Supplemental Information Appendix For:

Modeling Two Types of Zeros in Ordinal Data:

The Zero-inflated Ordered Probit (ZiOP) Model in Conflict Research

In this supplemental appendix, we first describe the ZiOPC model, and then define the likelihood function of the ZiOP and ZiOPC models. We then report a table containing the initial parameter values and distributions used in our Monte Carlo Experiments. Finally we report some model fit statistics and describe the methods and formulas that were used to calculate the marginal effects reported in our Besley and Persson (2009) application.

ZiOPC

Because it is plausible that the error terms from the first stage probit and the second stage OP outcome equation may be correlated The ZiOPC model permits one to model that correlation. Suppose that the error terms u_i and ε_i are correlated and follow— as assumed by Harris and Zhao (2007, p. 1077)— a bivariate normal distribution with correlation coefficient ρ. If (u_i, ε_i) follow a bivariate normal distribution with correlation coefficient ρ and with the identifying assumption of unit variances, then according to Harris and Zhao (2007, p. 1077), the augmented OP outcome equation of the ZiOPC model is

$$\Pr(y_i) = \left\{ \begin{array}{c} \Pr(y_i = 0|\, \mathbf{x}_i, \mathbf{z}_i) = [1 - \Phi(\mathbf{z}_i'\gamma)] + \Phi_2(\mathbf{z}_i'\gamma, -\mathbf{x}_i'\beta; -\rho) \\ \Pr(y_i = j|\, \mathbf{x}_i, \mathbf{z}_i) = \Phi_2(\mathbf{z}_i'\gamma, \alpha_j - \mathbf{x}_i'\beta; -\rho) - \Phi_2(\mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_i'\beta; \alpha_{j-1} - \mathbf{x}_i'\beta; \rho) \\ \Pr(y_i = J|\, \mathbf{x}_i, \mathbf{z}_i) = \Phi_2(\mathbf{z}_i'\gamma, \mathbf{x}_i'\beta - \alpha_{J-1}; -\rho), \end{array} \right\} \quad \text{(A.1)}$$

where $\Phi_2(.)$ denotes the cdf of the standardized bivariate normal distribution. Thus, the ZiOPC model's correlated disturbances are analogous to those commonly used within Heckman selection models (Heckman, 1979), though note that the ZiOPC model is distinct from an OP-selection model approach in that the ZiOPC accounts for selection processes that "inflate" (outcome stage) ordered dependent variables with *undesirable* observations, rather than for selection processes that "truncate" *desirable* observations from ordered dependent variables.

Equation 2 in our study and equation 1 here provide the full probabilities of the augmented OP (outcome) equation of the (i) ZiOP model and (ii) ZiOPC model. We label these probabilities as outcome probabilities for convenience. More importantly, observe that 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 zero 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—as shown by the Monte Carlo analysis below—allow researchers to obtain accurate estimates compared to a standard OP model, which is to say that the ZiOP(C) estimates are both less biased and have greater coverage of the probabilities.

Below we explain how one can use these unbiased coefficients to calculate quantities of interest that could otherwise not be estimated, and also derive the (log) likelihood functions for the full ZiOP and ZiOPC models, which allow one to consistently and efficiently estimate the ZiOP(C) models using maximum likelihood estimation. The authors have written code to permit users to estimate the ZiOP(C) models using `Stata` and `R`.

ZiOP(C) Likelihood Functions

To begin with, recall that $\theta = (\gamma', \beta', \mu')'$ for the full ZiOP model. The likelihood of the ZiOP model for an i.i.d sample of $i \in \{1, 2, ...N\}$ observations can thus be defined as

$$\begin{aligned}
\mathscr{L}(\theta) &= \prod_{i=1}^{N}\prod_{j=0}^{J}[\Pr(y_i = j|\, \mathbf{x}_i, \mathbf{z}_i, \theta)]^{d_{ij}} \\
&= \prod_{i=1}^{N}\prod_{j=0}[\Pr(s_i = 0) + \Pr(s_i = 1)\Pr(\widetilde{y}_i = j)]^{d_{ij}} \\
&\times \prod_{i=1}^{N}\prod_{j>0}[\Pr(s_i = 1)\Pr(\widetilde{y}_i = j)]^{d_{ij}}
\end{aligned} \tag{A.2}$$

where $(y_i = 0|\, \mathbf{x}_i, \mathbf{z}_i)$ was described earlier and where $d_{ij} = 1$ if outcome j is realized in i, or is $d_{ij} = 0$ otherwise. When the error terms in the split probit equation and the ordered probit outcome equation of the ZiOP model (that is, $u_i$and ε_i) are correlated, the zero-inflated model in equation 3 in the main paper can be generalized to have a bivariate distribution. Hence, similar to the ZiOP model, the zero-inflated ordered multinomial distribution of the ZiOPC model arises as a mixture of a degenerate distribution at 0 and the assumed distribution of the variable $\widetilde{y}_i$ as follows:

$$\Pr(y_i) = \left\{ \begin{array}{c} \Pr(s_i = 0|\mathbf{z}_i) + \Pr(s_i = 1|\mathbf{z}_i)\Pr(\widetilde{y}_i = 0|\, \mathbf{x}_i, s_i = 1) \text{ for } j = 0 \\ \Pr(s_i = 1|\mathbf{z}_i)\Pr(\widetilde{y}_i = j|\, \mathbf{x}_i, s_i = 1) \text{ for } j = 1, 2..J \end{array} \right\} \tag{A.3}$$

The likelihood function for the correlated model can be, therefore, defined as

$$
\begin{aligned}
\mathscr{L}(\widehat{\theta}) &= \prod_{i=1}^{N}\prod_{j=0}^{J}[\Pr(y_i = j|\ \mathbf{x}_i, \mathbf{z}_i, \widehat{\theta})]^{d_{ij}} \\
&= \prod_{i=1}^{N}\prod_{j=0}^{J}[\Pr(s_i = 0) + \Pr(s_i = 1, \widetilde{y}_i = 0)]^{d_{ij}} \\
&\times \prod_{i=1}^{N}\prod_{j>0}[\Pr(s_i = 1, \widetilde{y}_i = j)]^{d_{ij}}
\end{aligned}
\tag{A.4}
$$

Different choices of for the joint distribution of $(u_i,\ \varepsilon_i)$ gives rise to various zero inflated response models. If, for example, we assume the correlation between the errors terms is given by a bivariate normal distribution, then equation A.4 can serve as the likelihood function of the ZiOPC model.

