Evidence Against Fraudulent Votes Being Decisive in the Bolivia 2019 Election*

Walter R. Mebane, Jr.†

November 13, 2019

*Thanks to Alvaro Molina and Zach Gan for assistance, and to Diogo Ferrari and Kirill Kalinin for comments.

†Professor, Department of Political Science and Department of Statistics, Research Professor, Center for Political Studies, University of Michigan, Haven Hall, Ann Arbor, MI 48109-1045 (E-mail: wmebane@umich.edu).

The recent presidential election in Bolivia is controversial,[1] with fraud allegations and violent protests.

A new model called `eforensics`[2] offers evidence that fraudulent votes in the election were not decisive for the result. The statistical model operationalizes the idea that "frauds" occur when one party gains votes by a combination of manufacturing votes from abstentions and stealing votes from opposing parties. The Bayesian specification[3] allows posterior means and credible intervals for counts of "fraudulent" votes to be determined both for the entire election and for individual ballot boxes (mesas).

Using `eforensics` I estimate the posterior mean of the number of votes counted for the winner Morales (Movement Toward Socialism party, MAS) that were "fraudulent" is 22519.8 with a 99.5% credible interval of $[20479.8, 24663.8]$. Of these "fraudulent" counts `eforensics` estimates 5295.8 $[4751.1, 5880.2]$ are manufactured, while the rest are stolen. Reallocating all of the estimated "fraudulent" votes from MAS to the second-place Civic Community party (CC) using the mean (upper bound) estimate leaves a margin over CC of $(2889359 - 2240920 - 22519.8)/6137778 = .10198$ (.10163). Omitting the counts that the model says are manufactured and allocating the rest of the "fraudulent" votes to CC produces $(2889359 - 2240920 - (22519.8 - 5295.8))/(6137778 - 5295.8) = .10293$ (.10269). Even with estimated "fraudulent" votes removed, MAS has a margin of more than ten percent over CC.

The original draft of this note (everything except this paragraph) was produced on November 5, 2019. On November 13 messages from a couple of people lead me to think the best formula for the counterfactual vote proportion with frauds reallocated, if all "stolen" votes are credited to CC, is
$(2889359 - 2240920 - 2(22519.8 - 5295.8) - 5295.8)/(6137778 - 5295.8) =$
$0.09925756(.09866303)$, which would put the election results below the level need to avoid a

[1] `https://www.washingtonpost.com/politics/2019/10/30/is-bolivias-democracy-danger-heres-whats-behind-`

[2] `https://github.com/UMeforensics/eforensics_public`

[3] Ferrari, McAlister and Mebane (2018) and `http://www-personal.umich.edu/~wmebane/efslides.pdf`

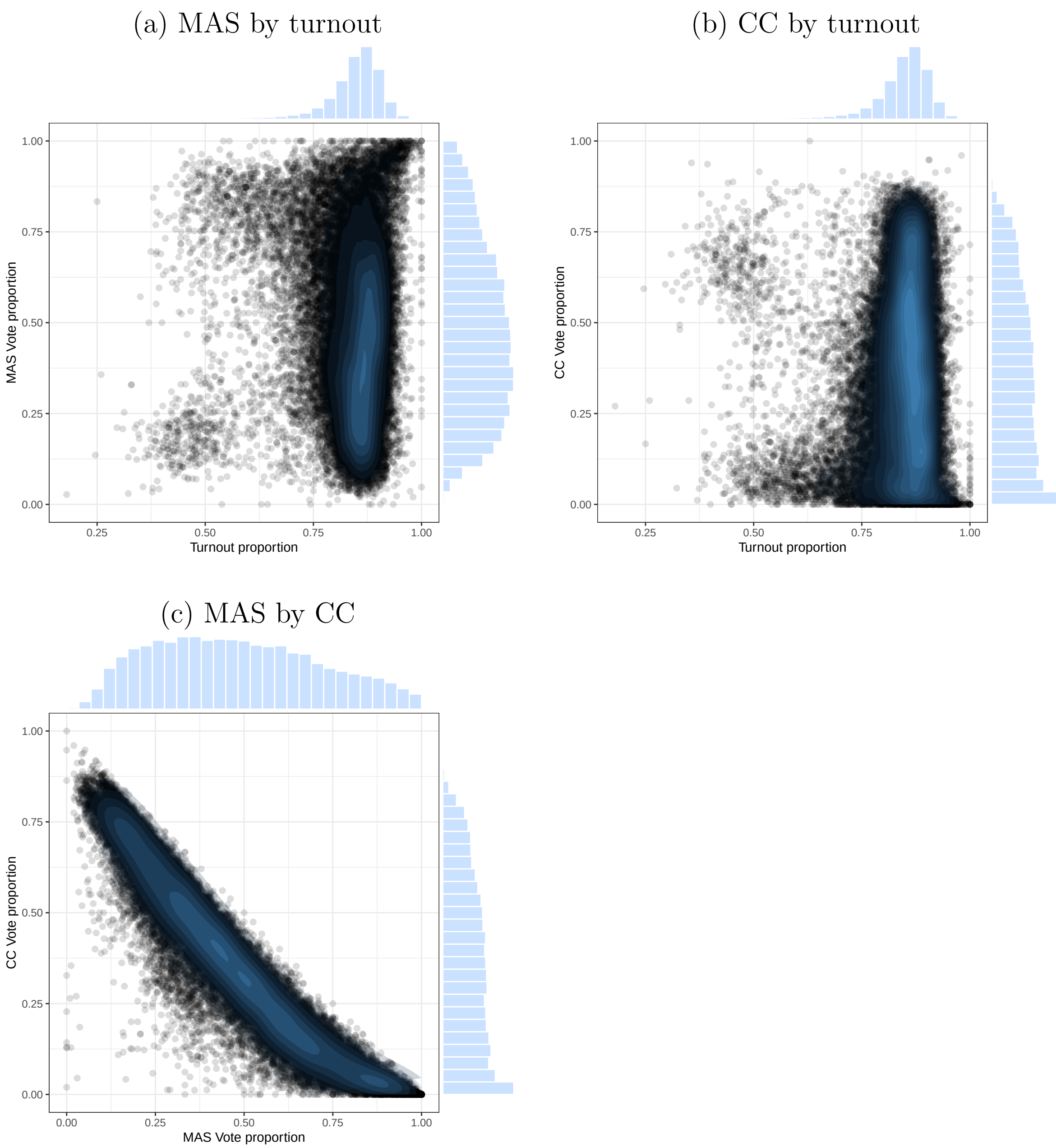
runoff election.

The "fraudulent" counts occur at 274 of the 34551 mesas for which votes are reported[4] All of these 274 mesas are for votes counted as cast in Bolivia and not in another country (the data[5] separate the votes coming from abroad).

Figure 1 shows the distribution of turnout and vote proportions across mesas. The mesas `eforensics` classifies as having "fraudulent" counts are those in the upper right part of Figure 1(a), which shows the proportions of votes for MAS plotted against turnout proportions. The most notable feature of Figure 1(b), which shows the proportions of votes for CC plotted against turnout proportions, is the high frequency of mesas in which CC receives zero votes. A striking feature of both Figures 1(a)and 1(b) is the scattering of mesas in which the turnout proprtion is lower than .7. The `eforensics` model does not do much to respond to such places where somewhat lower participation or votes are reported. Figure 1(c), which plots MAS vote proportions versus CC vote proportions, shows that the parties tend to be strong in different places, as one expects for opposing parties.

[4]Details are in tables at the end of this paper. Key **R** code snippets are also shown there.
[5]`https://computo.oep.org.bo/PubResul/acta.2019.10.25.21.09.30.xlsx`

Figure 1: Bolivia 2019 Presidential Election Data Plots



Note: plots show turnout (number voting/number eligible) and vote proportions (number voting for party/number voting) for the two leading parties in mesas in the Bolivia 2019 presidential election. Plots show scatterplots with estimated bivariate densities overlaid, with histograms along the axes.

As shown in Table 1, other election forensics tests of the vote counts for the top two parties based on digits and distributional features show signs of anomalies principally for CC.[6] The 2BL statistics suggest both MAS and CC gained strategic votes (Mebane 2013)[7], while the P05s statistics suggest manipulations as might be produced by corrupt agents only for CC votes (Rundlett and Svolik 2016; Kalinin 2017). The P05s value for CC stems from the abundant counts of zero votes evident in Figure 1(b). Strategic voting can explain why the election outcome is as close as it is to the threshold for a decisive result.

