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Modeling Two Types of Peace: The Zero-inflated Ordered Probit (ZiOP) Model in Conflict Research

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Abstract

A growing body of applied research on political violence employs split-population models to address problems of zero inflation in conflict event counts and related binary dependent variables. Nevertheless, conflict researchers typically use standard ordered probit models to study discrete *ordered* dependent variables characterized by excessive zeros (e.g., levels of conflict). This study familiarizes conflict scholars with a recently proposed split-population model—the zero-inflated ordered probit (ZiOP) model—that explicitly addresses the econometric challenges that researchers face when using a "zero-inflated" ordered dependent variable. We show that the ZiOP model provides more than an econometric fix: it provides substantively rich information about the heterogeneous pool of "peace" observations that exist in zero-inflated ordinal variables that measure violent conflict. We demonstrate the usefulness of the model through Monte Carlo experiments and replications of published work and also show that the substantive effects of covariates derived from the

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ZiOP model can reveal nonmonotonic relationships between these covariates and one's conflict probabilities of interest.

Keywords
zero-inflation, civil wars, militarized interstate disputes, ordered probit

Applied conflict researchers are becoming increasingly aware of a class of statistical models known as split-population, or zero-inflated,[1] models (e.g., Clark and Regan 2003; Moore and Shellman 2004; Svolik 2008; Xiang 2010).[2] These models address the econometric challenges that arise when a dependent conflict variable is characterized by an excess number of "peace" observations in its zero category (i.e., is zero inflated). Thus far, conflict scholars have used split-population models to deal with these problems of "zero inflation" primarily in the contexts of event counts[3] and binary dependent variables (Svolik 2008; Xiang 2010). Nevertheless, when analyzing zero-inflated ordered dependent variables, scholars of political violence typically use standard ordered probit (OP) or ordered logit (OL) models (Senese 1997, 1999; Huth 1998; Besley and Persson 2009; Wiegand 2011). As shown subsequently, analysis of zero-inflated ordered dependent variables raises methodological challenges that cannot be adequately addressed by these conventional techniques. This study, therefore, familiarizes conflict researchers with a split-population model known as the zero-inflated ordered probit (ZiOP) model (Harris and Zhao 2007), which explicitly addresses two main statistical issues prevalent in many quantitative studies of ordered conflict variables.

The first statistical issue involves researchers' coding of ordered dependent conflict variables. Specifically, scholars typically code "peace" observations in ordinal dependent variables of conflict as "zero" and then evaluate the impact of explanatory variables on such ordinal dependent conflict variables which contain excess zeros (i.e., are zero inflated). They also treat the excess zeros mentioned previously as a homogeneous group even though it is *empirically plausible* that there may be two different types of zeros in the set of "inflated" zero observations in the ordered conflict variable. For example, in the case of discrete ordered levels of interstate conflict, peace-year zeros will be recorded by scholars for countries separated by vast geographic distances that simply do not interact with each other, as well as for years in which "no conflict" (or the status quo) is observed for countries that have fought in the past and have active ongoing political disputes. Thus, it is likely that the two types of zeros posited previously may relate to two distinct sources. This implies that treating the zero observations as a homogeneous group in zero-inflated ordered dependent conflict variables is not statistically appropriate and may lead to biased estimates when evaluating the impact of covariates on ordered conflict measures that contain excess zeros.

The second issue is that scholars of political violence do not statistically account for the observable and latent factors that generate the high proportion of zero (i.e., peace) observations in ordinal dependent variables that have excess zeros (Senese 1997, 1999; Huth 1998; Besley and Persson 2009; Wiegand 2011). This occurs not only because these scholars treat excess zeroes as a homogeneous group but also because they use (as mentioned earlier) standard OP or OL models for hypothesis testing when analyzing zero-inflated ordered dependent conflict variables. Standard OP and OL models cannot econometrically account for the preponderance of zero observations in zero-inflated ordinal dependent variables, particularly when the zeros may relate to two distinct sources (Harris and Zhao 2007). Employing standard OP and OL models for testing the impact of covariates on zero-inflated ordinal dependent conflict variables may thus lead to model misspecification.

Our detailed analysis of the ZiOP model and the application of this statistical model to two different conflict data sets reveal that this estimator addresses the two statistical issues discussed previously. The ZiOP model thus provides more reliable estimates than the standard OP model when working with ordinal dependent variables of conflict that contain excessive zero observations. More specifically, we first show in this study that the ZiOP model allows researchers to statistically account for observable and latent factors that influence the probability of the two types of zero observations in zero-inflated ordinal dependent variables. As a result, the ZiOP estimator provides substantively rich information about the two types of zero observations that, as suggested previously, are prevalent in zero-inflated ordinal conflict variables. We can extract the kind of information posited previously because the ZiOP model is in essence a split-population model—a type of mixture model—that combines two probability distributions that are presumed to jointly produce the observed data. In fact, the ZiOP model presented in the next section combines a binary probit model with an OP model, thereby making it an appropriate statistical tool for scholars to use when they suspect a zero-inflated ordered dependent variable to be generated from different underlying populations.[4] Second, we conduct extensive Monte Carlo (MC) simulations that assess the performance of the ZiOP model with and without correlated errors—and compare its performance to the OP model—when an ordered dependent variable is zero inflated. The results from these simulations demonstrate that OP estimates are biased when an ordered dependent variable contains a split population of zeros, whereas ZiOP estimates systematically provide superior probability coverage and less bias. The MC studies also provide results to help applied conflict researchers make decisions about *when* to use the ZiOP model, depending upon their belief about the proportion of inflated zeroes in their sample.

Third, we apply the ZiOP model to data sets from the following two studies of conflict: (1) a published article on repression and civil war in the *American Economic Review* by Besley and Persson (2009) and (2) published studies by Senese (1997, 1999) on the escalation of interstate conflict. While the ZiOP model does not statistically capture the dynamics of strategic interaction in game-theoretic models of intrastate and interstate conflict,[5] we show subsequently that this statistical model provides more than an econometric fix for problems that emerge in ordinal conflict variables that are characterized by excessive zeros. Indeed, the application of the

ZiOP estimator to the two different data sets mentioned previously shows that this estimator statistically accounts for the observable and unobservable factors that generate the high proportion of peace observations in zero-inflated ordinal conflict variables. This, in turn, permits conflict scholars to avoid model misspecification when testing hypotheses with ordinal dependent variables that contain excessive zeros. Further, the marginal effect of covariates derived from the ZiOP model can reveal (as illustrated subsequently) *nonmonotonic* relationships between covariates and outcome probabilities, while standard econometric models such as the OP and OL model fail to detect such nonmonotonic effects. This allows researchers to carefully test theories of "conflict relevance" and other extant hypotheses (including comparative static predictions) when working with zero-inflated ordinal dependent variables.