The likelihood functions presented above can be used to derive the corresponding log likelihood functions for our ZiOP and ZiOPC models. Let $\theta = (\gamma', \beta', \mu')'$for the full ZiOP model and let $\widehat{\theta} = (\gamma', \beta', \mu', \rho)'$ for the full ZiOPC model. The log likelihood function of the ZiOP model is defined as $\ell(\theta)$=$\sum_{i=1}^{N}\sum_{j=0}^{J} d_{ij} \ln[\Pr(y_i = j|\mathbf{x}_i, \mathbf{z}_i, \theta)]$ where $d_{ij} = 1$ if outcome j is realized in i, or is $d_{ij} = 0$ otherwise. Likewise, the log likelihood function of the ZiOPC model is $\ell(\widehat{\theta})$=$\sum_{i=1}^{N}\sum_{j=0}^{J} d_{ij} \ln[\Pr(y_i = j|\mathbf{x}_i, \mathbf{z}_i, \widehat{\theta})]$.

Monte Carlo Experiments

We perform two primary MC experiments: one where the dependent variable follows a ZiOP d.g.p (i.e. no correlation between the error terms from the inflation, γ, and, outcome, β, equations) and a second where it follows a ZiOPC dgp In addition, each experiment then also evaluates our ZiOP, ZiOPC, and OP estimates under an OP dgp (i.e. no zero-inflation). The dependent variable, y, is a three category variable (0 to 2). The chosen values and distributions for the parameters and variables, as well as the sample sizes and number of iterations for our simulations, are reported in Table A.1 of the Supplemental Appendix.[1] To assess the performance of our models under different levels of inflation, γ_0, the constant from the inflation equation, is varied within each experiment to generate percentages of non-inflated zero observations of approximately 0%, 10%, 30,% 50%, 70%, 90%, and 100%.

[1]We assume in our MC experiments, as Harris and Zhao (2007) do, that the number of covariates in the outcome equation are greater than those in the inflation equation. This ensures that exclusion restrictions is met for the MC analysis.

Table A.1: Convergence Rates

	ZiOP dgp		ZiOPC dgp	
% Non-Inflation	ZiOP	ZiOPC	ZiOP	ZiOPC
0%	80.24%	39.66%	77.84%	35.58%
10%	100%	100%	100%	100%
30%	100%	99.76%	100%	99.88%
50%	100%	96.36%	100%	98.50%
70%	100%	95.96%	100%	92.78%
90%	73.10%	59.08%	84.18%	48.32%
100% (OP dgp)	87.88%	2.72%	87.94%	2.78%
All %	91.60%	70.51%	92.85%	68.26%

We first examine the convergence rates for each model. While the OP never encountered convergence problems in either experiment, the ZiOP converged 91.60% of the time under a ZiOP dgp and 92.85% of the time under a ZiOPC dgp[2] The ZiOPC model converged much less frequently, reaching convergence 70.51% of the time in the first experiment and 68.26% of the time in the second experiment. Convergence was strongly related to the proportion of non-inflated zero observations in the sample. As Table A.1 indicates, both models failed to converge most frequently at 0%, 90%, and 100% non-inflation. The ZiOPC in particular experienced severe problems under 100% non-infllation, converging only 2.72%–2.78% of the time. This is not altogether bad news since, as we discuss below, the bias and variability in the estimates from each model also varies strongly with the proportion of zero observations that are non-inflated, and are generally largest where the models fail to converge most frequently.

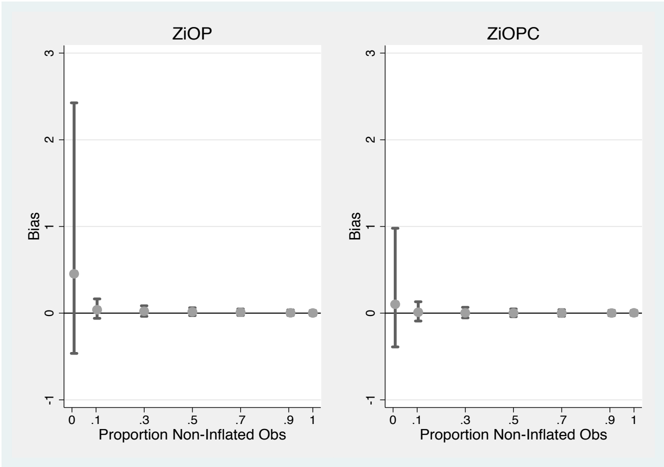
We now turn to our comparisons of the OP, ZiOP, and ZiOPC estimates for dependent variables that are drawn from OP, ZiOP, and ZiOPC dgp's. See figure A.1, which depicts the MC study that assumed a ZiOPC dgp. The results from the MC study that assumed ZiOP dgp produce similar results, as depcited in figure A.2, below.[3] As a result, we concentrate our discussion on the models' performance assuming the ZiOPC dgp. Bias is calculated as the mean coefficient estimate minus the true value.

Our first comparisons examine the bias in the coefficient estimates derived from our ZiOP and ZiOPC models. Since the OP estimates will be biased under all levels of non-inflation

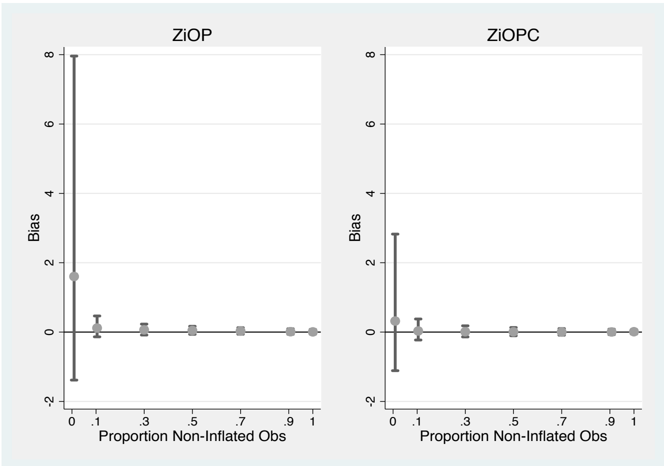
[2]Estimation was terminated if the model failed to converge after 100 iterations.
[3]The constant from the γ equation is excluded as it is varied in each experiment.