Table 1: Bolivia 2019 Presidential Votes Election Forensics Statistics

Party	2BL	LastC	P05s	C05s	DipT	Obs
MAS	3.776	4.47	.199	.201	.278	34551
	(3.746, 3.806)	(4.441, 4.498)	(.195, .203)	(.197, .205)	–	
CC	3.804	4.342	.206	.207	.003	34551
	(3.772, 3.836)	(4.311, 4.373)	(.201, .21)	(.202, .211)	–	

Note: "2BL," second-digit mean; "LastC," last-digit mean; "P05s," mean of variable indicating whether the last digit of the rounded percentage of votes for the referent party or candidate is zero or five; "C05s," mean of variable incicating whether the last digit of the vote count is zero or five; "DipT," p-value from test of unimodality; "Obs," number of precinct observations. Estimates in red differ significantly from the values expected if there are no anomalies. Values in parentheses are 95% nonparametric bootstrap confidence intervals.

The `eforensics` model is new with capabilities that remain to be fully understood. The model works well with data generated by processes that resemble the model formulation, but votes produced in other ways can also be classified as "fraudulent." To help intuition about the `eforensics` results for Bolivia I report results for a few other cases.

The Honduras 2017 election[8] featured procedural glitches similar to some that occurred in Bolivia with results that were questioned. The `eforensics` model estimates 89051.4 [84463.3, 91699.0] "fraudulent" votes for the winner—much larger than the margin of

[6] Hicken and Mebane (2015) (at `http://www.umich.edu/~wmebane/USAID15/guide.pdf`) describes the statistics.

[7] `http://www.umich.edu/~wmebane/pm13.pdf`

[8] `https://www.washingtonpost.com/news/monkey-cage/wp/2017/12/19/hondurans-are-in-the-streets-because-they-dont-believe-their-election-results/`

victory—with 62153.1 [59372.7, 64047.7] votes manufactured.

Among the proportional representation votes counted for the leading party United Russia in the 2016 Duma election in Russia,[9] 5685862 [5585224, 5741961] votes are "fraudulent" with 4111541 [3994888, 4170489] manufactured. The mean for the number "fraudulent" for the single-member district votes in 2016 is 5021386. For the elections of 2000, 2003 (PR and SMD), 2004, 2007, 2008, 2011 and 2012 the means are 1282576, 2479084, 2250655, 4227410, 5761006, 5613840, 5621965 and 4751109. The number "fraudulent" doubled in 2003 and again in 2004 and remained high subsequently.

For the first round of the 2016 election in Austria[10] `eforensics` estimates a mean of 10723.3 "fraudulent" and 26452.5 for the second round. The number "fraudulent" in the second round is less than the margin (30863), but that election was nonetheless annulled.

For elections in June and November of 2015 in Turkey[11] `eforensics` estimates means respectively of 552047 and 2369234.5 "fraudulent." "Fraudulent" counts occur more often in the eastern part of Turkey.

For Wisconsin[12] in the 2016 presidential election `eforensics` estimates a mean of 29854.3 "fraudulent." The "fraudulent" counts reflect not malfeasance that adds to the state's winner but instead the model's representation of voter suppression[13] in the state.

[9] https://www.washingtonpost.com/news/monkey-cage/wp/2017/01/11/when-the-russians-fake-their-election-results-they-may-be-giving-us-the-statistical-finger/?utm_term=.d9883a717ce5

[10] https://www.washingtonpost.com/news/monkey-cage/wp/2016/07/01/we-checked-austrias-extremely-close-may-2016-election-for-fraud-heres-what-we-found/

[11] https://www.washingtonpost.com/news/monkey-cage/wp/2016/02/15/were-there-irregularities-in-turkeys-2015-elections-we-used-our-new-forensic-toolkit-to-check/

[12] https://www.washingtonpost.com/news/monkey-cage/wp/2017/06/06/were-2016-vote-counts-in-michigan-and-wisconsin-hacked-we-double-checked/?utm_term=.ca70aea82a20

[13] https://www.motherjones.com/politics/2017/10/voter-suppression-wisconsin-election-2016/

References

Ferrari, Diogo, Kevin McAlister and Walter R. Mebane, Jr. 2018. "Developments in Positive Empirical Models of Election Frauds: Dimensions and Decisions." Presented at the 2018 Summer Meeting of the Political Methodology Society, Provo, UT, July 16–18.

Hicken, Allen and Walter R. Mebane, Jr. 2015. "A Guide to Election Forensics." Working paper for IIE/USAID subaward #DFG-10-APS-UM, "Development of an Election Forensics Toolkit: Using Subnational Data to Detect Anomalies".

Kalinin, Kirill. 2017. "The Essays on Election Fraud in Authoritarian Regimes: III. Theory of Loyalty: Signaling Games of Election Frauds." Ph.D. dissertation, University of Michigan.

Mebane, Jr., Walter R. 2013. "Election Forensics: The Meanings of Precinct Vote Counts' Second Digits." Paper presented at the 2013 Summer Meeting of the Political Methodology Society, University of Virginia, July 18–20, 2013.

Rundlett, Ashlea and Milan W. Svolik. 2016. "Deliver the Vote! Micromotives and Macrobehavior in Electoral Fraud." *American Political Science Review* 110(1):180–197.

Table 2: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

					Observed			Fraudulent Counts					
								Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
1	Belisario Boeto	1	Yunguillas	11693	111	105	103	13.5	11.1	15.1	56.7	49.7	61.5
1	Luis Calvo	1	Tentayapi	11777	238	226	226	29.1	24.9	32.1	121.8	109.3	130.4
1	Tomina	3	Sipicani	11292	32	31	31	4	2.9	4.7	16.6	13.4	18.6
1	Tomina	3	Mama Huasi	11296	201	192	189	24.6	20.9	27.3	102.8	91.4	110.4
1	Tomina	3	Chavarria	11298	124	119	117	15.2	12.6	17.2	63.7	55.7	69
2	Aroma	5	Chacoma	28462	109	107	96	13.5	11.1	15.2	54.9	48.6	59.5
2	Murillo	3	Jankosuni	23073	212	199	179	12.6	0	27.8	52.5	0	111.8
2	Omasuyos	2	Chojñapata	26403	96	96	85	12.1	9.8	13.7	48.4	42.6	52.4
2	Aroma	1	Achaya	28307	146	141	141	18	15	20.1	75.1	66.4	81.1
2	Aroma	1	Sora Sora	28312	228	219	201	20.8	0	30.7	86.3	0	123.1
2	Gualberto Villarroel	1	Janko Marca	28772	223	222	213	27.9	23.8	30.8	114.5	102.2	122.3
2	Gualberto Villarroel	1	Janko Marca	28773	156	154	151	19.4	16.2	21.7	80.3	71.1	86.7
2	Gualberto Villarroel	1	Ró Mulato Kari	28774	220	213	186	13.3	0	29.4	54.6	0	116.6
2	Gualberto Villarroel	1	Hunto Chico Bajo	28779	61	59	55	6.1	0	8.6	25.1	0	33.8
2	Loayza	1	Villa Litoral (Cutty)	27483	220	206	186	13.1	0	28.9	54.5	0	116.3
2	Loayza	1	Vilacora	27504	128	122	113	8	0	17.2	33.8	0	69
2	Loayza	2	Huancane (Sapa-haqui)	27514	221	213	174	13.2	0	29.4	53.3	0	113.5
2	Loayza	2	Huancane (Sapa-haqui)	27515	159	152	134	9.5	0	21.3	39.2	0	84

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 3: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
2	Loayza	2	Huayca	27542	53	53	48	6.7	5.1	7.8	26.8	22.8	29.6
2	Inquisivi	2	Mina Argentina	27653	205	203	203	25.6	21.8	28.2	105.7	94.8	113.6
2	Inquisivi	2	Mina Argentina	27654	147	146	122	13.7	0	20.4	54.6	0	78
3	Ayopaya	2	Sauce Rancho	32548	145	144	142	18.1	15	20.2	74.8	66.2	80.7
3	Ayopaya	2	Tuiruni Grande	32549	211	205	199	26	22.2	28.8	108	96	116
3	Esteban Arze	1	Huerta Mayu	32625	215	199	197	12.9	0	28.6	54.6	0	116.4
3	Arani	2	Rodeo A	32754	214	202	189	21	0	28.6	87.5	0	115
3	Arque	1	Huaycha	32778	231	220	219	28.3	24.2	31.2	118.1	105.4	126.8
3	Arque	1	Huaycha	32779	210	199	195	25.6	21.9	28.3	107.2	94.8	115.1
3	Arque	2	Auqui Pampa	32805	221	212	211	27.1	23.2	29.9	113.2	100.8	121.6
3	Arque	2	Yarviri Grande	32808	210	203	197	25.8	21.9	28.4	107.4	95.3	115.3
3	Campero	1	Tipa Pampa	32433	212	204	191	26	22.4	28.7	107.8	96.4	115.4
3	Ayopaya	1	Cuesta K'uchu	32513	166	163	162	20.6	17.3	23	85.4	75.9	92.3
3	Ayopaya	1	Colaya	32515	109	106	104	13.5	11.2	15.2	56.1	49	61
3	Chapare	1	Challviri	34889	241	230	216	29.5	25.3	32.4	122.6	110.3	130.9
3	Chapare	2	Candelaria	34928	224	215	198	20.4	0	30	84.3	0	120
3	Chapare	3	Cristal Mayu	34973	227	221	209	28	23.9	30.8	115.9	103.9	123.6
3	Chapare	3	Cristal Mayu	34976	229	214	199	20.2	0	30.3	84.3	0	123.6
3	Chapare	3	Cristal Mayu	34977	58	56	54	7.1	5.5	8.2	29.7	25.5	32.8

