Casting ballots when knowing results*

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Abstract

Access to information about candidates' performance has long stood as a key factor shaping voter behaviour but establishing how it impacts behaviour in real-world settings has remained challenging. In the 2018 Brazilian presidential elections, unpredictable technical glitches caused by the implementation of biometrics as a form of ID led some voters to cast ballots after official tallies started being announced. In addition to providing a source of exogenous variation of information exposure, runoff elections also enable us to distinguish between different mechanisms underlying the impact of information exposure. We find strong support for a vote-switching bandwagon effect: information exposure motivates voters to abandon losing candidates and switch support for the frontrunner—a finding that stands in the second round, when only two candidates compete against each other. These findings provide theoretical nuance and stronger empirical support for the mechanisms underpinning the impact of information exposure on voter behaviour.

Keywords: Voter behaviour; bandwagon effect; underdog effect; strategic voting; natural experiment; Brazil

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First, it's absurd, right? Queuing for four hours to vote. But I think the worst part was to vote knowing about the results. Man, I got desperate. [...] Everyone was desperate, without knowing what to do, who to vote for. [...] Like, I swear, I was shaking when voting. I was shaking. It was 10 minutes of desperation. Everyone talking to me on Instagram. How come Bolsonaro will win in the first round [of elections]? Like, [he has] 49% [of the votes], for Christ's sake. Seriously, it was exasperating.

In a WhatsApp audio message,[1] this is how a Brazilian voter described her state of mind while waiting in the queue to vote in the 2018 presidential elections. Her description is aligned with questions political scientists have asked for decades: does information about candidates' electoral performances impact voters' decisions?

Many studies argue that, yes, learning about candidates' electoral prospects—either through polls or earlier electoral results—impacts voters' behaviour. But how? One possible explanation is that information exposure changes voters' participation levels in ways that increase the frontrunner's lead over losing candidates, resulting in an observed "bandwagon effect" (e.g., Agranov et al., 2018; Dubois, 1983; Morton et al., 2015; Gartner, 1976). Another possibility is that learning about candidates' performances leads some voters to abandon predicted losers and switch support to the frontrunner (e.g., Gallup and Rae, 1940; Bischoff and Egbert, 2013; Evrenk and Sher, 2015). Information exposure may also prompt voters to adjust their preferences strategically to avoid a less-preferred outcome; in some instances, these strategic calculations could also increase the frontrunner's advantage over other candidates (e.g., Cox, 1997; Eggers and Vivyan, 2020; Kawai and Watanabe, 2013).

Although theoretically different, in naturally occurring elections, the empirical outcomes of these mechanisms are often observationally equivalent (Barnfield, 2019; Evrenk and Sher, 2015;

[1]Personally acquired by authors on 07 October 2018, translated from Portuguese, and reproduced here with written consent.

Chung et al., 2018). As such, many existing studies on the impact of information exposure on voter behaviour have relied on survey or laboratory experiments seeking to replicate electoral conditions (e.g., Fleitas, 1971; Farjam, 2020; Agranov et al., 2018; Morton and Ou, 2015; Bischoff and Egbert, 2013). In the current article, we exploit an unique source of exogenous variation to examine whether exposure to information impacts voters' behaviour in a real election; in so doing, we provide more fine-grained causal and theoretical assessments than previous studies.

In 2018, for the first time in Brazilian history, fingerprints were used as the main form of identification for 73.6 million voters—more than half of the electorate of 147.3 million people. Technical glitches associated with the use of the newly introduced biometric identification technology caused delays in voting processes, leading some voters to cast ballots after the release of the first official vote tallies. In other words, variation in delays in some polling stations meant that some voters cast ballots under different conditions of exposure to partial results. Using timestamp data of the last vote cast in each voting machine (N = 454,490), we identify the places where voters were still casting ballots after electoral results started being announced. This allows us to examine whether gaining knowledge of the results affects support for the predicted winner and losing candidates.

In addition to this empirical opportunity, the institutional set-up of Brazilian presidential elections also enables us to get past the equifinality and to not only estimate the impact of information exposure on voter behaviour, but also to locate the mechanism driving the observed effects. Specifically, the setting allows us to account for mobilization and candidate support rates, as well as to examine the impact of information exposure on voter behaviour under two scenarios: in the first round, when there are various candidates competing and strategic voting is possible; and in the second round, when only two candidates compete for the majority of votes and strategic vote-switching is not possible.

With data from the first round of elections, in which 8,548 (1.6%) of voting machines were "treated" as a result of technical glitches, we find support for the explanation that access to information about candidates' electoral performances leads to a bandwagon effect through conversion. Specifically, we find that exposure to electoral results increased support for the frontrunner by 5.69 percentage points (pp) and decreased support for the second and third runner-ups by 7.41 pp and 1.97 pp, respectively.

Because there are more than two candidates competing in the first round, however, these observed effects could have been the product of strategic voting. Employing data from the second round of elections, in which technical glitches resulted in 1,024 (0.24%) of machines remaining open past the time of announcement, we find that when only two candidates compete for the majority of votes, information exposure *still* resulted in a 11.76 pp increase in support for the predicted winner and a 12.14 pp loss for the predicted loser. This confirms that information exposure benefited the frontrunner through a vote-switching (i.e., conversion) bandwagon effect, not strategic voting.

A series of alternative model specifications provide further robustness to our findings. Notably, in analyses with data from the previous 2014 elections, we show that treated units were not in constituencies already more prone to supporting the frontrunner. In addition, in placebo tests, we show that our results cannot be explained by voters' experience of waiting in the queue alone: bandwagon effects *only* emerge in units where voters were still casting ballots after the threshold of exposure to electoral results.

Our findings show that gaining knowledge of a candidates' lead can convert voters' support in his favour even in the unlikely context of a highly polarized, high-stakes election. These findings have normative implications: in free and fair elections, every vote should count equally; but, because it prompts a bandwagon effect, exposure to information gives greater weight to early voters' preferences.

Information exposure and voter behaviour

Since Duverger (1954), generations of political scientists have sought to better understand the factors that shape voter decisions. Access to information has since stood as a key factor: even when candidate options and voters' ideological preferences are taken as given, evaluations of candidates' electoral prospects may still impact voters' choices (Downs, 1957; Gartner, 1976)—even if voters themselves underestimate the impact of information on their behaviours (Chung et al., 2018).

Voters can attain information about candidates' electoral prospects through various means. Most commonly this happens through pre-electoral polls (Hardmeier, 2008; Schmitt-Beck, 1996; Moy and Rinke, 2012). Electoral rules that make elections sequential, such as primaries or runoffs, also give voters knowledge about candidates' performances in a first race, allowing them to make estimations about candidates' electoral potential in subsequent races (Bartels, 1988; Morton and Williams, 1999).

Increasingly, however, new information about candidates' electoral prospects—via leaked exit polls, for example—emerge *while elections are taking place and voters can still cast ballots* (Morton et al., 2015). These instances are different from the previously mentioned in significant ways. First, these are cases of otherwise simultaneous elections that only become sequential as a result of the unanticipated dissemination of information. Second, the information released in these circumstances is more precise than in the aforementioned ones and reveal the *actual* choices of early voters.

Historically, scenarios prompting sequential voting in technically simultaneous elections have been more common in countries with multiple time zones, where polls close in some parts of the country while remaining open in others. The 1980 U.S. presidential race is perhaps the most notorious: Carter conceded to Reagan based on media coverage of East Coast results, but polls had not yet closed in the West—something that has been associated with lower turnout and support rates for Democrats also in Western congressional races (e.g., Carpini, 1984; Dubois, 1983).[2]

In spite of similar recurring occurrences in the U.S. and elsewhere since, the scholarship remains inconclusive about the direction and underlying mechanisms of the impact of information exposure on voter behaviour. According to some, access to information about candidates' prospects results in a bandwagon effect by encouraging conversion—that is, vote-switching away from predicted losers and in favour of the frontrunner (e.g., Gallup and Rae, 1940; Bischoff and Egbert, 2013; Evrenk and Sher, 2015; Kenney and Rice, 1994; McAllister and Studlar, 1991). This effect could be driven by various types of psychological motivations, including late voters' use of early voters' preferences as a heuristic for candidates' competence; individuals' desire to be associated with winners; or altruism (Barnfield, 2019; Morton and Ou, 2015; Moy and Rinke, 2012).

Others, have argued that voters do not change their preferences, but, instead, are more likely to undergo the cost of voting if their preferred candidate is expected to win. Conversely, learning about their preferred candidates' predicted losses could demobilize voters and result in lower turnout rates amongst supporters of the trailing candidate (e.g., Agranov et al., 2018;

[2]Some scholars have challenged these findings based on data quality and model specifications (see: Morton et al., 2015).

Großer and Schram, 2010; Grillo, 2017; Morton et al., 2015; Duffy and Tavits, 2008). While these mechanisms are distinct, their observable aggregate outcomes would be the same, making it difficult to disentangle between them.

Instead of a bandwagon effect, information exposure could also prompt the opposite: an "underdog effect"—a less common prospect (Hardmeier, 2008) that seems to be more likely in noncompetitive elections (Chatterjee and Kamal, 2020). Similarly to a bandwagon effect, the underlying mechanisms underpinning higher rates of support for the trailing candidate could also emerge from vote switching or changes in mobilization rates.

In addition, information exposure could also prompt "strategic voting". While definitions vary, strategic voting generally refers to processes whereby access to new information about candidates' electoral prospects leads voters to adapt their strategies (Cox, 1997). In these instances, voters may choose to forego casting a ballot for their favourite choice and support an alternative candidate when doing so could avoid a less-preferred outcome (e.g. Heath and Evans, 1994; Alvarez and Nagler, 2000; Blais et al., 2011; Kawai and Watanabe, 2013).

Unlike bandwagon/underdog effects, strategic voting does not predict vote-switching for a specific winner/trailing candidate. As such, the observable effects of strategic voting can vary and are not always indistinguishable from those of bandwagon/underdog effects (Evrenk and Sher, 2015; Riambau, 2015). For example, in the scenario proposed by Eggers and Vivyan (2020) in which a voter "is nearly indifferent between the two frontrunners and strongly opposed to the third-place candidate, she is best off with an insincere vote [for the frontrunner]" (478), the aggregate outcome of strategic voting would be observably indistinguishable to that of a bandwagon effect.

In sum, while the scholarship has found plentiful evidence that access to information meaningfully impacts voter behaviour, disentangling the mechanisms underlying observable aggregate outcomes of information exposure on voter behaviour is most often not possible (Barnfield, 2019; Evrenk and Sher, 2015; Chung et al., 2018). To address some of the methodological challenges faced by studies employing data from naturally-occurring settings (e.g. McAllister and Studlar, 1991; Morton et al., 2015; Riambau, 2015; Chatterjee and Kamal, 2020), many studies have relied on survey or laboratory experiments seeking to replicate electoral conditions (e.g., Fleitas, 1971; Farjam, 2020; Agranov et al., 2018; Morton and Ou, 2015; Bischoff and Egbert, 2013). While these methods improve causal estimations and enable researchers to better disentangle mechanisms, the approaches yield low external validity: simulations tend to take place in unrealistic settings that cannot replicate the stakes of elections and are most commonly carried out among homogeneous groups of participants.