To understand the advantages of the ZiOP model more clearly, consider the Besley and Persson (2009) article mentioned previously. The authors employ an ordered dependent variable in which a given country-year is assigned a zero for peace, a one for one-sided government violence, and a value of 2 when violence between dissidents and the state produces deaths above a given threshold and is thus classified as a civil war. The ordered dependent variable coded by Besley and Persson is "zero inflated" as it contains a substantial proportion of zero (peace) observations. This is not surprising: large-scale domestic violence is an inherently rare event. Less obvious is the fact that their ordered dependent variable includes *two types* of zero observations. The first type includes peace-year observations in advanced industrialized democracies where the probability of civil war is effectively zero, as high levels of economic and institutional development in these states arguably promote "harmony" or, in other words, compatibility of interests rather than violence between societal actors and the state.[6] In fact, in the Besley and Persson data, the aforementioned ordinal dependent variable for advanced democracies is coded as zero for *all* the years in which these states are observed, as these countries have not experienced a civil war. The second type of zero observations includes the years in which temporary peace is observed among Besley and Persson's remaining (civil war–prone) countries due to the absence of political–economic crises and shocks.

Thus, in contrast to the first type of peace where the possibility of large-scale violence is effectively zero, the probability that a transition may occur from the second type of peace to large-scale domestic violence is nontrivial. Unfortunately, Besley and Persson overlook the possibility that (1) the second type of peace observation is fundamentally different from the first type and (2) various factors could have a differential impact associated with the two types of zeros in their data. They also use an OL model for their statistical tests based on the presumption that all peace-year observations in their data are homogeneous. We show subsequently that their approach leads to biased statistical results. We also show that the ZiOP model estimates obtained from the Besley and Persson (2009) data are more reliable and provide the following substantive insights that challenge their main empirical results: (1) the relationship between per capita income and the probability of civil war is nonmonotonic and

(2) the effect of parliamentary democracies on the likelihood of civil war is, in contrast to the Besley and Persson finding, statistically insignificant.

Senese (1997, 1999) similarly uses an ordinal dependent variable to operationalize the escalation of interstate conflict. As shown subsequently, the ordered dependent variable in the international conflict data used by Senese contains a high proportion of zero (i.e., peace-year) observations at the dyadic level. This is not surprising since large-scale violent conflict between governments occurs very infrequently. Moreover, these data also contain two types of zeros. The first type of zero (dyadic peace-year) observation is produced, for instance, by a lack of interaction between countries separated by vast geographic distances or a mutual absence of capacity to engage in militarized conflict (Lemke and Reed 2001; Xiang 2010). In these dyads, the probability of full-fledged conflict is in effect zero, as the ordinal dependent variable of conflict escalation is coded as zero for all the years in which these dyads are observed in the Senese (1997, 1999) data. The second type of zero observations in the Senese (1997, 1999) data includes the year in which peace is observed in the remaining "conflict-prone" dyads. In this latter set of dyads, however, the ordinal dependent variable is *not* coded as zero for every year in which these dyads are observed, as these dyads do experience full-fledged conflict in some years owing to numerous reasons identified in the theoretical literature.[7]

Hence, in contrast to the first set of dyadic peace observations that are likely to never make a transition to conflict, the probability of transition from peace to full-scale conflict in the latter set of dyads mentioned previously is nontrivial. Additionally, certain key covariates likely have a differential impact on the probabilities associated with these two types of peace observations. It is thus important to distinguish between the two types of peace observations mentioned previously and a standard OP model simply does not permit researchers to do so. Applications of the ZiOP model to interstate conflict data in fact reveal (1) that many commonly studied covariates—including contiguity, alliances, and joint democracy—are strongly related to conflict relevancy and (2) that ignoring these relationships can lead to biased estimates of the effects of these covariates on actual conflict outcomes.

The remainder of the study is organized as follows. First, we briefly present the ZiOP model with and without correlated errors. We then report results from MC simulations that assess and compare the performance of the OP and ZiOP model when an ordered dependent variable contains various proportions of excess zeros. These simulations go beyond those reported in Harris and Zhao (2007) by examining the extent to which the distribution of excess zeros influences the model's performance, thus providing useful information for conflict scholars. This is followed by two replication analyses—focusing on the *intrastate* conflict data and models reported in Besley and Persson (2009) and on the *interstate* conflict data and models used by Senese (1997)—which show not only that the aforementioned studies' substantive results are meaningfully different when one uses a ZiOP, rather than an OP model, but also demonstrate the rich information one can extract from the ZiOP model. To conclude, we discuss the implications of our analysis for conflict research and briefly identify other potential applications of split-population models within the field of international relations.

The ZiOP and ZiOPC Models

Mixture models can be represented using two (or more) distinct equations, each of which contains a stochastic error term. Split-population models are mixture models, and thus one must make an assumption about whether the two stochastic terms are independent or correlated. Harris and Zhao (2007) developed two versions of their model: the ZiOP, which assumes that the errors are independent of one another, and the zero-inflated ordered probit with correlated errors (ZiOPC), which assumes that the two error terms are correlated with one another. We briefly present subsequently the ZiOP model without correlated errors and discuss the ZiOPC model in a Supplemental Appendix.[8]

The ZiOP estimator (with and without correlated errors) contains two latent equations: a split-probit equation in the first stage and an OP equation in the second (outcome) stage. To provide more detail, first suppose that we have a dependent variable y_i where $i \in \{1, 2, \ldots, N\}$. Suppose further that y_i is observable and assumes the discrete ordered values of $0, 1, 2, \ldots, J$. Let s_i denote a binary variable that indicates a *split* between regime 0 ($s_i = 0$) and regime 1, where $s_i = 1$. In the context of an international conflict data set, for example, the zero observations in regime 0 ($s_i = 0$) include "inflated" zero observations that never experience conflict, while zero observations in regime 1 ($s_i = 1$) includes cases for which the probability of transitioning into a nonzero conflict 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 split-probit equation, which we refer to as the "splitting (or inflation) equation,"

$$s_i^* = \mathbf{z}'_i \gamma + u_i. \tag{1}$$

The split probit in equation (1) constitutes the first stage of both the ZiOP model *without* correlated errors and the ZiOP model *with* correlated errors. In equation (1), $\mathbf{z}'_i$ is the vector of covariates, γ is the vector of coefficients, and u_i is a standard normal distributed error term. Hence the probability of i being in regime 1 is $\Pr(s_i = 1|\mathbf{z}_i) = \Pr(s_i^* > 0|\mathbf{z}_i) = \Phi(\mathbf{z}'_i \mathrm{g})$, and the probability that i is in regime 0 is $\Pr(s_i = 0|\mathbf{z}_i) = \Pr(s_i^* \leq 0|\mathbf{z}_i) = 1 - \Phi(\mathbf{z}'_i \gamma)$, where $\Phi(.)$ is the standard normal cumulative distribution function.

