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HOW TO POLL RUNOFF ELECTIONS

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Abstract We present a polling strategy to predict and analyze runoff elections using the 2017 French presidential race as an empirical case. This strategy employs rejective probability sampling to identify a small sample of polling stations that is balanced with respect to past election results. We then survey the voters' candidate evaluations in first-round exit polls. We poststratify the voter sample to first-round election returns to account for nonresponse and coverage issues, and impute missing candidate evaluations to emulate campaign learning. Next, the votes for eliminated competitors are redistributed according to their supporters' lower-order preferences. Finally, the predictions are validated against official results and other polls. We end with a discussion of the advantages and limitations of this approach.

Predicting election outcomes based on polls faces three essential challenges: Pollsters must identify which of their respondents will actually vote despite what they indicate, they must account for voters who make up or change their

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mind after being polled, and they must generalize from a likely voter sample to the electorate at large in the face of coverage and nonresponse issues (Prosser and Mellon 2018).

If surveyed properly, two-round elections should provide valuable leverage to make these challenges more tractable. In a two-round election, each voter casts one vote and the candidate with the majority of votes is elected. If none of the candidates wins a majority, a runoff is held, normally between the two top finishers. Two-round elections are widespread, used in 86 out of 113 countries where heads of state are elected directly (Institute for Democracy and Electoral Assistance 2019). They are also used in countless subnational elections around the world, including the United States.

Runoffs are commonly polled much like any other election (Jérôme, Jérôme, and Lewis-Beck 1999). We propose an alternative approach that capitalizes on information from both the current and past elections. This approach involves: (1) balanced probability sampling of polling stations using auxiliary data from past elections; (2) surveying of candidate preferences in first-round exit polls, where respondents are sampled systematically on site; (3) poststratification of the voter sample to official first-round returns; (4) imputation of missing evaluations of the runoff candidates to emulate campaign learning; and (5) forecasting of the runoff by redistributing the votes for eliminated competitors according to their supporters' lower-order preferences.

This strategy has advantages over common election polls in light of the aforementioned challenges. First, the possibility of targeting actual voters in exit polls enhances coverage of the prospective electorate. Second, measurements of preference structures permit theoretically informed predictions of how voters make up their minds between the ballots. Finally, first-round results provide powerful poststratification information to mitigate nonresponse bias. The polling and redistribution steps were previously tested in a local election (Selb et al. 2013). To scale the strategy up to national elections, this note focuses on sampling and validation in the context of the 2017 French presidential election. The first round, with 11 candidates in the running, took place on April 23.[1] The following sections detail the methodology of the exit poll fielded on that occasion. We then provide theoretical motivation and validation of our prediction of the runoff between Emmanuel Macron and Marine Le Pen on May 7. The final part discusses strengths and limitations, and suggests further improvements.

1. See section A of the Supplementary Material for a detailed description of the legal framework and campaign context.

Step 1: Sampling Polling Stations

The sampling of polling places for exit polls is generally facilitated by the availability of rich background information. Most importantly, past election results are often strong predictors of current support for candidates and parties. Exit polls in the United States and elsewhere use this information to stratify the population prior to sampling to get better estimates at lower cost (Barreto et al. 2006). In a multicandidate election, stratification by past results becomes difficult, especially if the number of polling sites to be selected is small. A tight budget limits the number of polling stations to be covered by our survey to 20 out of roughly 65,000. *Rejective sampling*, in which probability samples are drawn repeatedly until the sample statistics of auxiliary vectors are within a prespecified range of the population parameters (Valliant, Dorfman, and Royall 2000), is an alternative procedure to generate such *balanced* samples. Rather than defining arbitrary thresholds, we draw a sufficiently large number of samples of polling stations[2] and then select the sample that is most balanced regarding the 2012 first election round. The algorithm involves the following steps: (1) Draw k samples of m =20 polling stations, h, with probabilities proportionate to the size (PPS) of their local electorate in the previous election. (2) For each sample, estimate the national first-round vote share of each candidate, j, in the previous election using the vote share of j at station h. (3) For each sample, calculate the squared difference between the PPS weighted estimate and the actual nationwide vote share of all the J candidates in 2012. (4) Choose the sample that produces the smallest squared difference, on average, for conducting the exit poll.

To validate our sampling strategy, we replicate this process r = 1,000 times to get $r \times k$ =200,000 PPS samples, 1,000 of which are balanced with respect to the *previous* election result. For each of these samples, we estimate the *current* 2017 national vote shares using the official station-level results in round 1. Figure 1 presents the densities of the estimates from all PPS samples and the balanced samples for each of the four strongest candidates. The results for all 11 candidates can be found in table C1 in the Supplementary Material. The efficiency gains through balanced sampling turn out to be substantial. The ratios of the empirical variances of the estimates from the balanced relative to the standard PPS samples ("design effects") peak at 0.19 for Le Pen, with an average of 0.6 across candidates.