As we detail next, the 2018 Brazilian election provides an unique natural experimental setting, as well as an ideal institutional set-up that allows us to distinguish between different explanations of the impact of information exposure on voter behaviour.

The case of Brazil

The 2018 Brazilian presidential elections took place under contentious times, following the impeachment of Dilma Rousseff in 2016 and growing levels of voter distrust in political parties and elites (Hunter and Power, 2019). With 35 registered parties, 28 of which attained congressional seats in the 2014 elections, Brazil stands as one of the most highly fragmented party systems in the world (Power and Rodrigues-Silveira, 2019). Despite high party fragmentation, recent democratic history indicated the stability of a bi-partisan norm in presidential races, with candidates from the centre-left *Partido dos Trabalhadores* (Worker's Party, PT) and centre-right *Partido da Social Democracia Brasileira* (Brazilian Social Democratic Party, PSDB) generally competing for the country's highest office (Samuels and Zucco Jr, 2018).

In the months preceding the elections, increasing levels of polarization showed signs that the PT vs. PSDB race would not repeat itself in 2018: polls suggested the PSDB candidate, Geraldo Alckmin, to be highly unpopular; meanwhile, the imprisonment of PT's leader, former president Luiz Inácio Lula da Silva, meant that he had to be substituted for Fernando Haddad, a name that did not inspire voters to regain trust in the party (Hunter and Power, 2019).

At the same time, the growing popularity of far-right candidate Jair Bolsonaro, from *Partido Social Liberal* (Social Liberal Party, PSL)—a party that had secured only one seat in the Chamber of Deputies just four years prior—indicated voters' support for new leadership. While throughout the electoral campaign Bolsonaro and Haddad maintained the lead, they also retained the highest levels of voter rejection. This meant that, for many voters, keeping Bolsonaro or Haddad (i.e., the PT) out of office was the main goal (Rennó, 2020).

High rates of rejection towards the top two frontrunners provided the opportunity for other candidates to campaign as better alternatives to Bolsonaro and Haddad. As the election day approached, the centre-leftist Ciro Gomes, from *Partido Democrático Trabalhista* (Democratic Labour Party, PDT), took the lead as the most electorally viable third option.

If in the first round of elections none of the candidates is able to attain 50% (plus one) of the valid votes, the two candidates that receive the most votes compete in a second round. Although majoritarian in nature, the first round of elections thus grant voters the opportunity to signal their ideological preferences by casting a vote for a candidate closer to their ideological preferences—as a consequence, increasing the number of competitive candidates (Fujiwara, 2011; Guarnieri, 2015; Plutowski et al., 2020). In this second round, the candidate who secures the majority of the national votes wins.

The two rounds allow us to examine the impact of information exposure on voter behaviour in a race with multiple candidates and another with only two candidates—and thus to assess whether information exposure impacts voter behaviour in a scenario in which strategic voting is not possible. Critically, the highly polarized context of the 2018 Brazilian elections means that the first round of elections is a "most likely" case for the impact of information exposure on voter behaviour, but that the second round between Haddad and Bolsonaro—diametrically opposed candidates—presents a "least likely" scenario (Levy, 2008) for behavioural change, and thus a hard test for existing explanations on the impact of information on voter behaviour (Gartner, 1976).

Finally, the Brazilian case also offers granular data that allow us to distinguish between mechanisms driven by changes in mobilization and those prompted by vote-switching. This is because, besides casting ballots for specific candidates and parties, Brazilian voters can also display demobilization by casting blank or null ballots—options generally employed by those who are undecided, find all candidates inadequate, or choose to cast a protest vote (Zucco Jr and Nicolau, 2016)[3]. In addition, efforts to monitor compliance with compulsory voting also mean that we have precise information about the number of voters who did and did not turn up to vote. But although voting is compulsory, the penalty for not voting is a small fine of R$ 3.51 (US$ 0.90)[4] so abstention remains an option (Cepaluni and Hidalgo, 2016). In fact, an average of 20% of voters do not vote at each electoral cycle (Power, 2009), rates that are similar to those from countries with non-compulsory voting such as Sweden, South Korea, and New Zealand (Hutt, 2018). In the 2018 elections, the turnout rate was 79.95% in the first round and

[3]Null votes can sometimes also result from voters' inadvertent mistakes (Zucco Jr and Nicolau, 2016).
[4]On 8 October 2018, the day after the first round of the election, the exchange rate was 3.894.

78.84% in the second round.

Information exposure and the biometric system

Technical glitches that occurred in the 2018 elections also allow us to exploit a clear threshold of exposure to information about electoral results. Brazilian electoral regulation establishes that polls officially close at 17:00 local-time. Due to being home to three time zones, regulations stipulate that vote tallies can only start being released after the polls officially close in the last time zone, Zone 5 (encompassing the state of Acre and a small portion of Amazonas state). In practice, this regulation is meant to protect voters in all time zones from gaining knowledge about other regions' electoral preferences.

Severe delays in voting have traditionally been an unlikely prospect: in Brazil's modern democratic history, a number of electoral institutions have been put in place to facilitate the exercise of compulsory voting. Setting elections for a Sunday; assigning voters to electoral stations close to their registered residencies; limiting the number of voters per assigned polling station; and digitizing the voting experience through the use of electronic machines have generally meant that voting in Brazil was not a time-consuming affair (Nicolau, 2012).

Put differently, regulation establishing that the release of official results could only begin after the closing of polls in Zone 5 worked well in the past: elections were carried out efficiently and one- and two-hour differences across time zones ensured that voters from other regions of the country were done casting ballots before the official closing of elections in Zone 5, when the release of vote tallies began.

This was not the case in 2018. In this occasion, the use of fingerprints as a form of ID became mandatory for 73.6 million voters from 2,793 Brazilian municipalities (50.3% of the electorate).

The system was also available (but not mandatory) in another 1,533 municipalities, thus covering a total of 77.7% municipalities and 59% of the electorate. While the innovation did not cause disturbances in some voting stations, technical problems related to the identification of voters using fingerprint readers caused considerable delays in many others.

As explained by Giuseppe Dutra Janino, Head of the Secretariat for Information Technology of the *Tribunal Superior Eleitoral* (Superior Electoral Tribunal, TSE), technical errors happened when there were physical problems with the machines[5], or, more often, when reading voters' fingerprints took more than one try—a problem that emerged not only due to staff misplacing voters' fingers on the machines, but also from the inappropriate collection of biometric data in the period preceding the election (Clavery, 2018). To expedite the use of biometrics as a form of voter identification, the TSE operated a data sharing scheme with other government institutions. As such, the collection of voters' fingerprints was not all completed by electoral authorities, but also by other government authorities that issue ID cards (such as state transit departments, Detran) and whose main objective when collecting fingerprints is not their use as a form of identification (Mendonça and Albernaz, 2018).

As Figure 1 shows, technical problems that resulted from the use of biometrics meant that voters assigned to stations employing the system were significantly more likely to face delays and vote after 19:00 Brasília time (BRT)[6], when the TSE officially started disseminating vote tallies. Consequently, voters who cast ballots after the election's official closing time were plausibly better informed about predicted electoral outcomes than those who voted earlier[7].

[5]See Appendix A for more information on the machine used for fingerprint reading.

[6]One concern in our setting is that the implementation of the biometric system correlates with state capacity. In this case, we should expect a higher concentration of biometric voters in Brazil's wealthiest states. As Appendix B shows, this is not the case.

[7]"Official closing time" refers to established election hours, not the time of the last vote cast in a given machine. Voters who arrive at their assigned voting stations before their closing times can remain in queue and are guaranteed their right to cast a ballot. As such, the actual (i.e., recorded) time of closure of specific voting machines can be considerably later than their "official closing time."

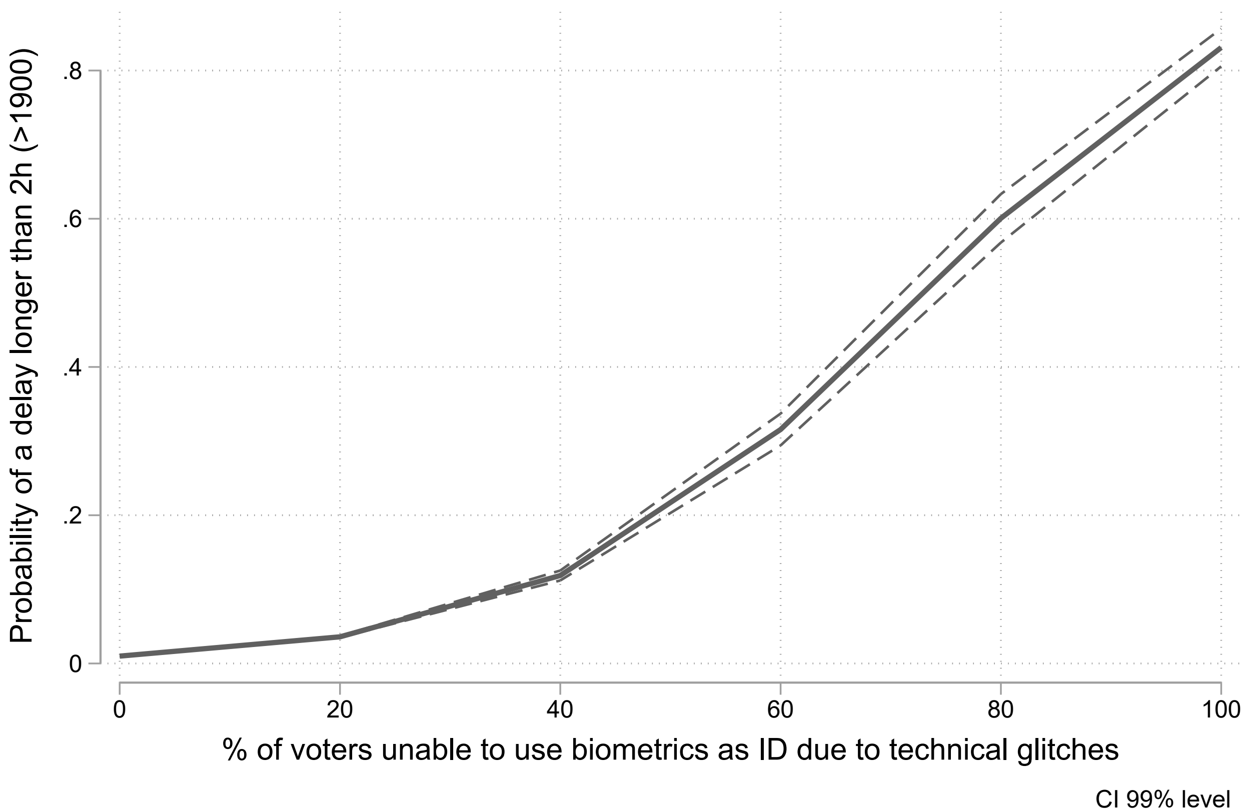
The rapid announcement of results and the vast employment of communication tools for political purposes in Brazil make it highly plausible that individuals still waiting in the queue at 19:00 BRT would have quickly become knowledgeable about early voters' preferences. First, the use of electronic voting machines means that electoral results are calculated speedily and start being publicly released immediately after the official closing time of polls in Zone 5. For example, in the first round of elections, when vote tallies started being released at 19:00 BRT, more than 65 million votes (44% of total votes) had already been counted (Grandin et al., 2018). Additionally, roughly 60% of Brazilian adults own smartphones and Brazil currently ranks third in the world in respect to number of hours spent in communication apps (Lopez, 2019). Critically, 99% of mobile phone users in Brazil communicate via WhatsApp—a tool that was key for the rapid dissemination of political information in the 2018 elections (Mello, 2020).