The outcome equation of the ZiOP(C) model is developed from a standard OP equation which is defined as

$$\widetilde{y}_i^* = \mathbf{x}'_i \beta + \varepsilon_i$$

$$\widetilde{y}_i = \left\{ \begin{array}{c} 0 \text{ if } \widetilde{y}_i^* \leq 0 \\ j \text{ if } \alpha_{j-1} < \widetilde{y}_i^* \leq \alpha_j (j = 1, \ldots, J-1) \\ J \text{ if } \alpha_{J-1} \leq \widetilde{y}_i^* \end{array} \right\}, \tag{2}$$

where $\mathbf{x}'_i$ is a vector of covariates, β is the vector of coefficients, ε_i is a standard normal distributed error term, and $j = 1, 2, \ldots, J-1$. α_j is the vector of boundary parameters that need to be estimated in addition to β. We assume throughout that $\alpha_0 = 0$. If we assume that the error terms from the first-stage probit equation and the second-stage OP outcome equation, that is, u_i and ε_i, are *not* correlated, then the augmented OP outcome equation of the ZiOP model is, according to Harris and Zhao (2007, 1076), given by

$$\Pr(y_i) = \begin{Bmatrix} \Pr(y_i = 0|\mathbf{x}_i, \mathbf{z}_i) = [1 - \Phi(\mathbf{z}_i'\gamma)] + [\Phi(\mathbf{z}'_i g)(\Phi(-\mathbf{x}'_i\beta))] \\ \Pr(y_i = j|\mathbf{x}_i, \mathbf{z}_i) = \Phi(\mathbf{z}'_i\gamma)[\Phi(\alpha_j - \mathbf{x}'_i\beta) - \Phi(\alpha_{j-1} - \mathbf{x}'_i\beta)](j = 1, \ldots, J-1) \\ \Pr(y_i = J|\mathbf{x}_i, \mathbf{z}_i) = \Phi(\mathbf{z}'_i\gamma)[1 - \Phi(\alpha_{J-1} - \mathbf{x}'_i\beta)] \end{Bmatrix}. \tag{3}$$

This is the takeaway: the probability of a zero observation in the augmented OP equation of the ZiOP(C) models is modeled conditional upon the probability of an observation being assigned a value of 0 in the OP process *plus* the probability of it being in regime 0 from the splitting (inflation) equation. As a result, when the ordered dependent variable is zero inflated, the ZiOP(C) models allow researchers to obtain accurate estimates compared to a standard OP model: subsequently, we briefly summarize MC studies (described in the Supplemental Appendix) which demonstrate that the ZiOP(C) estimates are both less biased and have greater empirical coverage probabilities.

Turning to statistical studies of conflict, the ZiOP(C) models allow one to estimate (1) conflict "relevance" (which corresponds to regime 1 in the splitting equation previously) and (2) a set of outcome-stage OP probabilities that are conditional on the probability of conflict relevance. Such a procedure offers a number of distinct advantages over similar approaches that utilize some form of case selection based on prior theory. As many have noted, conflict relevance (or "opportunity") is inherently unobservable, and no single theoretical variable or set of variables can perfectly predict which peace observations are relevant and which are not (e.g., Clark and Regan 2003; Xiang 2010). Accordingly, attempts to sample only "relevant" peace observations, as based upon some subset of covariates,[9] have been found to censor a large number of actual conflict cases from one's sample (Bennett and Stam 2004, 61) while simultaneously failing to omit many irrelevant observations (Xiang 2010). This in turn produces selection bias and faulty inference (Lemke and Reed 2001; Xiang 2010). By estimating "relevance" probabilistically, the ZiOP(C) models avoid these problems—while still accounting for sample heterogeneity—by conditioning one's outcome-stage estimates on these probabilities without dropping any observations entirely.

MC Summary

We conduct several MC experiments to assess the performance of the ZiOP and ZiOPC models in finite samples and to examine the consequences of estimating a standard OP model when the underlying data-generating process (DGP) produces data that contain zero inflation. To do so, we follow Harris and Zhao (2007) and use a variety of marginal effect estimates and measures of bias to compare the performance of the ZiOP, ZiOPC, and OP models under each model's respective DGP. However, our MC analyses differ from those reported in Harris and Zhao's study in two important respects. First, we evaluate how the *proportion* of noninflated zero observations in the sample influences each model's estimates. These results will help applied researchers make decisions about whether the ZiOP(C) models are useful for their studies. Second, we examine the frequency with which the ZiOP(C) models converge, given the proportion of noninflated zero observations in the sample, which should also be useful to applied researchers. To save space, we have described in detail and have systematically reported our MC results in Tables A.1 to A.18 and Figures A.1 to A.3 in the Supplemental Appendix to this study.[10] Here we discuss the practical implications of these results for substantive researchers who (potentially) face a zero-inflation problem in ordinal data.

Researchers considering whether to use a ZiOP or ZiOPC model believe there is some amount of zero inflation in their data, and our MC results suggest that their *belief* about *the extent* of this problem is critical in determining the usefulness of these models. We emphasize belief because the extent of the problem is inherently unobservable. However, researchers may use their substantive knowledge in conjunction with the information presented here to develop expectations about the utility of these models for their data. The usefulness of these models (i.e., their ability to produce unbiased, efficient estimates) declines when the size of the split in the population is very small or very large (roughly, less than 10 percent or greater than 90 percent "always-zero" observations). In the context of conflict studies, this would mean that more than 90 percent of the observations in one's sample are at risk for conflict or that less than 10 percent of one's sample is at risk for conflict. Given that many conflict studies (such as those examined subsequently) employ dependent variables that use relatively high violence thresholds to define positive levels of conflict, the first scenario (obtaining a sample where 90 percent of the observations are at risk for conflict) seems much less likely than the second.

If the zero-inflation problem is severe, this would produce data with a very high proportion of all observations having a value of 0 for the dependent variable. Under these circumstances (severe zero inflation), an OP is nearly certain to produce biased estimates, but estimates from the ZiOP(C) can also be quite biased. This is hardly surprising, given that as the proportion of observations in a sample that have values of 0 for the dependent variable gets closer to 1, it becomes more difficult to draw statistical inferences regardless of the model one employs. Thus, if the ZiOP(C) produces coefficient estimates (in β or γ) that seem unreasonably large in magnitude, this may indicate a severe zero-inflation problem, in which case the ZiOPC would be expected to produce less biased estimates in both β and γ than the ZiOP.

If, however, the underlying DGP is OP, the OP will (unsurprisingly) produce less biased and more efficient estimates than both the ZiOP and the ZiOPC. Additionally, when the zero-inflation problem is nearly absent, estimates of γ from the ZiOP become quite biased and variable, while the ZiOPC nearly always fails to converge. Thus, coefficient estimates in γ that seem unreasonably large may also indicate that the number of "always zero" observations is negligible and that estimating ZiOP(C) models is unnecessary. It should be noted, however, that even a small amount of inflation pushes an OP toward biased estimates of β, as can be seen on the right-hand side of Figure A.3 in the Supplemental Appendix, where 10 percent of the observations in the samples used for estimation were inflated observations. Thus, if researchers suspect that *any* amount of zero inflation is present, it is advisable to estimate both an OP model and a ZiOP(C) model and compare results.

Applications to Data

We now compare the performance of the OP, ZiOP, and ZiOPC models in a replication of Besley and Persson (2009). Besley and Persson develop and test comparative static results from a formal model in their article. The authors create an ordered dependent variable that distinguishes among three circumstances: neither government repression nor violent dissent; government repression with little violent dissent; and both government repression and violent dissent. This variable, *political violence*, is equal to 0 for country-years that experience no political violence (peace), equal to 1 for country-years that experience repression but no civil war, and equal to 2 for country-years that experience civil war involving both government and dissident violence.[11] Their sample includes all country-years with available data from 1976 to 1997, and yields a dependent variable, political violence, that is composed of roughly 81 percent of zero, or "peace-year," observations (Besley and Persson 2009, 294).

