Election Forensics Beyond Audits

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election forensics: frauds, strategies and incidents

- use statistical methods to determine whether the results of an election accurately reflect the intentions of the electors
  - detecting "anomalies" is relatively easy, and positive models of frauds exist
  - the hard part is discriminating intent: when anomalies reflect frauds as opposed to strategic behavior or other aspects of normal politics
- examples
  - Honduras 2017
  - US 2016 WI and MI
  - Kenya 2017
  - Russia 2017
  - Twitter Election Observatory 2016

Election Diagnostics Methods Desiderata

1. methods should be sensitive enough to detect anomalies: limit false negatives
2. methods should accurately detect anomalies: limit false positives
3. methods should involve systematic observation: analyze electoral results in their entirety, ideally at the most fine-grained level possible
4. methods should enable the identification of where, geographically, anomalies have occurred
5. methods should produce estimates of uncertainty, indicating how confident we can be in our conclusions

Features of Election Forensics Technology

1. Advantages
   - election forensics relies on objective data: reported election results, disaggregated to the level of electoral constituencies, precincts, and/or polling stations
   - election forensics allows for systematic analysis of reported votes from all contests in all localities
   - election forensics produces estimates of fraud that include statistical statements about the confidence of conclusions

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   - election forensics allows for systematic analysis of reported votes from all contests in all localities
   - election forensics produces estimates of fraud that include statistical statements about the confidence of conclusions
2. Disadvantages
   - producing the statistics requires sophisticated knowledge of quantitative methods and substantial computing power: the Electoral Forensics Toolkit presents a potential solution
   - election forensics does not produce definitive proof of frauds: the method produces probabilistic evidence
   - the methodology works best with detailed election results: an ideal is comprehensive polling place data on turnout, valid ballots and vote counts for all parties and candidates

Honduras 2017

Table : Honduras 2017 Presidential Election Vote Totals

variable	count
Nacional (National Party)	1,411,517
LibrePINU (Libre-PINU coalition)	1,359,170
Liberal (Liberal Party)	483,784
AP (Patriotic Alliance)	6,755
PAC (Anti-corruption Party)	6,090
DC (Christian Democratic Party)	5,935
UD (Democratic Unification Party)	4,667
FrenteAmplio (Broad Front Party)	3,158
Vamos (Go Solidarity Movement Party)	2,966
ValidVotes (valid votes)	3,283,860
votosblancos (blank votes)	58,776
votosnulos (null votes)	134,163
total	3,476,799
papeletasrecibidas (ballots received)	5,688,022
papeletassobrantes (ballots leftover)	2,411,005
papeletasutilizadas (ballots used)	3,277,017

Note: Based on $n = 18128$ polling station observations. Margin: 52,347 votes.

Honduras 2017

Table : Honduras 2017 Presidential Election Forensic Statistics

12/9/2017 Honduras_2017_pres_MER_t_EFT2.html

x

Level	Candidate's Name	_2BL	LastC	P05s	C05s	Skew	Kurt	DipT	Obs
National	Turnout	4.707	4.487	0.198	0.198	0.301	3.266	0.921	17080
		(4.663, 4.75)	(4.441, 4.532)	(0.193, 0.205)	(0.192, 0.205)	(0.251, 0.352)	(3.125, 3.397)	--	
National	Nacional	4.005	4.507	0.207	0.197	0.511	2.997	0.57	17080
		(3.963, 4.047)	(4.465, 4.549)	(0.201, 0.213)	(0.191, 0.203)	(0.478, 0.539)	(2.931, 3.057)	--	
National	LibrePINU	3.827	4.47	0.202	0.203	-0.307	2.53	0.368	17080
		(3.78, 3.872)	(4.424, 4.51)	(0.196, 0.208)	(0.197, 0.209)	(-0.331, -0.282)	(2.49, 2.568)	--	
National	Liberal	4.18	4.495	0.198	0.199	1.499	5.987	0.955	17080
		(4.132, 4.224)	(4.452, 4.537)	(0.192, 0.204)	(0.193, 0.205)	(1.444, 1.557)	(5.693, 6.309)	--	

Note: “2BL,” second-digit mean; “LastC,” last-digit mean; “C05s,” mean of variable indicating whether the last digit of the vote count is zero or five; “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; “Skew,” skewness; “Kurt,” kurtosis; “DipT,” *p*-value from test of unimodality; “Obs,” number of polling station observations. Values in parentheses are nonparametric bootstrap confidence intervals.
Nacional, National Party; LibrePINU, Libre-Innovation and Unity Party coalition; Liberal, Liberal Party.

