Distinguishing Occasional Abstention from Routine Ambivalence in Models of Vote Choice

Benjamin E. Bagozzi,† and Kathleen Marchetti‡

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Abstract

Political scientists are often interested in the factors affecting individual-level vote choice (e.g., whether individuals voted Republican, Democratic, or abstained). In these studies, researchers commonly employ multinomial logit (MNL) models to explain vote choice while treating “abstention” as the baseline (reference) category. Though many scholars have viewed abstainers as a homogeneous group, we argue that these respondents may emerge from two distinct sources. Some nonvoters are likely to be “occasional voters” who abstained from a given election due to temporary factors, such as a distaste for all candidates running in a particular election, poor weather conditions, or other circumstances which may have dissuaded their political participation. On the other hand, many nonvoters are unlikely to vote regardless of the current political or economic climate. This latter population of abstainers, which we term “routine nonvoters”, is consistently disengaged from the political process in a way that is distinct from that of occasional voters. Including both sets of nonvoters within a MNL model can bias the estimated effects of variables on candidate-selection or turnout, leading to faulty inferences. As a solution, we propose a baseline-inflated MNL estimator that models heterogeneous populations of nonvoters probabilistically, thus accounting for the presence of routine nonvoters within models of vote choice. We demonstrate the utility of this new model through a series of Monte Carlo simulations and replications of existing political behavior research.

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†Department of Political Science, University of Minnesota. Email: bbagozzi@umn.edu and kmarchet@umn.edu
Outcomes of discrete, polytomous choice are central to the study of politics. For instance, American and comparative politics scholars are frequently interested in whether individuals favor (or vote for) candidate A, candidate B, or neither candidate (i.e., abstention) in a given election. In a similar vein, many social scientists empirically examine whether citizens or governments prefer (or enact) policy A, policy B, or maintain the status quo within policy areas ranging from health care (Propper, 2000) to environmental conservation (Lehtonen et al., 2003) to minority language recognition (Liu, 2011). In American politics, party identification (e.g., Democrat, Republican, or Independent/Other) is often imagined in a comparable framework. Each of these examples envisions a dependent variable with a small set of discrete, unordered outcomes or choices. Accordingly, quantitative studies of such questions have favored the use of polytomous choice maximum likelihood models—most frequently the multinomial logit (MNL) model—to estimate the effects of covariates on a respondent’s probabilities of choosing each choice option over the others.

A second commonality shared by all of the dependent variables mentioned above, however, is the presence of a “status quo,” “neither,” or “abstention” category representing instances wherein a voter, a government, or another political actor favored doing nothing, or abstaining, rather than choosing either option A or option B. While the inclusion of these abstention responses is often necessary to ensure an unbiased sample for one’s dependent variable, they are usually of less interest to the researcher than are the other “active” political choices, and accordingly, the vast majority of polytomous choice models in political science treat these abstentions as the baseline (i.e., reference) category in estimation and interpretation. Although this framework may help to avoid selection on one’s outcomes of interest, observational sampling schemes of this sort risk polluting the baseline choice-category with an excess number of unrealistic observations that correspond to “inflated” individuals that will virtually never select a choice outcome other than “abstain”. With a baseline category inflated in this manner,

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1See, e.g., Hajnal and Lee (2012).
2As discussed below, we surveyed all recent (2009-2013) articles appearing in the American Political Science Review, American Journal of Political Science and Journal of Politics and found 42 studies that used a multinomial estimator in either a primary or robustness test. Of these articles, 93% favored the MNL model over other multinomial choice estimators.
MNL estimates are likely to be biased downward, as a significant portion of abstainers will be effectively impervious to the effects of covariates on transition probabilities from abstention to choice. Furthermore, when a subset of one’s covariates have dual effects on both the probability of routine abstention and the probability of multinomial choice, then unit homogeneity assumptions\(^3\) can be violated and MNL coefficients can become biased in indeterminate directions.

More succinctly, in instances where only a subset of a population actively encounters the choice scenario of interest, naïve samples of (or from) the entire population will contain an excess number of inactive choice-maker responses. Ignoring the heterogeneity that accordingly arises within one’s “abstain” response set can yield biased inferences. To illustrate these concerns, consider an example from the policy-adoption literature mentioned above. In a recent article, Liu (2011) examines the effects of political institutions on the passage of minority language recognition laws in democracies. Employing a sample of all democracies, 1945-2000, the author specifically uses an MNL model to assess the effects of her covariates of interest on a trichotomous dependent variable capturing whether a democracy exhibited (0) no recognition, (1) subject recognition, or (2) medium recognition of minority language rights (in education) in a given year. While sampling all democracies (1945-2000) clearly avoids any selection on Liu’s dependent variable, it nevertheless creates a sample of nearly 50 percent “no recognition” responses, many of which likely correspond to monolingual democracies that lack sizable minorities (e.g., Japan), or to democracies whose minority populations make no such language recognition demands in a given period. If true, then Liu’s “no recognition” category likely encompasses a heterogeneous mixture of both (i) democracy-years that actively weighed minority language pressures but decided against recognition and (ii) democracy-years with no minority-language demands that were coded “no recognition” by default.

A potentially more widespread, and theoretically intriguing, scenario may similarly arise within individual surveys of vote choice. Most major political surveys of American citizens (e.g., the American National Election Studies) include a number of questions designed to mea-

\(^3\)That is, the assumption that one’s dependent variable will take on the same expected values given a particular value on an independent variable (Braumoeller, 2013; King, Keohane and Verba, 1994, 91-93).
sure citizens’ voting behaviors and opinions. Often, such questions ask respondents to indicate which candidate they chose (or plan to choose) in a given election from a list of options (e.g., Barack Obama, Mitt Romney, or did not vote/neither). Researchers then typically analyze these responses using multinomial logit (MNL) models of vote choice (e.g., Arceneaux and Kolodny, 2009; Kalmoe and Piston, 2013). Misreporting of voting behavior is widespread in these contexts, and methods have recently been developed to address this problem in the binary setting (Katz and Katz, 2010).

However, even when reporting is perfect, scholarship suggests that “vote-abstention” responses typically arise from two distinct sources. On the one hand, some nonvoters are best seen as “routine nonvoters,” in that they have an abstention history that—due to slow moving or structural factors—is unlikely to change as a function of the unique characteristics of a given election (e.g., candidate personality or get out the vote [GOTV] efforts). On the other hand, a second subset of nonvoters are often instead characterized as “occasional voters,” who have voted in recent elections but who may not make the point to vote in each and every possible election (Gerber and Green, 2000; Niven, 2004; Hillygus, 2005; Parry et al., 2008). Drawing on this logic, past studies have frequently sought to distinguish between these two different groups of nonvoters when assessing the determinants of vote-abstention—often under the contention that the salience of each determinant is likely to vary as a function of nonvoter type—and have presented evidence to this effect (Zipp, 1985; Lacy and Burden, 1999; Sanders, 1999; Plane and Gershtenson, 2004).