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 4: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Chapare	3	Paractito	34993	189	182	173	23.2	19.8	25.6	96.4	86.2	103.4
3	Chapare	3	Paractito	34994	238	226	225	29.1	25	32.1	121.8	109.6	130.1
3	Chapare	3	Paractito	34995	182	169	166	16.8	0	24.3	71.1	0	99.4
3	Chapare	3	Eterazama	35006	231	213	205	19.8	0	30.7	83.4	0	124.1
3	Chapare	3	Eterazama	35015	226	213	203	13.5	0	29.9	56.7	0	121.1
3	Chapare	3	San Jose (Villa Tunari)	35022	228	215	205	14.7	0	30.2	61.5	0	122
3	Chapare	3	San Jose (Villa Tunari)	35023	221	211	206	27.1	23.2	29.8	112.9	101	121.3
3	Chapare	3	San Jose (Villa Tunari)	35024	231	219	215	28.2	24.2	31.1	118	105.4	126.7
3	Chapare	3	San Jose (Villa Tunari)	35025	231	221	217	28.3	24.3	31.1	118.1	105.6	126.8
3	Chapare	3	San Jose (Villa Tunari)	35026	230	216	213	28	24	30.7	117.3	105.2	125.8
3	Chapare	3	San Jose (Villa Tunari)	35027	230	220	217	28.2	24.2	31.1	117.7	106.2	126.4
3	Chapare	3	San Jose (Villa Tunari)	35028	218	209	208	26.7	22.7	29.5	111.7	100	120.1
3	Chapare	3	Samuzabeti	35030	233	220	206	21.1	0	31.1	87.9	0	125
3	Chapare	3	Samuzabeti	35031	229	214	210	21.6	0	30.6	90.8	0	125.2
3	Chapare	3	Samuzabeti	35033	232	222	212	23.2	0	31.1	96.5	0	125.7
3	Chapare	3	Samuzabeti	35034	229	219	214	28	23.9	30.9	116.8	104.2	125
3	Chapare	3	Samuzabeti	35037	226	214	214	27.6	23.8	30.4	115.6	103.2	124.2

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 5: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D^a	Provincia	M^b	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Chapare	3	Samuzabeti	35038	234	219	217	14.7	0	30.9	61.7	0	125.9
3	Chapare	3	Samuzabeti	35039	231	222	213	28.4	24	31.3	118	106.2	126.3
3	Chapare	3	Samuzabeti	35042	139	133	133	17.1	14.2	19.1	71.4	62.6	77.2
3	Chapare	3	Chipiriri	35045	222	211	197	14.8	0	29.5	61.7	0	119
3	Chapare	3	San Francisco	35058	238	231	226	29.4	25.2	32.5	121.9	109.2	130.6
3	Chapare	3	San Francisco	35059	125	117	112	7.5	0	16.9	31.8	0	67.7
3	Chapare	3	Isinuta	35069	30	30	30	3.8	2.6	4.6	15.9	12.8	17.8
3	Chapare	3	Villa 14 de Septiembre	35079	228	217	205	22.2	0	30.6	92	0	122.7
3	Chapare	1	Larati	34779	226	213	200	19.3	0	30.2	81.1	0	122.3
3	Chapare	3	San Gabriel	35099	227	216	213	27.8	23.8	30.5	116.1	103.5	124.4
3	Chapare	3	San Gabriel	35102	229	217	217	28	23.9	30.8	117.2	105	125.7
3	Chapare	3	San Gabriel	35107	226	208	208	15.4	0	30.1	64.3	0	122.2
3	Chapare	3	La Estrella	35110	223	213	209	27.3	23.3	30.1	114	102.3	122.1
3	Chapare	3	La Estrella	35111	227	219	213	27.9	23.9	30.8	116.1	103.4	124.5
3	Chapare	3	La Estrella	35112	181	172	170	22.1	18.5	24.6	92.6	82.5	99.9
3	Chapare	3	Moleto-Icoya	35113	232	227	223	28.7	24.8	31.7	119.1	106.8	127.9
3	Chapare	3	Moleto-Icoya	35114	234	227	224	28.9	24.5	31.8	120	107	128.3
3	Chapare	3	Moleto-Icoya	35115	238	230	227	29.3	25.1	32.3	122	108.8	130.8

Notes: All mesas are in *Pais* Bolivia; ^{a} departmento; ^{b} municipio.

Table 6: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Chapare	3	Moleto-Icoya	35116	100	100	97	12.6	10.2	14.2	51.7	44.7	56.3
3	Chapare	3	Nueva Aroma	35117	232	221	215	28.4	24.2	31.3	118.5	105.3	127.1
3	Chapare	3	Nueva Aroma	35118	236	225	221	24	0	31.7	100.6	0	129
3	Chapare	3	Nueva Aroma	35120	230	218	210	20.7	0	30.7	86.5	0	124.5
3	Chapare	3	Nueva Aroma	35121	207	192	187	12.6	0	27.4	53	0	111.9
3	Chapare	3	Villa Bolivar	35122	230	220	215	28.2	24	31.1	117.6	104.9	126
3	Chapare	3	Villa Bolivar	35123	227	216	215	27.8	23.7	30.5	116.2	104	124.6
3	Chapare	3	Villa Bolivar	35124	233	222	220	28.5	24.4	31.2	119.1	106.1	127.6
3	Chapare	3	Paraiso-Todo Santos	35127	229	216	210	27.9	23.7	30.8	116.6	105	124.8
3	Chapare	3	Nueva Tacopaya	35141	232	220	204	13.9	0	30.8	58.1	0	123.9
3	Chapare	3	Nueva Tacopaya	35142	233	224	221	28.6	24.4	31.6	119.4	107.1	128.3
3	Chapare	3	Nueva Tacopaya	35143	233	220	216	28.5	24.3	31.4	119.2	107.3	127.6
3	Chapare	3	Nueva Tacopaya	35144	231	223	218	28.4	24.4	31.4	118.3	105.9	126.8
3	Chapare	3	Nueva Tacopaya	35146	234	219	215	21.5	0	31	90.7	0	128
3	Chapare	3	Nueva Tacopaya	35147	233	223	223	28.6	24.6	31.4	119.3	106.6	127.8

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 7: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Chapare	3	Independencia (Villa Tunari)	35151	237	231	229	29.3	25.1	32.3	121.6	108.7	130.1
3	Chapare	3	Independencia (Villa Tunari)	35152	235	223	220	28.7	24.8	31.5	120.1	107.3	128.8
3	Chapare	3	Independencia (Villa Tunari)	35153	235	223	220	28.8	24.5	31.7	120.2	106.3	128.8
3	Chapare	3	Independencia (Villa Tunari)	35154	238	229	224	29.2	24.8	32.3	121.8	109.1	130.7
3	Chapare	3	Independencia (Villa Tunari)	35155	174	168	167	21.4	18.1	23.8	89.3	78.5	96.1
3	Chapare	3	Norte Galilea	35157	132	123	122	8.4	0	17.7	36	0	72.9
3	Chapare	3	Tocopilla	35159	236	224	218	28.9	24.5	31.8	120.5	107.9	129.1
3	Chapare	3	Tocopilla	35160	47	45	43	5.7	4.3	6.7	23.9	19.8	26.7
3	Chapare	3	Primero de Mayo	35163	235	221	220	22.9	0	31.6	96.4	0	128.4
3	Chapare	3	Uncia	35165	238	233	232	29.5	24.9	32.4	122.2	109.3	131.2
3	Chapare	3	Uncia	35166	236	226	222	29	24.8	31.8	120.8	108.1	129.3
3	Chapare	3	Uncia	35167	237	233	232	29.4	25.2	32.4	121.9	109.2	131.1
3	Chapare	3	Uncia	35168	29	29	29	3.7	2.6	4.4	15.4	12.2	17.2
3	Chapare	3	Yuracare Limo del Isiboro	35170	153	144	144	18.6	15.5	20.8	78.3	69.7	84.5

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 8: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