Honduras 2017

Table : Likelihood Finite Mixture Model Parameter Estimates for Honduras 2017 Presidential Election

Election	$\hat{f}_{\mathrm{i}}$	$\hat{f}_{\mathrm{e}}$	$\hat{\alpha}$	$\hat{\theta}$	$\hat{\tau}$	$\hat{\nu}$	$\hat{\sigma}_{\tau}$	$\hat{\sigma}_{\nu}$	LR	n
2017 President	.13	.00022	1.8	.38	.53	.41	.095	.13	11703.4	17,080

Note: LR is the likelihood ratio test statistic for the hypothesis that there are no frauds (i.e., that $f_{\mathrm{i}} = f_{\mathrm{e}} = 0$). n is the number of polling station observations.

Table : Estimated Fraudulent Vote Counts and Proportions for Honduras 2017 Election

Election	M_{i}	M_{e}	p_{i}	p_{e}	$p_{\mathrm{i}} + p_{\mathrm{e}}$
2017 President	55,836	690	.018	.00022	.018

Note: M_{i}, M_{e} are estimated numbers of votes produced by incremental and extreme frauds; p_{i}, p_{e} are fraudulent vote counts as proportions of the valid votes.

Wisconsin 2016

Table : Trump: recounted votes minus original votes, Wisconsion

	-25	-18	-16	-11	-10	-9	-7	-6	-5	-4	-3	-2	-1	0
Hand	1	1	0	0	1	1	2	2	5	9	15	43	167	1457
Machine	0	0	1	1	0	0	2	1	2	4	9	18	58	810
Mixed	0	0	0	0	0	0	0	0	0	2	3	3	21	199

	1	2	3	4	5	6	7	8	9	10	11	14	23	29
Hand	199	57	39	11	7	4	3	2	1	1	1	2	1	2
Machine	100	27	7	7	3	2	2	0	1	2	0	1	0	0
Mixed	31	8	3	1	2	0	0	1	0	0	0	0	0	0

	31	32	39	50	65	246
Hand	0	1	1	1	1	0
Machine	1	0	0	0	0	1
Mixed	0	0	0	0	0	0

Note: number of precincts that have each displayed value for the difference between the recounted vote total and the original vote total for Trump in a precinct.

Wisconsin 2016

Table : Recounted Votes Minus Original Votes, Mean by Reason, Wisconsin

Reason	N^a	Trump	Clinton
Ballots rejected during recount	316	−.199	.0158
Ballots found during recount	72	1.38	3.38
Nonstandard pens or ballots	4	13.8	16.9
Ballots marked incorrectly	296	.993	1.17
Lost ballots	23	−1.43	−1.17
Human counting error	37	.0213	−1.23
Paper jam	21	−.870	−.696
Ballots wrongfully rejected	73	1.09	1.82
Voting machine error	13	7.56	7.83
No explanation	759	.680	.389

Note: mean of nonzero differences between the recounted and original vote count in Wisconsin wards. [a] Number of occurrences of each reason. Multiple reasons are cited for some wards.

Wisconsin 2016

Table : Wisconsin Ward Voting Technologies and Recount Methods

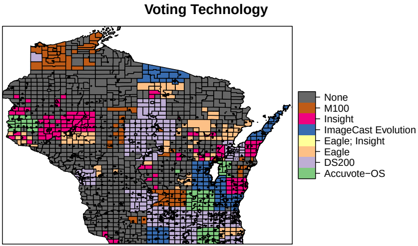
Voting Technology	
None	850
Accuvote-OS	154
DS200	1475
Eagle	294
Eagle; Insight	4
ImageCast Evolution	287
Insight	229
M100	205

Recount Method	
Hand	2126
Machine	1066
Mixed	286
other	22

Note: number of wards using each type of Voting Technology or recount method.

Wisconsin 2016

Figure : Wisconsin Technologies by Municipality



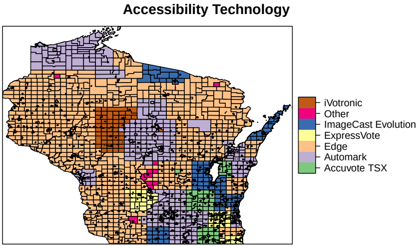
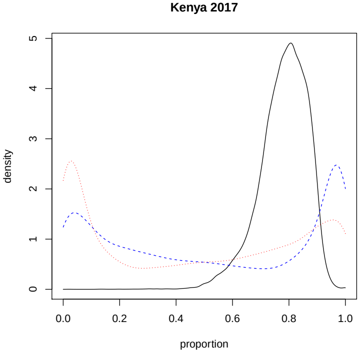