Given these dynamics, treating both types of nonvoters as a single homogeneous reference category within an MNL analysis will ensure that the heterogeneous effects of temporary and structural covariates on individual vote choice (relative to abstention) will be ignored. As such, the estimated effects of short term shocks and candidate characteristics on turnout—which likely have no effect on routine nonvoters—will be biased downwards relative to their actual effect(s) within the subsample of voters that researchers are often most interested in: occasional and routine voters. By contrast, the direct effect(s) of structural factors on vote choice or
turnout may be overstated—or misattributed to active voting behavior—when routine nonvoters and occasional voters are pooled, leading to faulty conclusions and biased GOTV-type policy prescriptions.\(^4\)

These dynamics have not gone unnoticed by past political science research. Unit heterogeneity in (electoral) choice outcomes, and the biases that arise when such heterogeneity is ignored, is well established (Rivers, 1988; Beger et al., 2011; Braumoeller, 2013). Yet, MNL models continue to be the default choice for political scientists seeking to analyze survey respondents’ polytomous vote choices, as well as for researchers studying the related political-economic outcomes mentioned earlier. As the above examples demonstrate, these practices may be especially problematic when one is interested in parsing out the effects of individual and societal factors on the determinants of active political choices—a central theoretical goal of behavioral and institutional research in American and comparative politics. To address these concerns, this paper presents a novel empirical model that accounts for baseline inflation in polytomous choice outcomes—and the heterogeneity that it causes—\textit{probabilistically} to ensure that one’s primary choice estimates are unbiased. Drawing on a number of recently developed zero inflated estimators, the model that we propose does so by combining a logit stage for the estimation of an observation’s probability of being inflated (or not) with a second, MNL outcome stage. By estimating these two stages as a single system of equations, we are able to account for the possibility of baseline category inflation through the use of theoretically-informed covariates, and to then derive unbiased estimates of the direct effects of one’s covariates on the polytomous choice set of interest—now conditioned on the probability of each estimate being a “non-inflated” observation.

Our proposed model, hereafter referred to as the Baseline Inflated Multinomial Logit (BIMNL), accordingly addresses instances where one’s theory suggests that a \textit{single} choice-category in

\(^4\)These dynamics may arise within other survey settings as well. For instance, Adams and Cuecuecha (2010, Table 4) model Guatemalan household survey responses on remittance receipts (0 no remittances; 1 internal remittances; 2 international remittances) as an MNL function of a wide variety of household and individual level characteristics. It is plausible that two types of non-receivers exist in their sample: individuals who do not receive remittances during a given period due to temporary economic shocks and (inflated) individuals who have received no remittances simply because all family members continue to live within their designated community.
a polytomous dependent variable is inflated along the lines mentioned above.\footnote{Extensions to address instances where inflation exists across multiple choice categories are noted below in our discussion of Jackson (1993) and in the conclusion.} Hence, the BIMNL model is one that brings a commonly used discrete choice model (the MNL) closer to our substantive knowledge of voter behavior, and political phenomena more generally. For ease of exposition, we present this new model for the case where one’s inflated (i.e., “abstention” or “status quo”) category is treated as the (omitted) baseline category in the multinomial analysis as this is the most common practice in the literature. However, it is important to note that the baseline category in multinomial models is arbitrarily determined, typically for convenience of interpretation, and our applications of BIMNL model could be easily modified to account for single category inflation within a non-baseline response category instead.

This study proceeds as follows. In the next section we formally derive the BIMNL model and briefly mention several test statistics that can be used to evaluate the “fit” of the this model relative to the MNL model. This is followed by a discussion of the BIMNL model in relation to the multinomial-choice and zero-inflation methodological literatures, as well as a summary of our Monte Carlo experiments examining the BIMNL and MNL models’ relative performances under different data generating processes (d.g.p’s). We then present the results of two replication exercises, in which the BIMNL model is applied to existing political science studies of vote choice. We conclude by suggesting that the BIMNL model can be extended in a number of useful directions, including additional applications to survey responses of candidate preference, as well as the creation of a baseline inflated multinomial probit model with and without correlated errors.

1. The Baseline Inflated Multinomial Logit Model

In deriving the BIMNL model below, we build upon Long’s (1997) presentation of the MNL model and Harris and Zhao’s (2007) derivation of the zero inflated ordered probit (ZIOP) model. At its core, the BIMNL estimator combines two latent equations: a “split” logit equation which we denote as the “first stage” estimator and a multinomial logit (MNL) equation.
hereafter referred to as the “outcome stage” estimator. To motivate this model, consider a dependent variable $Y_i$ with $i \in \{1, 2, \ldots, N\}$ respondents (e.g., individuals). Suppose further that $Y_i$ is observable and assumes the discrete unordered values of $0, 1, \ldots, J$, with value $Y_i = 0$ representing a baseline “abstain” category. Next, let $s_i$ denote a binary variable that indicates a split between regime 0 ($s_i = 0$) and regime 1 ($s_i = 1$); wherein $s_i = 0$ denotes “inflated abstainers” that will always fall within the residual baseline category of $Y_i$ and $s_i = 1$ denotes “non-inflated abstainers”, who may choose to abstain in a given instance, but who may also potentially select an option in $1, \ldots, J$. In the context of a vote choice survey data set, the abstain responses in regime 0 ($s_i = 0$) would include routine nonvoters that never choose to vote, while responses in regime 1 ($s_i = 1$) include occasional nonvoters whose probability of transitioning to a candidate vote choice outcome is not zero. Note that $s_i$ is related to the latent dependent variable $s^*_i$ such that $s_i = 1$ for $s^*_i > 0$ and $s_i = 0$ for $s^*_i \leq 0$. The latent variable $s^*_i$ represents the propensity for entering regime 1 and is given by the following linear additive specification, which we refer to as the latent “splitting” (or inflation) equation:

$$s^*_i = z'_i \gamma + u_i$$  \hspace{1cm} (1)

The inflation equation in 1, once re-stated via a binary (logistic) response model for our dichotomous regime indicator $s_i$, constitutes the first stage of the BIMNL model. In equation 1, $z'_i$ is the vector of covariates, $\gamma$ is the vector of coefficients and $u_i$ is a standard-logistic distributed error term. Hence the probability of $i$ being in regime 1 is $Pr(s_i = 1|z_i) = Pr(s^*_i > 0|z_i) = \Lambda(z'_i \gamma)$, and the probability that $i$ is in regime 0 is $Pr(s_i = 0|z_i) = Pr(s^*_i \leq 0|z_i) = 1 - \Lambda(z'_i \gamma)$ where $\Lambda(\cdot)$ is the logistic c.d.f.

If $s_i = 1$, then the observations in regime 1 are given by the discrete unordered variable $\tilde{Y}_i$ which can take on any of $J$ unordered values, and where $Pr(\tilde{Y}_i = j) = P_{ij}$. In noting that by definition, $\sum_{j=0}^J P_{ij}$, we then allow the probability of $\tilde{Y}_i = j \in J$ to vary as a function of some $k$ independent variable(s) $x_{ik}$ indexed by a $K \times 1$ vector of parameters specific to outcome $\beta_j$ by

\[ \text{...} \]
restricting the probabilities to be positive and sum to one as so:

$$\Pr(\tilde{Y}_i = j) \equiv P_{ij} = \frac{e^{x_i'\beta_j}}{\sum_{j=0}^{J}e^{x_i'\beta_j}}$$

(2)

Hence, observation $i$'s probability associated with category $j$ is expressed as a fraction of the sum of all of observation $i$'s probabilities across the various categories $J$. This ensures that $Pr(Y_i = j) \in (0, 1)$ and that $\sum_{j=0}^{J} Pr(\tilde{Y}_i = j) = 1$. Under the assumption that the corresponding error term ($\varepsilon_i$) for equation 2 is independently and identically distributed according to a Type I Extreme Value distribution, equation 2 denotes the primary statement of probability for the MNL model. However, this model is also unidentified: knowing the $(J - 1) \times k$ values of $\beta_0, \beta_1, \ldots, \beta_{J-1}$, also provides one with the probability of choosing the remaining alternative. To identify the above MNL probabilities for estimation, we follow common practice and set the parameters for the first of the $J$ alternatives to zero, i.e., $\beta_0$, which we refer to hereafter as the baseline category. Doing so allows us to restate the probabilities for the baseline category $\left(Pr(\tilde{Y}_i = 0)\right)$ and the other $J - 1$ categories separately as:

$$Pr(\tilde{Y}_i) = \begin{cases} 
Pr(\tilde{Y}_i = 0 | x_i, s_i = 1) = \frac{1}{1 + \sum_{j=1}^{J} e^{x_i'\beta_j}} \\
Pr(\tilde{Y}_i = j | x_i, s_i = 1) = \frac{e^{x_i'\beta_j}}{1 + \sum_{j=1}^{J} e^{x_i'\beta_j}} \ (j = 1, \ldots, J) 
\end{cases}$$

(3)

where $\beta_j = \beta_j - \beta_0$ are now “rescaled” parameters in that they express the influence of the various $x$’s on $Pr(\tilde{Y}_i = j)$ relative to $Pr(\tilde{Y}_i = 0)$.