Figure A.1: Bias in Coefficient Estimates (ZIOPC DGP)

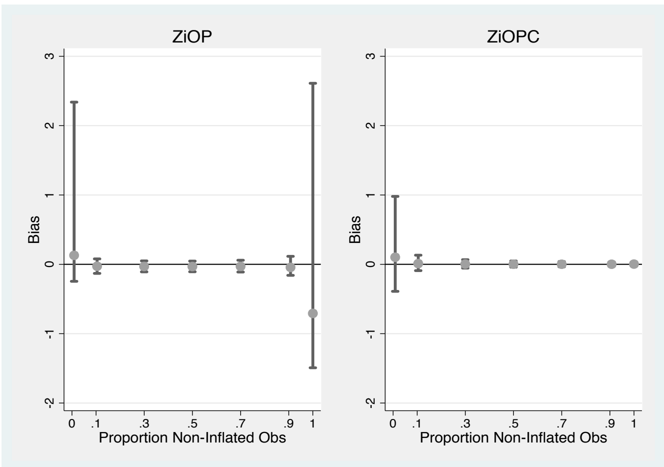
(a) Bias in Estimates of β_1



(b) Bias in Estimates of β_2



(c) Bias in Estimates of γ_1



except 100%, we limit these comparisons to estimates of β_1, β_2, and γ_1 from the ZiOP and ZiOPC models. Figures A.2a and A.2b depict graphically the relationship between the bias in estimates of β and the proportion of non-inflated observations in the sample, while figure A.2c depicts the relationship between this proportion and estimates of γ. The vertical axes in figures A.2a, A.2b, and A.2c represent the amount of bias in the coefficient estimates, with the lines at 0 indicating no bias, while the horizontal axes represent the proportion of the sample that has "observable" (i.e., non-inflated) outcomes. The dots in each figure show the bias in the coefficient estimates, the bars are 95% confidence intervals. Figures A.2a–A.2c make it quite clear that model-performance varies in response to the proportion of non-inflated zero observations in the data, so we compare results from each model conditional on this proportion.

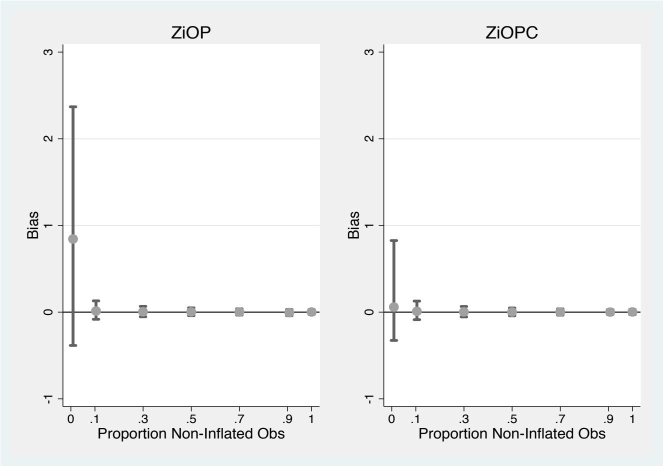
Figures A.1a–A.1b demonstrate that estimates of β from the ZiOP and ZiOPC are most biased when the proportion of non-inflated observations approaches 0 (the leftmost point on the horizontal axis). Under this condition the ZiOPC is both less biased and more efficient than the ZiOP, and this is generally the case for the other proportions of zero-inflation examined in our experiments. The bias in estimates of β from both models approaches zero as the level of non-inflation increases beyond 0%. A similar pattern is present in estimates of γ from the ZiOP(C) models. Figure A.2c indicates that the bias and variability in estimates of γ_1 from the ZiOP become larger as the proportion of non-inflated observations nears 0 or 1, and are smallest in between these two extremes. Estimates of γ from the ZiOPC are most biased and variable at 0% non-inflation, but are slightly less biased and more efficient than those from the ZiOP, and the bias in the ZiOPC estimates virtually disappears beyond 0% non-inflation. Though the ZiOPC estimates exhibit none of the bias and variability of those from the ZiOP at 100% non-inflation, the ZiOPC converged so infrequently under these conditions that any conclusions about its performance at this level of non-inflation must be tentative.

Figure A.3 and Table A.2 compare the estimated marginal effects of the outcome stage covariates included within our ZiOP, ZiOPC, and OP models.[4] In line with Harris and Zhao (2007), we focus our comparisons herein on the root mean squared errors (RMSEs) and em-

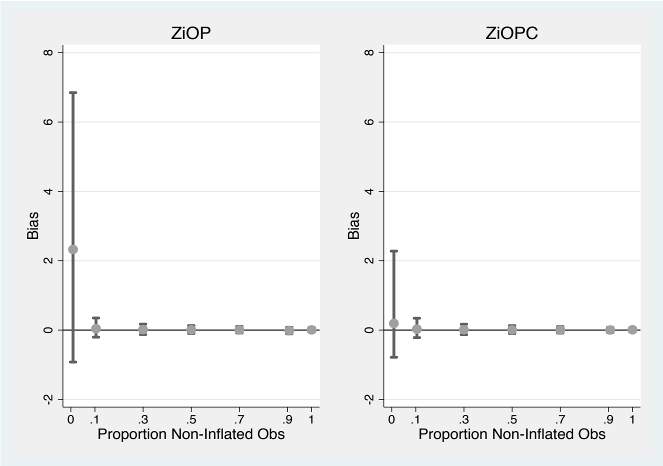
[4]We used bootstraps of $M = 1000$ to calculate these marginal effects, with all other variables held to their means or modes.

Figure A.2: Bias in Coefficient Estimates (ZIOP DGP)