Table : Distribution and Digit Tests, Kenya 2017 Presidential

Name	2BL	LastC	P05s	C05s	DipT	Obs
Turnout	4.439	4.515	.201	.202	.945	40818
	(4.412, 4.468)	(4.487, 4.541)	(.197, .205)	(.198, .206)	——	
Kenyatta	4.302	4.297	.231	.214	0	40818
	(4.272, 4.331)	(4.268, 4.325)	(.227, .235)	(.21, .217)	——	
Odinga	4.278	4.29	.24	.206	0	40818
	(4.25, 4.31)	(4.261, 4.318)	(.235, .244)	(.202, .21)	——	

Figure : Turnout and Kenyatta and Odinga Vote Proportions: Empirical Densities



Legend: solid black line, turnout; blue dashed line, Kenyatta; red dotted line, Odinga.
Note: empirical densities using 40,818 polling stations from across Kenya. Vote count data scraped on August 23, 2017.

Figure : Turnout and Kenyatta and Odinga Vote Proportions: Empirical Densities

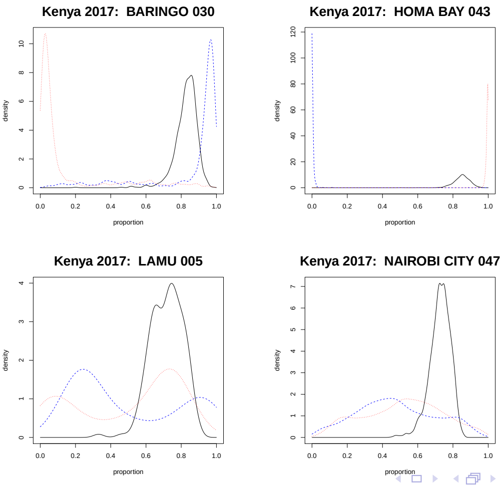


Table : Distribution and Digit Tests, Kenya 2017 Presidential

County	Name	2BL	LastC	P05s	C05s	DipT	Obs
MOMBASA	Turnout	4.509	4.311	.209	.218	.985	933
		(4.323, 4.706)	(4.116, 4.51)	(.184, .236)	(.192, .244)	——	
MURANG'A	Turnout	4.467	4.514	.198	.211	.725	1130
		(4.293, 4.633)	(4.35, 4.673)	(.175, .22)	(.187, .235)	——	
NAIROBI CITY	Turnout	4.395	4.43	.208	.2	.352	3377
		(4.285, 4.497)	(4.342, 4.524)	(.195, .221)	(.186, .213)	——	
MOMBASA	Kenyatta	3.652	4.397	.219	.193	.996	933
		(3.465, 3.824)	(4.21, 4.573)	(.19, .245)	(.167, .22)	——	
MURANG'A	Kenyatta	4.477	4.468	.265	.23	0	1130
		(4.308, 4.647)	(4.3, 4.638)	(.241, .289)	(.204, .257)	——	
NAIROBI CITY	Kenyatta	4.344	4.512	.207	.2	.906	3377
		(4.256, 4.44)	(4.411, 4.607)	(.193, .22)	(.187, .213)	——	
MOMBASA	Odinga	4.886	4.418	.212	.19	.996	933
		(4.695, 5.08)	(4.238, 4.602)	(.186, .239)	(.166, .213)	——	
MURANG'A	Odinga	3.824	2.69	.476	.25	0	1130
		(3.41, 4.228)	(2.552, 2.827)	(.447, .504)	(.223, .273)	——	
NAIROBI CITY	Odinga	4.259	4.515	.204	.213	.908	3377
		(4.165, 4.362)	(4.414, 4.61)	(.19, .217)	(.2, .227)	——	

Table : Estimated Numbers of Votes Due to "Incremental Fraud"

County	Kenyatta	Odinga	County	Kenyatta	Odinga
Baringo	17	—	Marsabit	79	810
Bomet	0	1537	Meru	0	221
Bungoma	1456	362	Migori	—	73
Busia	1573	101	Mombasa	56	297
Elgeyo/Marakwet	0	491	Murang'a	0	—
Embu	36	—	Nairobi City	17601	0
Garissa	918	896	Nakuru	2966	3602
Homa Bay	—	26	Nandi	0	—
Isiolo	1	238	Narok	6	3706
Kajiado	155	139	Nyamira	56	144
Kakamega	583	24	Nyandarua	2	—
Kericho	0	—	Nyeri	0	—
Kiambu	0	6327	Samburu	136	127
Kilifi	1517	277	Siaya	—	—
Kirinyaga	0	—	Taita Taveta	165	56
Kisii	91	86	Tana River	779	0
Kisumu	—	0	Tharaka - Nithi	0	273
Kitui	1110	16	Trans Nzoia	1810	39
Kwale	1550	598	Turkana	490	372
Laikipia	0	—	Uasin Gishu	347	3421
Lamu	1987	89	Vihiga	451	0
Machakos	248	0	Wajir	417	184
Makueni	284	5	West Pokot	18	19
Mandera	0	534	Prisons	0	1
Total	36907	25093			