In brief, Besley and Persson's formal model predicts that per capita income and parliamentary democracy will have a negative effect on the probability of political violence. Because the ZiOP(C) models are, of course, new, it is not surprising that Besley and Persson (2009) use an OL model to estimate the impact of gross domestic product (GDP) per capita and parliamentary democracy on the probability of observing the three levels of political violence. In one primary specification, Besley and Persson include as independent variables *ln GDP* per capita and *parliament* as well as *primary product exporter*, *weather shocks*, and *oil exporter*.[12] They find that their key independent variables, ln GDP per capita and *parliament*, monotonically decrease the probability of political violence.

Besley and Persson's (2009) results are insightful. Yet, as mentioned previously, their ordered dependent variable (political violence) contains a high proportion of zero observations, and we believe the zeros are comprised of two distinct types. The first type of zero observations encompasses peace-years that reflect sufficient *harmony* (compatibility) *of interests* that structural and societal forces ensure that dissident groups do not violently challenge the state over grievances and the state does not need to threaten repression, regardless of the temporary crises or shocks experienced. We label this set of observations "harmony" years. The second type of zero peace observations represent country-years that are structurally prone to violence, but nevertheless avoided the temporary economic, political, or environmental shocks that often provoke such violence in a given year (referred to hereafter as "nonharmony" year observations). Note that the probability with which observations in the "nonharmony" year group may make a transition to repression or civil war is not zero as conflicts of interest can subsequently induce dissidents to use violence.

Given the high proportion of heterogeneous zeros in Besley and Persson's (2009) ordered dependent variable, we anticipate that their OL model may not be an appropriate econometric tool for statistically testing their theoretical claims. Rather, our MC results indicate that the ZiOP(C) model will provide more accurate estimates than a standard OP model in this case. We also claimed previously that the ZiOP(C) coefficient estimates can be employed to extract additional substantive information about the two types of zero observations in a zero-inflated ordinal dependent variable. In the context of Besley and Persson's study, this implies that we can use the estimates from the split-probit equation of the ZiOP(C) model to obtain substantively interesting information about the proportion and characteristics of "harmony" and "nonharmony" year observations in the Besley and Persson sample. Finally, we suggested in the introduction section that calculation of substantive (i.e., marginal) effects from an OP model that is used to study data produced by a ZiOP(C) DGP potentially overlooks nonmonotonic relationships between the variables of interest and the outcome probabilities.

To evaluate these claims, we first estimate a main specification used by Besley and Persson (2009) via a standard OP model. We report the results from this OP model in Table 1. Second, we estimate ZiOP and ZiOPC models for the Besley and Persson data in which the outcome equation covariates are identical to those incorporated in the OP model. As this is a methods exercise, we limit our specification effort for the inflation equation to identifying plausible indicators and include the following two variables in the inflation equation of the ZiOP and ZiOPC models: ln GDP per capita and *parliament*. The results from the ZiOP and ZiOPC models in which just two variables, ln GDP per capita and *parliament*, are included in the inflation equation are also reported in Table 1. In the inflation equation, we include the two variables mentioned previously because a higher level of per capita income and the presence of a parliamentary legislature plausibly promote compatibility of interests between the state and societal actors and thus influences the probability that a country always experiences peace. That said, we wanted to ensure that our results are not driven by our decision to include only ln GDP per capita and *parliament* in the inflation equation. Hence, we estimated a full ZiOPC (labeled ZiOPC2) and ZiOP model in which all the covariates in the outcome equation are also included in the inflation equation. To save space, we report only the results from the full ZiOPC2 model in Table 1.

Table 1. OP, ZiOP, and ZiOPC Models of Political Violence, 1976 to 1997.

	OP	ZiOP	ZiOPC	ZiOPC2
Outcome equation				
Ln GDP pc	−0.212** (0.034)	0.041 (0.053)	0.331* (0.156)	0.204* (0.098)
Parliament	−0.538** (0.101)	−0.095 (0.174)	0.310 (0.649)	−0.013 (0.301)
WeatherShock	0.220** (0.026)	0.265** (0.032)	0.198** (0.047)	0.244** (0.042)
Oil Exporter	0.907** (0.364)	1.707** (0.465)	1.183** (0.457)	1.891** (0.504)
Primary Expo	−0.427 (0.250)	−0.422 (0.272)	−0.237 (0.213)	−0.580 (0.345)
τ_1	−1.073** (0.259)	0.772* (0.385)	2.756** (1.054)	1.910** (0.677)
τ_2	−0.230 (0.259)	1.678** (0.395)	3.563** (1.007)	2.718** (0.668)
Splitting equation				
γ *Constant*		18.782** (2.869)	11.610** (2.504)	12.44** (1.642)
Ln GDP pc		−2.802** (0.316)	−1.281** (0.264)	−1.33** (0.175)
Parliament		−0.293 (0.331)	−0.368 (0.594)	−0.021 (0.404)
Weather Shock				−0.129 (0.094)
Oil Exporter				−1.916 (0.985)
Primary Exporter				0.854 (0.844)
ρ			−0.889** (0.094)	−0.912** (0.052)
Log likelihood	−1,432	−1,386	−1,374	−1,370
AIC	2,878	2,792	2,770	2,768

Note: AIC = Akaike information criterion; OP = ordered probit; ZiOP = zero-inflated ordered probit. *N* = 1,984.
**p* < .05; values in parentheses are standard errors. ***p* < .01.

Figure 1. ZiOPC estimated probability "nonharmony" regime.

We first discuss subsequently the results obtained in the split-probit equation of the ZiOP and ZiOPC models (see Table 1). We then discuss the estimates reported in the OP model and in the outcome equation of the ZiOP and ZiOPC models. To start with, the coefficients reported in the splitting equation of the ZiOP(C) models reveal that ln GDP per capita has a negative and significant effect—while *parliament* has a negative but insignificant effect—on the likelihood of a country-year *not being* among the "always zero" group and then experiencing any level of political violence. The inflation equation results also provide valuable insight into the relationship between per capita income and the two types of peace-year observations mentioned earlier: "harmony" and "nonharmony" observations.

To see this more clearly, we map in Figure 1 the average of the annual predicted probability of a country being a "nonharmony" year observation conditional on our inflation equation covariates via a world map. To do so, we used the coefficient estimates from the inflation equation of the ZiOPC model in Table 1 and the relevant marginal effect formula to calculate the average in sample predicted probabilities of "nonharmony" for each country in the sample. We then plotted these country-level predicted probabilities of "nonharmony" onto the world map in Figure 1. The results illustrated in this map are intuitive, as they suggest that our sample's predicted probabilities of "nonharmony" are highest within the least developed regions of the world, such as sub-Saharan Africa, South and Southeast Asia. By contrast, highly developed democracies, such as those found within North America and Europe, exhibit extremely high probabilities of belonging to the group of "harmony" year observations in the sample.