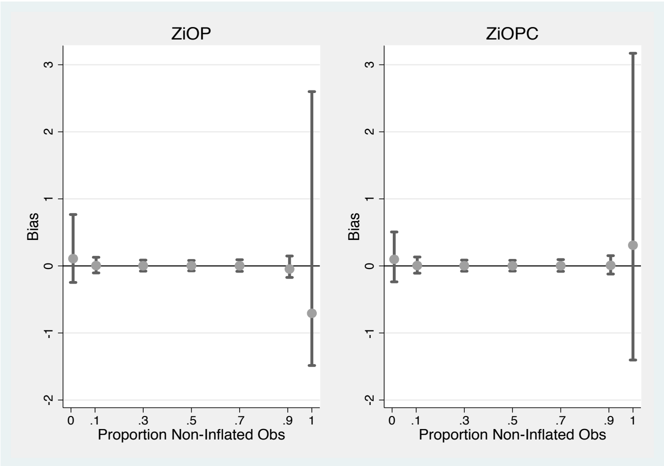
(a) Bias in Estimates of β_1



(b) Bias in Estimates of β_2



(c) Bias in Estimates of γ_1

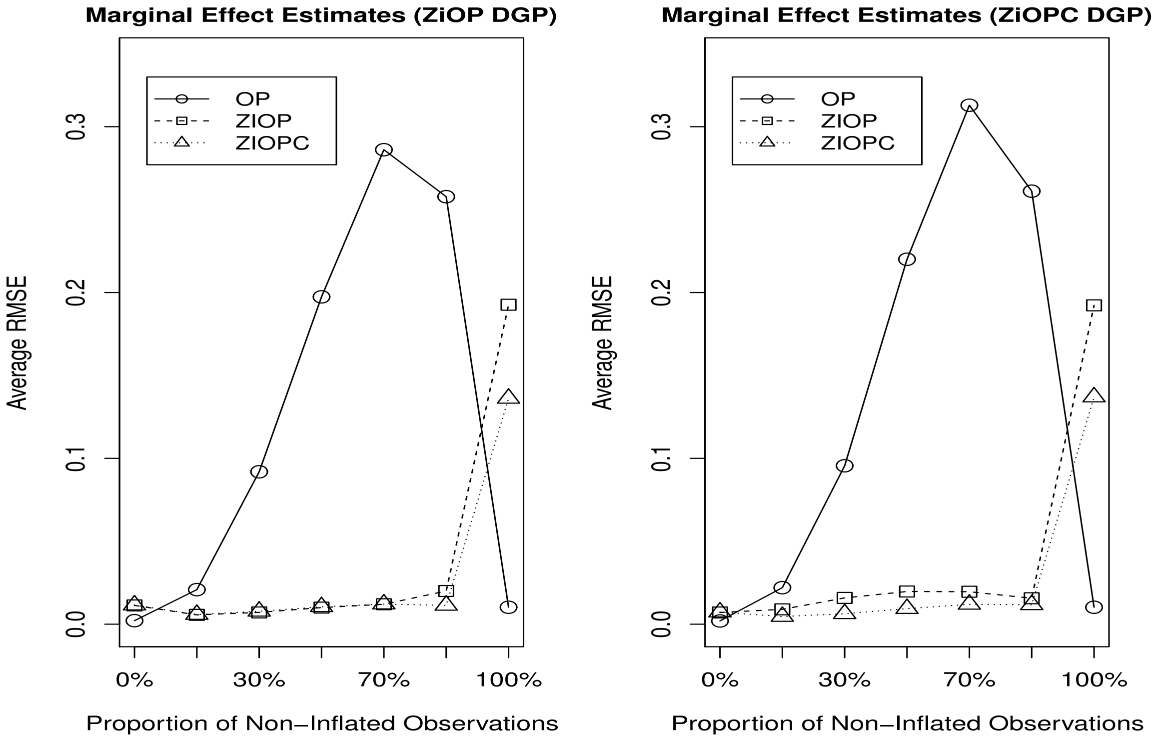


pirical coverage probabilities[5] (CPs) of these marginal effects. Figure A.3 reports the marginal effect RMSE's, averaged across all y outcomes and all outcome stage covariates (i.e, x_1 and x_2), at each proportion of (non-)inflation evaluated. This figure demonstrates that, under a ZiOP or ZiOPC d.g.p, the OP-derived marginal effects are significantly more biased and less efficient than the ZiOP or ZiOPC marginal effects for all proportions of inflation other than the 0% non-inflated zero-case (for which the *true* outcome-stage marginal effects are effectively zero) and the 100% non-inflated case (i.e. an OP dgp). Not surprisingly, our OP marginal effects dramatically decline in bias as the proportion of non-inflated zeroes approaches 1, whereas the ZiOP(C) models both perform notably worse under these circumstances. Comparing the ZiOP and ZiOPC, each model preforms commensurately under the ZiOP d.g.p, whereas the ZiOPC model outperforms the ZiOP model when the dgp is either ZiOPC or OP. Taken together, the RMSEs reported in Figure A.3 indicate that when the proportion of non-inflated zero observations lies between 0.1-0.9, the ZiOP(C) models outperform the OP model in recovering unbiased marginal effects.

Table A.2 reinforces these conclusions. This table presents OP, ZiOP, and ZiOPC marginal effects separately for each of our $y = 0, ..., J$ outcomes and each x, along with their respective RMSEs and CPs, while averaging across all proportions of (ZiOPC dgp) zero-inflation evaluated. We report a comparable table for our ZiOP dgp results, along with separate tables for each individual level of (ZiOP and ZiOPC dgp) inflation, in the Supplemental Appendix. Across all levels of inflation, our ZiOP(C) models yield marginal effect and boundary parameter estimates that are notably more accurate than those obtained from our OP model. Interestingly, even where the OP model's marginal effects exhibit RMSEs that approach those of the ZiOP(C) models (indicating comparable accuracy), the coverage probabilities for the OP remain far worse, suggesting that in such instances, the type I error rate ("false positive") will remain high for the OP model. The reported RMSEs and CPs also reveal that the ZiOP model's relative under-performance within the ZiOPC d.g.p-case arises from the ZiOP model's inability to obtain accurate marginal effect and boundary parameter estimates for the $y = 0$ probabilities, wherein the significantly lower ZiOP CPs in this instance imply that type I error rates will

[5] Calculated as the percentage of iterations where the true coefficient value fell between the upper and lower bounds of the 95% confidence interval.

Figure A.3: RMSEs of Marginal Effects Across Proportions of Non-Inflation



increase significantly as the dgp approaches ZiOPC and the correlation is ignored. Finally, the average estimates for ρ under our ZiOP and ZIOPC experiments are 0.001 and 0.483, with respective CPs of 0.92 and 0.93, thereby indicating that the ZiOPC model does an admirable job of obtaining accurate estimates of the correlation parameter under both a ZiOP and ZiOPC dgp

To briefly summarize the results from our experiments, the ZiOP(C) models provide considerably greater coverage probabilities than the OP model when the data have a split population of zeros. In these instances, the ZiOPC (generally) provides less biased and more efficient estimates than the ZiOP/OP, while the ZiOP provides less biased and more efficient estimates than the OP, unless the proportion of non-inflated zero observations is quite high (>.9). Conversely, the OP model significantly outperforms the ZiOP(C) models under conditions of an OP d.g.p, wherein our ZiOP(C) ME estimates become increasingly biased and variable as the proportion of non-inflated zero observations approaches 1. Finally, estimates of γ from the ZiOP(C) become more biased and variable as this proportion nears 0, as do the ZiOP estimates when this