When the results started being announced, Bolsonaro had 48.83% of the counted votes, just 1.17% short of reaching the 50% (plus one vote) required to win on the first round. The second runner-up, the PT's Fernando Haddad, came 22.75 pp behind, with 26.08% of the votes, and the third runner-up, PDT's Ciro Gomes, had 12.50% of the votes. Throughout the counting (and announcement) of votes, Bolsonaro led by a wide margin of at least 16.45 pp (Grandin et al., 2018). In the second round, when results started being announced at 19:00 BRT, Bolsonaro had 55.7% of the votes and a 11.4 pp lead over Haddad (G1, 2018).

Hypotheses

By examining the share of ballots cast for specific candidates, as well as blank and null votes, we can identify and better disentangle the two underlying mechanisms of a bandwagon or an underdog effect; meanwhile, by comparing voters' behaviour in the first and second rounds

Figure 1: Probability of being exposed to information in the first round of the 2018 Brazilian elections



Note: The unit of analysis is voting machine (N = 453,319). We cluster standard errors at the level of voting machine (where the treatment took place). We run all logit estimates with controls for turnout rate, age (avg.), % of women voters, and years of schooling (avg.). All graphs in this article were produced using the plotplain developed by Bischof (2017).

of elections we can differentiate between bandwagon/underdog effects and strategic voting. Formally, our case and empirical strategy allow us to test five different hypothesized scenarios:

H1, demobilizing bandwagon effect: *Access to information induces a bandwagon effect by demobilizing voters who would otherwise support predicted losers*.

Since it is not possible to capture this at the individual-level (due to secret ballots), if this mechanism is in place we should observe no changes in the vote share of the predicted winner (Bolsonaro), but drops in the vote shares of the predicted losers (Haddad, the second place candidate, and Gomes, third place candidate in the first round), and higher shares of blank and null votes.

In theory, it is also plausible that a demobilizing bandwagon effect could emerge from differential rates of turnout, whereby voters who would have otherwise abstained would become motivated to support the frontrunner, while supporters of losing candidates would be more likely to withdrawal their participation in the election. In the 2018 Brazilian elections, however, only the latter was possible.

Information exposure was a product of technical glitches and only affected voters still in queue after their voting stations' official closing times. As per Brazilian electoral law, individuals who arrive after the station's official closing time are banned from entering voting stations and casting ballots, but voters who are *already in queue to vote* at a polling station's official closing time can still cast ballots. As such, in the 2018 elections, information exposure could only change turnout rates by prompting voters already in the queue to withdrawal. As we further detail in our empirical strategy, we account for this by controlling for turnout rates in all of our estimates.

H2, vote-switching bandwagon effect: *Access to information induces a bandwagon effect by* *prompting voters to abandon the predicted loser and switch votes to the frontrunner*.

Observably this would mean that exposure to information should result in a higher vote share for the predicted winner (Bolsonaro), lower vote shares for his losing competitors—Haddad (second place) and Gomes (third place in the first round)—and no changes in the shares on blank and null votes.

H3, mobilizing underdog effect: *Access to information induces an underdog effect by mobilizing voters who would otherwise abstain to support the predicted loser*.

If information exposure drives an underdog effect through mobilization, then we should observe no change in the vote shares of the predicted winner (Bolsonaro) or second place candidate (Haddad), but an increase in the vote shares of the third place candidate (Gomes)[8], and lower shares of blank and null votes [9].

H4, vote-switching underdog effect: *Access to information induces an underdog effect by prompting voters to abandon other candidates and switch votes to the predicted loser*.

Observably, this would result in a decrease in the vote shares of at least one of the two top contenders (Bolsonaro and/or Haddad), an increase in the vote share of the trailing candidate (Gomes), and no change in the shares of blank and null votes.

H5, strategic voting: *Access to information induces strategic vote-switching.*

Unlike expectations about bandwagon and underdog effects, strategic voting does not yield a single possible outcome and is shaped by voters' electoral preferences and less-preferred choices. Accordingly, in the first round of the 2018 Brazilian elections, strategic voting could yield a number of distinct outcomes: first, upon learning about Bolsonaro's lead, his sincere

[8]We restrict our analyses to the first three most popular candidates, instead of all 13. As such, we consider the "trailing" candidate to be Gomes.

[9]As previously conveyed in the case of the 2018 Brazilian elections, a mobilizing underdog effect could not be prompted by higher rates of turnout, given that voters arriving at their voting stations after information exposure (i.e., stations' official closing times) would have been barred from entering.

voters should not change their behaviour. The supporters of Haddad (second place) should also not change their behaviour in an attempt to ensure that Bolsonaro does not achieve the 50% (plus 1) threshold of votes that would win him the presidency in the first round.

Meanwhile, upon learning that Gomes is in the third place and has no chance of moving to the second round, Gomes' supporters could vote strategically. If their less-preferred outcome is an Haddad win, then they should vote-switch to Bolsonaro. If their less-preferred outcome is a Bolsonaro win, then they could vote-switch to Haddad if they believe that doing so would strengthen Haddad's perceived viability and chances of winning in the second round. However, it is also possible that Gomes' supporters whose less-preferred outcome is a Bolsonaro win would not change their behaviour, as doing so would not directly help defeat Bolsonaro in the first round.

Since Gomes' supporters plausibly have heterogeneous preferences regarding their less-preferred choices, it is unclear how strategic voting should observably impact candidates' vote shares. If at least some of Gomes' supporters who engage in strategic voting prefer Bolsonaro to Haddad, however, then Bolsonaro's vote share should increase. In the first round of elections, this observable effect would be indistinguishable from a vote-switching bandwagon effect. In the second round, however, only two candidates compete and strategic voting is not possible, so an increase in Bolsonaro's vote shares could only indicate a bandwagon effect.

Empirical strategy

In the 2018 Brazilian elections, unpredictable technical glitches that resulted from the implementation of biometrics as a form of ID caused delays and led some voters to cast ballots after official tallies were already being announced. This exogenous source of information exposure, combined with information about the timing of closure of voting machines, and granular electoral data from the first and second rounds of the presidential elections, allow us to enhance causal estimations of the impact of information exposure on voter behaviour and disentangle between its possible underlying mechanisms.

Data

In Brazil, citizens between the ages of 18 and 70[10] are assigned to a specific voting zone ("zona"), voting place ("local de votação"), and voting station ("seção") that become their permanent voting assignment[11]. A voting place could be a public school and a station could be a particular classroom within said public school where a voter would go to cast a ballot in every election. In each station, there is one voting machine—our unit of analysis[12]. This set-up means that technical glitches associated with the implementation of biometrics took place at the level of voting machines. That is, in some cases, voters assigned to the same public school but different classrooms could have voted under different conditions of information exposure.

Official data are available for each round of the election for all 454,490 of Brazil's voting machines[13]. On average, 323 voters are registered to cast ballots in each voting machine. With these data, we code five different outcome variables: 1) share of votes for Bolsonaro (frontrunner); 2) share of votes for Haddad (second place); 3) share of votes for Gomes (third place)[14]; 4) share of blank votes; and 5) share of null votes.

[10]Voting is optional for those between the ages of 16 and 18 or over 70.

[11]Unless they change domiciles or the electoral authorities redesign voting distributions (e.g., due to demographic growth).

[12]To be clear, voting stations and machines correspond to the same level of analysis.

[13]Not all voting machines contained ballots cast for our five outcome variables, hence the varying number of observations across our models.

[14]While there were 13 candidates competing in the first round of elections, the total vote shares of the first three contenders corresponded to 87.78% of the total valid votes. Furthermore, if no candidate attains 50% (plus 1) votes, only two contenders move onto the second round. This means that the first three contenders are the ones effectively competing for a straight win in the first round or one of the two spots in the second round. As such,

Official data also include the time of actual closure of each voting machine (i.e., when the last vote was cast). This allows us to identify which voting machines remained open after electoral results started being announced. Using this information, we identify our treatment and control units: machines that remained open *after* preliminary results started being announced (at 19:00 BRT) are considered to be treated and assigned a value of 1; machines that closed *before* 19:00 are in our control group and assigned a value of 0. In the first round, a total of 8,548 (1.6%) observations are in our treatment group. After significant delays in the first round, the electoral authorities sought to address problems with the implementation of the biometric system, so the number of units that were exposed to information dropped substantially. In the second round, 1,084 (0.24%) of voting machines were treated.

As illustrated in Figure 1 and Appendix C, technical glitches associated with the implementation of the biometric system increased the likelihood of information exposure in both rounds. In other words, exposure to electoral results overwhelmingly occurred in places where higher shares of voters had been registered to use the biometric system. As shown in Appendix B, Brazilian electoral authorities did not introduce the biometric system across the entire country at once. In the 2018 elections, higher shares of voters from the North and Northeast had been registered to use the system. By definition, the uneven adoption of the system throughout the country means that treated and untreated units are dissimilar across characteristics of the electorate: the North and Northeast are the poorest regions of the country and the electorate in these regions are younger and less educated than in other regions.

This, however, does not invalidate our identification strategy since the probability of occurrence of technical glitches was presumably the same in all voting stations using the

we restrict our analyses to the three most competitive candidates.

biometric system[15]. In sum, there is no reason to believe that the occurrence of technical glitches is associated with attributes of the electorate. As we show in the baseline models in Appendix D, pre-treatment controls for characteristics of the electorate do not change our estimates.

Identification

Using the previously described data, we estimate whether late voters' access to information about early voters' preferences affects their voting behaviour in each round of the election. We estimate Ordinary Least Squares (OLS) models for each outcome variable (i.e., Frontrunner, Second place, Third place, Blank, and Null) following the general specification:

$$Y_{ig} = \beta_0 + \beta_1 Treatment_{ig} + W_{ig} + \epsilon_{ig} \quad (1)$$

The dependent variable is Y, and the subscript $_i$ indicates that this varies across voting machines. Following the approach formulated by Abadie et al. (2017), $_g$ denotes that standard errors are clustered at the level of voting machines, where technical glitches occurred. *Treatment* is a dummy that takes a value of 1 for voting machines that closed after the results started being released at 19:00 BRT (i.e., the treatment group), and 0 for voting machines not affected by the release of information at 19:00 BRT (i.e., the control group).

Our models also include a vector of covariates, as represented by W_i in equation 1. Voting conditions may change over time for all units, regardless of whether or not they are treated. To

[15]Election procedures in Brazil are centralized, led, and regulated by national-level authorities and systematically implemented throughout the country. This means that the type of biometric machines employed and the training given to election staff on how to operate the machines, were also systematically adopted throughout the country. For example, all election staff were trained to attempt reading an individual's fingerprint four times before using another form of ID to identify them. In other words, there is no indication that exposure to information in some units results from something other than technical glitches.

account for this, we control for the timing of closure of voting machines with the variable *closure delay (in minutes)*. There are also other factors that could be associated with the likelihood of information exposure, so we control for the share of voters that faced technical issues when attempting to use the biometric system (% *error in biometrics*), and the *time zone* of the machine's location.