We further take advantage of the inflation equation estimates to obtain information about the aggregate predicted proportions of "harmony" and "nonharmony" observations in the Besley–Persson sample. The procedure adopted to derive this proportion is described formally in the supplemental appendix. Stated briefly, we first used the inflation equation estimates to calculate the predicted probability of transition to the ordered regime for each observation in the sample. We label this predicted probability $\widehat{s_i}$. Observations for which this predicted probability $(\widehat{s_i})$ is equal to or greater than 0.5 are classified as "nonharmony" (as they are more likely be at risk for political violence), while observations where $\widehat{s_i}$ is less than 0.5 are classified as "harmony." We then calculated the proportion of these "harmony" and "nonharmony" observations. We repeated the exercise described previously for two additional thresholds that are used to classify each observation into the "harmony" category: $\widehat{s_i} < 0.25$ and $\widehat{s_i} < 0.75$. Using the three aforementioned thresholds, we find that the proportion of peace-year observations in the sample that are predicted to belong to the (1) "harmony" category are 14 percent (when $\widehat{s_i} < 0.25$), 22 percent $(\widehat{s_i} < 0.5)$, and 36 percent $(\widehat{s_i} < 0.75)$, respectively, and (2) "nonharmony" category are 86 percent $(\widehat{s_i} < 0.25)$, 78 percent $(\widehat{s_i} < 0.5)$, and 64 percent $(\widehat{s_i} < 0.75)$, respectively.[13] Thus, the share of peace-year observations with effectively zero probability of experiencing violence ranges from 14 percent to 36 percent, while the share of peace-year observations whose probability of experiencing repression or conflict is nonzero ranges from 64 percent to 86 percent.

The preceding results provide at least two main substantive insights. First, Figure 1 allows us to identify *which countries* in our sample of peace-year observations are more likely to make a transition to the ordered regime and thus experience some level of political violence. Second, the results discussed previously provide precise information about the exact share of peace-year observations that never experience repression or conflict versus those that experience peace in some years but can potentially make a transition to political violence in other years. This is important insofar that it statistically confirms our intuition that the population of zero observations in Besley and Persson's political violence variable are indeed heterogeneous and produced by distinct DGPs. This empirical finding is not obvious a priori given that unobservable factors generate a significant share of the zero observations in their ordered dependent variable. Furthermore, the possibility that zero-inflated ordinal dependent variables (e.g., political violence) are produced by distinct DGPs suggests that researchers may need to develop and test theories about the processes that produce different types of zeros within ordinal conflict measures.

In addition to the inflation equation findings, the estimates from the outcome equation of the ZiOP(C) models provide intriguing results about the effects of ln GDP per capita and *parliament*. Turning first to the OP model estimates in Table 1, we can note that these results are comparable to Besley and Persson's (2009) OL results, in that the estimated effect of both ln GDP per capita and *parliament* on political violence is negative and statistically significant. The coefficient estimates for ln GDP per capita and *parliament* in the outcome equation of the ZiOPC and

ZiOPC2 model are, however, no longer consistent with their respective OP estimates.[14] Indeed, contrary to the results reported within the OP model, ln GDP per capita is now estimated to have a positive (and significant, in the case of the ZiOPC models) effect on the likelihood that a country experiences political violence, conditional on that country being *able* to experience such violence. Second, although the ZiOP(C) outcome-stage coefficient estimates for *parliament* remain negative (as was reported in the OP model), these estimates are no longer statistically distinguishable from zero in either model. Finally, with regard to the ZiOPC models, the estimates of ρ are negative and significant, suggesting that our allowance for correlated disturbances between the two stages of the ZiOP is justified.

It is not merely the estimated coefficients of ln GDP per capita and *parliament* that vary across the OP, ZiOP, and ZiOPC models. Rather, we also find that the marginal effect of these two key variables differs substantially across the three estimated models in Table 1. To see this more clearly, we used parametric bootstraps and the formula for the full ZiOPC probabilities in equation (A.1), as well as the relevant marginal effect formulas described in the Supplemental Appendix (equations A.5 and A.6), to calculate the effect of ln GDP per capita on the probability of observing each outcome of political violence (peace, repression, or civil war) in the Besley and Persson (2009) sample. The marginal effect of ln GDP per capita was calculated for each value of ln GDP per capita within its observed range, holding all other variables to their means or modes. Repeating this process 1,000 times for each value of ln GDP per capita, we then plot the mean marginal effect obtained for each value of ln GDP per capita, as well as the 90 percent confidence intervals around this mean value.[15] The results from this exercise are illustrated in Figure 2, which depicts the marginal effects of ln GDP per capita on each outcome, across the entire range of ln GDP per capita. Specifically, the columns of Figure 2 correspond to the OP, ZiOP, and ZiOPC models reported previously and the rows correspond to the three outcomes for political violence ($0 =$ *Peace*, $1 =$ *Repression*, $2 =$ *Civil War*).

Regarding the OP marginal effects, column 1 of Figure 2 indicates that increases in ln GDP per capita monotonically increase the probability of observing peace (row 1) and monotonically decrease the probability of observing repression (row 2) and civil war (row 3) across the entire range of ln GDP per capita. These results are consistent with the findings reported by Besley and Persson (2009). However, for the ZiOP and ZiOPC models (columns 2 and 3 of Figure 2), we see that for countries with low-to-medium levels of ln GDP per capita, an increase in ln GDP per capita has a null or slightly positive net effect on the probability of observing either repression or civil war, and a null to slightly negative effect on the probability of observing peace. The ZIOP and ZiOPC marginal effects then indicate that once a country achieves a certain "threshold" with respect to the mean of ln GDP per capita—this threshold is roughly equal to a per capita GDP of US$5,000—further increases in ln GDP per capita rapidly decrease the probability of observing violence within a country, and rapidly increase the probability of peace. Thus, the marginal effects from the ZiOP and ZiOPC models reveal a nonmonotonic relationship between ln

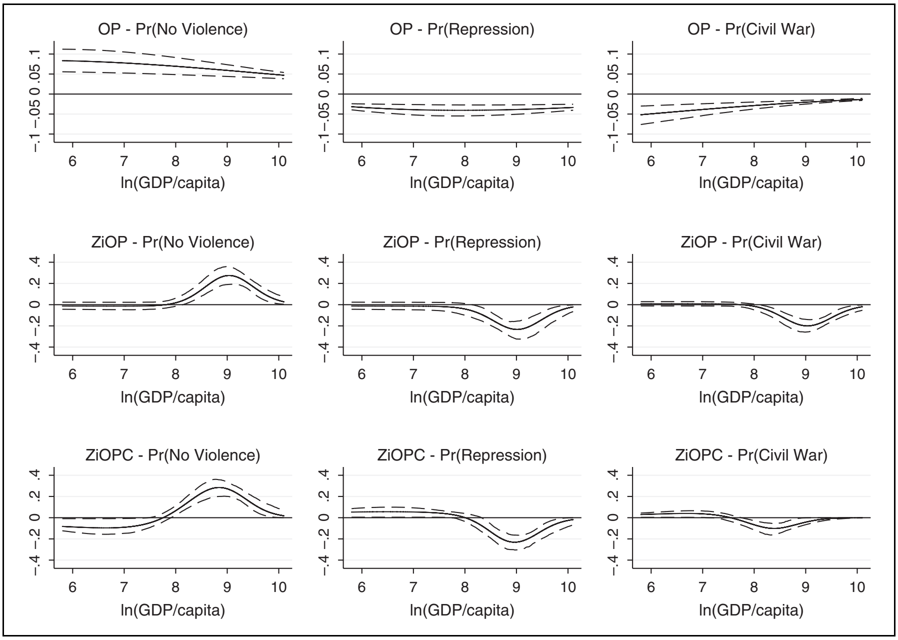

Figure 2. Marginal effect of ln GDP per capita and the probability of political violence.