					Observed			Fraudulent Counts					
								Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Chapare	3	Puerto Patiño	35171	238	228	222	29.2	25	32.1	121.7	109.3	130.5
3	Chapare	3	Puerto Patiño	35172	238	226	225	29.1	24.8	32	121.6	108.9	130.4
3	Chapare	3	16 de Julio Capihuara	35174	238	229	227	29.3	25.2	32.2	121.8	109.4	130.4
3	Chapare	3	16 de Julio Capihuara	35175	224	217	215	27.6	23.6	30.4	114.8	102.5	123
3	Tapacari	1	Katariri	35227	228	212	212	27.7	23.6	30.5	116.4	104.5	125.1
3	Tapacari	1	Katariri	35228	227	214	214	27.6	23.6	30.5	115.8	103.6	124.6
3	Tapacari	1	Katariri	35229	37	36	36	4.6	3.4	5.5	19.2	16	21.4
3	Tapacari	1	Arasaya	35235	237	227	227	29.1	24.7	32	121.4	108.6	130.4
3	Tapacari	1	Arasaya	35236	27	27	27	3.4	2.4	4.1	14.3	11.4	16
3	Carrasco	1	Rodeo Grande	35266	135	126	122	8.5	0	18	35.8	0	73.5
3	Quillacollo	1	El Paso	33521	247	236	196	14.8	0	32.2	60.1	0	128
3	Quillacollo	2	Sauce Rancho	33647	239	230	194	14.4	0	31.7	58.6	0	123.7
3	Quillacollo	2	Viloma Cala Cala	33705	240	233	205	14.5	0	32	59.7	0	126.4
3	Quillacollo	2	Viloma Cala Cala	33706	239	225	207	21.6	0	31.7	90.3	0	128.7
3	Mizque	2	Siquimira	35752	227	214	209	21.8	0	30.4	91.3	0	123.8
3	Mizque	4	Santiago	35781	231	216	215	28.2	24.2	31	118.3	106.4	126.8
3	Mizque	4	Santiago	35782	125	118	112	8.8	0	16.9	37	0	67.5
3	Tiraque	1	Iluri Grande	36041	216	202	197	18.2	0	28.8	76.7	0	118.2
3	Tiraque	2	Santa Rosa "Ñ"	36110	229	217	206	20.8	0	30.7	87.1	0	124.5
3	Tiraque	2	San Isidro(Shinahota)	36115	234	223	212	28.6	24.6	31.4	119.1	107.1	127.2

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 9: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D^a	Provincia	M^b	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Tiraque	2	San Isidro(Shinahota)	36116	234	224	221	28.7	24.3	31.6	119.7	106.6	128.4
3	Tiraque	2	San Isidro(Shinahota)	36117	234	223	212	20.7	0	31.4	86	0	127.3
3	Tiraque	2	San Isidro(Shinahota)	36118	237	227	216	29.1	24.7	31.9	120.8	108.3	129.1
3	Tiraque	2	San Isidro(Shinahota)	36119	210	205	201	26	21.9	28.7	107.7	96.2	116
3	Tiraque	2	4 de Abril	36120	231	223	220	28.4	24.3	31.3	118.3	105	127
3	Tiraque	2	4 de Abril	36121	120	114	112	14.6	12.1	16.4	61.3	53.8	66.4
3	Tiraque	2	12 de Agosto	36122	236	219	215	28.7	24.7	31.5	120.5	107.9	128.8
3	Tiraque	2	12 de Agosto	36123	73	71	71	9	7.1	10.4	37.8	32.4	41.4
3	Tiraque	2	Majo Pampa	36124	237	228	219	29.1	24.9	32	121.1	108.7	130
3	Tiraque	2	Majo Pampa	36125	137	135	128	17	14.3	19.1	70.2	62.1	75.7
3	Tiraque	2	San Luis	36128	235	221	211	21.8	0	31.4	91.4	0	128.1
3	Tiraque	2	San Luis	36129	150	141	137	14.5	0	20.3	60.9	0	82.3
3	Tiraque	2	Lauca Eñe	36130	236	224	201	14.1	0	31.2	58.6	0	125
3	Tiraque	2	Lauca Eñe	36131	235	226	201	14.7	0	31.4	59.8	0	125.4
3	Tiraque	2	Lauca Eñe	36132	71	68	65	8.7	6.8	10	36.2	30.9	39.8
3	Tiraque	2	Agrigento B	36133	239	225	215	14.4	0	31.7	60.5	0	128.4
3	Tiraque	2	Agrigento B	36134	92	88	84	11.2	9.1	12.7	46.9	41	51.1
3	Carrasco	2	Yuthupampa	35295	138	129	127	8.2	0	18.5	34.8	0	76.1
3	Carrasco	2	Palca “C”	35297	222	212	203	22	0	29.7	91.8	0	121.3
3	Carrasco	2	Rodeo “C”	35300	196	194	169	24.4	20.7	26.9	98.3	88.9	104.7

Notes: All mesas are in *Pais* Bolivia; ^{a} departmento; ^{b} municipio.

Table 10: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Carrasco	2	La Habana	35303	230	218	208	21.3	0	30.9	89.4	0	125
3	Carrasco	2	Thago Laguna	35305	61	59	54	3.9	0	8.5	16.2	0	33.7
3	Carrasco	3	Conda Baja	35326	229	214	203	13.6	0	30.2	57.3	0	122.6
3	Carrasco	4	Entre Rios (Tacuaral)	35384	228	216	211	27.9	24	30.6	116.6	104	124.7
3	Carrasco	4	Entre Rios (Tacuaral)	35386	26	26	25	3.3	2.3	4	13.4	10.7	15
3	Carrasco	4	Cesar Zama (Chimore)	35391	228	217	206	20.1	0	30.6	83.7	0	123.2
3	Carrasco	4	Cesar Zama (Chimore)	35393	224	210	200	18.5	0	30	77.2	0	120.5
3	Carrasco	4	Cesar Zama (Chimore)	35394	233	224	215	28.6	24.4	31.5	118.9	106.1	127.2
3	Carrasco	4	Cesar Zama (Chimore)	35395	237	226	224	29	24.7	31.9	121.3	107.9	130
3	Carrasco	4	Cesar Zama (Chimore)	35397	227	212	207	22.2	0	30.3	92.9	0	122.7
3	Carrasco	4	San Andres	35407	227	215	214	22.2	0	30.5	93.1	0	123.7
3	Carrasco	4	San Andres	35408	230	219	218	28.1	23.8	30.9	117.7	105.6	125.9
3	Carrasco	4	San Andres	35409	148	144	142	18.3	15.3	20.5	76.1	67.2	82.5

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 11: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Carrasco	4	Senda "F" 27 de Mayo	35412	237	229	218	29.2	25.2	32.1	121	108.3	129.2
3	Carrasco	4	Senda "F" 27 de Mayo	35413	38	38	37	4.8	3.5	5.7	19.8	16.3	21.9
3	Carrasco	4	Senda "3"	35415	239	226	200	14.2	0	31.5	58.9	0	125.4
3	Carrasco	5	Libertad	35484	231	216	207	13.8	0	30.6	58.5	0	125.3
3	Carrasco	5	Valle Ivirza	35490	230	219	212	28.2	24	31	117.5	104.8	125.9
3	Carrasco	5	Valle Ivirza	35492	229	216	208	27.9	24	30.7	116.4	104.1	124.4
3	Carrasco	5	Valle de Sacta	35498	232	218	205	19.1	0	30.9	79.5	0	124.5
3	Carrasco	5	Valle de Sacta	35500	237	227	221	29.1	24.9	32	121.2	108.5	129.7
3	Carrasco	5	Valle de Sacta	35501	225	212	206	15.3	0	30.1	64.1	0	120.9
3	Carrasco	5	Valle de Sacta	35504	230	217	211	28.1	23.9	30.9	117.3	104.8	125.5
3	Carrasco	5	Valle de Sacta	35505	223	211	204	27.2	23.2	29.9	113.8	101.9	121.8
3	Carrasco	5	Valle de Sacta	35506	231	219	210	20.7	0	30.8	86.8	0	125.9
3	Carrasco	5	Valle de Sacta	35509	228	215	205	14.3	0	30.4	59.8	0	121.8
3	Carrasco	5	Valle de Sacta	35510	226	218	207	27.8	23.6	30.5	115.2	102.7	123.2
3	Carrasco	5	Valle de Sacta	35513	233	219	212	13.9	0	30.9	59	0	126.9