Note that neither $\tilde{Y}_i$ nor $s_i$ are observable in terms of the observed baseline outcomes. However, they are observed by the criterion $Y_i = \tilde{Y}_i \times s_i$. The aforementioned expression thus implies that the (baseline) outcome $Y_i = 0$ can occur when $s_i = 0$ or when $s_i = 1$ and $\tilde{Y}_i = 0$. It also indicates that we can observe $Y_i = 1 \ldots J$ only when $s_i = 1$ and $\tilde{Y}_i = 1 \ldots J$. Accordingly, the baseline inflated MNL distribution arises as a mixture of a degenerate distribution in the baseline
category and the assumed distribution of the variable $\tilde{Y}_i$ as follows:

$$
Pr(Y_i) = \begin{cases} 
Pr(s_i = 0 | z_i) + Pr(s_i = 1 | z_i) Pr(\tilde{Y}_i = 0 | x_i, s_i = 1) \text{ for } j = 0 \\
Pr(s_i = 1 | z_i) Pr(\tilde{Y}_i = j | x_i, s_i = 1) \text{ for } j = 1, 2, \ldots, J 
\end{cases}
$$

(4)

Under the assumption that $u_i$ and $\varepsilon_i$ identically and independently follow standard Type I Extreme Value distributions, the BIMNL model can thus be defined as:

$$
Pr(Y_i) = \begin{cases} 
Pr(Y_i = 0 | x_i, z_i) = [1 - \Lambda(z_i' \gamma)] + \left( \frac{\Lambda(z_i' \gamma)}{1 + \sum_{j=1}^{J} e^{x_i' \beta_j}} \right) \\
Pr(Y_i = j | x_i, z_i) = \left( \frac{\Lambda(z_i' \gamma) e^{x_i' \beta_j}}{1 + \sum_{j=1}^{J} e^{x_i' \beta_j}} \right) \ (j = 1, \ldots, J) 
\end{cases}
$$

(5)

where, as above, $\Lambda(\cdot)$ is the logistic c.d.f. The expression in 5 thus provides the full probabilities of the BIMNL Model. Herein, the probability of observing a baseline-choice observation within the baseline equation of the BIMNL model is modeled conditional upon the probability of an observation being assigned a baseline value in the multinomial data generating process plus the probability of it being in regime 0 from the splitting (or inflation) equation. As a result, when the unordered dependent variable is baseline-inflated and thus has two types of baseline observations, the BIMNL model—as shown by the Monte Carlo analysis below—allows researchers to obtain more accurate estimates relative to a standard MNL model, which is to say that the BIMNL estimates are both less biased and have greater coverage probabilities. The other probabilities in 5 (i.e., for $j = 1, \ldots, J$) then correspond to the conditional probabilities of an observation choosing a polytomous choice value other than the baseline value, conditional on an observation being in the MNL state of the world.

Having described the conditional probabilities for the BIMNL model above, we can now define the likelihood and the log-likelihood function of the BIMNL model. Specifically, let $\theta = (\gamma', \beta', u', \varepsilon')'$ for the full BIMNL model. The likelihood of the BIMNL model for an i.i.d
sample of $i \in \{1, 2, \ldots, N\}$ observations can thus be defined as

$$L(\theta) = \prod_{i=1}^{N} \prod_{j=0}^{J} [\Pr(y_i = j \mid x_i, z_i, \theta)]^{d_{ij}}$$

$$= \prod_{i=1}^{N} \prod_{j=0}^{0} [\Pr(s_i = 0) + \Pr(s_i = 1) \Pr(\tilde{y}_i = j)]^{d_{ij}} \times \prod_{i=1}^{N} \prod_{j=1}^{J} [\Pr(s_i = 1) \Pr(\tilde{y}_i = j)]^{d_{ij}}$$  \hspace{1cm} (6)$$

where $(y_i = j \mid x_i, z_i)$ was described earlier and where $d_{ij} = 1$ if outcome $j$ is realized in $i$, or is $d_{ij} = 0$ otherwise. The log likelihood function of the full BIMNL model where $\theta = (\gamma, \beta', u', \epsilon')'$ can therefore be written succinctly as

$$\ell(\theta) = \sum_{i=1}^{N} \sum_{j=0}^{J} d_{ij} \ln[\Pr(y_i = j \mid x_i, z_i, \theta)]$$

$$= \sum_{i=1}^{N} \sum_{j=0}^{0} d_{ij} \ln \left[ 1 - \Lambda(z_i' \gamma) + \frac{\Lambda(z_i' \gamma)}{1 + \sum_{j=1}^{J} e^{x_i' \beta_j}} \right] + \sum_{i=1}^{N} \sum_{j=1}^{J} d_{ij} \ln \left( \frac{\Lambda(z_i' \gamma) e^{x_i' \beta_j}}{1 + \sum_{j=1}^{J} e^{x_i' \beta_j}} \right)$$  \hspace{1cm} (7)$$

The log-likelihood function in 7 can be consistently and efficiently estimated using maximum likelihood which yields asymptotically normally distributed maximum likelihood estimates.\(^6\) Moreover, because the BIMNL’s estimation structure is equivalent to that of extant zero inflated models, parameter identification for this estimator is technically achievable even in cases of perfect overlap among the independent variables used in each stage of the BIMNL model (i.e., without an exclusion restriction).\(^7\) Even so, challenges to maximum likelihood estimation may arise in these contexts when outliers are present or when parameter effects are poorly separated (Hall and Shen, 2010). Thus, when available, the use of exclusion restrictions in the BIMNL’s inflation or outcome stage specification will likely improve estimation precision; as would—in suspected cases of more severe estimation challenges—artificial iden-

\(^6\)For instance, numerical methods using quasi-Newton algorithms (such as BFGS) can be used to estimate the model’s parameters. The authors of this paper have written code to permit users to estimate the BIMNL model using these methods in R.

\(^7\)In both theory and practice, zero inflated count and (zero) inflated ordered estimators (without correlated errors) can achieve parameter identification without exclusion restrictions—although explicit exclusion restrictions can help guard against misspecification and computational problems in these contexts (Harris and Zhao, 2007; Bagozzi and Mukherjee, 2012; Staub and Winkelmann, 2012; Burger, van Oort and Linders, 2009, 176).
tifiability constraints (ICs) on the parameter space and/or alternate estimation approaches such as robust expectation-solution estimation (Hall and Shen, 2010).