GDP per capita and the likelihood of political violence that is conditional on the threshold effect described previously. This nonmonotonic relationship is overlooked in the marginal effects from the OP model. Instead, the OP model imposes a monotonic relationship between ln GDP per capita and political violence.

We also find substantial differences in the marginal effect of the *parliament* dummy across the OP, ZiOP, and ZiOPC models. These marginal effects (on each outcome probability) are not illustrated to save space. We did find, however, that for the OP model, becoming a parliamentary democracy significantly (in the statistical sense) (1) decreases the probability that a country-year observes repression or civil war by an average of roughly −10 percent and −5 percent, respectively and (2) increases the probability of peace by roughly 15 percent. These findings are consistent with Besley and Persson (2009). However, the marginal effects of the *parliament* democracy dummy on the outcome probabilities in the ZiOP(C) models, while still negative on average, are not statistically significant. In sum, we find that unlike the ZiOP and ZiOPC model, the estimated coefficients and marginal effects from the OP model are likely to be misleading when the DGP of the ordered dependent variable is zero inflated.

Having established that our ZiOP(C) models yield interesting findings for the study of intrastate conflict, we next evaluate the performance of our ZiOP and ZiOPC model estimates when applied to a study of *interstate* war. This empirical exercise builds on Senese (1997), who explores whether pairs of countries with democratic political institutions exhibit markedly lower levels of interstate *hostility* across a range of militarized disputes levels. Building empirically on the early democratic peace literature, Senese hypothesizes that democratic dyads will exhibit lower levels of militarized interstate dispute (MID) activity. To test this hypothesis, the author empirically examines the effect of his key independent (dummy) variable, *joint* (dyadic) *democracy*,[16] on the highest hostility level reached within dyadic MIDs[17] while controlling for other variables such as *alliance*, *dyadic maturity*, and *contiguity*. His dependent variable of interest, labeled hostility, is ordered across four categories encompassing (1) the threat of force, (2) the display of force, (3) the use of force,[18] and (4) war.[19] Senese (1997) then uses an OL model to test the theory mentioned previously on an 1816–1993 MID dyad-year sample.

Senese reports an unexpected finding: across a variety of specifications, the *joint democracy* dummy variable produces either a positive and statistically significant, or a nonsignificant impact upon the level of hostility. He concludes the article by calling for additional research due to his observation that "it appears that a piece of the dyadic conflict puzzle has been isolated that does not fall neatly within the democratic peace" (Senese 1997, 24). It turns out that this finding is partly due to sample selection bias: rather than study all (relevant) dyads, Senese restricted his sample to only those dyad-years that experienced a militarized conflict as defined by the MID data set. As would become well known after the publication of this study, sample selection bias can produce the sort of results Senese reported (Reed 2000). Yet, by using the ZiOP(C) models to reanalyze his data, we are able to show that Senese's 1997 findings are a statistical artifact due not only to sample selection bias but also due to the high proportion of dyadic peace-year observations (which he excludes from his sample) that emerge from two distinct DGPs.

To do so, we began by reproducing Senese's data, but for all dyads, not just those that had experienced an MID. In doing so, we assigned the value of 0, for peace-year, to all dyad-years that Senese excluded from his sample, thus creating a modified hostility variable that is ordered across five categories: (0) peace, (1) a threat of force, (2) a display of force, (3) a use of force, and (4) war. After creating the modified hostility variable, we find that the peace-year observations in this variable do not form a homogeneous population. Rather, as exemplified by the distinction that researchers seek to draw between relevant and irrelevant dyads,[20] the first type of zero observations in this case include "relevant" dyad-years that might have exhibited militarized conflict in a given year, but did not due to various temporary circumstances. We denote these as "nonharmony" year observations. The second type of zero observations are, as suggested by Lemke and Reed (2001) and Xiang (2010), produced by structural constraints such as geographic distance, a mutual lack of military capacity, or some combination thereof (we label these as "harmony" year observations).

This consideration informs our specification for the inflation equation in the ZiOP(C) models. To capture the likelihood of harmony of interests we use the

Table 2. OP, ZiOP, and ZiOPC Models of Interstate Hostility, 1816 to 1993.

	Truncated OP	ZiOP	ZiOPC
Outcome, *B*			
Contiguity	−0.349** (0.056)	−1.017** (0.101)	−0.787** (0.290)
Alliance	−0.144* (0.068)	−0.211** (0.038)	−0.210** (0.038)
Joint Democracy	−0.166 (0.110)	−0.441** (0.061)	−0.448** (0.062)
One Mature	0.309** (0.082)	0.093* (0.044)	0.093** (0.031))
None Mature	0.368** (0.082)	0.068 (0.044)	0.069* (0.044)
τ_1	−1.755** (0.089)	0.514** (0.108)	0.748* (0.297)
τ_2	−0.679** (0.078)	0.536** (0.146)	0.770* (0.323)
τ_3	1.092** (0.079)	0.674** (0.161)	0.909** (0.331)
τ_4		1.488** (0.169)	1.727** (0.335)
Splitting, γ			
γ*; Constant*		−2.733** (0.042)	−2.765** (0.059)
Contiguity		3.750** (0.317)	3.593** (0.373)
Alliance		0.283** (0.056)	0.294** (0.060)
Joint Democracy		−0.152* (0.071)	−0.154* (0.074)
Major Power		1.007** (0.030)	1.045** (0.057)
ρ			0.106 (0.132)
Log likelihood	−1,984	−11,901	−11,901
AIC	3,984	23,830	23,832
N	1,956	428,831	428,831

Note: AIC = Akaike information criterion; OP = ordered probit; ZiOP = zero-inflated ordered probit. Values in parentheses are standard errors.
*$p < .05$. **$p < .01$.

alliance variable from Senese's study. As a measure of interaction, we include the contiguity variable in the inflation equation. Additionally, as an indicator of a dyad's ability to become militarily engaged, we employ a dichotomous measure of whether or not at least one dyad member is a major power. Finally, given that numerous studies suggest that governments in democracies are less likely to resort to conflict when interacting with other democratic states,[21] we also add *joint democracy* to the splitting equation of the ZiOP(C) model.

Table 2 reports the results from three statistical models. The first is an OP model that matches the model in Senese (1997); with the sample restricted to only those dyads in the MID data set. The other two models use the full sample of all dyads. The second column of Table 2 lists the coefficient estimates from a ZiOP model that includes in the split-probit equation the four covariates noted previously. The covariates in the outcome equation of the ZiOP model are similar to those included in Senese's primary specification: alliance, contiguity, *joint democracy*, *one mature*, and *none mature*.[22] Column 3 reports the same set of variables using the ZiOPC model. To check the robustness of the results, we also evaluated ZiOP(C) models that included all outcome-stage covariates in the inflation equation. Those results did not vary from the ones reported in Table 2 and are hence not reported to save space.

