional*
Choice Model		
Constant	−5.7∗∗	−2.0∗
	1.9	0.03
Racial resentment	1.8∗∗	0.99∗∗
	0.67	0.03
Economic individualism	−0.12	−0.37∗∗
	0.22	0.03
Egalitarianism	5.4∗∗	2.1∗∗
	1.9	0.03
Spending preferences	2.5∗∗	0.44∗∗
	0.88	0.03
Liberal-conservative placement	0.16∗	0.02
	0.10	0.05
Party ID	−0.24∗	−0.14
	0.17	0.03
τ_2	0.86∗∗	0.22∗∗
	0.28	0.02
τ_3	2.0∗∗	0.51∗∗
	0.64	0.02
Variance Model		
Chronic information	−0.13	−0.58∗∗
	0.15	0.03
Racial resentment vs. egalitarianism	0.23	0.02
	0.31	0.07
Racial resentment vs. individualism	0.06	−0.85∗∗
	0.28	0.05
Egalitarianism vs. individualism	−0.05	−0.18∗∗
	0.19	0.04
N	1053	181
Mean Log-Likelihood	−1.220	−8.350
Heterogeneity test	2.25	5.10

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE F.5. Welfare: More Kids

	Individual	*Congressional*
Choice Model		
Constant	$-1.2**$	-0.28
	0.52	0.23
Racial resentment	$0.60**$	0.17
	026	0.15
Economic individualism	$-0.18*$	-0.11
	0.11	0.10
Egalitarianism	$0.86**$	0.38
	0.42	0.32
Spending preferences	$0.53**$	-0.07
	0.25	0.09
Liberal-conservative placement	$-0.06*$	-0.05
	0.04	0.04
Party ID	-0.00	0.00
	0.06	0.03
τ_2	$0.28**$	$0.07*$
	0.11	0.05
τ_3	$0.57**$	$0.15*$
	0.21	0.10
Variance Model		
Chronic information	$-0.57**$	$-0.52**$
	0.18	0.30
Racial resentment vs. egalitarianism	-0.19	$-2.1**$
	0.36	0.75
Racial resentment vs. individualism	$-0.62**$	$-0.86*$
	0.30	0.64
Egalitarianism vs. individualism	-0.17	0.31
	0.25	0.54
N	1082	181
Mean Log-Likelihood	-1.119	-7.853
Heterogeneity test	$16.73*$	$10.98*$

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE F.6. Welfare: Time Limits

	Individual	*Congressional*
Choice Model		
Constant	−0.93**	−0.75
	0.37	0.76
Racial resentment	0.44**	0.78
	0.19	0.73
Economic individualism	−0.10	−0.09
	0.09	0.17
Egalitarianism	0.56**	0.28
	0.29	0.44
Spending preferences	0.43**	0.22
	0.21	0.29
Liberal-conservative placement	−0.06*	−0.08
	0.04	0.09
Party ID	0.00	0.03
	0.06	0.12
τ_2	0.35**	0.25
	0.12	0.22
τ_3	0.62**	0.43
	0.20	0.38
Variance Model		
Chronic information	−0.28**	−0.07
	0.16	0.28
Racial resentment vs. egalitarianism	−0.58**	0.36
	0.35	0.78
Racial resentment vs. individualism	−0.45*	−2.2**
	0.29	0.89
Egalitarianism vs. individualism	−0.33*	−0.09
	0.23	0.48
N	1103	181
Mean Log-Likelihood	−1.046	−7.460
Heterogeneity test	8.27	2.00

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE F.7. Gays and Equal Protection

	Individual	*Congressional*
Choice Model		
Constant	−1.9**	−2.6**
	0.67	0.73
Racial resentment	0.85**	2.1**
	0.39	0.67
Economic individualism	−0.21	−0.48*
	0.18	0.38
Egalitarianism	2.5**	2.8**
	0.82	0.77
Spending preferences	1.1**	0.65
	0.42	0.67
Liberal-conservative placement	−0.43**	−0.41**
	0.14	0.20
Party ID	−0.09	−0.31
	0.11	0.28
τ_2	0.52**	0.45**
	0.16	0.12
τ_3	1.4**	1.2**
	0.41	0.30
Variance Model		
Chronic information	−0.19*	0.10
	0.15	0.27
Racial resentment vs. egalitarianism	−0.36*	−1.3**
	0.29	0.66
Racial resentment vs. individualism	0.19	0.79*
	0.26	0.51
Egalitarianism vs. individualism	−0.19	−0.05
	0.21	0.64
N	1067	181
Mean Log-Likelihood	−1.207	−8.457
Heterogeneity test	18.03*	6.20

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

TABLE F.8. Gays in the Military

	Individual	*Congressional*
Choice Model		
Constant	−0.94∗∗	−1.9∗∗
	0.45	1.1
Racial resentment	0.92∗∗	1.5∗
	0.46	0.97
Economic individualism	−0.15	0.37
	0.14	0.35
Egalitarianism	1.3∗∗	1.3∗
	0.54	0.97
Spending preferences	0.39∗	0.76
	0.24	0.64
Liberal-conservative placement	−0.38∗∗	−0.45∗
	0.14	0.28
Party ID	−0.00	−0.30
	0.10	0.26
τ_2	0.18∗∗	0.18∗∗
	0.07	0.10
τ_3	0.81∗∗	0.77∗∗
	0.29	0.42
Variance Model		
Chronic information	−0.37∗∗	0.28
	0.17	0.28
Racial resentment vs. egalitarianism	−0.41	−0.95∗
	0.37	0.72
Racial resentment vs. individualism	0.11	−0.29
	0.28	0.58
Egalitarianism vs. individualism	−0.32∗	0.21
	0.22	0.6011
N	1090	181
Mean Log-Likelihood	−1.148	−8.177
Heterogeneity test	21.84∗	4.06

Note: Entries are maximum-likelihood estimates. * indicates a $p \leq .10$ level of statistical significance, one-tailed tests; ** indicates a $p \leq .05$ level of statistical significance, one-tailed tests.