Although it is not possible for information exposure to change voter behaviour through an increase in turnout rates (since voters arriving at their stations after the time of information exposure, i.e., stations' closing times, would have been barred from entering), exposure to electoral results could still depress turnout, so it is possible that turnout rates are associated with changes in candidates' vote shares. To address this, we also control for turnout rates[16].

Finally, characteristics of the electorate could also affect voter behaviour, so we additionally control for the characteristics of voters registered to cast ballots in each voting machine, specifically: average *age*, incidence of *women voters*[17], and average *years of schooling*. Descriptive statistics for all variables are available in Appendix E.

Results

We begin by analyzing the impact of information exposure on the first round of elections, when there are more than two candidates. Figure 2 summarizes our findings (see Appendix F for the table of results).

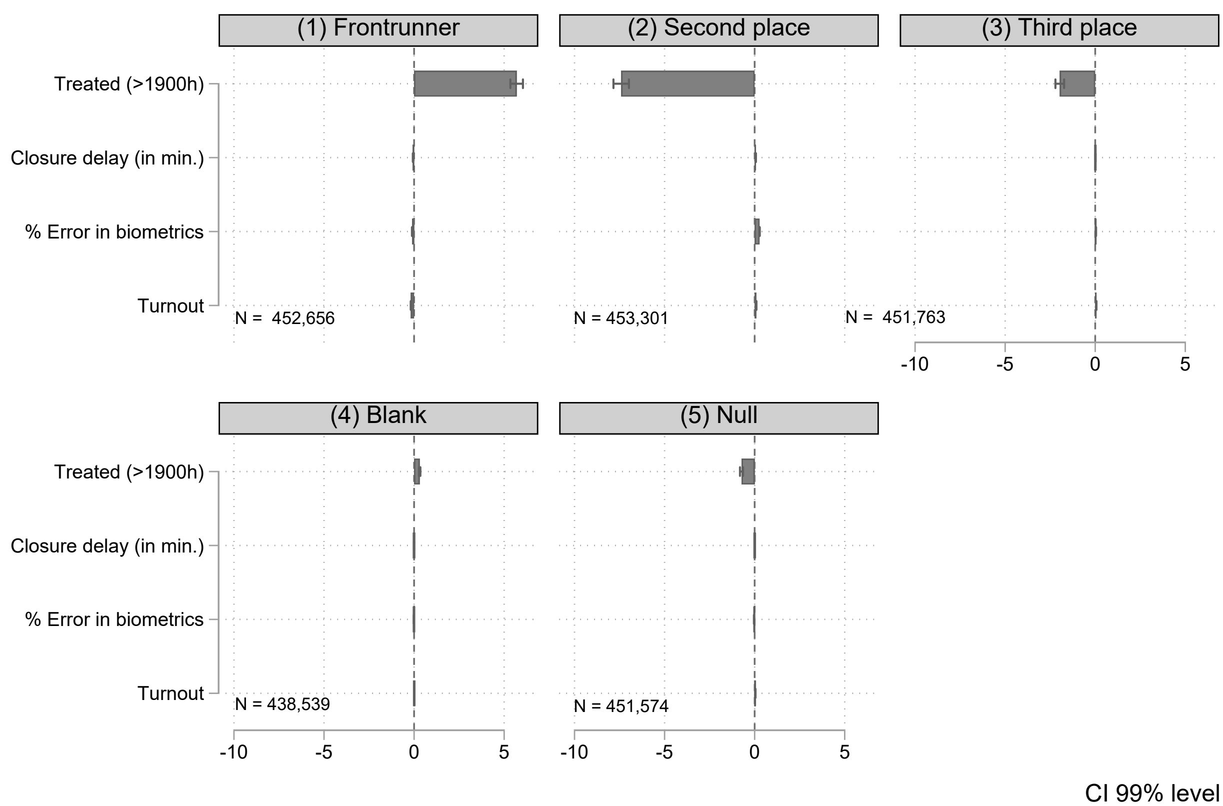
The positive and statistically significant treatment effect produced by Model 1 already hints that information exposure does not affect voters through the demobilization of disillusioned

[16]This is calculated by dividing the number of voters who turned-up to vote in a given voting machine by the total number of voters registered to vote in the same voting machine.

[17]This is an indicator that varies between 2 and 4. Values closer to 4 indicate higher incidence of women voters in a given voting machine.

voters (H1). Results from models 4-5 are mixed: although the treatment effect produced by Model 4 is positive and statistically significant, it is substantively small, indicating a negligible increase of 0.31 pp of blank votes in treated units. Conversely, the treatment effect produced by Model 5 is statistically significant but negative (the opposite of what this mechanism anticipates), indicating a decrease of 0.73 pp in the share of null votes in treated units. If anything, results from Model 5 suggest that information exposure might have led individuals planning on casting invalid ballots to, instead, vote for the frontrunner. Together, our models provide weak support for H1 and suggest that information exposure does not benefit the frontrunner through demobilization.

Figure 2: The effect of information exposure on voting behaviour (first round)



Note: The unit of analysis is voting machine. We cluster standard errors at the level of voting machine (where the treatment occurred). We run all OLS estimates with controls for time zone, age (avg.), % of women voters, and years of schooling (avg.).

Instead, our results provide stronger support for bandwagon conversion (H2): in addition to our finding that support for the announced frontrunner is 5.69 pp higher in treated units (Model 1), the treatment effects that emerge from Models 2 and 3 also indicate that information exposure led to a decrease in support for losing candidates. More specifically, we find that the rates of support for the second and third place candidates are, respectively, 7.41 pp and 1.97 pp lower in treated units. Taken together, our estimates indicate that, influenced by information about the electoral results, some voters abandoned their preferred choices of a losing candidate and switched their votes to the predicted winner.

Substantively, these results translate into an average increase of 14% in the vote shares of Bolsonaro in treated units and an average loss of 26% and 18% in the respective vote shares of Haddad (second place) and Gomes (third place)[18]. To ensure the integrity of elections, voting machines shuffle the order of individual votes. This means that while there is a timestamp to register when each machine is closed (which we use to derive our treatment), it is not possible to know how many voters cast ballots after the threshold of information exposure. In other words, we cannot provide precise estimations for the number of votes Bolsonaro gained and Haddad and Gomes lost due to information exposure. Nonetheless, in Appendixes G-I we provide estimations for a range of possible substantive effects.

In addition, the negative coefficient produced by Model 3 further indicates that we can reject the hypotheses of both mobilization-driven (H3) and vote-switching underdog effects (H4). In other words, information exposure does not seem to lead to an aggregate-level underdog effect in favour of the trailing candidate.

[18]We use the standard formula of percentage growth to estimate these effects. For example, in the first round, an average voting machine contained 41.12 votes for Bolsonaro (starting value). As per Model 1, the estimated effect of information exposure is 5.7 pp. We use these values in the standard formula of percentage growth by dividing the estimated effect by the starting value: 5.69/41.12 = 0.138 x 100 = 13.83, or roughly 14%.

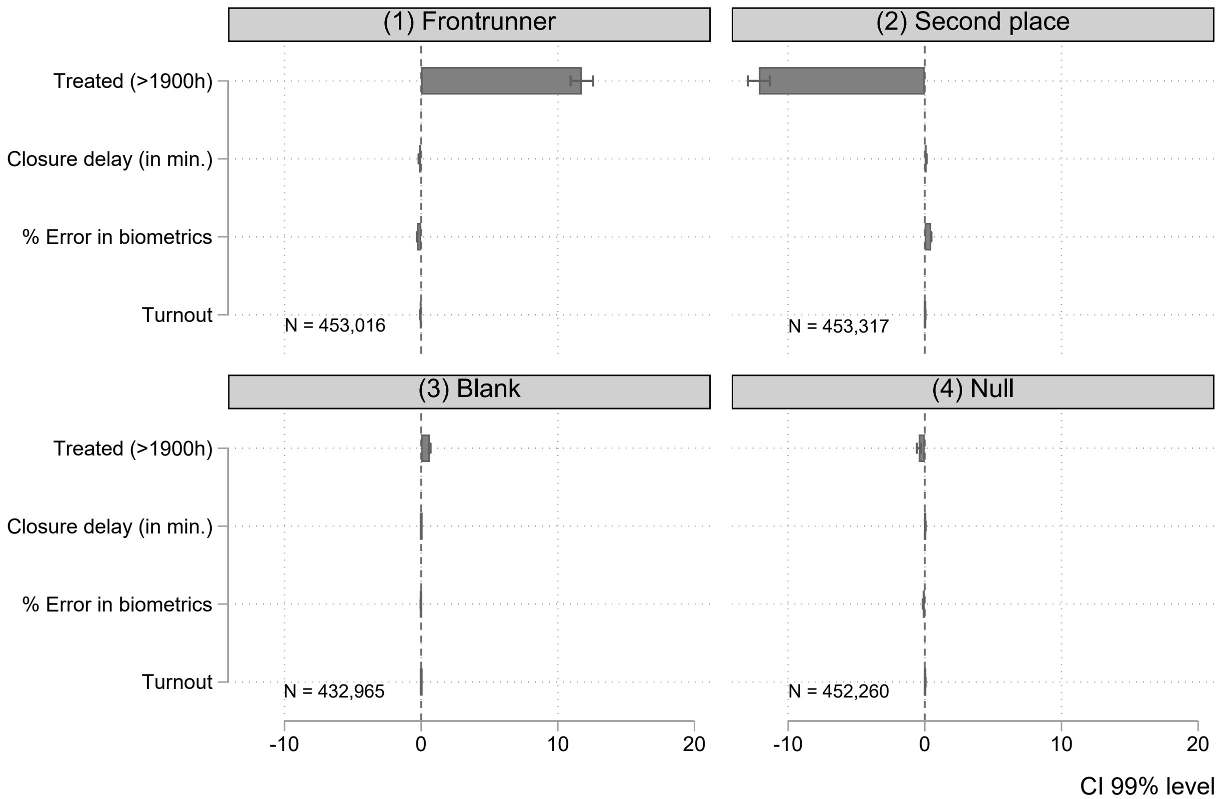
While coefficients across our models provide more cohesive support for H2, our analyses cannot fully reject that information exposure prompts strategic voting (H5): our findings are still consistent with a scenario in which a conversion bandwagon effect (H2) and strategic voting (H5) are simultaneously taking place, and thus where: 1) Gomes' supporters whose less-preferred candidate was Haddad switched votes to Bolsonaro; *and* 2) would-have-been supporters of Haddad jumped on the bandwagon of the predicted winner and switched support for Bolsonaro. Even in this scenario, however, strategic voting alone could not explain our results: vote-switching among Haddad supporters would still have to be operating. In sum, while we cannot fully reject H5 at this stage of the analysis, we can attest that our findings are, at least in part, driven by a vote-switching bandwagon effect (H2).

To rule out the possibility that the frontrunner's advantage (and contenders' electoral losses) emerges from strategic voting, we next examine whether information exposure impacted voting behaviour in the second round of the election—when the number of candidates is reduced to two and strategic voting is not possible.