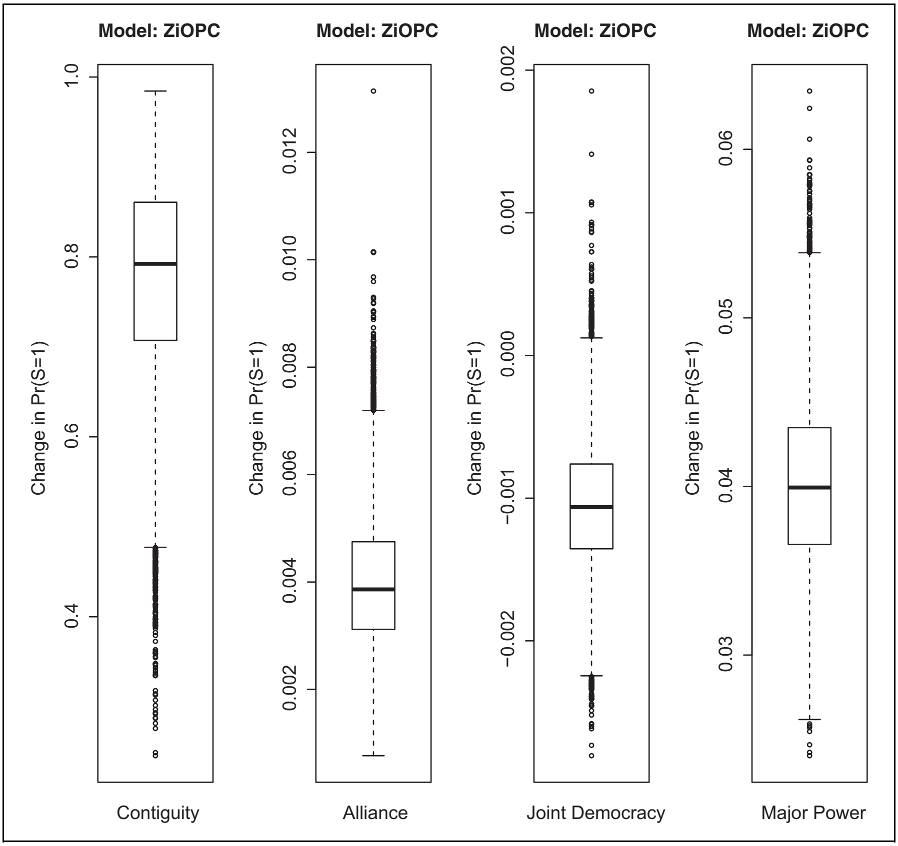

Figure 3. Effect of covariates on the probability of dyadic "nonharmony."

To illustrate the rich information available in the ZiOP(C) models, we first present the split-probit (inflation) equation results in Table 2. The estimates of contiguity, alliance, and major power are each positive and significant while joint democracy is negative and significant in the inflation equations of these models. We also use the inflation equation results to evaluate the relationship between each covariate in the inflation equation and the two types of peace-year observations in the sample of all dyads: "harmony" and "nonharmony" year observations. To this end, we compute the effect of a zero-to-one change in each dummy variable in the inflation equation—contiguity, alliance, joint democracy, and major power—on the probability that a dyad-year will belong to the "nonharmony" group (when other variables are held at their modes).

We represent via boxplots in Figure 3 the resultant distributions of predicted probabilities. Moving from left to right, the first two boxplots show that (1) becoming contiguous is predicted to increase the probability of a dyad being in the nonharmony group by roughly 78 percent and (2) having an alliance is expected to increase the probability of nonharmony by merely 0.4 percent. These results are intuitive as geographically contiguous states are usually more conflict-prone, while states that belong to the same alliance are less likely to fight against each other. The third boxplot reveals that becoming jointly democratic is expected to decrease the probability of dyadic nonharmony by 0.1 percent. This result arguably corroborates the democratic peace thesis, although the substantive effect is surprisingly small. The fourth boxplot shows that having at least one major power in a dyad (as opposed to none) is expected to increase the probability of dyadic nonharmony by 4 percent.

Additionally, to calculate the aggregate predicted proportion of dyad-years that belong to the categories of "harmony" and "nonharmony" in our interstate conflict data, we make use of the inflation equation estimates from Table 2. We find that—depending on the threshold $(\widehat{s_i})$ that we used to classify each observation into the "nonharmony year" category—our ZiOP and ZiOPC models predict (within 95 percent confidence levels) that the percentage share of all dyad-years that belong to the "nonharmony" year category ranges from 10 percent to 16 percent. Given the rarity of actual conflict occurrence in the data set, this implies that roughly 10 percent to 16 percent of the peace-year observations in the interstate conflict data have conflicting interests but consciously opt to refrain from conflict, whereas the remaining peace-years in our sample remain at peace due to structural factors (e.g., "irrelevance"). Identifying "nonharmony" peace-years is important to conflict research, as these cases encompass the subset of dyads that actually have a nonzero transition probability to the remaining ordered hostility categories (including war).

We next discuss the reported OP estimates as well as the outcome estimates of the ZiOP(C) models in Table 2. In the OP model, contiguity and alliance have a statistically significant impact on the highest MID level among dyads that experience an MID, as do the democratic maturity measures. *Joint democracy* does not have a statistically significant impact on hostility (among MID dyads) in the OP model. However, in the outcome equation of the ZiOP(C) models, *joint democracy* is negative and statistically significant, and *none mature* is no longer significant. The aforementioned finding departs from Senese's main results which, as mentioned earlier, found that the *joint democracy* dummy variable produces either a positive and statistically significant or a nonsignificant impact upon the level of hostility. More broadly, the negative and significant estimate for *joint democracy* in the outcome equation of the ZiOP(C) models suggests that democratic dyads indeed have a pacifying effect on interstate hostility as anticipated in some extant studies (e.g., Maoz and Russett 1993).

Conclusion

This study advances the growing conflict literature on split-population models in four main ways. First, existing studies of political violence primarily use split-population models to analyze event counts or binary dependent variables. However, conflict researchers also often work with zero-inflated ordered dependent variables where the excess zeros may relate to two distinct sources. We therefore study the properties of the ZiOP model with and without correlated errors developed by Harris and Zhao (2007) which accounts for zero inflation in discrete ordered dependent variables. Although our MC exercises build on Harris and Zhao's study, we also—unlike Harris and Zhao —use our MC experiments to assess how the *proportion* of inflated observations in zero-inflated discrete ordered data affects the accuracy and convergence of estimates across three different models: the OP model, the ZiOP, and the ZiOPC model. These experiments reveal that ZiOP(C) estimates are more reliable and consistent compared to estimates from an OP model when an ordered dependent variable contains excessive zeros, but that the utility of the ZiOP(C) models depends strongly on the proportion of excess zeros in one's sample. Thus, the MC results presented here will help conflict researchers to assess *when* the ZiOP(C) model will be useful for their research.

Second, extant quantitative studies of intra or interstate conflict often treat the high proportion of "peace" observations that exist in ordinal dependent conflict variables as a homogeneous category. These studies do not statistically account for factors that may both produce the high proportion of zeros in zero-inflated ordered dependent variables and have a differential impact on the probabilities of the two types of peace that exist in such dependent variables. In contrast, the ZiOP(C) model treats the excess zeros in an ordinal dependent variable as a heterogeneous group of peace observations. Additionally, the ZiOP(C) model statistically accounts for observable and latent factors that produce the different types of peace in zero-inflated ordinal conflict variables. As a result, the ZiOP(C) model produces more accurate coefficient estimates of key independent variables (e.g., democracy, per capita income) on conflict outcomes and provides substantively interesting insights about the different types of "peace" observations that exist in such data. This is an important contribution; for while the bias caused by irrelevant observations in conflict analyses is well known (Maoz and Russett 1993; Lemke and Reed 2001), and the use of zero-inflated methods to address this bias is becoming well established (Clark and Regan 2003; Xiang 2010), the application of such techniques to ordinal conflict measures has been virtually nonexistent.