The demonstrable accuracy gain notwithstanding, a drawback of rejective sampling is that it may modify initial inclusion probabilities in an unknown manner (Valliant, Dorfman, and Royall 2000). However, a comparison of

2. Simulation results suggest that the marginal increase in balance diminishes with $k > 100$ samples. See figure C1 in the Supplementary Material. We choose $k = 200$, with an additional 100 samples as a "safety net."

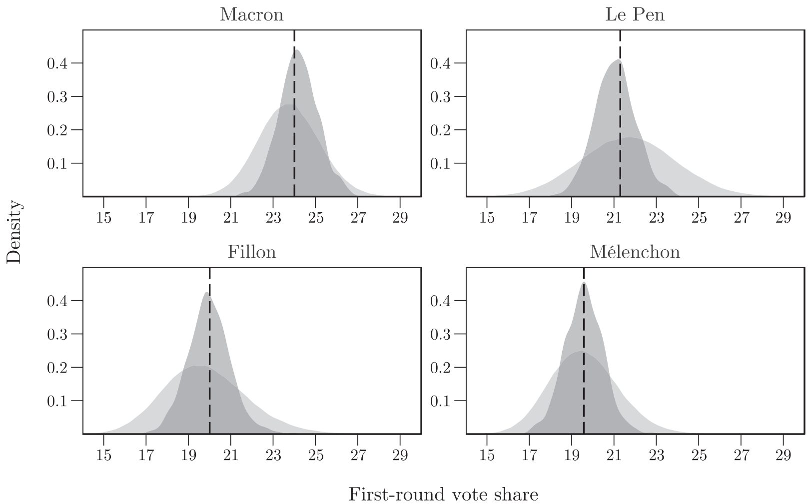

Figure 1. Standard PPS versus balanced samples: simulation results. Densities of the estimates from $r \times k = 200{,}000$ PPS samples of size $m = 20$ in light gray; in dark gray, those from the 1,000 balanced samples. Vertical lines indicate actual 2017 vote shares.

initial with empirical inclusion probabilities from our simulation (see columns 5 and 6 in table C2 in the Supplementary Material) and a replication of our predictions in tables 1 and 2 using the empirical inclusion probabilities (see tables C3 and C4 in the Supplementary Material) suggest that these discrepancies are negligible.[3] Therefore, we use the design inclusion probabilities to calculate the point estimates but approximate their stage 1 sampling variances with the delete-1 Jackknife technique (Wolter 2007).

Step 2: Sampling Voters and Surveying Their Candidate Preferences

PPS sampling in stage 1 helps us focus scarce interviewer resources on larger polling stations that contribute more to the national election result. For analytic ease, our on-site sampling strategy aims at establishing equal overall inclusion probabilities for voters, through constant sample sizes in stage 2. This target turns the spotlight on Avignonet-Lauragais, the place with the smallest

3. With roughly 65,000 polling stations and a sample size of just 20, the empirical inclusion probabilities are too bumpy after only 1,000 draws of balanced samples. Therefore, we boost the simulation to produce 25,000 balanced samples.

Table 1. Predicted and official first- and second-round results

	Round 1				Round 2	
Step	Macron	Le Pen	Fillon	Mélenchon	Macron	Le Pen
Sample	25.0	19.8	18.3	21.5	68.7	31.3
	(1.3)	(2.0)	(1.9)	(1.8)	(2.8)	(2.8)
Survey	27.1	13.5	15.3	26.3	73.5	26.5
	(1.4)	(1.6)	(1.8)	(2.7)	(3.2)	(3.2)
Poststratification	–	–	–	–	64.2	35.8
					(1.3)	(1.3)
Imputation	–	–	–	–	66.0	34.0
					(1.6)	(1.6)
Official	24.0	21.3	20.0	19.6	66.1	33.9

NOTE.—Jackknife standard errors appear in parentheses. Sample: estimated vote shares based on official results from the sample of polling stations. Survey: reported vote shares (Round 1), shares of redistributed votes (Round 2) from the exit poll. Poststratification: shares of redistributed votes, re-weighted by national round 1 results. Imputation: shares of redistributed votes based on imputed candidate ratings, re-weighted by official round 1 results. Official: official election results. Figures for minor candidates are reported in table C5 in the Supplementary Material.

electorate included in our sample ($N_h = 254$), as it sets the limit for the maximum possible constant sample size in stage 2. Under the assumptions that (1) 40 percent of the voters will vote during the field period (interviews were limited from 11:00 to 16:00 to account for the travel time required to reach the polling places), (2) 10 percent of the selected voters will be missed at busy times, and (3) 40 percent of the contacted voters will refuse to participate in the survey, and the tightest possible sampling interval of 1 (i.e., every voter leaving the polling place will be approached), the second-stage sample size will be $254 \times 0.4 \times 0.9 \times 0.6 \times 1 \approx 55$.