Though theory, first and foremost, should guide one’s decision on when to use a BIMNL model, several model fit statistics may enable researchers to accurately test between the MNL and BIMNL models. In line with conceptualizations of extant inflated models (Greene, 2011; Harris and Zhao, 2007, 1079), the MNL model is not directly nested in the BIMNL model via parameter restrictions, though akin to the ZiOP/OP model case, the BIMNL model converges to an MNL model as \( z' \gamma \rightarrow \infty \) in equation 5 (i.e., as the probability of non-inflation goes to one). Hence, in choosing between BIMNL and MNL models, non-nested model test statistics are preferable to nested hypotheses tests. One frequently used test statistic for such model comparisons is the Vuong test for non-nested models (Vuong, 1989), which in the case of the (B)MNL model, assigns \( m_i \) as the natural logarithm of the ratio of the predicted probability that \( Y_i = j \) for one’s MNL model (in the numerator) and one’s BIMNL model (in the denominator) and evaluates \( m_i \) via a bidirectional test statistic of

\[
v = \frac{\sqrt{N} \left( \frac{1}{N} \sum_i^N m_i \right)}{\sqrt{\frac{1}{N} \sum_i^N (m_i - \bar{m})^2}}
\]

where \( v < -1.96 \) favors the more general (BIMNL) model, \(-1.96 < v < 1.96 \) lends no support to either model, and \( v > 1.96 \) favors the MNL model (Vuong, 1989).

Generalized likelihood ratio (LR) tests, Akaike information criterion (AIC), and Bayesian information criterion (BIC) may each similarly serve as appropriate model selection criteria for our particular non-standard model comparisons given previous research on non-nested (inflated) models (Harris and Zhao, 2007, 1079). The Monte Carlo simulations presented below

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8 For inflated models (with correlated disturbances), a common artificial IC involves the restriction of the effects of at least one inflation stage parameter to be positive (or negative). See McLachlan and Peel (2000) and Jasra, Holmes and Stephens (2005) for more general discussions of artificial IC usage within the maximum likelihood and Bayesian estimation of finite mixture models, respectively.

9 See, e.g., Greene (2011); Harris and Zhao (2007); Bagozzi et al. (2014); Bagozzi and Mukherjee (2012).

10 With degrees of freedom corresponding to the additional parameters estimated within the BIMNL model.

11 Although the LR test is not strictly appropriate in this instance, given the non-nesting of inflated and comparable non-inflated models (Greene, 2011; Harris and Zhao, 2007, 1079).
confirm these expectations. Lastly, one could also plausibly use in-sample predicted probabilities (for outcomes $Y_i = 0...J$) to compare how well the MNL and BIMNL models replicate (and hence “fit”) the observed distribution of outcomes on $Y_i$ via a proportion reduction in error ($PRE$) statistic. A $PRE$ comparison for our models would first employ the probability statements appearing in equations 3 and 5 to calculate the in-sample predicted probabilities of each $Y_i = 0...J$ outcome and for each observation as a function of the values on $x_i$ and $z_i$. Classifying each observation based on the highest $Y_i = 0...J$ predicted probability it receives, one can then quantify the proportion of “errors” that the MNL and BIMNL correctly classify, relative to a null model that always predicts the most frequent outcome on $Y_i$.

In its design, the BIMNL model shares a number of notable similarities with extant limited dependent variable models. As alluded to above, the BIMNL model can be most directly situated within the family of limited dependent variable finite mixture models known as “split population” or “inflated” models. Like the BIMNL model, these models are explicitly designed to account for inflation within a single category of one’s dependent variable. Well known existing inflated models include zero inflated Poisson (ZIP) and negative binomial count models (ZINB; Greene, 1994), zero and middle inflated ordered probit (ZIOP and MIOP) models for discrete ordered outcomes (Harris and Zhao, 2007; Bagozzi and Mukherjee, 2012; Brooks, Harris and Spencer, 2012), and split population models for binary choice sets, such as the split population logit (Beger et al., 2011). Each of these models includes a system of two equations that allow one to estimate the effects of two potentially overlapping sets of covariates on (i) the probability of an observation arising from an inflation process specific to a single (usually $Y_i = 0$ outcome) and (ii) the probability of one’s discrete outcomes of interest, conditional on an observation not being inflated. What makes the BIMNL model novel in this case is its ability to estimate these inflation processes within an unordered polytomous dependent variable, which to our knowledge is the first such estimator to explicitly do so.

These inflation processes are distinct from the choice dynamics underlying other multi-equation discrete choice models, such as selection models, as baseline inflation does not pre-
sume that one’s first stage process truncates all cases for that choice outcome from one’s set of outcome stage choice categories. Rather, an inflation process *augments* unwanted cases to the observed set of outcome choices. Hence, the BIMNL model conceives of vote choice differently from earlier multi-equation models of vote choice (e.g., Born, 1990; Sanders, 1999) in that it maintains “abstention” as an available multinomial outcome stage category—albeit one in which the response set has been deflated by the inflation equation estimates. This framework thereby allows researchers to correctly model vote choice in situations where candidate choice cannot be assumed to be conditional upon *all* individuals making a separate, earlier decision of whether or not to turnout for an election at all. Examples not only include measures of vote choice where distinct populations of nonvoters are believed to be present within one’s abstention category, but also encompass survey questions that ask individuals to choose from a single response set that is comprised of both candidate choices and an abstention option, or instances where individuals are asked to provide their candidate preference—rather than vote choice—from a response set that includes an option of “neither” or “none of the above”.

In its motivation and design, the BIMNL model also builds upon several other existing polytomous choice estimators. The notion that heterogeneous correlates can bias MNL estimates was earlier argued by Rivers (1988) and Glasgow (2001), who respectively use Completely Ordered Logit (COLOGIT) and mixed logit (MXL) models to explicitly account for heterogeneous electoral choice probabilities. Baseline inflation could be seen as similarly inducing heterogeneity into vote choice response sets, and thereby violating the MNL model’s independence of irrelevant alternatives (IIA) assumption. Thus, the BIMNL model, like the MXL and COLOGIT models, enables one to estimate unbiased choice probabilities in (some) instances where the MNL homogeneity assumption is violated. The models diverge, however, with the COLOGIT and MXL models’ greater flexibility in estimating heterogeneity in polytomous choice data, in the manner in which the COLOGIT treats (unobserved) heterogeneity as part of one’s d.g.p. of interest, and in the COLOGIT’s dependence on rank ordered choices for estimation. The multinomial survey-response mixture model proposed by Jackson (1993) also

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12I.e., rather than arising from a separate inflation process and systematically modeling it as such.
accommodates heterogeneous mixtures of polytomous responses. Jackson specifically develops an unordered variant of the latent multi-indicator, multicause (MIMC) model to uncover choice mixtures arising from two distinct d.g.p.’s within an observed survey response set. As such, Jackson’s model and the BIMNL each similarly generalize the MNL model to accommodate responses arising from two distinct d.g.p.’s. However, the former is more aptly designed for mixtures in response sets that arise across all discrete outcomes of one’s dependent variable, and accordingly requires a more constrained estimation routine—and one that is arguably more susceptible to problems of identification.