Table A.2: Marginal Effects for all Proportions of Inflation (ZIOPC DGP)

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.059	-0.110	-0.055	-0.039	x_1	-0.208	-0.046	-0.181	-0.186
	RMSE		(0.052)	(0.018)	(0.005)			(0.164)	(0.037)	(0.011)
	CP		0.196	0.460	0.968			0.279	0.996	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.061	-0.184	-0.058	-0.040	x_2	-0.334	-0.109	-0.294	-0.276
	RMSE		(0.125)	(0.020)	(0.005)			(0.227)	(0.053)	(0.012)
	CP		0.215	0.468	0.972			0.276	0.986	0.995
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.267	0.156	0.236	0.225	τ_2	2.000	0.671	2.226	2.041
	RMSE		(0.114)	(0.041)	(0.010)			(1.337)	(0.352)	(0.182)
	CP		0.420	0.998	1.000			0.135	0.945	0.946
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.395	0.293	0.352	0.317	ρ	0.500	.	.	0.483
	RMSE		(0.109)	(0.064)	(0.012)			.	.	(0.124)
	CP		0.380	0.995	1.000			.	.	0.927

proportion reaches 1. At 100% non-inflation the ZiOPC produces unbiased estimates but is very unlikely to converge.

Monte Carlo Parameters

Table A.3 reports all of the initial parameter values that were used in our Monte Carlo experiments.

Model Fit Statistics

We also evaluated the model fit of the ZiOP(C) models relative to the OP model for both the (Besley and Persson, 2009) and (Senese, 1997) replications. Beginning with the Besley and Persson results, Akaike information criterion (AIC) values reported for all models in table 1 of our study strongly favor the ZiOP(C) models over the OP model. The AICs also indicate that our ZiOPC models perform better than the ZiOP model. Harris and Zhao (2007) additionally suggest that one can use a variant of the Vuong test (Vuong, 1989) to compare the ZiOP(C) models' performances to that of the OP model. The Vuong test denotes m_i as the natural logarithm of the ratio of the predicted probability that $y_i = j$ of one's simpler (OP) model (in the numerator) and one's more general (ZiOP/ZiOPC) model (in the denominator)

Table A.3: Parameter Values and Variable Distributions for Monte Carlo Experiment

Parameter	Value/Distribution
β_0	1.0
β_1	0.5
β_2	1.5
γ_0	-6.0, -4.4, -3.3, -2.5, -1.7, -0.5, 3.0
γ_1	1.0
α_1	2.0
ρ^*	0.5
Variable	Distribution
X_1	$unif(min = -5.0, max = 5.0)$
X_2	$norm(mean = 0.0, sd = 2.0)$
Z_1	$binom(n = 5.0, p = 0.5)$

*note: ρ = 0 for ZiOP experiment
$N = 4000$ and $sims = 5000$

and evaluates m_i via a bidirectional test statistic of $v = \frac{\sqrt{N}(\frac{1}{N}\sum_i^N m_i)}{\sqrt{\frac{1}{N}\sum_i^N (m_i - \bar{m})^2}}$ where $v < -1.96$ favors the more general (ZiOP/ZiOPC) model, $-1.96 < v < 1.96$ lends no support to either model, and $v > 1.96$ supports the simpler (OP) model. The Vuong test results favor the ZiOP model over the OP model ($v = -4.909$) and similarly favors the ZiOPC models over the OP model ($v = -5.427$ and $v = -6.236$). Thus, the performance of the ZiOP and especially the ZiOPC model is better than the OP model in the Besley and Persson (2009) sample. Vuong tests for the Senese (1997) model (table 2 in the study) favored our limited and full ZiOP models over the OP model ($v = -7.869$ and $v = -9.81$) and favored comparable ZiOPC models over the OP model ($v = -7.87$ and $v = -9.84$) as well.

ZiOP(C) Marginal Effects Formulas

We next describe below the procedure employed to derive the predicted proportion of "harmony" year and "non-harmony" year observations in the Besley and Persson (2009) sample. To begin with, we first calculate the in-sample predicted probability that each observation may enter or belong to the ordered regime ($s_i = 1$) by using the marginal effect formula $\frac{\partial \Pr(s_i=1)}{\partial g_i}$, our vector of covariates in the splitting equation (z_i') and the coefficient estimates from the splitting stage of the ZiOPC model in table 2 of our main paper. We used parametric bootstraps to draw m=1,000 coefficient values for each observation in z_i' to recover the 95% confidence intervals. We then created a dichotomous variable *non-harmony* that is set equal to 1 for those observations where the *predicted* probability of s_i (that is $\widehat{s_i}$) is $\widehat{s_i} \geq 0.5$,and is set equal to 0 for $\widehat{s_i} < 0.5$. Finally, we summed the cases in our sample where *non-harmony* = 0, and the cases where *non-harmony* = 1, and divided each sum by the total sample size N to create the proportions. Thus, the predicted proportion of *non-harmony* years is given by $\frac{1}{N}\sum_i^N(\widehat{s_i} \geq 0.5)$ and the predicted proportion of "harmony" years is $\frac{1}{N}\sum_i^N(\widehat{s_i} < 0.5)$. We repeated the exercise described above for $\widehat{s_i} < 0.25$ and $\widehat{s_i} < 0.75$. We next turn to describe the formulas for the marginal effect of the covariates of interest on the ordered outcome probabilities. Since *ln GDP per capita* (hereafter denoted as g_i) measure is included in the split probit (first stage) *and* ordered probit outcome equation (second stage) of the ZiOP(C) models, the *total* marginal effect of g_i on the outcome probability of observing zero $[\Pr(y_i = 0)]$ (i.e., "peace") is given by the marginal effect that it has on the probability of (i) $s_i = 0$ (observations that are always 0) and (ii) $y_i = 0$ given $s_i = 1$ (observations that may enter the ordered regime but where no political violence, i.e. peace, occurs). Hence, the marginal effect of *ln GDP per capita* (g_i) on $[\Pr(y_i = 0)]$ is,

$$\frac{\partial \Pr(y_i = 0)}{\partial g_i} = -\phi(-\mathbf{z}_i'\gamma)\gamma_{g_i} + \left\{ \left[\Phi\left(\frac{-\mathbf{x}_i'\beta + \rho\mathbf{z}_i'\gamma}{\sqrt{1-\rho^2}} \right) \right] \phi(\mathbf{z}_i'\gamma)\gamma_{g_i} - \left[\Phi\left(\frac{\mathbf{z}_i'\gamma - \rho\mathbf{x}_i'\beta}{\sqrt{1-\rho^2}} \right) \phi(-\mathbf{x}_i'\beta)\beta_{g_i} \right] \right\} \quad \text{(A.5)}$$