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 12: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Carrasco	5	Valle de Sacta	35514	228	215	210	21.4	0	30.5	89.8	0	123.5
3	Carrasco	5	Valle de Sacta	35515	231	218	202	13.8	0	30.5	57.8	0	123
3	Carrasco	5	Valle de Sacta	35517	227	219	212	27.9	23.9	30.7	116	103.2	124.1
3	Carrasco	5	Valle Hermoso	35521	227	217	207	27.8	23.8	30.6	115.7	103.1	123.3
3	Carrasco	5	Valle Hermoso	35523	227	213	207	20.8	0	30.3	87.8	0	123.6
3	Carrasco	5	Valle Hermoso	35525	226	218	215	27.8	23.7	30.7	115.8	103.2	124.2
3	Carrasco	5	Valle Hermoso	35527	235	221	211	21.2	0	31.2	89	0	127.6
3	Carrasco	5	Villa Nueva	35531	234	221	215	22.7	0	31.3	94.9	0	126.7
3	Carrasco	5	Villa Nueva	35532	223	211	200	27.1	23.4	29.9	113.2	101.2	121.1
3	Carrasco	5	Mariposas	35539	223	211	193	13.8	0	29.6	57.1	0	119.8
3	Carrasco	5	Mariposas	35544	226	214	204	27.6	23.6	30.4	115	103.2	123.2
3	Carrasco	5	Ayopaya (Pto. Villarroel)	35547	226	215	210	27.6	23.5	30.5	115.4	103.4	123.9
3	Carrasco	5	Ayopaya (Pto. Villarroel)	35548	233	221	209	15.8	0	31	66.4	0	126.1
3	Carrasco	5	Ayopaya (Pto. Villarroel)	35549	232	217	209	28.1	23.9	31.1	117.8	104.6	125.9
3	Carrasco	5	Ayopaya (Pto. Villarroel)	35551	20	20	19	1.3	0	3.1	5.4	0	11.5

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 13: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

					Observed			Fraudulent Counts					
								Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Carrasco	5	Cesar Zama (Pto. Villarroel)	35552	233	228	218	28.9	24.4	31.7	119.2	107	127.5
3	Carrasco	5	Cesar Zama (Pto. Villarroel)	35553	45	44	42	5.6	4.2	6.6	23.1	19.2	25.5
3	Carrasco	5	Senda 6	35554	226	216	205	20.8	0	30.3	86.4	0	122.4
3	Carrasco	5	Senda 6	35557	226	211	204	22	0	29.8	92.5	0	122.9
3	Carrasco	5	Senda 6	35559	229	221	211	28.1	23.9	31.1	116.9	104.1	124.9
3	Carrasco	5	Valle Tunari	35562	235	228	220	29	24.9	31.9	120.2	107.7	128.7
3	Carrasco	5	Valle Tunari	35563	229	217	213	28	24	30.8	117	104.5	125.2
3	Carrasco	5	Valle Tunari	35564	230	216	210	16.2	0	30.6	68.1	0	124.4
3	Carrasco	5	Valle Tunari	35566	223	211	208	27.3	23.4	30	114.1	102.9	122.3
3	Carrasco	5	Valle Tunari	35567	232	217	209	14.2	0	30.8	60	0	126.2
3	Carrasco	5	Valle Tunari	35568	226	211	205	21.9	0	30.1	92.3	0	123.3
3	Carrasco	5	Valle Tunari	35569	231	218	212	28.2	24.1	31	118	105.7	126.2
3	Carrasco	5	Valle Tunari	35570	179	170	163	17.7	0	24.2	74.2	0	97.8
3	Carrasco	5	2 de Marzo	35571	232	225	223	28.6	24.3	31.8	119	105.8	127.7
3	Carrasco	5	2 de Marzo	35572	236	230	222	29.1	24.9	32.2	120.8	108.4	129.3
3	Carrasco	5	2 de Marzo	35574	169	161	159	20.7	17.4	22.9	86.5	77.3	93.1

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 14: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Carrasco	5	Israel	35576	233	223	211	21.7	0	31.3	90.4	0	125.7
3	Carrasco	5	Israel	35577	236	228	222	29.1	24.7	32	120.8	107.9	129.9
3	Carrasco	6	Isarzama	35610	225	212	202	22.7	0	30.1	94.6	0	122.4
3	Carrasco	6	Isarzama	35611	230	213	210	27.8	23.8	30.6	117	104.3	125.3
3	Carrasco	6	Isarzama	35612	229	221	211	28.2	24	31	116.9	104.3	125
3	Carrasco	6	Isarzama	35613	225	212	206	27.4	23.5	30.2	114.6	102.9	122.7
3	Carrasco	6	Isarzama	35614	231	217	207	28	24	30.9	117.1	104.5	125.4
3	Carrasco	6	Isarzama	35615	232	221	213	28.4	24.2	31.3	118.6	106.4	126.8
3	Carrasco	6	Isarzama	35617	229	216	213	27.9	24	30.8	116.9	104	125.5
3	Carrasco	6	Isarzama	35618	225	209	201	14.8	0	29.6	62.3	0	121.1
3	Carrasco	6	Entre Rios	35632	227	217	203	14.5	0	30.2	60.6	0	122
3	Carrasco	6	Entre Rios	35665	234	225	217	28.8	24.6	31.7	119.5	106.6	127.9
3	Carrasco	6	Entre Rios	35666	235	226	210	28.8	24.6	31.7	119.2	107.4	127.2
3	Carrasco	6	Entre Rios	35667	235	218	209	14.8	0	31	61.4	0	126.5
3	Carrasco	6	Entre Rios	35668	233	220	216	22.4	0	31.2	94.1	0	127.6
3	Carrasco	6	Entre Rios	35669	231	217	201	14.4	0	30.4	60.1	0	123
3	Carrasco	6	Entre Rios	35670	234	225	212	28.7	24.7	31.7	119	106.6	127.3
3	Carrasco	6	Entre Rios	35673	240	224	214	14.3	0	31.7	60.1	0	128.2
3	Carrasco	6	Entre Rios	35674	233	218	212	28.3	24.1	31.2	118.9	106	127.6
3	Carrasco	6	Entre Rios	35676	233	219	215	28.4	24.2	31.4	119	106.7	127.4
3	Carrasco	6	Entre Rios	35677	234	224	211	21.4	0	31.5	89.2	0	126.5
3	Carrasco	6	Entre Rios	35678	236	221	214	28.7	24.5	31.6	120.2	107.9	128.6
3	Carrasco	6	14 De Septiembre	35687	237	229	223	29.2	24.9	32.2	121.3	109.7	129.8
3	Carrasco	6	14 De Septiembre	35688	140	138	137	17.4	14.4	19.5	72.3	63.9	78.4

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 15: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
3	Carrasco	6	Urbanización Chancadora	35689	238	229	220	29.1	25.1	32.1	121.2	108.9	129.7
3	Carrasco	6	Urbanización Chancadora	35690	239	231	224	29.4	25.1	32.5	122.2	109.7	131
3	Carrasco	6	Urbanización Chancadora	35691	184	177	170	22.6	19.1	25.1	94	83.6	100.9
5	General Bernardino Bilbao	1	Qoaraca	52152	123	116	112	14.9	12.3	16.9	62.6	54.6	68.1
4	Ladislao Cabrera	1	Puqui	41456	54	54	45	6.8	5.2	8	26.6	22.6	29.4
4	Sur Carangas	1	Orinoca	41565	220	205	194	14.5	0	29.2	60.2	0	118.4
4	Sur Carangas	1	Orinoca	41567	91	88	86	11.2	9.1	12.8	46.8	40.6	50.9
5	Modesto Omiste	1	Lonte	52331	75	74	73	9.4	7.5	10.7	38.9	33.3	42.5
4	Cercado	4	Lequepalca	41104	36	36	33	4.5	3.3	5.4	18.3	15.1	20.4
4	Abaroa	1	Cacachaca	41195	217	210	187	19.8	0	29.3	81.3	0	115.4
4	Abaroa	1	Cacachaca	41196	216	204	198	22.2	0	28.9	93.4	0	118.2
5	Alonso de Ibáñez	1	Cachari	51575	237	236	233	29.6	25.3	32.7	122	108.4	131
5	Alonso de Ibáñez	1	Cachari	51576	36	36	35	4.6	3.4	5.4	18.7	15.4	20.7
5	Alonso de Ibáñez	1	Pichuya	51577	256	255	253	32	27.5	35.1	131.7	118.4	141.3

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 16: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