APPENDIX G

Methodological Materials for Chapter 9

TABLE G.1. Choice Component of Heteroskedastic Ordered Probit Estimates for Models of Civilian Control of Military.

Variable	*Civilians Decide Use*	*Civilians Decide Type*	*Civilian Control Safe*	*Domestic Politics Determines*	*In War, Military Control*
Constant	0.15	0.38	2.08	0.95	0.71
	(0.10)	(0.18)	(0.72)	(0.34)	(0.29)
Threat	0.21	0.08	−0.63	−0.42	−0.24
	(0.10)	(0.07)	(0.24)	(0.17)	(0.11)
Pro-military	−0.11	−0.01	−0.16	0.39	−0.02
	(0.08)	(0.07)	(0.17)	(0.17)	(0.07)
Moral traditionalism	0.09	0.05	−0.45	−0.23	−0.29
	(0.07)	(0.06)	(0.17)	(0.12)	(0.12)
Elite?	−0.24	0.10	0.01	0.41	0.19
	(0.10)	(0.06)	(0.07)	(0.14)	(0.08)
White?	−0.06	0.01	−0.07	−0.11	−0.03
	(0.04)	(0.03)	(0.06)	(0.06)	(0.02)
Male?	−0.15	−0.03	−0.20	0.004	−0.05
	(0.07)	(0.03)	(0.09)	(0.05)	(0.03)
Age	0.003	−0.0007	−0.01	−0.01	−0.003
	(0.001)	(0.001)	(0.01)	(0.003)	(0.001)
Social trust	−0.02	0.001	0.01	0.03	0.03
	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)
Conf. in military	−0.05	0.04	−0.18	−0.02	−0.06
	(0.04)	(0.04)	(0.09)	(0.07)	(0.04)
Conf. in executive	−0.05	−0.05	0.05	0.11	0.01
	(0.03)	(0.03)	(0.04)	(0.05)	(0.02)
Conf. in TV	0.06	−0.01	0.01	0.03	−0.03
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
Military service?	−0.15	0.05	0.29	0.08	0.004
	(0.07)	(0.03)	(0.05)	(0.05)	(0.03)
In reserves?	0.03	0.01	−0.08	−0.09	−0.05
	(0.04)	(0.03)	(0.06)	(0.06)	(0.04)
Family in military?	0.003	0.02	−0.03	−0.005	0.001
	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)
τ_2	0.29	0.32	0.76	0.96	0.37
	(0.12)	(0.13)	(0.26)	(0.30)	(0.14)
τ_3	0.50	0.66	1.49	1.68	0.68
	(0.20)	(0.27)	(0.51)	(0.54)	(0.25)
N	2133	2140	2106	2056	2141

Note: Cell entries are maximum-likelihood estimates of heteroskedastic ordered probit model; standard errors are in parentheses below coefficients. *Source:*Triangle Institute for Security Studies Survey on the Military in the Post-Cold War Era.

TABLE G.2. Variance Component of Heteroskedastic Ordered Probit Estimates for Models of Civilian Control of Military.

Variable	*Civilians Decide Use*	*Civilians Decide Type*	*Civilian Control Safe*	*Domestic Politics Determines*	*In War, Military Control*
Education	−0.29	−0.26	−0.01	−0.20	0.11
	(0.18)	(0.18)	(0.15)	(0.14)	(0.16)
Coincidence (threat, pro-mil.)	−0.57	−0.52	−0.99	−0.51	−0.58
	(0.34)	(0.33)	(0.28)	(0.26)	(0.31)
Coincidence (threat, moral trad.)	−0.25	0.18	0.81	0.12	−0.49
	(0.37)	(0.35)	(0.29)	(0.30)	(0.36)
Coincidence (moral trad., pro-mil.)	0.06	−0.27	0.04	0.44	0.11
	(0.36)	(0.34)	(0.28)	(0.26)	(0.32)
Elite	−1.74	−0.69	0.34	−0.27	−1.20
	(0.49)	(0.48)	(0.43)	(0.38)	(0.49)
Elite × Education	0.34	0.42	0.01	0.40	0.35
	(0.24)	(0.22)	(0.19)	(0.18)	(0.20)
Elite × Coincidence (threat, pro-mil.)	0.98	0.53	1.15	0.44	0.42
	(0.42)	(0.40)	(0.37)	(0.33)	(0.38)
Elite × Coincidence (threat, moral trad.)	0.16	−0.29	−1.07	−0.34	0.45
	(0.43)	(0.42)	(0.36)	(0.36)	(0.42)
Elite × Coincidence (moral trad., pro-mil.)	0.37	−0.03	−0.73	−0.47	0.22
	(0.43)	(0.40)	(0.35)	(0.31)	(0.37)
N	2133	2140	2106	2056	2141

Note: Cell entries are maximum-likelihood estimates of heteroskedastic ordered probit model; standard errors are in parentheses below coefficients. *Source:* Triangle Institute for Security Studies Survey on the Military in the Post-Cold War Era.

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