The marginal effect of $g_i$on the outcome probabilities $j = 1(repression), 2(civilwar)$ is:

$$\frac{\partial \Pr(y_i = j)}{\partial g_i} = \left[\Phi\left(\frac{\alpha_j - \mathbf{x}_i'\beta + \rho\mathbf{z}_i'\gamma}{\sqrt{1-\rho^2}} \right) - \Phi\left(\frac{\alpha_{j-1} - \mathbf{x}_i'\beta + \rho\mathbf{z}_i'\gamma}{\sqrt{1-\rho^2}} \right) \right] \phi(\mathbf{z}_i'\gamma)\gamma_{g_i} + \left[\Phi\left(\frac{\mathbf{z}_i'\gamma + \rho(\alpha_{j-1} - \mathbf{x}_i'\beta)}{\sqrt{1-\rho^2}} \right) \phi(\alpha_{j-1} - \mathbf{x}_i'\beta) - \Phi\left(\frac{\mathbf{z}_i'\gamma + \rho(\alpha_j - \mathbf{x}_i'\beta)}{\sqrt{1-\rho^2}} \right) \phi(\alpha_j - \mathbf{x}_i'\beta) \right] \beta_{g_i} \quad \text{(A.6)}$$

Equations A.5 and A.6 reveal that the total marginal effect of *ln GDP per capita* (g_i)on each outcome probability in the ZiOPC model consists of two parts: the effects emerging from the split probit equation of the model and the component that stems from the ordered probit outcome equation. The marginal effect of $g_i$on the outcome probabilities in the ZiOP model without correlated errors is simply obtained by setting $\rho = 0$ in equations A.5 and A.6. Finally, the marginal effect of a dummy regressor (e.g. *parliamentary*) on the outcome probabilities in

Table A.4: Marginal Effects for all Proportions of Inflation (ZIOP DGP)

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.076	-0.112	-0.065	-0.064	x_1	-0.182	-0.043	-0.156	-0.154
	RMSE		(0.037)	(0.014)	(0.007)			(0.141)	(0.032)	(0.011)
	CP		0.224	0.850	0.934			0.271	0.996	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.080	-0.190	-0.069	-0.068	x_2	-0.330	-0.104	-0.284	-0.280
	RMSE		(0.111)	(0.016)	(0.008)			(0.228)	(0.051)	(0.012)
	CP		0.214	0.870	0.944			0.270	0.985	0.995
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.258	0.155	0.221	0.218	τ_2	2.000	0.688	2.181	2.029
	RMSE		(0.105)	(0.040)	(0.010)			(1.319)	(0.329)	(0.179)
	CP		0.421	0.996	1.000			0.135	0.945	0.948
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.410	0.294	0.353	0.348	ρ	0.000	.	.	0.001
	RMSE		(0.121)	(0.060)	(0.013)			.	.	(0.150)
	CP		0.423	0.995	1.000			.	.	0.921

Table A.5: Marginal Effects For ZIOP DGP with 0% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.000	-0.002	-0.002	-0.004	x_1	-0.000	0.001	-0.009	-0.005
	RMSE		(0.002)	(0.004)	(0.007)			(0.001)	(0.009)	(0.006)
	CP		0.936	0.909	0.973			0.900	0.998	0.999
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.000	-0.004	-0.006	-0.011	x_2	-0.000	0.001	-0.015	-0.012
	RMSE		(0.004)	(0.007)	(0.011)			(0.002)	(0.016)	(0.012)
	CP		0.995	0.929	0.982			0.955	0.997	0.998
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.000	0.001	0.011	0.009	τ_2	2.000	0.167	3.347	2.205
	RMSE		(0.001)	(0.011)	(0.010)			(1.833)	(1.896)	(0.935)
	CP		0.954	0.999	0.999			0.000	0.923	0.892
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.000	0.003	0.021	0.023	ρ	0.000	.	.	0.082
	RMSE		(0.003)	(0.021)	(0.023)			.	.	(0.466)
	CP		0.998	1.000	1.000			.	.	0.788

the ZiOP(C) model is the difference in the probability evaluated at 1 and 0, conditional on the observable value of the covariates.

Table A.6: Marginal Effects For ZIOP DGP with 10% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.004	-0.022	-0.006	-0.007	x_1	-0.010	0.007	-0.015	-0.013
	RMSE		(0.017)	(0.002)	(0.003)			(0.017)	(0.005)	(0.004)
	CP		0.140	0.999	1.000			0.000	1.000	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.005	-0.048	-0.007	-0.008	x_2	-0.019	0.015	-0.027	-0.027
	RMSE		(0.044)	(0.002)	(0.004)			(0.034)	(0.008)	(0.008)
	CP		0.000	0.999	1.000			0.000	1.000	1.000
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.015	0.015	0.021	0.020	τ_2	2.000	0.240	2.055	2.041
	RMSE		(0.003)	(0.006)	(0.006)			(1.760)	(0.219)	(0.217)
	CP		0.995	1.000	1.000			0.000	0.953	0.951
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.024	0.033	0.034	0.035	ρ	0.000	.	.	0.004
	RMSE		(0.010)	(0.010)	(0.011)			.	.	(0.150)
	CP		0.974	1.000	1.000			.	.	0.919

Table A.7: Marginal Effects For ZIOP DGP with 30% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.032	-0.067	-0.033	-0.034	x_1	-0.077	0.020	-0.080	-0.079
	RMSE		(0.035)	(0.005)	(0.006)			(0.097)	(0.008)	(0.009)
	CP		0.042	0.998	1.000			0.000	1.000	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.034	-0.148	-0.035	-0.036	x_2	-0.140	0.039	-0.145	-0.145
	RMSE		(0.114)	(0.005)	(0.006)			(0.179)	(0.009)	(0.009)
	CP		0.000	0.998	1.000			0.000	1.000	1.000
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.109	0.047	0.113	0.112	τ_2	2.000	0.336	2.018	2.014
	RMSE		(0.062)	(0.007)	(0.007)			(1.664)	(0.118)	(0.118)
	CP		0.000	1.000	1.000			0.000	0.953	0.951
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.173	0.109	0.180	0.180	ρ	0.000	.	.	0.000
	RMSE		(0.065)	(0.009)	(0.010)			.	.	(0.093)
	CP		0.000	1.000	1.000			.	.	0.943