Lastly, whereas our focus here is on developing a baseline inflated MNL model, one could conceivably extend our approach to the multinomial probit (MNP) context. Doing so would allow for a full relaxation of the MNL model’s IIA assumption while also facilitating the inclusion of correlated disturbances between one’s inflation and outcome equations. While this extension is intriguing, we currently choose to focus on the (BI)MNL model for the following three reasons. First, the MNL model’s IIA shortcomings aside, it remains the workhorse multinomial choice estimator within applied political science research. Surveying the past five years (2009-2013) of the *American Political Science Review*, *American Journal of Political Science*, and *Journal of Politics*, we found 42 articles that employed a multinomial estimator in a primary or robustness test (listed in the Supplemental Appendix). Of these 42 articles, only two used an MNP model as opposed to an MNL model,13 and in both cases the authors mentioned doing so only in a footnote as a robustness check to their primary MNL model of interest. Second, the costs of using an MNP model often outweigh its benefits. As Dow and Endersby (2004) demonstrate in this regard, the IIA assumption is not overly restrictive for most vote choice applications, while the MNP model is often fraught with estimation challenges in these contexts.14 Finally, though an allowance for correlated disturbances between our estimating stages is a promising extension, we do not consider this to be an overriding concern at present, given the heightened identification problems associated with this allowance (Xiang, 2010; Bagozzi

13 Or, in three instances, as opposed to the MNL model’s conditional logit reformulation.
14 Though more recent Bayesian estimation strategies have helped to address this latter concern (Imai and van Dyk, 2005).
and Mukherjee, 2012, 373) and the fact that an absence of this feature has far from impeded the applicability and usage of extant zero inflated models (most notably, the ZIP and ZINB).

2. Monte Carlo Simulations

We conduct two Monte Carlo experiments to compare the performance of our BIMNL model against that of the MNL model. The first experiment examines the performance of the BIMNL and MNL models under conditions of moderate baseline category inflation in an unordered dependent variable. Second, we compare BIMNL and MNL model performance when the d.g.p. is instead MNL. These two experiments are presented in full in the supplemental appendix, and we summarize the key findings here. In the case of Experiment 1, we find that the BIMNL outperforms the MNL substantially, and increasingly, in both accuracy and empirical coverage as one’s number of observations increases beyond 1,000. By contrast, the MNL marginally outperforms the BIMNL model in accuracy, and to a lesser extent in empirical coverage, when the d.g.p. is MNL (Experiment 2). Notably, the BIMNL model’s modest shortcomings in accuracy for Experiment 2 largely dissipate as one’s $N$ increases beyond approximately 5,000. Overall, the BIMNL model’s convergence problems were negligible when the true d.g.p. was BIMNL, but were significant when the d.g.p. was MNL. In both cases, BIMNL nonconvergence levels were similar to ZIOP(C) convergence problems reported under comparable levels of inflation when one’s d.g.p. was either ZIOP or OP (Harris and Zhao, 2007; Bagozzi et al., 2014). In sum, when one suspects even a low to moderate level of baseline category inflation, the BIMNL model generally provides more accurate estimates of one’s outcome stage covariates relative to the MNL model. However, convergence problems may suggest that one’s BIMNL model is in fact being misapplied to a MNL-generated dependent variable.

The Monte Carlo experiments also shed light on the aforementioned model fit statistics’ abilities to properly distinguish between the BIMNL and MNL model under each model’s respective d.g.p. To this end, Experiments 1 and 2 indicate that standard information-based model selection criteria, such as $BIC$ and $AIC$, correctly choose between the BIMNL and MNL mod-
els (under each d.g.p.) nearly 100 percent of the time. LR tests perform comparably, correctly choosing the BIMNL and MNL models in 95-100 percent of our simulations. These three results are very consistent with the OP/ZIOP simulation results reported in Harris and Zhao (2007). Also in line with these OP/ZIOP findings, the generalized Vuong test statistic described above was highly accurate in choosing the BIMNL model when the d.g.p. was BIMNL, but performed poorly in selecting the MNL model when the d.g.p. was MNL. The PRE fared even worse in the MNL d.g.p. case and in most simulations favored neither model over the other, though when the d.g.p. was BIMNL, the PRE correctly selected the BIMNL model with relatively high accuracy. For both the Vuong test and the PRE, accuracy was notably worse at low sample sizes (i.e., $N < 2,000$) within each experiment. Hence, researchers interested in using model fit statistics to supplement their (BIMNL versus MNL) model selection decisions should employ a combination of the test statistics mentioned above, and should place more weight in the $BIC$, $LR$ test, and $AIC$, relative to the Vuong test and the PRE.

3. Applications

3.1. Replication I

To further illustrate the utility of the BIMNL model, this section presents two replications of existing research. In the first, we replicate Arceneaux and Kolodny’s (2009) analysis of phone and door-to-door canvassing endorsements during the 2006 Pennsylvania (PA) state house elections. One core facet of Arceneaux and Kolodny’s study employs a MNL model to examine the effects of the aforementioned endorsement strategies (when undertaken by a liberal interest group) upon the following individual vote choice options: Democrat, Republican/Other, No response, or Abstained (their MNL baseline category). The corresponding dependent variable and sample include individual survey responses from approximately 2,000 randomly-selected field experiment subjects across two PA house districts. More detailed operationalizations of all variables used in the survey and analysis are reported in the supplemental appendix.

In brief, Arceneaux and Kolodny hypothesize that a liberal interest group’s Democratic
candidate endorsement may have crosscutting effects on potential voters depending upon these potential voters’ party identification. Herein, the authors posit that a liberal group’s endorsement may increase Republican-identifying individuals’ support for a Democratic candidate if endorsements serve to educate potential voters on Democratic candidates’ actual issue positions, but may decrease potential Republican-leaning respondents’ support for a Democratic candidate if liberal interest group endorsements instead serve as a “liberal” heuristic. In testing these claims on individual vote choice, the authors find only weak support for the latter expectation. In particular, while the liberal phone and canvassing treatments each have a negative effect on Republican-identifying individuals’ probabilities of Democratic candidate vote choice, each fails to achieve statistical significance at the $p < .10$ level (one-tailed). Moreover, Arceneaux and Kolodny (2009, 763) also surprisingly find that each endorsement strategy has no effect upon either Independent or Democratic identifying individuals’ probabilities of Democratic vote choice.

Given the arguments and Monte Carlo results presented above, we suspect that these muted findings may be partially attributable to a heterogeneous mixture of routine and occasional nonvoters within the baseline (“abstain”) category of the authors’ MNL model. As mentioned previously, we contend that nonvoters are best viewed as two distinct groups. The first group correspond to routine nonvoters who virtually never vote and pay little regard to election-specific factors in their repeated decisions to abstain from voting and from politics in general. By contrast, we characterize the second group as occasional voters, who vote intermittently but who may abstain from a given election due to extemporaneous shocks such as temporary resource or knowledge constraints, candidate specific distastes, or weather conditions.

Past research has confirmed that these two distinct sets of nonvoters exist, and moreover has demonstrated that the effects of voter mobilization efforts and related variables on individual-level turnout will differ according to individuals’ differential levels of (non)voting propensity. For example, Parry et al. (2008) find that even in high-profile races, the most important determinant of individual-level voter turnout is vote history, and identify a positive effect for campaign
communication among “seldom” voters (registered but rarely active) as opposed to intermittent (occasional) and routine voters. Hillygus (2005) draws a similar conclusion, in finding that seldom voters and self-described “unintended” voters are the most likely to be positively influenced by campaign contact. Niven (2004) also distinguishes among different (non)voter types when considering the effect that campaign tactics have on turnout, finding that while contact increases the likelihood of turnout generally, the effect was most dramatic for intermittent voters (those who cast at least one ballot in the recent past) who float in and out of the electorate.