Note: expected counts of votes in each county due to "incremental fraud" based on county- and candidate-specific estimates of the likelihood finite mixture model. Estimates for the candidate with the most votes in each county is highlighted in grey. "—" indicates a value that could not be calculated because the model could not be estimated.

Russia

Table : "Signaling" Digit Tests for National Votes

	2000	2003 PR	2004	2007
Turnout	0.221	0.217	0.236	0.228
	(0.218, 0.223)	(0.214, 0.22)	(0.233, 0.239)	(0.225, 0.23)
United Russia	0.202	0.202	0.207	0.21
	(0.199, 0.204)	(0.199, 0.204)	(0.204, 0.209)	(0.207, 0.212)

	2008	2011	2012	2016 PR
Turnout	0.232	0.219	0.22	0.225
	(0.229, 0.235)	(0.216, 0.221)	(0.218, 0.223)	(0.222, 0.228)
United Russia	0.204	0.209	0.209	0.208
	(0.202, 0.207)	(0.207, 0.212)	(0.207, 0.212)	(0.205, 0.21)

Note: the statistic is the mean of a variable indicating whether the last digit of the rounded percentage of votes for the referent party or candidate at each polling station is zero or five. Values in parentheses are nonparametric bootstrap confidence intervals.

Russia

Table : Finite Mixture Model Parameter Estimates for Russian Elections

Election	$\hat{f}_{\mathrm{i}}$	$\hat{f}_{\mathrm{e}}$	$\hat{\alpha}$	$\hat{\theta}$	$\hat{\tau}$	$\hat{\nu}$	LR	*n*
2000 President	.033	.000032	3.3	.71	.71	.54	22,286	91,306
2003 Duma PR	.16	.0033	3.3	.27	.58	.36	106,850	95,077
2004 President	.049	.000087	1.7	.44	.69	.72	20290	95,424
2007 Duma	.040	.00016	1.7	.53	.67	.66	18694	95,802
2008 President	.013	.0000017	1.7	.53	.76	.70	586	96,242
2011 Duma	.12	.0032	1.8	.36	.61	.48	69244	95,166
2012 President	.084	.0020	3.4	.35	.65	.65	55352	95,413
2016 Duma PR	.22	.022	1.7	.27	.48	.49	233724	94,987

Note: LR is the likelihood ratio test statistic for the hypothesis that there are no frauds (i.e., that $f_{\mathrm{i}} = f_{\mathrm{e}} = 0$). *n* is the number of polling station observations.

Russia

Table : Estimated Fraudulent Vote Counts and Proportions for Russian Elections

Election	M_{i}	M_{e}	p_{i}	p_{e}	$p_{\mathrm{i}} + p_{\mathrm{e}}$
2000 President	135,061	1,452	.00187	.0000202	.00190
2003 Duma PR	256,759	185,278	.00430	.00311	.00741
2004 President	203,955	4,951	.00297	.0000721	.00304
2007 Duma	270,490	11,914	.00395	.000174	.00413
2008 President	84,933	113	.00116	.00000155	.00116
2011 Duma	680,082	260,254	.0105	.00403	.0146
2012 President	292,339	189,912	.00413	.00268	.00681
2016 Duma PR	739,005	1,080,856	.0145	.0212	.0356

Note: M_{i}, M_{e} are estimated numbers of votes produced by incremental and extreme frauds; p_{i}, p_{e} are fraudulent vote counts as proportions of the valid votes.

General Election Categories for Coding

3. Line Length, Waiting Time	0: There is no crowd or line at the polling place; 1: There was a small crowd or short line or wait; 2: There was a long line or wait (20 minutes or longer).
4. Polling Place Event	0: did not function as expected or information is incorrect 1: Neutral polling place description 2: did function correctly or information is correct
5. Electoral System	0: the electoral system did not function appropriately 1: neutral statement about the electoral system 2: the electoral system functioned appropriately
6. Absentee, Mail-In	0: system did not function appropriately 1: neutral observation 2: system functioned correctly
9. Registration	0: an individual was not able to register to vote 1: neutral observation 2: an individual was able to register to vote