								Fraudulent Counts					
					Observed			Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
5	Chayanta	3	Collana Tuica	51283	217	207	198	26.4	22.5	29.3	110.3	98.8	118
5	Chayanta	3	Collana Tuica	51284	222	213	208	27.2	23.3	30	113.5	101.3	121.7
5	Charcas	1	Ipote	51393	222	215	213	27.4	23.4	30.1	113.9	101.9	122.2
5	Charcas	1	Banduriri	51401	25	25	23	1.6	0	3.8	6.4	0	14.2
5	Charcas	1	Sacana	51405	156	149	136	14.8	0	21.1	61.4	0	84.2
5	Charcas	1	Llallaguani	51406	130	126	126	16	13.3	18	66.9	58.8	72.8
5	Charcas	2	Tambo Khasa	51427	214	209	205	26.5	22.6	29.3	109.8	97.8	117.8
5	Charcas	2	Tambo Khasa	51428	167	160	160	20.5	17.3	22.8	85.7	76.1	92.3
5	Charcas	2	Pocosuco	51432	219	206	201	20.7	0	29.2	86.8	0	119.6
5	Charcas	2	Vaqueria	51433	135	127	123	16.3	13.7	18.3	68.7	60.9	74.1
5	Charcas	2	Layme Cotani	51435	91	90	89	11.4	9.1	12.9	47.2	40.9	51.5
5	Charcas	2	Quirusillani	51436	123	116	115	14.9	12.4	16.8	62.8	55.1	68.3
5	Alonso de Ibáñez	1	Sillu Sillu	51541	221	206	206	19.4	0	29.4	81.9	0	121.1
5	Alonso de Ibáñez	1	Sillu Sillu	51542	216	211	211	26.7	22.8	29.6	111	99.4	119.3
5	Alonso de Ibáñez	1	Sillu Sillu	51543	39	39	39	4.9	3.7	5.8	20.6	17.1	22.8
5	Alonso de Ibáñez	1	Carcoma	51546	217	201	200	12.8	0	28.7	54.4	0	117
5	Alonso de Ibáñez	1	Iturata	51549	222	210	206	21.7	0	29.8	91.1	0	122
5	Alonso de Ibáñez	1	Iturata	51550	71	70	63	8.8	6.9	10.2	35.8	30.6	39.1

Notes: All mesas are in *País* Bolivia; [a] departmento; [b] municipio.

Table 17: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

					Observed			Fraudulent Counts					
								Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
5	Alonso de Ibáñez	1	Laytogo	51553	215	203	193	21.2	0	28.8	88.3	0	116
5	Alonso de Ibáñez	1	Ovejeria	51562	221	220	216	27.6	23.4	30.3	113.7	101.8	122.3
5	Alonso de Ibáñez	1	Ovejeria	51563	115	112	112	14.2	11.7	16.1	59.4	51.8	64.4
5	Alonso de Ibáñez	1	Vila Vila.	51564	218	216	210	27.2	23.2	30	111.9	99	120.5
5	Alonso de Ibáñez	1	Vila Vila.	51565	224	218	218	27.7	23.6	30.5	115	103.3	123.7
5	Alonso de Ibáñez	1	Vila Vila.	51566	229	224	223	28.4	24.2	31.4	117.7	105.4	126.1
5	Alonso de Ibáñez	1	Camacachi	51572	105	101	99	12.9	10.4	14.7	53.9	47.5	58.5
7	Velasco	1	Comunidad Campesina Agroecológica Tierra Hermosa	76182	203	192	186	24.7	21	27.4	103.5	92.9	111

Notes: All mesas are in *Pais* Bolivia; [a] departmento; [b] municipio.

Table 18: Estimated Fraudulent Vote Counts for Bolivian Election Mesas

					Observed			Fraudulent Counts					
								Turnout	T 99.5% CI		Votes	V 99.5% CI	
D[a]	Provincia	M[b]	Localidad	Mesa	NVoters	NValid	Votes	Mean	lo	up	Mean	lo	up
7	Ńuflo de Chavez	1	Integracion A	77998	239	231	217	29.4	25	32.4	121.7	108.8	130
7	Ńuflo de Chavez	2	San Pablo	78036	124	115	114	4.5	0	16	19.2	0	65.7
7	Ńuflo de Chavez	5	Monterito	78195	236	221	220	21.8	0	31.3	91.8	0	128
7	Ńuflo de Chavez	5	Monterito	78196	43	42	41	5.3	4	6.3	22.2	18.7	24.8
7	Ńuflo de Chavez	5	Palmira	78199	128	121	121	15.6	12.9	17.6	65.6	57.9	71.2
7	Sara	2	Ró Nuevo	76806	210	202	185	21.6	0	28.4	88.6	0	113.2
7	Sara	2	San Juan del Pari	76807	238	226	203	14.8	0	31.6	60.6	0	126.8
7	Cordillera	1	Buena Vista	76850	27	26	26	3.3	2.3	4	14	11.3	15.7
7	Cordillera	1	Potrerillos Los Pozos	76851	140	134	123	17.1	14.3	19.1	70.6	62.9	76
9	Madre de Dios	2	Genechiquia	90315	142	140	140	17.7	14.9	19.8	73.4	65.1	79.4