Thus, there is good reason to suspect that for any given election, voting-age abstainers will be comprised of a mixture of temporary nonvoters and routine nonvoters. Moreover, the broad-based sampling scheme used in Arceneaux and Kolodny’s field experiment—which randomly selected registered Democrats, unaffiliated voters, and registered Republicans while placing a preference on infrequently voting Republicans (2009, 758)—likely reinforced these dynamics for the election at hand. If these contentions are true—and the baseline category of the aforementioned vote choice variable does indeed contain sizable proportions of both routine and occasional nonvoters—then our Monte Carlo results (summarized above) imply that Arceneaux and Kolodny’s MNL coefficient estimates may be attenuated or biased in unknown directions. Note that this will be the case even while the authors’ turnout treatments are randomly assigned, given the nonrandom assignment of—and likely differential levels of inflated abstainers within—the authors’ binary measures of survey respondents’ party identifications (which are interacted with both treatments).

To evaluate these claims, we replicate the “pooled” MNL model reported in Arceneaux and Kolodny (2009, 763: Table 2) using both the MNL and BIMNL estimators. In so doing, we keep the outcome (i.e., MNL) stage specifications for both models identical to those reported in Arceneaux and Kolodny (2009, 763: Table 2), and then include a set of theoretically-informed covariates for the inflation stage of our BIMNL model. While our choices for inflation stage covariates are limited to the control variables collected in Arceneaux and Kolodny’s original study, several such variables likely predict individuals’ propensities for being occasional non-
voters rather than routine nonvoters. First and foremost, the authors’ measure of whether or not individuals voted in the past election (Vote 2004) is expected to be a strong predictor of this dichotomy according to past findings (Niven, 2004; Parry et al., 2008). Likewise, the open seat race in District 156 may constitute a relatively higher proportion of occasional nonvoters, given that the opposing district in the authors’ study is characterized as one dominated by a Republican incumbent whose district had proven safe since 1978 (Arceneaux and Kolodny, 2009, 759-760).\footnote{Since an absence of close or competitive elections may compel lower turnout (Nevitte et al., 2000; Blias, 2000, 60), thereby increasing the population of routine nonvoters.} In addition, we add a number of demographic controls—such as age and female—to the BIMNL inflation stage in order to capture additional structural factors that past research suggests may be related to habitual or temporary nonvoting (Verba and Nie, 1972; Wolfinger and Rosenstone, 1980; Shields and Godel, 1997).

We report the complete table of outcome and inflation stage coefficient estimates for our MNL and BIMNL models in the supplemental appendix, and focus our attention here on discussing substantive quantities of interest and model fit statistics. To begin, the left side of Table 1 reports the estimated effects of changes in each of our BIMNL model’s inflation stage covariates upon the predicted probability of a nonvoter being an occasional, rather than routine, nonvoter.\footnote{Calculated via parametric bootstraps ($m = 1000$), while holding all other variables at their means or modes.} In line with expectations, the BIMNL’s inflation stage results suggest that having voted in 2004 is associated with a statistically significant 39 percent increase in a nonvoter’s likelihood of being an occasional nonvoter rather than a routine one. Similarly, and relative to District 161, nonvoters in District 156 are significantly more likely to be occasional nonvoters, perhaps owing to the higher contemporary levels of competitiveness in this district. The only significant demographic predictor of nonvoter type is age, which here implies that older nonvoters are associated with higher propensities for routine nonvoting—a relationship which may be attributable to the (likely) nonlinear effects of age in this context. Lastly, the right side of Table 1 indicates that all five of our model fit statistics consistently favor the BIMNL model over the MNL model. Taken together, Table 1 thereby provides an assortment of evidence to suggest that the BIMNL model may offer an improvement over the MNL model in modeling...
Arceneaux and Kolodny’s vote choice dependent variable.

Table 1: Inflation Stage & Model Fit Results for 2006 PA Vote Choice

<table>
<thead>
<tr>
<th>Inflation Covariate</th>
<th>First Differences in Pr(Occasional Nonvoter)</th>
<th>Model Fit Statistics</th>
<th>MNL</th>
<th>BIMNL</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 → 1 Δ in Vote 2004</td>
<td>0.39 (0.18 ↔ 0.60)</td>
<td>ℓ</td>
<td>-2110.59</td>
<td>-2069.97</td>
</tr>
<tr>
<td>53 → 71 Δ in Age</td>
<td>-0.05 (-0.08 ↔ -0.02)</td>
<td>Vuong</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>0 → 1 Δ in Female</td>
<td>0.01 (-0.02 ↔ 0.04)</td>
<td>PRE</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>2 → 4 Δ in House Size</td>
<td>0.01 (-0.02 ↔ 0.04)</td>
<td>AIC</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>0 → 1 Δ in District 156</td>
<td>0.06 (0.02 ↔ 0.10)</td>
<td>BIC</td>
<td>✓</td>
<td></td>
</tr>
</tbody>
</table>

Changes in non-binary variables ≈ mean +1SD changes. First differences calculated over 1,000 simulations while holding other variables at their means or modes. Values in parentheses are 90% confidence intervals.

We next consider the outcome stage vote choice estimates obtained from our MNL and BIMNL models which, as mentioned above, each treat abstention as the baseline category. In deriving quantities of interest for these estimates, we hold our BIMNL inflation stage fixed at \( \text{pr(none-inflation} = 1) \) which enables us to directly compare our MNL model’s estimates for all individuals to the BIMNL’s hypothetical estimates for only non-inflated individuals.\(^{17}\) This matches the claims made above, as we argued that by better accounting for routine nonvoters, the BIMNL model provides more accurate estimates of covariate effects among what is typically researchers’ primary sample of interest: occasional and routine voters. Note however that in other applications, the simultaneous effects of covariates across both stages of one’s BIMNL model may be of most interest,\(^{18}\) and these quantities can also be easily derived from the probability statements in equation 5. In line with the Arceneaux and Kolodny’s original study, our substantive focus here is then on the estimated effects of \(0 → 1\) changes in the authors’ phone and canvassing treatments on the predicted probabilities of Republican, Democrat,

\(^{17}\)These quantities are comparable to those reported for the MIOP(C) models in Bagozzi and Mukherjee (2012).

\(^{18}\)See for example, Bagozzi et al. (2014), for a derivation of such quantities in a related zero inflated model.
and Independent individuals each voting for the Democratic candidate. Given the claims made above, we specifically estimate these first differences in predicted probabilities relative to (non-inflated) abstention, and plot the resultant mean estimates and confidence intervals in Figure 1.19

Figure 1: Effects of Phone & Canvassing on Predicted Probabilities of 2006 PA Vote Choice

(a) Republicans

(b) Independents

(c) Democrats

19Parametric bootstraps (m = 1,000) are used to calculate these effects, while holding all other variables to their means or modes. To ensure comparability to the authors’ reported results (Table 4, page 765) we report 90% one-tailed confidence intervals in these simulations, though the significant BIMNL findings discussed below are also significant at the equivalent two-tailed threshold.
We begin with the Republican identifier subsample (Figure 1a). Consistent with the results reported in Arceneaux and Kolodny (2009), our MNL results in this case suggest that both phone and canvassing treatments have a significant negative effect on Republican voters’ probability of voting for the Democratic candidate. Yet, in replicating these results with the BIMNL model, we find that once routine nonvoters have been partitioned from our sample, the effects of either treatment are no longer statistically distinguishable from zero at traditional levels. Turning next to Independents (Figure 1b), we find that whereas our MNL model’s estimated effects (like those of the authors’) yield no significant findings, our BIMNL estimates for these two treatments present mean estimates that are each positive and over double in size to those of the MNL model, and which are statistically significant in the case of the phone treatment. This intuitively suggests that (i) phone treatments increase an Independent’s probability of voting Democratic and (ii) the effects of liberal endorsements on this (generally uninformed, nonpartisan) group are attenuated when routine nonvoters are unaccounted for in one’s analysis. Finally, in line with Arceneaux and Kolodny (2009), we find no significant effect of either treatment among Democratic identifiers (Figure 1c), a null finding that we believe, like Arceneaux and Kolodny, may be attributable to the ceiling imposed by the initial high levels of initial Democratic candidate support among this group. Taken together, it is therefore not evident that liberal group endorsements are a net negative for Democratic candidate voter support (as the authors’ original findings imply), as our estimates indicate that, if anything, the net statistically distinguishable effect of these treatments is positive.