Is it really a bandwagon effect? Examining information exposure in the second round of elections

Vote-switching should be particularly unlikely in a highly polarized election with only two opposing candidates. If results from Figure 2 are the product of strategic voting, we should not observe a bandwagon effect in our analyses of the second round. However, given Bolsonaro's lead at the time of announcement of second-round vote tallies, if a vote-switching bandwagon effect (H2) is indeed in place, we should observe an increase in the vote share of Bolsonaro among the treated units, a decrease in the vote share of Haddad, and no changes in the shares of blank and null ballots.

Figure 3: The effect of information exposure on voting behaviour (second round)



Note: The unit of analysis is voting machine. We cluster standard errors at the level of voting machine (where the treatment occurred). We run all OLS estimates with controls for time zone, age (avg.), % of women voters, and years of schooling (avg.).

This is precisely what we find. As Figure 3 shows (also see Appendix F for the table of results), when only two candidates compete for the final electoral outcome, information exposure still drives high levels of support to the frontrunner. As indicated by the treatment effect produced by Model 1, Bolsonaro's vote share increases by 11.76 pp in voting machines where voters were exposed to information.

Similarly to our previous findings, our analyses of voting behaviour in the second round suggest that the frontrunner's gained advantage is accompanied by a decrease of 12.14 pp in the vote share of the losing candidate in treated voting machines. As before, the impact of information exposure on mobilization rates is mixed and substantively small: the share of blank ballots is 0.62 pp higher, but the share of null votes is 0.44 pp lower in treated units.

These results indicate that information exposure benefits the frontrunner not because of strategic voting (H5), but through a bandwagon effect—more specifically, vote-switching away from the predicted loser and in favour of the frontrunner (H2). Substantively, our results translate into an estimated gain of 24% of support for Bolsonaro (frontrunner) in treated units and a loss of 28% for Haddad (second place). Appendixes F-G provide additional analyses of estimated substantive effects.

Robustness Checks

Our results also remain stable in a series of robustness checks. First, in natural experiments, it is possible that certain observations may be in a position to always receive the treatment or to have a zero probability of being in the control condition (Titiunik, 2020). Due to time zone differences, voting machines located in the state of Acre officially close at 19:00 BRT, which corresponds to our threshold for information exposure. As such, even minor voting delays in Acre would necessarily place Acre-based voting machines in the treatment condition. In Appendix J, we rerun our estimates without Acre-based observations and find results that are consistent with those summarized in Figures 2 and 3.

Second, 41% of the electorate was not registered to use biometrics as a form of voter ID, so not all voting machines were exposed to an increased probability of closing with delays (and, thus, information exposure). To address this, we also rerun our estimates on a restricted sample of observations where at least one instance of a biometrics-related technical glitch was recorded. As shown in Appendix K, our results are also robust to this test.

It is also possible that the effect of information exposure is heterogeneous and affects smaller and larger voting stations differently. If this is the case, our results could be driven by changes in voting behaviour in one type of voting station. In Appendix L, we test for this by producing separate models for voting machines with 0-220 registered voters (25th percentile), 220-339 registered voters (50th percentile), and more than 339 registered voters (75th percentile). Results across these models are largely consistent with the ones from our main estimates. The only difference comes from our analyses of the first round of elections restricted to the smallest stations: in this context, exposure to electoral results still produced an increase in the vote share of Bolsonaro (first place) and a decrease in the vote shares of Haddad (second place), but it also seems to have *increased* voter support for Gomes, the third-place candidate.

Finally, it is also possible that voters in treated units were already more prone to supporting the frontrunner, Bolsonaro, than voters in untreated units. Polls of voting intentions are not available at the level of voting machines, preventing us from conducting a direct analysis. We do the next best thing and examine the electoral preferences of treated and untreated units in the 2014 presidential elections. Before 2018, neither Bolsonaro nor his party had ever run for the presidency. However, the centre-left PT, the party of the second-place candidate, Haddad, was one of the main contenders. The PSDB, a centre-right party, was its main competitor. If units treated in 2018 were more prone to supporting the far-right frontrunner, we would expect them to have displayed disfavour towards the centre-left PT and a preference for the centre-right PSDB in 2014.

As shown in Appendix M, when we replicate our 2018 estimates with 2014 data, this is the opposite of what we find. In fact, units exposed to information in 2018 were more prone supporting the left-wing PT and less supportive of the centre-right PSDB. In other words, there is no evidence to suggest that units treated in 2018 were already more predisposed to supporting Bolsonaro; instead, their past electoral behaviour suggests that they would be, on average, more opposed to switching votes to a far-right candidate than other units.

In sum, across model specifications we find consistent evidence that information exposure results in a vote-switching bandwagon effect (H2). However, by assigning treatment status to voting machines that remained open after official electoral results started being announced, our empirical strategy captures the impact of information exposure indirectly. In a real-world setting, it is virtually impossible to know whether the release of vote tallies indeed meant that individual voters *saw* this information before casting their ballots—and, thus, that it was knowledge of electoral results that shaped their behaviour. For example, it is possible that it was not knowledge of results, but voters' experiences of waiting in queue that led late voters to behave differently from early voters. Because Bolsonaro ran as an anti-system candidate (Hunter and Power, 2019; Rennó, 2020), having an unpleasant voting experience could have also led voters to punish "insider" candidates that they more closely associated with state capacity and election logistics. We address this next.

Examining *non*-information exposure through placebo tests

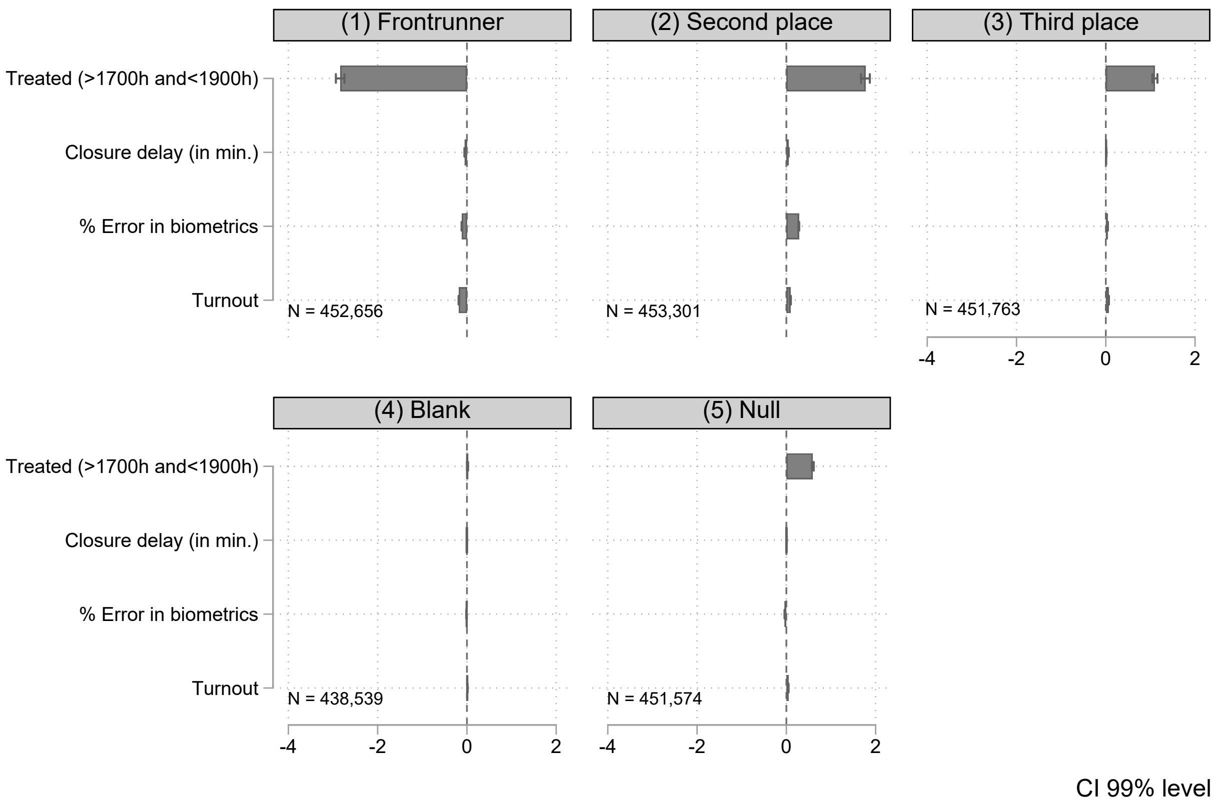
To ensure that our results emerge from gaining knowledge of results and not another mechanism related to voters' experience of waiting in queue, we run additional robustness checks with a placebo treatment. To be considered treated units in our placebo analyses, voting machines would have had to close with a delay (after 17:00 local-time) but before the announcement of electoral results (19:00 BRT). In other words, for these analyses, treated units encompass voting machines where voters faced delays and stayed in the queue but could not have been exposed to information.

Figure 4 summarizes our results for the first round of elections. As indicated by the direction of estimated effects, our placebo treatment shows no indication of a bandwagon effect. In fact, the direction of treatment effects in all models is opposite to what we would expect from a bandwagon effect: the frontrunner's vote share is *decreasing* before information exposure and the support for his contenders is *increasing*. We also find that our placebo treatment is associated with an increase in the share of null votes. This indicates that while waiting in queue does not lead voters to support the anti-system frontrunner (as indicated by Model 1), it potentially increases their tendency to cast protest ballots.

Estimates for the second round of elections confirm that the observable bandwagon effect does not emerge when voters face delays that do not surpass the threshold of information exposure (see Appendix N). As before, we also find that that the placebo treatment is associated with a decrease in the vote share of the frontrunner and an increase in the vote share of the losing candidate in the second round. Also similarly to our placebo analyses of the first round, in our second-round analyses, the placebo treatment is associated with increases in the share of protest ballots (i.e., blank and null votes).

In sum, our placebo tests of the two rounds of election indicate that a bandwagon effect *only* emerges when the treatment corresponds to units that faced delays past the time threshold of information exposure. These results provide further indication that our treatment indeed captures access to information and that a vote-switching bandwagon effect only occurs when late voters gain knowledge of early voters' electoral preferences.

Figure 4: The effect of non-information exposure on voting behaviour - Placebo treatment (first round)



Note: The unit of analysis is voting machine. We cluster standard errors at the level of voting machine (where the treatment occurred). We run all OLS estimates with controls for time zone, age (avg.), % of women voters, and years of schooling (avg.).

Conclusion

Does having access to information about candidates' electoral prospects before they cast their ballots impact voters' behaviour?—While the literature examining the impact of information exposure on voter behaviour is vast, the context of naturally-occurring elections has imposed key methodological challenges to tackling this question in a real-world setting, rendering scholars to widely rely on laboratory and survey experiments. Taking advantage of the unique conditions of the 2018 Brazilian presidential elections and of granular electoral data, we provide the first assessment of the impact of exposure to electoral results on the behaviour of voters in a single real-world election.

In addition to improving causal estimation strategies while maintaining high external validity, the Brazilian institutional set-up of runoff elections also offers us the opportunity of going beyond equifinality and distinguishing between different mechanisms through which information exposure could impact voter behaviour.