On election day, interviewers operated in teams of two. One interviewer monitored the sampling procedure and indicated the target voters to the second interviewer, who invited them to complete a short, self-administered questionnaire. The questionnaire asked respondents to indicate the candidate for whom they had voted, to evaluate each of the 11 candidates on a seven-point sympathy scale with an additional "don't know" category, and to indicate their gender and age group (see fig. C2 in the Supplementary Material).

Overall, the realized sample includes $n = 1{,}060$ respondents, which is very close to the targeted $20 \times 55 = 1{,}100$. One hundred respondents failed to report their vote choice and were excluded from the analysis. Further information on the sampling and data collection process is given in table C2 in the Supplementary Material.

Table 2. Predicted redistribution of first-round votes

First-round candidate	Macron	Le Pen	Abstention
Macron	8,467,238	189,108	0
	(113,895)	(113,895)	(0)
Le Pen	757,217	6,921,274	0
	(245,632)	(245,632)	(0)
Fillon	3,908,756	1,782,150	1,522,089
	(396,617)	(247,120)	(273,195)
Mélenchon	4,253,901	504,282	2,301,768
	(209,588)	(121,568)	(178,013)
Hamon	1,641,708	148,934	500,646
	(100,929)	(56,604)	(107,415)
Dupont-Aignan	594,020	530,843	570,136
	(100,185)	(128,481)	(123,615)
Lassalle	252,475	49,515	133,311
	(77,319)	(36,689)	(60,546)
Poutou	198,239	89,750	106,516
	(76,253)	(62,984)	(66,200)
Asselineau	57,008	192,402	83,137
	(39,732)	(55,664)	(41,584)
Arthaud	138,501	18,591	75,292
	(49,114)	(22,690)	(49,170)
Cheminade	16,397	16,396	32,793
	(18,454)	(18,454)	(21,308)
Total	20,285,460	10,443,245	5,325,690
	(590,089)	(473,654)	(368,629)
Official	20,743,128	10,638,475	4,672,790

NOTE.—Entries are estimated vote totals transferred from the first-round candidates in the rows to the runoff candidates in the columns, with jackknife standard errors in parentheses. Our method does not discriminate between abstention, blank, and invalid votes; they are all subsumed in the column Abstention.

Step 3: Poststratification to National First-Round Results

Nonresponse may bias inferences from election polls if the preferences of the respondents differ from those of the nonrespondents. Indeed, some observers consider nonresponse as one of the major culprits in recent polling failures (Kennedy et al. 2018; Sturgis et al. 2018). The refusal rate in our exit poll was 34 percent and thus somewhat lower than the 40 percent we had anticipated. Table 1 ("Survey") suggests considerable nonresponse bias: Le Pen and Fillon supporters are markedly underrepresented in our exit poll, while Mélenchon supporters are overrepresented. Given that our interviewers were mostly students from political science departments, this may well be due to differential reactions of would-be respondents to the social style of the interviewers (Dohrenwend, Colombotos, and Dohrenwend 1968). Other possible reasons for the discrepancies include coverage errors due to different groups of voters voting at different times of the day (Busch and Lieske 1985). Whatever the reason, we poststratify our voter sample to reflect the distribution of first-round national election results. Variance estimates are then adapted according to Valliant (1993). Assuming that the lower-order candidate preferences of the respondents do not systematically differ from those of the nonrespondents, poststratification restores the representativeness of the preference distribution in our voter sample.

Step 4: Imputation of Missing Candidate Ratings

Seven percent of the respondents who voted for an eliminated candidate in round 1 failed to rate either or both Macron and Le Pen. We impute the missing ratings using valid reports on round 1 vote choice, candidate ratings, polling station affiliation, sex, and age group.[4] The imputations implicate limited campaign dynamics in the sense that voters with incomplete preferences learn about the runoff candidates' positions and personalities between election rounds. But they only learn what other, presumably better-informed, voters already knew in advance. These voters' (complete) response patterns are thus informative for the missing candidate ratings. Otherwise we assume stated preferences to be stable between election rounds. A look at the bivariate distribution of sympathies for the runoff candidates before and after imputation (see fig. C3 in the Supplementary Material) suggests that most voters with incomplete candidate preferences "learned" that they either disliked both candidates or liked Macron while they disliked Le Pen.