To summarize, this replication provides supporting evidence—in the form of model fit statistics and inflation stage estimates—to suggest that the BIMNL model may outperform the MNL model in modeling the heterogeneous population of abstainers within Arceneaux and Kolodny’s vote choice dependent variable. With this evidence in hand, we re-evaluated the MNL analysis corresponding to one of the authors’ primary hypotheses while using a BIMNL model. In contrast to Arceneaux and Kolodny’s original findings, our BIMNL replication suggests that liberal interest group-directed phone and door-to-door canvassing endorsements of
PA Democratic House candidates have no significant negative effect on Republican-identifiers’ choice of voting for a Democratic candidate, but have a positive (and in the case of phone treatment, significant) effect on the likelihood of Democratic candidate vote choice among Independents. Given the substantive magnitude of our BIMNL findings for Independents, this replication has important theoretical and policy implications for interest groups’ candidate endorsement tactics, a point to which we return in the conclusion.

3.2. Replication II

Our second application replicates a recent analysis of individuals’ 2004 U.S. presidential vote choice (Campbell and Monson, 2008). In this study, the authors evaluate the interactive effects of (i) gay marriage ban (GMB) ballot initiatives and (ii) potential voters’ religious affiliations on an unordered polytomous dependent variable measuring survey respondents’ stated 2004 vote choice of: Bush, Kerry, or abstention (the baseline category). Drawing on a representative sample of approximately 1,500 individuals from a 2004 Election Panel Study (EPS), Campbell and Monson ultimately find empirical evidence to suggest that the presence of GMBs increased mobilization for Bush among evangelical Protestants but increased abstention levels (relative to voting for either candidate) among secular voters. We provide detailed operationalizations for these, and all other, covariates in our supplemental appendix.

While Campbell and Monson’s findings are insightful, we suspect that the same heterogeneous mixture of routine nonvoters and occasional nonvoters discussed above may be present in the baseline abstention category of the authors’ polytomous dependent variable. Indeed, the EPS survey likely includes substantial proportions of both types of nonvoters, given its nationally-representative sample of potential voters, and given the extant literature on distinct nonvoter types (summarized earlier). If this is in fact the case, then as above, the authors’ multinomial estimates may be biased due to heterogeneity in their nonvoting subsample of respondents. We attempt to ascertain whether this is indeed the case by replicating Campbell and Monson’s primary specification using MNL and BIMNL models below.²⁰

²⁰Our (B)MNL replications differ from Campbell and Monson in several respects. Most notably, Campbell
As above, our choice of BIMNL inflation stage covariates is limited to the variables available in Campbell and Monson’s study. We accordingly attempt to identify a number of plausible inflation stage predictors from Campbell and Monson’s available covariates. First, we include education, as it has proven to be a consistent predictor of voting behavior and political participation in past research (Smets and van Ham, 2013). We posit that educated nonvoters will have higher likelihoods of being temporary, rather than routine, nonvoters. For similar reasons, we include the authors’ mobilization index measure which is also anticipated to be a positive predictor of occasional, rather than routine, nonvoting. We next add Campbell and Monson’s dichotomous indicator of individuals reporting their religion as secular, with the expectation that nonreligious individuals may simultaneously be less active in other areas of associational life, such as politics or voting. Finally, we again include age, but omit female, given the inflation stage findings obtained in our earlier application.

The left portion of Table 2 reports estimated changes in the predicted probabilities of non-inflation (i.e., of being an occasional nonvoter rather than routine nonvoter), given reasonable changes in each of our inflation stage covariates. Beginning first with education, we find that a realistic increase in education is associated with a small, but significant, positive increase in a nonvoter’s likelihood of being an occasional, rather than routine, nonvoter, which is in line with our expectations. Similarly, increases in an individual’s mobilization index also positively affect the likelihood of non-inflation. In contrast to our earlier application, age (now measured on a limited ordinal scale, rather than individual years) is also a positive predictor of occasional nonvoting—a departure we find somewhat unsurprising given the different operationalizations and nonmonotonicities that likely underlie this particular relationship. Finally, we find that secularism is associated with a large (nine percent) and significant decrease in the probability that a nonvoter is an occasional—rather than routine—nonvoter, which is consistent with our

The authors also use robust standard errors, whereas we do not. Given that (i) this is a methods exercise, (ii) the benefits of robust standard errors have recently come under question (King and Roberts, 2012), and (iii) the authors state that their main substantive results remain unchanged even when employing a MNL model (Campbell and Monson, 2008, Footnote 13: 408), we do not believe our departures to be particularly problematic.

For arguments to this effect, see, e.g., Verba, Schlozman and Brady (1995); Jones-Correa and Leal (2001).

Calculated via parametric bootstraps ($m = 1000$) while holding all other variables at their means or modes.
expectation that nonreligious individuals are less likely to be politically active on the whole.

Table 2: Inflation Stage & Model Fit Results for 2004 Presidential Vote Choice

<table>
<thead>
<tr>
<th>Inflation Covariate</th>
<th>First Differences in Pr(Occasional Nonvoter)</th>
<th>Model Fit Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$5 \rightarrow 7 \Delta in Education$</td>
<td>0.01</td>
<td>$\ell$ -553.50</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1 \rightarrow 2 \Delta in Mobilization$</td>
<td>0.02</td>
<td>MNL</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2 \rightarrow 3 \Delta in Age$</td>
<td>0.01</td>
<td>BIMNL</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$0 \rightarrow 1 \Delta in Secular$</td>
<td>$-0.09$</td>
<td>BIC</td>
</tr>
</tbody>
</table>

|                            |                                               |                      |

Changes in non-binary variables $\approx$ mean $\pm$ 1SD changes. First differences calculated over 1,000 simulations while holding other variables at their means or modes. Values in parentheses are 90% confidence intervals.

However, as the model fit statistics in the right portion of Table 2 reveal, we find only mixed support for the BIMNL model’s “goodness of fit” in this application. In particular, two of our three more accurate fit statistics (according to our Monte Carlo experiments) favor the BIMNL model, while the third favors the MNL model. The less accurate PRE and Vuong statistics are similarly split between the two models. These inconclusive findings are relatively unsurprising given the low $N$ for the study, but nevertheless underscore the need to be cautious in drawing broader theoretical conclusions from the outcome stage results presented below.

We next turn to the outcome stages of our MNL and BIMNL models. As before, the coefficient estimates for our models’ respective estimation stages are reported in the supplemental appendix. The present section compares our MNL and BIMNL derived first differences in predicted probabilities of votes for Bush and votes for Kerry, denoted by $pr(\text{non-inflation} = 1)$ to facilitate comparisons of our “all respondents” MNL estimates to the BIMNL model’s more specific estimated subset of “voters and occasional voters”.

$^{23}$As above, each first difference in predicted probability is estimated relative to a (non-inflated) voter choosing to abstain, using parametric bootstraps ($m = 1,000$) with all other variables held to their means or modes.
We report these quantities of interest, along with 90% confidence intervals, in Figure 2.