runef4_Bolivia2019Clean_4c.Rout:

```
R version 3.4.4 (2018-03-15) -- "Someone to Lean On"
Copyright (C) 2018 The R Foundation for Statistical Computing
Platform: x86_64-pc-linux-gnu (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> # eforensics model applied to various datasets
>
> library(eforensics);


 ---------------------------------------
 Election Forensics Package (eforensics)
 ---------------------------------------

 Authors:
   - Diogo Ferrari
   - Walter Mebane
   - Kevin McAlister
   - Patrick Wu

 Supported by NSF grant SES 1523355



>
> # Bolivia 2019 president
>
> dat <- read.csv("~/wxchg/data/Bolivia/Bolivia2019Clean.csv");
> names(dat);
 [1] "X"                    "Pa..s"                "N..mero.departamento"
 [4] "Departamento"         "Provincia"            "N..mero.municipio"
 [7] "Municipio"            "Circunscripci..n"     "Localidad"
```

```
[10] "Recinto"              "N..mero.Mesa"         "C..digo.Mesa"
[13] "Elecci..n"            "Inscritos"            "CC"
[16] "FPV"                  "MTS"                  "UCS"
[19] "MAS...IPSP"           "X21F"                 "PDC"
[22] "MNR"                  "PAN.BOL"              "Votos.V..lidos"
[25] "Blancos"              "Nulos"                "Estado.acta"
[28] "NVoters"              "NValid"               "Votes"
> dim(dat);
[1] 34551    30
> #> names(dat);
> # [1] "X"                     "Pas"                  "Nmero.departamento"
> # [4] "Departamento"          "Provincia"             "Nmero.municipio"
> # [7] "Municipio"             "Circunscripcin"      "Localidad"
> #[10] "Recinto"               "Nmero.Mesa"           "Cdigo.Mesa"
> #[13] "Eleccin"              "Inscritos"            "CC"
> #[16] "FPV"                   "MTS"                   "UCS"
> #[19] "MAS...IPSP"            "X21F"                  "PDC"
> #[22] "MNR"                   "PAN.BOL"               "Votos.Vlidos"
> #[25] "Blancos"               "Nulos"                 "Estado.acta"
> #[28] "NVoters"               "NValid"                "Votes"
> #> dim(dat);
> #[1] 34551    30
>
> sapply(dat[,14:26],sum,na.rm=TRUE);
     Inscritos             CC            FPV            MTS            UCS
       7314446        2240920          23725          76827          25283
    MAS...IPSP           X21F            PDC            MNR        PAN.BOL
       2889359         260316         539081          42334          39826
Votos.V..lidos        Blancos          Nulos
       6137778          93507         229337
> #> sapply(dat[,14:26],sum,na.rm=TRUE);
> #    Inscritos             CC            FPV           MTS           UCS
> #      7314446        2240920          23725         76827         25283
> #   MAS...IPSP           X21F            PDC           MNR       PAN.BOL
> #      2889359         260316         539081         42334         39826
> #Votos.Vlidos       Blancos          Nulos
> #      6137778          93507         229337
>
> dat$NVoters <- dat$Inscritos;
> dat$NValid <- apply(as.matrix(dat[,15:23]),1,sum,na.rm=TRUE);
> dat$Votes <- dat$MAS...IPSP;
>
> kidx <- !is.na(dat$NVoters) & (dat$NVoters >= dat$NValid) &
+   (dat$NValid > 0) & (dat$NValid >= dat$Votes);
> if (any(is.na(kidx))) kidx[is.na(kidx)] <- FALSE;
```

```
> table(kidx);
kidx
 TRUE
34551
> dat <- dat[kidx,];
> dim(dat);
[1] 34551    30
>
> dat$NAbst <- dat$NVoters-dat$NValid;
>
> ## mcmc parameters
> ## ---------------
> mcmc    = list(burn.in=5000, n.adapt=1000, n.iter=2000, n.chains=4)
>
> ## samples
> ## -------
> ## help(eforensics)
>
> efout <- eforensics(
+   Votes ~ 1,  NAbst ~ 1,  data=dat,
+   eligible.voters="NVoters",
+   model="qbl",  mcmc=mcmc,
+   parameters = "all",  parComp = TRUE,  autoConv = TRUE,  max.auto = 2,
+   mcmc.conv.diagnostic = "MCMCSE",
+   mcmc.conv.parameters = c("pi"),  mcmcse.conv.precision = .05,  mcmcse.combine = TRUE
+ )

Burn-in: 5000

Number of MCMC samples per chain: 2000

MCMC in progress ....

Calling 4 simulations using the parallel method...
Following the progress of chain 1 (the program will wait for all chains
to finish before continuing):
Welcome to JAGS 4.3.0 on Mon Oct 28 18:02:39 2019
JAGS is free software and comes with ABSOLUTELY NO WARRANTY
Loading module: basemod: ok
Loading module: bugs: ok
. . Reading data file data.txt
. Compiling model graph
   Resolving undeclared variables
   Allocating nodes
Graph information:
```

```
   Observed stochastic nodes: 69102
   Unobserved stochastic nodes: 380082
   Total graph size: 2670483
. Reading parameter file inits1.txt
. Initializing model
. Adapting 1000
-------------------------------------------------| 1000
++++++++++++++++++++++++++++++++++++++++++++++++++ 100%
Adaptation successful
. Updating 5000
-------------------------------------------------| 5000
************************************************** 100%
. . Updating 2000
-------------------------------------------------| 2000
************************************************** 100%
. . . . Updating 0
. Deleting model
Following the progress of chain 2 (the program will wait for all chains
to finish before continuing):
Welcome to JAGS 4.3.0 on Mon Oct 28 18:02:39 2019
JAGS is free software and comes with ABSOLUTELY NO WARRANTY
Loading module: basemod: ok
Loading module: bugs: ok
. . Reading data file data.txt
. Compiling model graph
   Resolving undeclared variables
   Allocating nodes
Graph information:
   Observed stochastic nodes: 69102
   Unobserved stochastic nodes: 380082
   Total graph size: 2670483
. Reading parameter file inits2.txt
. Initializing model
. Adapting 1000
-------------------------------------------------| 1000
++++++++++++++++++++++++++++++++++++++++++++++++++ 100%
Adaptation successful
. Updating 5000
-------------------------------------------------| 5000
************************************************** 100%
. . Updating 2000
-------------------------------------------------| 2000
************************************************** 100%
. . . . Updating 0
. Deleting model
```

```
All chains have finished
Simulation complete.  Reading coda files...
Coda files loaded successfully
Calculating summary statistics...
Calculating the Gelman-Rubin statistic for 3 variables....
Finished running the simulation

Burnin Finished.
Capturing the samples ...

Calling 4 simulations using the parallel method...
Following the progress of chain 1 (the program will wait for all chains
to finish before continuing):
Welcome to JAGS 4.3.0 on Tue Oct 29 06:51:27 2019
JAGS is free software and comes with ABSOLUTELY NO WARRANTY
Loading module: basemod: ok
Loading module: bugs: ok
. . Reading data file data.txt
. Compiling model graph
   Resolving undeclared variables
   Allocating nodes
Graph information:
   Observed stochastic nodes: 69102
   Unobserved stochastic nodes: 380082
   Total graph size: 2670483
. Reading parameter file inits1.txt
. Initializing model
. Adapting 1000
-------------------------------------------------| 1000
++++++++++++++++++++++++++++++++++++++++++++++++++ 100%
Adaptation successful
. NOTE: Stopping adaptation

. . . . . . . . . . . . . Updating 2000
-------------------------------------------------| 2000
************************************************** 100%
. . . . Updating 0
. Deleting model
Following the progress of chain 3 (the program will wait for all chains
to finish before continuing):
Welcome to JAGS 4.3.0 on Tue Oct 29 06:51:27 2019
JAGS is free software and comes with ABSOLUTELY NO WARRANTY
Loading module: basemod: ok
Loading module: bugs: ok
. . Reading data file data.txt
```

```
. Compiling model graph
   Resolving undeclared variables
   Allocating nodes
Graph information:
   Observed stochastic nodes: 69102
   Unobserved stochastic nodes: 380082
   Total graph size: 2670483
. Reading parameter file inits3.txt
. Initializing model
. Adapting 1000
-------------------------------------------------| 1000
++++++++++++++++++++++++++++++++++++++++++++++++++ 100%
Adaptation successful
. NOTE: Stopping adaptation

. . . . . . . . . . . . Updating 2000
-------------------------------------------------| 2000
************************************************** 100%
. . . . Updating 0
. Deleting model
.
All chains have finished
NOTE: The JAGS output file(s) appear(s) to be very large - they may
take some time to read.  Have you accidentally included a large vector
in "monitor", or are you trying to run too many iterations without
specifying "thin"?If the read-in process fails (or is aborted), use ?results.jags and th
read.monitor argument to retrieve the simulationSimulation complete.  Reading coda files
Coda files loaded successfully
Note: Summary statistics were not produced as there are >50 monitored
variables
[To override this behaviour see ?add.summary and ?runjags.options]
FALSEFinished running the simulation

Convergence diagnostic: MCMCSE
# A tibble: 0 x 4
# ... with 4 variables: Parameter <int>, MCMCSE <dbl>, MCMCSE.criterium <dbl>,
#   Converged <lgl>


Estimation Completed

>
> save(efout,file="runef4_Bolivia2019Clean_4c.RData");
>
> summary(efout);
```

```
$`Chain 1`
    Parameter         Covariate         Mean           SD    HPD.lower
1       pi[1]          No Fraud  0.9924773465 0.0005785503  9.91301e-01
2       pi[2] Incremental Fraud  0.0003864678 0.0002929926  1.48889e-07
3       pi[3]     Extreme Fraud  0.0071361877 0.0005044873  6.14445e-03
4    beta.tau       (Intercept)  1.7166579850 0.0106668545  1.68790e+00
5     beta.nu       (Intercept) -0.1045734954 0.0136564322 -1.27484e-01
6 beta.iota.m       (Intercept) -0.0174899248 0.0181483790 -5.69653e-02
7 beta.iota.s       (Intercept) -0.0348312605 0.0066016235 -4.71452e-02
8  beta.chi.m       (Intercept) -0.3338680365 0.0119406331 -3.54708e-01
9  beta.chi.s       (Intercept)  0.1955873730 0.0096970780  1.76718e-01
     HPD.upper
1  0.993592000
2  0.000932117
3  0.008105520
4  1.730440000
5 -0.076490500
6  0.006106840
7 -0.024166400
8 -0.312070000
9  0.210340000

$`Chain 2`
    Parameter         Covariate         Mean           SD    HPD.lower
1       pi[1]          No Fraud  0.9927843670 0.0005490212  9.91591e-01
2       pi[2] Incremental Fraud  0.0003258427 0.0002351087  1.23068e-07
3       pi[3]     Extreme Fraud  0.0068897918 0.0004763863  6.01357e-03
4    beta.tau       (Intercept)  1.7265722950 0.0105278763  1.70732e+00
5     beta.nu       (Intercept) -0.0981726238 0.0100272867 -1.17531e-01
6 beta.iota.m       (Intercept)  0.0396192940 0.0118185317  2.58306e-02
7 beta.iota.s       (Intercept)  0.0611360010 0.0140609892  3.30056e-02
8  beta.chi.m       (Intercept) -0.1868573970 0.0143058370 -2.11973e-01
9  beta.chi.s       (Intercept)  0.5010675160 0.0398472915  4.28249e-01
     HPD.upper
1  0.993759000
2  0.000773622
3  0.007863480
4  1.747300000
5 -0.078518400
6  0.059809200
7  0.081006300
8 -0.167900000
9  0.554310000

$`Chain 3`
```

```
    Parameter          Covariate          Mean           SD    HPD.lower
1       pi[1]           No Fraud  0.9915581630 0.0006050236  9.90303e-01
2       pi[2] Incremental Fraud  0.0004318741 0.0002502098  3.65805e-05
3       pi[3]     Extreme Fraud  0.0080099639 0.0005418588  6.92579e-03
4    beta.tau        (Intercept)  1.7150409550 0.0080916626  1.70022e+00
5     beta.nu        (Intercept) -0.1009840489 0.0091813541 -1.19823e-01
6 beta.iota.m        (Intercept) -0.0659426044 0.0131354319 -8.11853e-02
7 beta.iota.s        (Intercept)  0.0874979450 0.0078811226  7.50677e-02
8  beta.chi.m        (Intercept) -0.3449911565 0.0056981201 -3.55295e-01
9  beta.chi.s        (Intercept)  0.2952925160 0.0399865023  2.33002e-01
     HPD.upper
1  0.992689000
2  0.000899037
3  0.009013080
4  1.730970000
5 -0.084383400
6 -0.037474400
7  0.101862000
8 -0.333423000
9  0.363672000

$`Chain 4`
    Parameter          Covariate          Mean           SD    HPD.lower
1       pi[1]           No Fraud  0.9867276210 0.0007672637  9.85209e-01
2       pi[2] Incremental Fraud  0.0004147004 0.0003610805  1.53966e-07
3       pi[3]     Extreme Fraud  0.0128576734 0.0007135009  1.15418e-02
4    beta.tau        (Intercept)  1.7088835450 0.0131037522  1.68483e+00
5     beta.nu        (Intercept) -0.1148054847 0.0139168839 -1.38886e-01
6 beta.iota.m        (Intercept) -0.2411824705 0.0118042231 -2.56822e-01
7 beta.iota.s        (Intercept) -0.5472241795 0.0109064378 -5.63867e-01
8  beta.chi.m        (Intercept) -1.5187331400 0.0244596309 -1.54933e+00
9  beta.chi.s        (Intercept) -0.2538778370 0.0187851430 -2.85696e-01
    HPD.upper
1  0.98822600
2  0.00113301
3  0.01435950
4  1.72973000
5 -0.08679060
6 -0.21645200
7 -0.52911200
8 -1.47431000
9 -0.21178100
```