Third, the application of the ZiOP(C) model to published conflict findings indicates that the marginal effects of covariates derived from the ZiOP(C) models may reveal the presence of nonmonotonic relationships between many of the most commonly used conflict covariates and one's conflict outcomes. This has crucial implications for statistical inference since the standard OP model may not detect such nonmonotonic effects. Fourth, we find that the ZiOP(C) models will enable conflict scholars to econometrically account for irrelevant dyads when empirically assessing (ordered) measures of conflict occurrence. This feature thereby allows researchers to accurately test for, and model, the effects of many commonly studied structural variables—such as contiguity, distance, and income per capita—on the extent to which dyads are relevant within zero-inflated ordered measures of conflict.

Our study can be extended in at least three main directions. First, the statistical framework presented here can be used as a foundation to develop an inflated multinomial logit (MNL) model. Doing so would allow conflict scholars to obtain more accurate estimates from data sets that contain discrete dependent conflict variables that are multinomial as well as inflated in their "peace" category.[23] Second, it is also plausible that intermediate categories in discrete ordered dependent variables—for instance, $y_i = 1$ for $y_i \in (0, 1, 2)$—may be inflated and characterized by two types of $y_i = 1$ observations. If so, then the "middle-inflated" variant of the ZiOP(C) models (Bagozzi and Mukherjee 2012) could potentially be used in international relations research to account for split-population issues in the intermediate categories of discrete ordered dependent variables. Such a model may be useful, for example, in studies that analyze whether a country's exchange rate is wholly floating, wholly fixed, or set to some intermediary category (e.g., Singer 2010). Third, unlike the Quantal Response Equilibrium (QRE) statistical model, the ZiOP(C) approach does not (as mentioned earlier) statistically capture the dynamics of strategic interaction in game-theoretic models of intra and interstate conflict, as this estimator is not directly derived from such game-theoretic models. More effort needs to be invested toward deriving a split-population OP statistical model directly from game-theoretic models of conflict. Although deriving such a statistical model will be technically challenging, it will help researchers to directly assess ordinal claims from game-theoretic models of conflict.

Authors' Note

Paper presented at the New Faces in Political Methodology meeting, Penn State, April 30, 2011. Data and .do files for empirical analyses are available at jcr.sagepub.com. To obtain the code needed to estimate the ZiOP model using Stata, please visit http://myweb.fsu.edu/dwh06c/. To estimate the ZiOP model in R, please visit www.benjaminbagozzi.com.

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Notes

1. Split-population (zero-inflated) models have yet to be identified as a distinct group of mixture models. Neither label is especially intuitive: "split population" indicates that one value of a binary, ordinal, or integer variable has two populations, and "zero inflated" suggests that in addition to the "proper" zeros in the variable, there are "extra" zeroes, thus inflating the number of zeros. We prefer split population to zero inflated, but in deference to Harris and Zhao (2007), who named their model the zero-inflated ordered probit, we use both terms interchangeably.
2. Also see Hill, Moore, and Mukherjee (2013) and Young and Dugan (2011). Braumoeller and Carson (2011) propose the Boolean logit model as an alternative to split-population models in some of the applications noted previously.
3. For example, King (1989), Moore and Shellman (2004), and Benini and Moulton (2004).
4. Beger et al. (2011) introduce the split-population logit model which permits researchers to study zero-inflated binary variables that arise from different underlying populations.
5. We thank an anonymous reviewer for pointing this out. An example of a statistical model that does capture strategic interaction directly in game-theoretic models of conflict is the Quantal Response Equilibrium (QRE) model developed and analyzed by Signorino (1999).
6. We are extending Keohane's (1984, 51-54) use of the term harmony from interstate relations to relations among domestic actors.
7. These include the evolution of territorial disputes (Huth 1998), balance of power considerations (Bennett and Stam 2004, 77-78), and various explanations for the democratic peace (Maoz and Russett 1993; Senese 1997, 1999).
8. Harris and Zhao (2007) provide a more detailed description of both the models.
9. Such as contiguity or major power in the "relevant dyads" literature.
10. For each data-generating process (DGP) examined, Figures A.1 and A.2 compare the bias in ZiOP(C) coefficient estimates, Figure A.3 compares the root mean square errors (RMSEs) of the zero-inflated ordered probit (ZiOP), ZiOPC, and ordered probit (OP) marginal effects, and Tables A.2 and A.4 to A.18 present the means, empirical coverage probabilities, and RMSEs of our ZiOP(C) and OP marginal effect estimates. Table A.1 reports the ZiOP(C) convergence rates across experiments, and Table A.3 reports the parameter values used in each experiment.
11. Repression is coded using the Political Terror Scale (Gibney, Cornett, and Wood 2007). Civil wars are coded based on the Correlates of War (COW) intrastate war data.
12. *Weather shocks* is measured as a yearly count of the number of floods and heat waves experienced by a given country as indicated by the Emergency Disasters Database data set (Besley and Persson 2009). Primary product exporter equals 1 for country-years in which more than 10 percent of a country's gross domestic product (GDP) was generated by primary product exports and 0 otherwise. Oil exporter equals 1 for country-years in

which more than 10 percent of a country's GDP was generated by oil exports and 0 otherwise.

13. The derived proportions reported previously in the "harmony" and the "nonharmony" category for each of the three thresholds is statistically significant $(\widehat{s}_i)$ at the 95 percent confidence level.
14. The ZiOP(C) outcome stages reported previously are robust to the exclusion of *parliament* from the inflation stage, as well as to the inclusion of primary product exporter, weather shock, and oil exporter in the inflation stage.
15. Values for ln GDP per capita were changed simultaneously within the inflation and outcome stages of the ZiOP(C) models. This is consistent with the marginal effect formulas in equations (A.5–A.6), and the approach used by Harris and Zhao (2007).
16. Measured dichotomously, and set equal to 1 if the Polity score of both states in a dyad is $\geq +6$.
17. Taken from the Correlates of War (COW) project's militarized interstate dispute (MID) data set.
18. That is, deadly interstate militarized interstate disputes (MIDs) resulting in fewer than 1,000 battle deaths.
19. Coded as violent interstate conflicts resulting in more than 1,000 battle deaths.
20. See Maoz and Russett (1993), Lemke and Reed (2001), and Xiang (2010).
21. For example, Maoz and Russett (1993), Reed (2000), and Bennett and Stam (2004).
22. None mature is equal to 1 for dyad-years in which neither dyad-member had a regime that had persisted for twenty-five years or more. One mature is coded when only one member of a dyad had a regime coded as having persisted for twenty-five years or more. Polity II was used to define regime persistence.
23. Recent studies of economic interdependence and militarized interstate disputes (MIDs) employ multinomial logit (MNL) models to test extant hypotheses in this issue area (e.g., Aydin 2008; Lu and Theis 2010). It is plausible that an inflated MNL model may not only apply to the research mentioned previously but may also provide empirical results that add to these studies' insights.

Supplemental Materials

The online supplemental appendices are available at http://jcr.sagepub.com/supplemental.

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