Figure 2: Effects of Selected Covariates on Predicted Probabilities of 2004 Vote Choice

(a) 0 → 1 change in Secular (When GMB=0)          (b) 0 → 1 change in South

Turning to this figure, we first discuss the substantive effects for secularism (here when GMB is set equal to 0). In addition to identifying the abstention inducing effects of GMB among secular individuals, Campbell and Monson’s reported estimates also suggest a puzzling finding, in that the individual coefficient estimate for secularism is negative and significant within the “Vote Kerry versus Abstain” equation. This implies that in states without GMB’s,
secular individuals are less likely (than the omitted category of mainline Protestant individuals) to vote for Kerry than to abstain. As Figure 2a indicates, we find an equivalent effect in our MNL replication. However, once routine abstainers are partitioned from the sample, our comparable BIMNL estimates reveal that this effect goes away, as the estimates are now statistically indistinguishable from zero; a potentially more accurate representation of this relationship.

Our estimated quantities of interest for two key control variables also highlight interesting differences between the MNL and BIMNL estimates. In Figure 2b for example, the estimated effect for South—which is insignificant in the MNL model case—intuitively becomes a positive and significant predictor of individuals’ probabilities of voting for Bush (but not Kerry) once estimated with the BIMNL model. This finding perhaps suggests that the presence of routine nonvoters in the baseline abstention category of our MNL model was attenuating the positive short term effects of Bush’s mobilization efforts in the South among occasional and actual voters. The final quantities of interest demonstrate that a well known positive determinate of turnout, education, appears to have no direct effect on vote choice (relative to abstention), once its significant effects on the probability of abstention inflation are accounted for—a finding that potentially alters how we interpret the moderating effects of education within GOTV type mobilization efforts.

In sum, our second application further highlights the benefits of the BIMNL model over the MNL model, but also underscores some potential challenges. While we obtained a number of theoretically consistent findings for the inflation stage of our BIMNL model—such as those related to education, mobilization index, and secularism—our model fit statistics were ambiguous as to whether the BIMNL did, in fact, provide a better model fit than a comparable MNL model. Because such inconclusive findings are apt to occur in practice—especially when applied to data sets with fewer than 2,000 observations (as was the case here)—we encourage researchers to be cautious and to rely on theory when selecting between the BIMNL and MNL model in such instances. These weak foundations notwithstanding, our outcome stage estimates do suggest that the BIMNL model offers novel improvements in theory testing. Specifically,
the puzzling estimated effect for secularism among individuals’ propensities to vote for Kerry dissipates once baseline inflation is accounted for, while the effects of Southern states, and education become more robust, and more nuanced, respectively. Hence we believe that the BIMNL model holds future promise for the study of these specific correlates of vote choice, particularly when researchers encounter survey data sets of at least 2,000 observations.

4. Conclusion

Questions of individual vote choice, when applied via representative surveys of voting age citizens, are apt to include heterogeneous mixtures of nonvoters. Extant research suggests that one subset of these self-reported nonvoters will correspond to occasional nonvoters, who abstain from voting in a specific election due to temporary factors such as short term economic shocks, weather conditions, or personal factors. Yet, many other nonvoters are likely to be routine nonvoters who, due to structural or personal reasons, have chosen to abstain from the political process entirely. These nonvoters are thus largely immune to the short-term factors affecting the occasional abstainers mentioned above. Ignoring this distinction can bias the estimated direct effect of both sets of determinants on nonvoting and, by implication, the factors affecting actual voters’ candidate choices in MNL models. Hence, it is imperative that American and comparative politics scholars account for these disparate populations of nonvoters when “did not vote/abstain” serves as the reference category in empirical models of vote choice.

This paper presents a new discrete choice estimator—the Baseline Inflated Multinomial Logit (BIMNL) model—to allow researchers to more accurately account for this variation in populations of nonvoters. After deriving this model, we demonstrate via both Monte Carlo simulations and replications of extant research that ignoring baseline-choice category inflation within empirical studies of vote choice can potentially bias one’s parameter estimates. Moreover, we show that this is the case across all choice categories of estimation, not only for the instances where the baseline category is of most interest. Regarding our replications in particular, our findings offer new theoretical insights into the determinants of individual vote choice in
American elections. For instance, our first application demonstrates that the effects of a liberal interest group’s Democratic candidate endorsement may in fact produce a net positive outcome for Democratic candidates across all potential voters, rather than a net negative, once routine nonvoters are accounted for in the BIMNL model. Similarly, our second application suggests that a number of commonly understood direct predictors of turnout and vote choice, such as education and secularism, may instead primarily affect these outcomes through their effects on routine versus occasional nonvoting, rather than through any direct effect on individuals’ active decisions to vote or abstain in a given election.

This study can be extended in three main directions. First, as mentioned above, the BIMNL model developed above could be generalized to the MNP or MXL setting. Notwithstanding the MNP concerns raised earlier, such extensions would afford researchers the opportunity to properly account for baseline category inflation in instances where they believe their polytomous dependent variable to be both unordered and in broader violation of the IIA assumption. Furthermore, a BIMNP model could also provide a feasible framework for the provision of correlated error terms between the two estimation stages of an inflated polytomous choice model (under assumptions of bivariate normality). Allowances for correlated disturbances between inflation and outcome equations, although challenging for estimation and identification, have been shown to be extremely useful to both theory and estimation within inflated ordered probit (IOP) estimators (Harris and Zhao, 2007; Bagozzi et al., 2014; Bagozzi and Mukherjee, 2012), as well as in applications of inflated probit estimators (e.g., Xiang, 2010), and thus would likely be of great interest to survey researchers within the polytomous choice setting as well.

A second promising extension would involve the augmentation of our current BIMNL model with random effects techniques akin to the sort recently developed for the consistent estimation of IOP and zero inflated count models on panel data (Hall, 2000; Brooks, Harris and Spencer, 2012). In addition to providing a feasible framework for applying the BIMNL model to panel survey studies of vote choice, a random effects BIMNL panel model would also afford researchers the opportunity to account for polytomous baseline inflation within the broader set
of (non-survey based) panel data sets. For instance, with such a framework one could evaluate the potential effects of baseline choice-category inflation within studies of polystomous civil wars onset (Buhaug, 2006; Buhaug and Gleditsch, 2008), of international dispute joining (Aydin, 2008), and of country level policy adoption (Lehtonen et al., 2003; Liu, 2011)—all of which are frequently examined with MNL models while treating status quo as the baseline category. Moreover, these random effects adjustments could then be further elaborated upon to develop a fully Bayesian BIMNL model. Hence, the BIMNL model, especially when supplemented with random effects or related Bayesian extensions, has the potential to improve our understandings of polystomous choice outcomes across multiple subfields of political science, including international relations, American politics, and comparative politics.

The insights presented above may also facilitate future research within the area of political behavior by allowing researchers to better test and develop theories of routine and occasional nonvoting. As such, our paper has important implications for political behavior research both within academia as well as in the more applied settings of political campaigns and activism. Specifically, by accounting for routine nonvoters, the BIMNL model provides more nuanced, and less biased, estimates of how various factors affect the voting behavior of the very individuals that campaigns and scholars (arguably) want to understand and motivate the most: those who have voted in past elections but not necessarily routinely. Indeed, it is this population of disproportionately nonpartisan, uninformed, and heuristic-dependent (non)voters who, if effectively mobilized, can have a substantively large effect on an electoral outcome. As the 2008 election demonstrated, the ability to encourage voter turnout among populations of Americans with inconsistent voting records (e.g., young voters between the ages of 18-29) can significantly bolster support for one party, or candidate, over another. Thus, accurately understanding how GOTV activities differentially affect occasional versus routine nonvoters could be crucial for many political campaigners, interest organizations, and scholars of political behavior.
REFERENCES