wrkef2a_Bolivia2019Clean_4c.Rout:

```
R version 3.4.4 (2018-03-15) -- "Someone to Lean On"
Copyright (C) 2018 The R Foundation for Statistical Computing
Platform: x86_64-pc-linux-gnu (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> # eforensics model applied to various datasets
>
> library(eforensics);


 ---------------------------------------
 Election Forensics Package (eforensics)
 ---------------------------------------

 Authors:
   - Diogo Ferrari
   - Walter Mebane
   - Kevin McAlister
   - Patrick Wu

 Supported by NSF grant SES 1523355



> source("wrkef.R");
> source("obsfrauds_ciS.R")
>
> # Bolivia 2019 president
>
> dat <- read.csv("~/wxchg/data/Bolivia/Bolivia2019Clean.csv");
> names(dat);
```

```
 [1] "X"                    "Pa..s"                "N..mero.departamento"
 [4] "Departamento"         "Provincia"            "N..mero.municipio"
 [7] "Municipio"            "Circunscripci..n"     "Localidad"
[10] "Recinto"              "N..mero.Mesa"         "C..digo.Mesa"
[13] "Elecci..n"            "Inscritos"            "CC"
[16] "FPV"                  "MTS"                  "UCS"
[19] "MAS...IPSP"           "X21F"                 "PDC"
[22] "MNR"                  "PAN.BOL"              "Votos.V..lidos"
[25] "Blancos"              "Nulos"                "Estado.acta"
[28] "NVoters"              "NValid"               "Votes"
> dim(dat);
[1] 34551    30
> #> names(dat);
> # [1] "X"                    "Pas"                  "Nmero.departamento"
> # [4] "Departamento"         "Provincia"             "Nmero.municipio"
> # [7] "Municipio"            "Circunscripcin"       "Localidad"
> #[10] "Recinto"              "Nmero.Mesa"           "Cdigo.Mesa"
> #[13] "Eleccin"             "Inscritos"            "CC"
> #[16] "FPV"                  "MTS"                   "UCS"
> #[19] "MAS...IPSP"           "X21F"                  "PDC"
> #[22] "MNR"                  "PAN.BOL"               "Votos.Vlidos"
> #[25] "Blancos"              "Nulos"                 "Estado.acta"
> #[28] "NVoters"              "NValid"                "Votes"
> #> dim(dat);
> #[1] 34551    30
>
> sapply(dat[,14:26],sum,na.rm=TRUE);
     Inscritos             CC            FPV            MTS            UCS
       7314446        2240920          23725          76827          25283
    MAS...IPSP           X21F            PDC            MNR        PAN.BOL
       2889359         260316         539081          42334          39826
Votos.V..lidos        Blancos          Nulos
       6137778          93507         229337
> #> sapply(dat[,14:26],sum,na.rm=TRUE);
> #    Inscritos             CC            FPV            MTS            UCS
> #      7314446        2240920          23725          76827          25283
> #   MAS...IPSP           X21F            PDC            MNR        PAN.BOL
> #      2889359         260316         539081          42334          39826
> #Votos.Vlidos        Blancos          Nulos
> #      6137778          93507         229337
>
> dat$NVoters <- dat$Inscritos;
> dat$NValid <- apply(as.matrix(dat[,15:23]),1,sum,na.rm=TRUE);
> dat$Votes <- dat$MAS...IPSP;
>
```

```
> kidx <- !is.na(dat$NVoters) & (dat$NVoters >= dat$NValid) &
+   (dat$NValid > 0) & (dat$NValid >= dat$Votes);
> if (any(is.na(kidx))) kidx[is.na(kidx)] <- FALSE;
> table(kidx);
kidx
 TRUE
34551
> dat <- dat[kidx,];
> dim(dat);
[1] 34551    30
>
> dat$NAbst <- dat$NVoters-dat$NValid;
>
> load("runef4_Bolivia2019Clean_4c.RData");
>
> summary(efout, join.chains=TRUE);
    Parameter         Covariate          Mean          SD    HPD.lower
1      pi[1]          No Fraud  0.9908868744 0.002523558  9.85871e-01
2      pi[2] Incremental Fraud  0.0003897213 0.000291750  1.23068e-07
3      pi[3]     Extreme Fraud  0.0087234042 0.002488432  6.11167e-03
4    beta.tau       (Intercept)  1.7167886950 0.012479284  1.68742e+00
5     beta.nu       (Intercept) -0.1046339132 0.013447711 -1.31152e-01
6 beta.iota.m       (Intercept) -0.0712489264 0.105916829 -2.54851e-01
7 beta.iota.s       (Intercept) -0.1083553735 0.257659082 -5.60062e-01
8  beta.chi.m       (Intercept) -0.5961124325 0.536580404 -1.54364e+00
9  beta.chi.s       (Intercept)  0.1845173920 0.277695162 -2.71450e-01
     HPD.upper
1  0.993628000
2  0.000939541
3  0.013629700
4  1.737890000
5 -0.079023000
6  0.056201500
7  0.099526700
8 -0.169461000
9  0.551338000
>
> options(width=120)
> elist <- effrauds_obs(dat, efout);
> if ((!is.null(elist$CIcombo)) && dim(elist$CIcombo[["all"]][["Nfraud95"]])[[1]]>0) {
+   print("***** COMBO *****")
+   n <- dim(elist$CIcombo[["all"]][["Nfraud95"]])[[1]];
+   v <- c(dim(dat)[1]-n,n);
+   names(v) <- c("no fraud","fraud");
+   print(v);
```

```
+
+   evec <- c(elist$CIcombo[["all"]][["Ntfraudtotalmean"]],
+     elist$CIcombo[["all"]][["Ntfraudtotal95"]],elist$CIcombo[["all"]][["Ntfraudtotal99
+     elist$CIcombo[["all"]][["Nfraudtotalmean"]],
+     elist$CIcombo[["all"]][["Nfraudtotal95"]],elist$CIcombo[["all"]][["Nfraudtotal995"
+   names(evec) <- c("Ntfraudtotalmean",
+     paste("Nttotal95",c("lo","hi"),sep="."),paste("Nttotal995",c("lo","hi"),sep="."),
+     "Nfraudtotalmean",
+     paste("Ntotal95",c("lo","hi"),sep="."),paste("Ntotal995",c("lo","hi"),sep="."));
+   print(evec);
+
+   emat <- cbind(elist$CIcombo[["wdat"]][,c("NVoters","NValid","Votes")],
+     elist$CIcombo[["all"]][["Ntfraudmean"]],
+     elist$CIcombo[["all"]][["Ntfraud95"]],elist$CIcombo[["all"]][["Ntfraud995"]],
+     elist$CIcombo[["all"]][["Nfraudmean"]],
+     elist$CIcombo[["all"]][["Nfraud95"]],elist$CIcombo[["all"]][["Nfraud995"]]);
+   dimnames(emat)[[2]] <- c("NVoters","NValid","Votes","Ntfraudmean",
+     paste("Nt95",c("lo","hi"),sep="."),
+     paste("Nt995",c("lo","hi"),sep="."),
+     "Nfraudmean",
+     paste("N95",c("lo","hi"),sep="."),
+     paste("N995",c("lo","hi"),sep="."));
+   print(emat);
+
+   cbind(elist$CIcombo[["wdat"]][,c(2,3,5,6,9,11)],
+     emat[,c(1:3,4,7:8,9,12:13)]);
+ }
[1] "***** COMBO *****"
no fraud    fraud
   34277      274
Ntfraudtotalmean     Nttotal95.lo     Nttotal95.hi    Nttotal995.lo    Nttotal995.hi
        5295.798         4910.488         5734.178         4751.090         5880.218
  Nfraudtotalmean      Ntotal95.lo      Ntotal95.hi     Ntotal995.lo     Ntotal995.hi
        22519.818        20842.281        24395.891        20479.794        24663.779
```