Employing a variety of model specifications from two rounds of elections, we consistently find that access to information about candidates' performances with early voters considerably impacts the behaviour of late voters. Specifically, our results indicate that information exposure encourages late voters to abandon their preferred but losing candidates in favour of the predicted winner. Results from additional analyses reinforce the notion that information exposure and vote-switching are indeed what yield the observed bandwagon effect: in analyses of second round results when strategic voting is not possible, we still observe vote switching in favour of the frontrunner; additionally, in placebo tests, we find that a bandwagon effect does not emerge in delayed but non-exposed voting machines.

Our findings have significant institutional and normative implications. First, our results indicate that the implementation of a new form of voter identification inadvertently exposed voters to information that influenced their behaviour. Although the total number of votes gained and lost as a result of information exposure would not change electoral outcomes, this is only the case because Brazilian electoral technologies and institutions are highly efficient: despite the glitches, the number of voting machines that remained open after vote tallies started being announced would not be sufficient to alter electoral results at the national level. Nonetheless, as Morton et al. (2015) and Morton and Ou (2015) have argued, the effects of sequential voting on electoral behaviour should be increasingly discussed, especially given that many institutional and technological innovations advocated for facilitating voter participation (e.g., convenience voting) could also increase the likelihood of information diffusion while elections are still taking place.

Second, there are normative implications to consider. Exposure to information gives early voters' preferences greater weight in elections, but democratic electoral processes are rooted in the notion that every vote counts equally (Thompson, 2004). This means that discussions about the potential consequences of information exposure are a matter of electoral integrity.

Our findings also open possibilities for future scholarship. Unlike much of the literature on bandwagon effects, our results emerge from a situation of exposure to vote tallies, not pre-electoral polls. As such, it is possible that the size of effects and dynamics uncovered here are also shaped by levels of trust and sense of urgency when confronted with information from actual results. This points to the need of considering the *type* of information to which voters are exposed.

Previous scholarship from elsewhere suggests that the effects we uncover here are not unique to Brazil and are likely to emerge in different types of political systems and contexts, including Britain (McAllister and Studlar, 1991), France (Morton et al., 2015), India (Chatterjee and Kamal, 2020), and Israel (Riambau, 2015). But as we show, there are also characteristics that are specific to the Brazilian context—such as, for example, the impossibility of a bandwagon effect emerging from higher rates of turnout. Future works should continue to consider the ways in which institutional set-ups may condition the potential impacts of information exposure on voter behaviour.

References

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. (2017). When should you adjust standard errors for clustering? Technical report, National Bureau of Economic Research.

Agranov, M., Goeree, J. K., Romero, J., and Yariv, L. (2018). What Makes Voters Turn Out: The Effects of Polls and Beliefs. *Journal of the European Economic Association*, 16(3):825–856.

Alvarez, R. M. and Nagler, J. (2000). A new approach for modelling strategic voting in multiparty elections. *British Journal of Political Science*, 30(1):57–75.

Barnfield, M. (2019). Think twice before jumping on the bandwagon: Clarifying concepts in research on the bandwagon effect. *Political Studies Review*, 18(4):553–574.

Bartels, L. M. (1988). *Presidential primaries and the dynamics of public choice*. Princeton University Press.

Bischof, D. (2017). New graphic schemes for stata: plotplain and plottig. *The Stata Journal*, 17(3):748–759.

Bischoff, I. and Egbert, H. (2013). Social information and bandwagon behavior in voting: An economic experiment. *Journal of Economic Psychology*, 34:270–284.

Blais, A., Labbé-St-Vincent, S., Jean-François, L., Sauger, N., and van der Straeten, K. (2011). Strategic vote choice in one-round and two-round elections: An experimental study. *Political Research Quarterly*, 64(3):637–645.

Carpini, M. X. D. (1984). Scooping the Voters? The Consequences of the Networks' Early Call of the 1980 Presidential Race. *The Journal of Politics*, 46(3):866–885.

Cepaluni, G. and Hidalgo, F. D. (2016). Compulsory voting can increase political inequality: Evidence from Brazil. *Political Analysis*, 24(2):273–280.

Chatterjee, S. and Kamal, J. (2020). Voting for the underdog or jumping on the bandwagon? evidence from India's exit poll ban. *Public Choice*.

Chung, S., Heo, Y.-J., and Moon, J.-H. (2018). Perceived versus actual polling effects: Biases in perceptions of election poll effects on candidate evaluations. *International Journal of Public Opinion Research*, 30(3):420–442.

Clavery, E. (2018). Cadastro de biometria detecta 25 mil títulos de eleitor duplicados. *Exame*, https://exame.com/brasil/cadastro-de-biometria-detecta-25mil-titulos-de-eleitor-duplicados/.

Cox, G. W. (1997). *Making Votes Count: Strategic Coordination in the World's Electoral Systems*. Cambridge University Press, New York.

Downs, A. (1957). An economic theory of political action in a democracy. *Journal of Political Economy*, 65(2):135–150.

Dubois, P. L. (1983). Election night projections and voter turnout in the West: A Note on the Hazards of Aggregate Data Analysis. *American Politics Quarterly*, 11(3):349–364.

Duffy, J. and Tavits, M. (2008). Beliefs and Voting Decisions: A Test of the Pivotal Voter Model. *American Journal of Political Science*, 52(3):603–618.

Duverger, M. (1954). *Political parties: Their organization and activity in the modern state*. Methuen.

Eggers, A. C. and Vivyan, N. (2020). Who votes more strategically? *American Political Science Review*, 114(2):470–485.

Evrenk, H. and Sher, C.-Y. (2015). Social interactions in voting behavior: distinguishing between strategic voting and the bandwagon effect. *Public Choice*, 162(3-4):405–423.

Farjam, M. (2020). The bandwagon effect in an online voting experiment with real political organizations. *International Journal of Public Opinion Research*.

Fleitas, D. W. (1971). Bandwagon and Underdog Effects in Minimal-Information Elections. *American Political Science Review*, 65(2):434–438.

Fujiwara, T. (2011). A Regression Discontinuity Test of Strategic Voting and Duverger's Law. *Quarterly Journal of Political Science*, 6(3-4):197–233.

G1 (2018). Jair Bolsonaro é eleito presidente com 57,8 milhões de votos. *G1*, https://g1.globo.com/politica/eleicoes/2018/apuracao/presidente.ghtml.

Gallup, G. and Rae, S. F. (1940). Is there a bandwagon vote? *Public Opinion Quarterly*, 4(2):244–249.

Gartner, M. (1976). Endogenous bandwagon and underdog effects in a rational choice model. *Public Choice*, 25(1):83–89.

Grandin, F., Oliveira, L., Esteves, R., and Melo, A. (2018). Bolsonaro chegou a ter 62% dos votos válidos durante a apuração; Haddad liderou por 10 minutos. *G1*, https://g1.globo.com/politica/eleicoes/2018/eleicao-em-numeros/noticia/2018/11/01/bolsonaro-chegou-a-ter-62-dos-votos-validos-durante-a-apuracao-haddad-liderou-por-10-minutos.ghtml.

Grillo, A. (2017). Risk aversion and bandwagon effect in the pivotal voter model. *Public Choice*, 172(3-4):465–482.

Großer, J. and Schram, A. (2010). Public Opinion Polls, Voter Turnout, and Welfare: An Experimental Study. *American Journal of Political Science*, 54(3):700–717.

Guarnieri, F. (2015). Voto estratégico e coordenação eleitoral testando a Lei de Duverger no brasil. *Revista Brasileira de Ciências Sociais*, 30(89):77–92.

Hardmeier, S. (2008). The effects of published polls on citizens. *The SAGE Handbook of Public Opinion Research*, pages 504–513.

Heath, A. and Evans, G. (1994). Tactical voting: concepts, measurement and findings. *British Journal of Political Science*, 24(4):557–561.

Hunter, W. and Power, T. J. (2019). Bolsonaro and Brazil's Illiberal Backlash. *Journal of Democracy*, 30(01):68–82.

Hutt, R. (2018). These are the countries with the highest voter turnout. *World Economic Forum*, https://www.weforum.org/agenda/2018/11/these-countries-have-some-of-the-highest-voter-turnout-in-the-world/.

Kawai, K. and Watanabe, Y. (2013). Inferring strategic voting. *American Economic Review*, 103(2):624–62.

Kenney, P. J. and Rice, T. W. (1994). The psychology of political momentum. *Political Research Quarterly*, 47(4):923–938.

Levy, J. S. (2008). Case studies: Types, designs, and logics of inference. *Conflict Management and Peace Science*, 25(1):1–18.

Lopez, B. (2019). Brazil is the 5th Country in Smartphone Usage. *PagBrasil*, https://www.pagbrasil.com/insights/smartphone-usage-in-brazil/.

McAllister, I. and Studlar, D. T. (1991). Bandwagon, underdog, or projection? Opinion polls and electoral choice in Britain, 1979-1987. *The Journal of Politics*, 53(3):720–741.

Mello, P. C. (2020). *A máquina do ódio: notas de uma repórter sobre fake news e violência digital*. Companhia das Letras.

Mendonça, A. V. and Albernaz, B. (2018). Biometria 'de surpresa', urnas quebradas e filas de até 3 h marcam 1º turno no RJ. https://g1.globo.com/rj/rio-de-janeiro/eleicoes/2018/noticia/2018/10/07/biometria-de-surpresa-e-urnas-quebradas-formam-filas-em-secoes-no-rj.ghtml.

Morton, R. B., Muller, D., Page, L., and Torgler, B. (2015). Exit polls, turnout, and bandwagon voting: Evidence from a natural experiment. *European Economic Review*, 77:65–81.

Morton, R. B. and Ou, K. (2015). What motivates bandwagon voting behavior: Altruism or a desire to win? *European Journal of Political Economy*, 40:224–241.

Morton, R. B. and Williams, K. C. (1999). Information Asymmetries and Simultaneous versus Sequential Voting. *American Political Science Review*, 93(1):51–67.

Moy, P. and Rinke, E. M. (2012). Attitudinal and Behavioral Consequences of Published Opinion Polls. In *Opinion Polls and the Media*, pages 225–245. Palgrave Macmillan UK, London.

Nicolau, J. M. (2012). *Eleições no Brasil: do Império aos dias atuais*. Zahar, São Paulo.

Plutowski, L., Weitz-Shapiro, R., and Winters, M. S. (2020). Voter beliefs and strategic voting in two-round elections. *Political Research Quarterly*, page 1065912920940791.

Power, T. J. (2009). Compulsory for Whom? Mandatory Voting and Electoral Participation in Brazil, 1986-2006. *Journal of Politics in Latin America*, 01(01):97–122.

Power, T. J. and Rodrigues-Silveira, R. (2019). Mapping Ideological Preferences in Brazilian Elections, 1994-2018: A Municipal-Level Study. *Brazilian Political Science Review*, 13(1).

Rennó, L. R. (2020). The Bolsonaro voter: Issue positions and vote choice in the 2018 Brazilian presidential elections. *Latin American Politics and Society*, 62(3).

Riambau, G. (2015). Bandwagon or strategic voting in Israel? note on Bargsted and Kedar 2009. *Electoral Studies*, 37:63–72.

Samuels, D. J. and Zucco Jr, C. (2018). *Partisans, antipartisans, and nonpartisans: Voting behavior in Brazil*. Cambridge University Press.

Schmitt-Beck, R. (1996). Mass media, the electorate, and the bandwagon. a study of communication effects in Germany. *International Journal of Public Opinion Research*, 8(3):266–291.