Table A.8: Marginal Effects For ZIOP DGP with 50% True Zeroes

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.076	-0.120	-0.075	-0.075	x_1	-0.181	0.031	-0.182	-0.182
	RMSE		(0.044)	(0.007)	(0.008)			(0.213)	(0.012)	(0.013)
	CP		0.052	0.985	0.998			0.000	1.000	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.079	-0.254	-0.079	-0.079	x_2	-0.330	0.050	-0.329	-0.330
	RMSE		(0.175)	(0.008)	(0.009)			(0.380)	(0.012)	(0.012)
	CP		0.000	0.982	0.998			0.000	1.000	1.000
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.257	0.089	0.257	0.257	τ_2	2.000	0.445	2.011	2.008
	RMSE		(0.168)	(0.010)	(0.010)			(1.555)	(0.084)	(0.084)
	CP		0.000	1.000	1.000			0.000	0.962	0.960
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.409	0.204	0.409	0.409	ρ	0.000	.	.	0.001
	RMSE		(0.205)	(0.010)	(0.011)			.	.	(0.085)
	CP		0.000	1.000	1.000			.	.	0.940

Table A.9: Marginal Effects For ZIOP DGP with 70% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.120	-0.181	-0.118	-0.117	x_1	-0.286	0.033	-0.284	-0.286
	RMSE		(0.062)	(0.009)	(0.009)			(0.319)	(0.016)	(0.016)
	CP		0.006	0.870	0.942			0.000	1.000	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.125	-0.351	-0.124	-0.123	x_2	-0.519	0.020	-0.516	-0.518
	RMSE		(0.226)	(0.010)	(0.010)			(0.539)	(0.014)	(0.014)
	CP		0.000	0.859	0.944			0.000	0.999	1.000
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.405	0.148	0.402	0.403	τ_2	2.000	0.611	2.005	2.003
	RMSE		(0.257)	(0.012)	(0.012)			(1.389)	(0.068)	(0.068)
	CP		0.000	1.000	1.000			0.000	0.946	0.949
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.645	0.331	0.640	0.641	ρ	0.000	.	.	-0.000
	RMSE		(0.314)	(0.011)	(0.011)			.	.	(0.088)
	CP		0.000	1.000	1.000			.	.	0.940

Table A.10: Marginal Effects For ZIOP DGP with 90% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.148	-0.242	-0.145	-0.149	x_1	-0.355	-0.030	-0.347	-0.352
	RMSE		(0.094)	(0.010)	(0.008)			(0.324)	(0.026)	(0.016)
	CP		0.000	0.439	0.587			0.000	0.968	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.155	-0.363	-0.154	-0.157	x_2	-0.644	-0.195	-0.628	-0.641
	RMSE		(0.208)	(0.011)	(0.009)			(0.449)	(0.030)	(0.014)
	CP		0.000	0.528	0.653			0.000	0.937	0.958
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.503	0.272	0.491	0.501	τ_2	2.000	1.018	1.977	1.989
	RMSE		(0.230)	(0.021)	(0.012)			(0.982)	(0.085)	(0.054)
	CP		0.000	0.968	1.000			0.000	0.922	0.951
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.799	0.558	0.782	0.797	ρ	0.000	.	.	-0.003
	RMSE		(0.241)	(0.022)	(0.009)			.	.	(0.136)
	CP		0.000	0.967	0.998			.	.	0.928

Table A.11: Marginal Effects For ZIOP DGP with 100% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.152	-0.152	-0.086	-0.100	x_1	-0.362	-0.362	-0.206	-0.259
	RMSE		(0.007)	(0.067)	(0.046)			(0.015)	(0.157)	(0.117)
	CP		0.391	0.627	0.537			1.000	0.999	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.159	-0.159	-0.090	-0.105	x_2	-0.659	-0.658	-0.374	-0.461
	RMSE		(0.008)	(0.070)	(0.048)			(0.013)	(0.285)	(0.201)
	CP		0.504	0.696	0.627			0.936	0.949	0.978
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.514	0.514	0.291	0.360	τ_2	2.000	2.001	2.006	2.004
	RMSE		(0.011)	(0.223)	(0.160)			(0.049)	(0.049)	(0.047)
	CP		1.000	1.000	1.000			0.945	0.949	0.978
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.818	0.818	0.464	0.565	ρ	0.000	.	.	-1.192
	RMSE		(0.008)	(0.354)	(0.248)			.	.	(2.409)
	CP		0.990	0.991	0.993			.	.	0.649

Table A.12: Marginal Effects For ZIOPC DGP with 0% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.000	-0.002	-0.000	-0.000	x_1	-0.000	0.000	-0.007	-0.007
	RMSE		(0.002)	(0.002)	(0.003)			(0.001)	(0.007)	(0.007)
	CP		0.950	0.854	0.943			0.954	0.996	0.999
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.000	-0.004	-0.003	-0.003	x_2	-0.000	0.001	-0.009	-0.010
	RMSE		(0.004)	(0.004)	(0.004)			(0.001)	(0.010)	(0.010)
	CP		0.997	0.866	0.951			0.996	0.996	0.998
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.000	0.001	0.007	0.007	τ_2	2.000	0.133	3.632	2.378
	RMSE		(0.001)	(0.007)	(0.008)			(1.867)	(2.146)	(1.022)
	CP		0.957	0.999	0.999			0.000	0.920	0.918
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.000	0.003	0.012	0.013	ρ	0.500	.	.	0.364
	RMSE		(0.003)	(0.012)	(0.013)			.	.	(0.387)
	CP		0.997	0.999	1.000			.	.	0.844

Table A.13: Marginal Effects For ZIOPC DGP with 10% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.000	-0.021	-0.002	-0.001	x_1	-0.011	0.006	-0.020	-0.017
	RMSE		(0.020)	(0.002)	(0.001)			(0.017)	(0.009)	(0.005)
	CP		0.034	0.638	0.997			0.000	1.000	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.000	-0.046	-0.002	-0.001	x_2	-0.012	0.012	-0.026	-0.019
	RMSE		(0.045)	(0.002)	(0.001)			(0.025)	(0.014)	(0.007)
	CP		0.000	0.610	0.996			0.000	1.000	1.000
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.012	0.015	0.022	0.018	τ_2	2.000	0.212	2.123	2.043
	RMSE		(0.004)	(0.011)	(0.006)			(1.788)	(0.240)	(0.219)
	CP		0.983	1.000	1.000			0.000	0.949	0.948
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.013	0.033	0.029	0.020	ρ	0.500	.	.	0.500
	RMSE		(0.021)	(0.016)	(0.008)			.	.	(0.117)
	CP		0.092	1.000	1.000			.	.	0.928