Step 5: Redistribution of Votes for Eliminated Candidates

The key element of our forecasting strategy is the redistribution of votes for eliminated competitors in line with the Downsian model of voting. Accordingly, voters compare the expected utilities they would receive were each candidate in office. Assuming there are only two candidates competing, if the expected utility differential is positive, the voter votes for the first candidate; if it is negative, she votes for the second candidate; if it is zero, the voter is indifferent and abstains (Downs 1957, pp. 36–45). Lewis-Beck (1996)

4. Specifically, we use *multiple imputation with chained equations* with only the main effects (MICE; see White, Royston, and Wood 2011).

provides validation results for the measurement of expected utilities using sympathy ratings in a French election survey.

Our strategy deviates from other polls that directly survey hypothetical runoffs. One problem of this approach is that the effort quickly increases with the number of candidates. For example, with 11 first-round candidates, the number of hypothetical runoffs between pairs of candidates {1, 2}, {1, 3}, ..., {1, 11}, {2, 3}, ..., {10, 11} is 55 (that is, the binomial coefficient given two candidates to be chosen from among 11). French pollsters therefore include only the plausible scenarios. In 2002, however, many polls failed to include the actual runoff, Jacques Chirac versus Jean-Marie Le Pen (Miguet 2002). For a theoretical and empirical assessment of ratings and pairwise comparisons, see Jacoby (2006).

Table 2 reports the estimated voter transitions from round 1 to round 2. Strikingly, our projection suggests that at least 20 percent of the supporters of eliminated candidates abstained or voted blank in round 2. This proportion was particularly high concerning Mélenchon voters, who were the most likely to feel alienated by both the extreme-right Le Pen and the candidacy of Macron, who had been systematically portrayed by Mélenchon as being overly liberal and a danger for social rights. Still, according to our estimates, a clear majority of Mélenchon voters supported Macron in the runoff. The same holds for supporters of Fillon and socialist candidate Hamon. Curiously, a substantial share of first-round supporters of Le Pen voted for Macron in round 2 (i.e., gave higher ratings to Macron). A potential explanation for this puzzling observation is "pushover tactics" (Bouton and Gratton 2015).

The additional votes won by Le Pen came mainly from the supporters of Fillon, Mélenchon, and Dupont-Aignan, accounting for about 80 percent of her second-round gains. Among supporters of minor candidates, Le Pen was most successful with those who had backed either Asselineau, whose main proposal was a French exit from the EU, or Dupont-Aignan, who was as conservative as Le Pen on social issues (see fig. B1 in the Supplementary Material) and the only presidential hopeful to have endorsed her before the runoff.

Validation and Comparison to Other Polls

The bottom row in table 2 displays official election results for validation. The predictions for both Macron and Le Pen are close to the official figures, well within one standard deviation of their sampling distribution. As to abstention (which also includes blank and invalid votes), this method predicts a sharper decline in valid turnout than actually observed. One possible reason for this discrepancy is that the voters with candidate differentials of zero turned out anyway, and relied on implicit attitudes to render a judgment (Ryan 2017).

Another possibility is that these tied voters behaved exactly as we predicted, but that fresh voters who did not turn out in round 1 blurred the predicted turnout decrease among round 1 voters (a point to which we return in the conclusion). Figure 2 pits our forecast against common vote intention polls conducted after round 1, this time in terms of estimated vote shares instead of totals to warrant comparability.[5]

Apparently, our prediction outperforms all the other polls. Finally, table 1 unravels the contribution of each of our method's steps to the final predictions. While our sample of polling stations is reasonably balanced with respect to round 1 results, the respondent pool in our exit poll is a skewed representation of first-round voters. Poststratification to first-round results dramatically improves our predictions and is thus an integral part of our method. What we find particularly interesting, however, is the extent to which the imputation step contributes to the accuracy of the final predictions. Considering the limited dynamics the imputation approach entails between election rounds, this result supports the paradigmatic view of minimal campaign effects (Bennett and Iyengar 2008).