Thompson, D. F. (2004). Election Time: Normative Implications of Temporal Properties of the Electoral Process in the United States. *American Political Science Review*, 98(1):51–64.

Titiunik, R. (2020). Natural experiments. In Druckman, J. and Green, D., editors, *Advances in Experimental Political Science*. Cambridge University Press.

Zucco Jr, C. and Nicolau, J. M. (2016). Trading old errors for new errors? The impact of electronic voting technology on party label votes in Brazil. *Electoral Studies*, 43:10–20.

Casting ballots when knowing results

Online Appendix

Victor Araújo[*] & Malu A. C. Gatto[†]

Contents

A The biometric system of voter identification

In 2018, the use of fingerprints as a form of identification became mandatory for 73.6 million voters from 2,793 Brazilian municipalities (50.3% of the electorate). Figure 1 shows the machine used across Brazilian voting stations to identify voters through their fingerprints. While the innovation did not cause disturbances in some voting machines, technical problems related to the identification of voters using fingerprint readers caused considerable delays in many others. In effect, these problems led some voters to only cast ballots after the official closing time of the election, when the results were already being counted and announced.

Figure 1: Biometrics' machine used in the 2018 Brazilian elections to identify voters

Source: Agência Brasil. http://agenciabrasil.ebc.com.br/politica/noticia/2014-10/saiba-como-melhorar-leitura-das-digitais-na-hora-do-voto.

B The implementation of the biometric system across regions

The North and the Northeast, Brazil's poorest regions, had the highest concentration of registered biometric voters in the country, with 89% and 88% of voters registered to use the system, respectively. They were followed by the Center-West, with 79% of voters with registered biometrics, and the South, with 71%. By contrast, only 36% of voters in Brazil's wealthiest region, the Southeast, were registered to vote using the biometric system.

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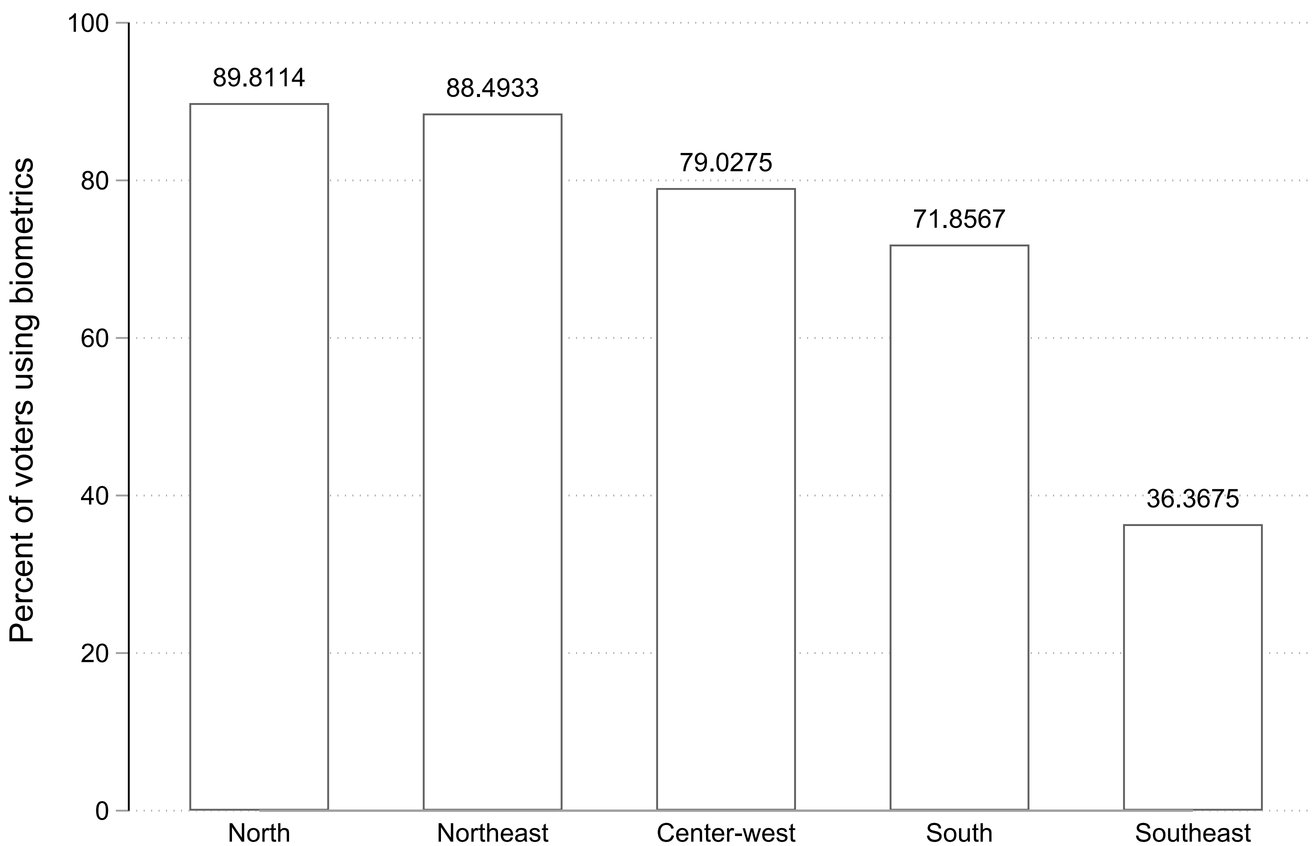
Figure 2: Percentage of biometric voters, by region (2018)

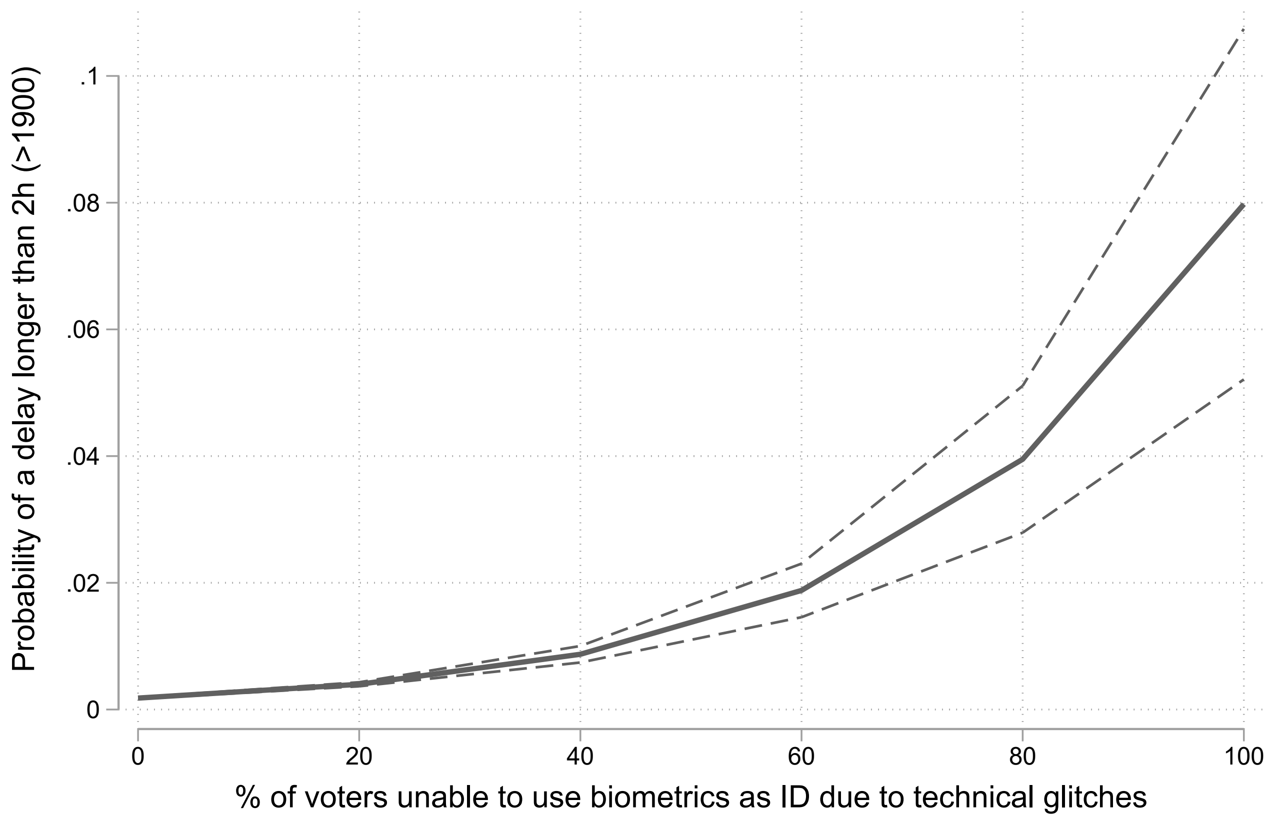


Note: Compiled by authors with data from the TSE. Each bar shows the percentage of voters registered to use the biometric system of voter ID in the 2018 Brazilian elections in each region.

C Probability of being exposed to information in the second round

Technical problems associated with the implementation of the biometric system meant that voters assigned to stations employing the system were significantly more likely to face delays and vote after 19:00 BRT, when the TSE officially started announcing electoral results. Figure 3 shows the results of our logit estimates for the second round of elections.

Figure 3: Probability of being exposed to information in the second round of the 2018 Brazilian elections



Note: The unit of analysis is voting machine (N = 453,319). We cluster standard errors at the level of voting machine (where the treatment took place). We run all logit estimates with controls for turnout rate, age (avg.), % of women voters, and years of schooling (avg.).

D Baseline estimates

Table 1 and 2 show our baseline estimates without controls for characteristics of the electorate included in other models, namely: average age, share of women voters, and average years of schooling.

Table 1: The effect of information exposure on voting behaviour (first round)

	(1) Frontrunner	(2) Second place	(3) Third place	(4) Blank	(5) Null
Treated (>1900h)	8.941***	-11.60***	-1.454***	0.210***	-0.937***
	(0.247)	(0.300)	(0.126)	(0.0194)	(0.0452)
Closure delay (in min.)	-0.117***	0.132***	0.00757***	-0.00289***	0.0109***
	(0.000877)	(0.00106)	(0.000468)	(0.0000722)	(0.000162)
% Error in biometrics	-0.149***	0.307***	0.0525***	-0.0101***	-0.0321***
	(0.00371)	(0.00433)	(0.00173)	(0.000378)	(0.000675)
Time zone	8.290***	0.453***	-4.590***	-0.885***	-1.824***
	(0.0973)	(0.113)	(0.0260)	(0.00698)	(0.0137)
R^2	0.085	0.075	0.026	0.026	0.043
Observations	452980	453653	452066	438741	451802
N.Clusters	452980	453653	452066	438741	451802

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-5) at the level of voting machine (where the treatment occurred).