Table A.14: Marginal Effects For ZIOPC DGP with 30% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.006	-0.065	-0.019	-0.008	x_1	-0.107	0.017	-0.105	-0.109
	RMSE		(0.059)	(0.012)	(0.003)			(0.124)	(0.008)	(0.007)
	CP		0.000	0.151	0.998			0.000	1.000	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.006	-0.142	-0.019	-0.008	x_2	-0.129	0.033	-0.148	-0.134
	RMSE		(0.136)	(0.013)	(0.003)			(0.162)	(0.019)	(0.009)
	CP		0.000	0.138	0.999			0.000	1.000	1.000
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.114	0.048	0.123	0.117	τ_2	2.000	0.312	2.041	2.014
	RMSE		(0.066)	(0.011)	(0.007)			(1.688)	(0.123)	(0.117)
	CP		0.000	1.000	1.000			0.000	0.945	0.947
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.135	0.109	0.167	0.142	ρ	0.500	.	.	0.499
	RMSE		(0.027)	(0.032)	(0.010)			.	.	(0.076)
	CP		0.580	1.000	1.000			.	.	0.940

Table A.15: Marginal Effects For ZIOPC DGP with 50% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.031	-0.117	-0.052	-0.032	x_1	-0.253	0.027	-0.223	-0.251
	RMSE		(0.086)	(0.021)	(0.006)			(0.279)	(0.030)	(0.013)
	CP		0.000	0.179	0.999			0.000	0.999	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.031	-0.245	-0.054	-0.032	x_2	-0.339	0.042	-0.336	-0.339
	RMSE		(0.214)	(0.023)	(0.006)			(0.381)	(0.011)	(0.011)
	CP		0.000	0.159	0.998			0.000	1.000	1.000
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.284	0.090	0.275	0.283	τ_2	2.000	0.425	2.019	2.009
	RMSE		(0.193)	(0.012)	(0.010)			(1.575)	(0.086)	(0.084)
	CP		0.000	1.000	1.000			0.000	0.953	0.951
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.370	0.204	0.390	0.371	ρ	0.500	.	.	0.500
	RMSE		(0.167)	(0.020)	(0.011)			.	.	(0.070)
	CP		0.000	1.000	1.000			.	.	0.938

Table A.16: Marginal Effects For ZIOPC DGP with 70% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.081	-0.177	-0.096	-0.080	x_1	-0.356	0.027	-0.325	-0.354
	RMSE		(0.096)	(0.015)	(0.008)			(0.383)	(0.031)	(0.017)
	CP		0.000	0.481	0.994			0.000	0.992	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.082	-0.340	-0.099	-0.082	x_2	-0.545	0.010	-0.523	-0.543
	RMSE		(0.258)	(0.017)	(0.009)			(0.556)	(0.024)	(0.014)
	CP		0.000	0.438	0.994			0.000	0.997	1.000
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.436	0.150	0.421	0.433	τ_2	2.000	0.597	2.008	2.004
	RMSE		(0.287)	(0.017)	(0.012)			(1.403)	(0.069)	(0.067)
	CP		0.000	1.000	1.000			0.000	0.949	0.948
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.628	0.330	0.622	0.625	ρ	0.500	.	.	0.498
	RMSE		(0.298)	(0.012)	(0.011)			.	.	(0.074)
	CP		0.000	1.000	1.000			.	.	0.941

Table A.17: Marginal Effects For ZIOPC DGP with 90% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.140	-0.237	-0.134	-0.145	x_1	-0.370	-0.038	-0.373	-0.362
	RMSE		(0.097)	(0.009)	(0.008)			(0.332)	(0.021)	(0.017)
	CP		0.000	0.387	0.777			0.000	0.987	0.999
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.145	-0.353	-0.141	-0.150	x_2	-0.654	-0.203	-0.641	-0.649
	RMSE		(0.208)	(0.010)	(0.009)			(0.451)	(0.021)	(0.014)
	CP		0.000	0.489	0.805			0.000	0.949	0.953
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.510	0.275	0.507	0.507	τ_2	2.000	1.014	2.000	1.986
	RMSE		(0.235)	(0.015)	(0.012)			(0.986)	(0.067)	(0.055)
	CP		0.000	0.987	1.000			0.000	0.944	0.949
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.799	0.556	0.782	0.799	ρ	0.500	.	.	0.486
	RMSE		(0.243)	(0.018)	(0.009)			.	.	(0.114)
	CP		0.000	0.975	0.999			.	.	0.926

Table A.18: Marginal Effects For ZIOPC DGP with 100% Non-Inflated Observations

		$Pr(Y=0)$ Marginal Effect					$Pr(Y=1)$ Marginal Effect			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	-0.152	-0.152	-0.086	-0.101	x_1	-0.362	-0.362	-0.206	-0.258
	RMSE		(0.007)	(0.067)	(0.046)			(0.015)	(0.157)	(0.118)
	CP		0.386	0.627	0.547			1.000	0.998	1.000
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	-0.159	-0.159	-0.090	-0.106	x_2	-0.659	-0.658	-0.375	-0.458
	RMSE		(0.008)	(0.070)	(0.048)			(0.013)	(0.285)	(0.204)
	CP		0.505	0.695	0.606			0.936	0.949	0.964
		$Pr(Y=2)$ Marginal Effect					Estimates			
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_1	*Mean*	0.514	0.514	0.292	0.359	τ_2	2.000	2.001	2.006	2.007
	RMSE		(0.011)	(0.223)	(0.161)			(0.049)	(0.049)	(0.048)
	CP		1.000	1.000	1.000			0.947	0.948	0.964
		True	OP	ZiOP	ZiOPC		True	OP	ZiOP	ZiOPC
x_2	*Mean*	0.818	0.818	0.465	0.565	ρ	0.500	.	.	-0.313
	RMSE		(0.008)	(0.354)	(0.249)			.	.	(2.627)
	CP		0.992	0.989	0.993			.	.	0.613

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