- Tweet 792442434215145472 (Las Vegas, 2016-10-29), text: "Let your voice be heard... Get out and go vote early!!! #MakeAChoice #EveryVoteCounts<< @ Lowes See this Instagram photo by @thewrightroad 78 likes"

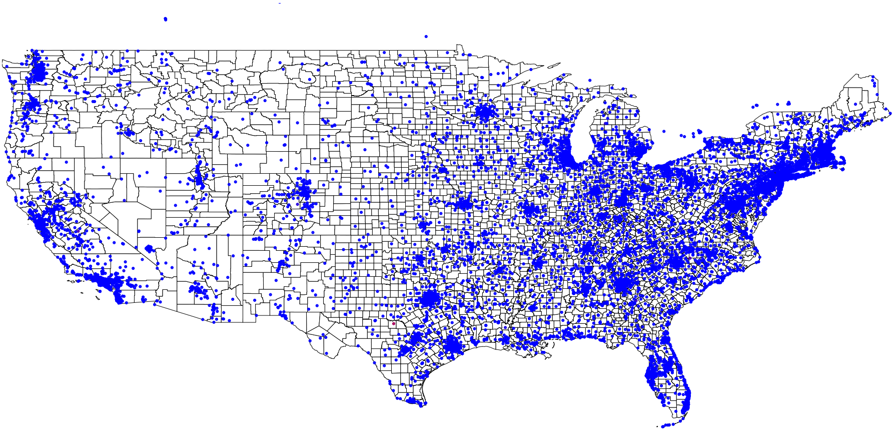
Types of Incidents

Table : General Election Types of Incidents in 2016 ($n = 315,180$)

		Adjective		
Class	Raw	0	1	2
Line Length, Waiting Time	27,167	2,159	1,060	23,869
Polling Place Event	58,871	1,946	15,445	49,561
Electoral System	49,359	10,378	38,831	—
Absentee or Early Voting Issue	105,577	9,127	31,816	65,168
Registration	49,020	17,578	32,160	6,325
Not an incident	89,917	*	*	*

Note: Overall $n = 315,180$ incident Tweets. An asterisk indicates a class that is not defined.
Overall there are 57,410 adverse incidents and 97,194 success incidents.

Figure : 2016 General Election Incident Observations by Location



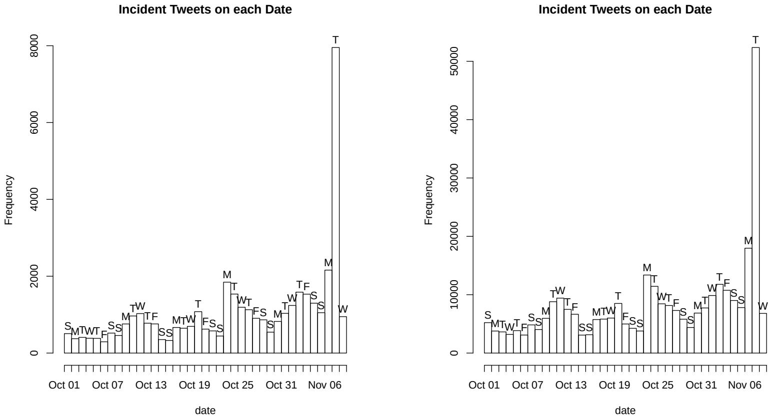
Note: 12,467 unique locations.

Thanks to Adam Rauh for creating lat-lon search tools.

Figure : 2016 General Election Incident Observations by Date

(a) Tweets with `place` information

(b) all Tweets



Note: (a) incidents by day for 40,678 Tweets with `place` information. (b) incidents by day for 315,180 Tweets with or without `place` information.

Divergent Observations and Communications Silos

- trump/donald/realdonaldtrump/maga/republican users report election incidents differently than do clinton/hillary/hillaryclinton/strongertogether/democrat users
  - compared to the latter, the former are
    - less likely to report unspecified line length incidents or long lines
    - less likely to report unspecified polling place incidents, neutral polling place incidents or success voting
    - less likely to report unspecified registration incidents or neutral registration incidents but more likely to report registration problems
    - less likely to report unspecified electoral system incidents or neutral electoral system incidents
- the incident tweeters are speaking to ("in-reply-to") people who tend to have partisan associations similar to theirs
- this appears to manifest communication silos and motivated reporting, probably not divergent real experiences

Twitter Election Observatory in 2018

- 2018
  - we have about 65 million original Tweets collected from STREAM API during Oct 1-Nov 6, 2018
  - classifying a subset ($n = 19.3$ million) of the Tweets using the 2016 classifier suggests we'll obtain about 1.5 million "hits" from the whole set

Support

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