Discussion

We presented a versatile polling strategy to predict and analyze voting in runoff elections that has some merits over standard election polls. Methodologically, first-round exit polls are less vulnerable to coverage errors than common preelection polls that have to rely on self-reports subject to social desirability issues, or on statistical models to identify likely voters (Prosser and Mellon 2018). Moreover, first-round election results provide powerful poststratification information to mitigate nonresponse bias and other errors of representation, and to increase the statistical efficiency of the estimates. Finally, accuracy gains through balanced sampling limit the required number of polling stations, and thus even allow researchers with small budgets to use the method. Our sampling strategy is not limited to two-round elections and could prove equally valuable for traditional exit polls used for election-night forecasting, which have recently come under criticism (Salvanto 2018). Also, the measurement part of our method is easily integrated with any commercial exit polls that are already conducted in many countries with two-round elections (though not in France; see Pina 2019).

A drawback of our sampling approach as well as other rejective methods for selecting balanced samples is that they may alter initial inclusion probabilities in unknown ways and thus make it difficult to determine estimates and

5. To our knowledge, all these polls use quota samples based on age, gender, occupation, region, and community size from online access panels.

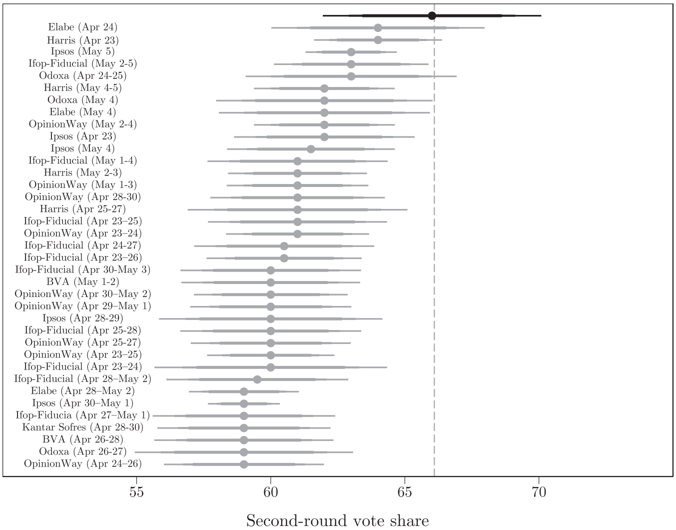

Figure 2. Poll-based forecasts of Macron's second-round vote share. The dashed line indicates Macron's official second-round vote share. The black point indicates our forecast and gray points poll predictions together with 90 percent, 95 percent, and 99 percent confidence intervals. The polling results were taken from https://en.wikipedia.org/wiki/Opinion_polling_for_the_French_presidential_election,_2017.

their sampling variances analytically. The *cube method* (Deville and Tillé 2004) is an alternative balanced sampling scheme that preserves design-based inclusion probabilities.[6] Another problem inherent in our method is its inability to incorporate fresh voters. A projection of the runoff result based on the redistribution of votes for eliminated round 1 candidates implies that the second-round electorate is identical to, or a subset of, the first-round electorate. However, official election data reveal that 6.2 percent of the round 2 electorate were indeed fresh voters (Buisson and Penant 2017). We "solved" this problem by tacitly assuming that fresh voters have preferences that do not systematically differ from those of the persistent voters. If this problem is considered virulent, a better solution would be to use past election statistics or additional survey data to predict the behavior of fresh voters (Salvanto 2018). Likewise, absentee and early voting (which is not permitted in France) is often an issue in exit polling (Mokrzycki, Keeter, and Kennedy 2009).

Substantively, the data collected offer analytic potential beyond its original use for election forecasting. This includes the analysis of hypothetical runoff

6. We are grateful to a reviewer for pointing this out.

scenarios to ascertain the Condorcet winner and the spatial analysis of candidate evaluations (see section B of the Supplementary Material). That way, our method helps increase the scholarly relevance of election polls. As van der Eijk (2005) notes, we usually learn little about elections and voting behavior from forecasting exercises, largely because of their weak micro-foundations. Our forecast is built bottom-up from theoretically sound predictions of individual candidate choices. Confronting our election forecast with empirical reality thus also provides a way to evaluate the method's theoretical underpinnings. Still, aggregate validation leaves plenty of room for ambiguities. For instance, is our overestimation of the decrease in valid votes between round 1 and 2 due to supposedly indifferent first-round voters participating at higher rates than predicted, or is it due to fresh voters entering the runoff? Are candidate preferences really stable between the election rounds? Do voters with incomplete preferences learn about the runoff candidates in accordance with our imputation approach? These questions are hard to answer with official statistics as the only yardstick. A promising step forward would be to implement a panel study in which respondents are contacted again after the runoff to learn about their second-round candidate evaluations and choices.

Supplementary Material

SUPPLEMENTARY MATERIAL is freely available at *Public Opinion Quarterly* online.

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