Table 2: The effect of information exposure on voting behaviour (second round)

	(1) Frontrunner	(2) Second place	(3) Blank	(4) Null
Treated (>1900h)	7.524***	-8.210***	0.607***	-0.176**
	(0.452)	(0.467)	(0.0329)	(0.0719)
Closure delay (in min.)	-0.139***	0.0933***	0.00312***	0.0472***
	(0.00972)	(0.00962)	(0.000699)	(0.00401)
% Error in biometrics	-0.380***	0.538***	-0.0247***	-0.132***
	(0.00427)	(0.00452)	(0.000291)	(0.000750)
Time zone	9.349***	-6.208***	-2.814***	-2.421***
	(0.109)	(0.113)	(0.0520)	(0.0146)
R^2	0.038	0.043	0.032	0.108
Observations	453342	453670	433194	452545
N.Clusters	453342	453670	433194	452545

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-4) at the level of voting machine (where the treatment occurred).

E Descriptive statistics

First round of elections

Table 3: Descriptive statistics - 2018 Brazilian presidential elections (first round)

Variable	Obs	Mean	Std.Dev.	Min	Max
Outcome variables					
% votes for Frontrunner (Bolsonaro)	452,998	41.12	17.60	.2673	95
% votes for Second place (Haddad)	453,671	28.12	20.20	.2923	100
% votes for Third place (Gomes)	452,084	11.19	8.395	.25	80.52
% Blank votes	438,758	2.698	1.628	.2242	27.27
% Null votes	451,820	6.105	3.126	.2237	50
Treatments and controls					
Treatment	453,671	.0188	.1359	0	1
Treatment (placebo)	453,671	.7948	.4037	0	1
Closure delay (in min.)	453,653	16.84	40.15	0	657
Turnout	453,671	79.95	6.901	1.851	100
% Error in biometrics	453,671	7.223	7.494	0	100
Age (avg.)	453,319	45.26	5.376	19	95
Women voters*	453,319	3.074	.0894	2	4
Year of schooling (avg.)	453,319	4.429	.8106	1	8
Number of registered voters	453,671	323.5	75.39	9	596

Note: Compiled by authors with data from the *Tribunal Superior Eleitoral* (Superior Electoral Court, TSE). The unit of analysis is voting machine. **Women voters* is an indicator that varies between 2 and 4. Values closer to 4 indicate higher incidence of women voters in a given voting machine.

Second round of elections

Table 4: Descriptive statistics - 2018 Brazilian presidential elections (second round)

Variable	Obs	Mean	Std.Dev.	Min	Max
Outcome variables					
% votes for Frontrunner (Bolsonaro)	453,372	48.80	19.81	.2865	98.14
% votes for Second place (Haddad)	453,700	41.84	20.79	.5102	100
% Blank votes	433,222	2.196	1.232	.2364	25
% Null votes	452,575	7.309	3.529	.2724	47.12
Treatments and controls					
Treatment	453,700	.0023	.0488	0	1
Treatment (placebo)	453,700	.5447	.4979	0	1
Closure delay (in min.)	453,670	1.382	3.542	0	421
% Error in biometrics	453,700	7.045	7.219	0	98.85
Turnout	453,700	78.84	7.251	4.950	100
Age (avg.)	453,347	45.26	5.377	19	95
Women voters*	453,347	3.074	.0894	2	4
Year of schooling (avg.)	453,347	4.429	.8106	1	8
Number of registered voters	453,700	323.5	75.42	9	596

Note: Compiled by authors with data from the TSE). The unit of analysis is voting machine. **Women voters* is an indicator that varies between 2 and 4. Values closer to 4 indicate higher incidence of women voters in a given voting machine.

F Main estimates

Table 5 and 6 summarize our main estimates. These tables replicate the results of Figures 2 and 3 reported in the main text.

First round of elections

Table 5: The effect of information exposure on voting behavior (first round)

	(1) Frontrunner	(2) Second place	(3) Third place	(4) Blank	(5) Null
Treated (>1900h)	5.694***	-7.408***	-1.968***	0.310***	-0.729***
	(0.178)	(0.219)	(0.123)	(0.0197)	(0.0437)
Closure delay (in min.)	-0.0646***	0.0662***	0.0164***	-0.00456***	0.00662***
	(0.000657)	(0.000769)	(0.000462)	(0.0000747)	(0.000159)
% Error in biometrics	-0.113***	0.277***	0.0431***	-0.0119***	-0.0382***
	(0.00288)	(0.00317)	(0.00177)	(0.000382)	(0.000689)
Turnout	-0.178***	0.0922***	0.0643***	0.0126***	0.0458***
	(0.00360)	(0.00397)	(0.00224)	(0.000449)	(0.000830)
Time zone	9.636***	-1.973***	-4.209***	-0.854***	-1.672***
	(0.0766)	(0.0868)	(0.0263)	(0.00717)	(0.0135)
Age (avg.)	0.521***	-0.705***	0.0106***	-0.00451***	0.0172***
	(0.00403)	(0.00444)	(0.00229)	(0.000523)	(0.000891)
Women voters	-4.680***	-7.549***	6.306***	1.192***	3.611***
	(0.238)	(0.252)	(0.149)	(0.0288)	(0.0528)
Years of schooling (avg.)	12.95***	-16.40***	2.471***	-0.458***	-1.310***
	(0.0287)	(0.0317)	(0.0168)	(0.00340)	(0.00611)
Constant	-38.98***	151.6***	-12.43***	3.031***	1.671***
	(0.822)	(0.895)	(0.504)	(0.101)	(0.185)
R^2	0.439	0.538	0.103	0.069	0.140
Observations	452656	453301	451763	438539	451574
N. Clusters	452656	453301	451763	438539	451574

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-5) at the level of voting machine (where the treatment occurred).

Second round of elections

Table 6: The effect of information exposure on voting behavior (second round)

	(1) Frontrunner	(2) Second place	(3) Blank	(4) Null
Treated (>1900h)	11.76***	-12.14***	0.622***	-0.436***
	(0.420)	(0.410)	(0.0325)	(0.0726)
Closure delay (in min.)	-0.166***	0.119***	0.00256***	0.0471***
	(0.00995)	(0.00781)	(0.000671)	(0.00395)
% Error in biometrics	-0.305***	0.468***	-0.0247***	-0.137***
	(0.00323)	(0.00355)	(0.000297)	(0.000780)
Turnout	-0.0738***	0.0302***	0.00445***	0.0368***
	(0.00379)	(0.00407)	(0.000322)	(0.000869)
Time zone	10.28***	-7.685***	-0.492***	-2.010***
	(0.0907)	(0.0922)	(0.00613)	(0.0149)
Age (avg.)	0.768***	-0.881***	0.0157***	0.0883***
	(0.00426)	(0.00461)	(0.000386)	(0.00101)
Women voters	-7.593***	3.270***	0.343***	3.484***
	(0.265)	(0.283)	(0.0224)	(0.0603)
Years of schooling (avg.)	14.99***	-14.80***	0.132***	-0.447***
	(0.0317)	(0.0349)	(0.00255)	(0.00680)
Constant	-52.35***	155.0***	1.162***	-1.256***
	(0.901)	(0.963)	(0.0769)	(0.206)
R^2	0.447	0.428	0.047	0.137
Observations	453016	453317	432965	452260
N.Clusters	453016	453317	432965	452260

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-4) at the level of voting machine (where the treatment occurred).

G Estimated substantive effects for the frontrunner

It is not possible to know how many voters cast ballots after the threshold of information exposure (i.e., 19:00 BRT). However, we can provide estimations for a range of possible scenarios.

After identifying the number of votes that the frontrunner (Bolsonaro) attained, we established a range of possible exposure targets (from 5% to 100%) and calculated the number of voters that would have been exposed to information for each target level. We then multiplied that by the effect estimated in our models (5.7pp or 14%) to derive the estimated number of votes that the frontrunner would have gained from the bandwagon effect across different levels of information exposure.

As shown, in a conservative estimation that assumes that only 5% of voters in the treated units cast ballots after information exposure in the first round, Bolsonaro would have gained a total of 5,517 votes; if, instead, 25% of voters in affected units voted after 19:00 BRT, then Bolsonaro would have gained an estimated total of 27,587 votes.

Table 7: Simulations of estimated substantive effects for the frontrunner (first round)

Total	% exposed	# exposed	effect (pp)	effect (%)	votes gained
788204	5%	39410	5.7	14	5,517
788204	10%	78820	5.7	14	11,034
788204	25%	197051	5.7	14	27,587
788204	50%	394102	5.7	14	55,174
788204	75%	591153	5.7	14	82,761
788204	100%	788204	5.7	14	110,348

Note: Compiled by authors with data from the TSE.

As shown, in a scenario where 5% of voters were exposed to information in the second round, Bolsonaro would have gained a total of 2,017 votes due to bandwagon. Meanwhile, if 25% had been affected, then we estimate that Bolsonaro would have gained 10,086 votes.

Table 8: Simulations of estimated substantive effects for the frontrunner (second round)

Total	% exposed	# exposed	effect (pp)	effect (%)	votes gained
168110	5%	8405	11.8	24	2,017
168110	10%	16811	11.8	24	4,034
168110	25%	42027	11.8	24	10,086
168110	50%	84055	11.8	24	20,173
168110	75%	126082	11.8	24	30,259
168110	100%	168110	11.8	24	40,346

Note: Compiled by authors with data from the TSE.

H Estimated substantive effects for the second place

It is not possible to know how many voters cast ballots after the threshold of information exposure (i.e., 19:00 BRT). However, we can provide estimations for a range of possible scenarios.

After identifying the number of votes that the second place candidate (Haddad) attained, we established a range of possible exposure targets (from 5% to 100%) and calculated the number of voters that would have been exposed to information for each target level. We then multiplied that by the effect estimated in our models (7.4pp or 26%) to derive the estimated number of votes that the second place candidate would have lost from the bandwagon effect across different levels of information exposure.

For example, in a scenario where only 5% of voters are exposed to information in the first round, Haddad would have lost an estimated total of 14,012 votes. If 25% of voters were exposed, then Haddad would have lost a total of 70,063 votes. While even in our least conservative estimates the number of votes gained by Bolsonaro and lost by Haddad would not have changed electoral outcomes, this is only the case because, despite the glitches associated with the implementation of the biometric system, only a low percentage of voting machines remained open after the threshold of information exposure.

Table 9: Simulations of estimated substantive effects for the second place (first round)

Total	% exposed	# exposed	effect (pp)	effect (%)	votes lost
1077904	5%	53895	7.4	26	14,012
1077904	10%	107790	7.4	26	28,025
1077904	25%	269476	7.4	26	70,063
1077904	50%	538952	7.4	26	140,127
1077904	75%	808428	7.4	26	210,191
1077904	100%	1077904	7.4	26	280,255

Note: Compiled by authors with data from the TSE.

As shown, in a scenario where 5% of voters were exposed to information in the second round, Haddad would have lost a total of 745 votes due to bandwagon. Meanwhile, if 25% had been affected, then we estimate that Haddad would have lost 3,728 votes.

Table 10: Simulations of estimated substantive effects for the second place (second round)

Total	% exposed	# exposed	effect (pp)	effect (%)	votes lost
53269	5%	2663	12	28	745
53269	10%	5326	12	28	1,491
53269	25%	13317	12	28	3,728
53269	50%	26634	12	28	7,457
53269	75%	39951	12	28	11,186
53269	100%	53269	12	28	14,915

Note: Compiled by authors with data from the TSE.

I Estimated substantive effects for the third place

It is not possible to know how many voters cast ballots after the threshold of information exposure (i.e., 19:00 BRT). However, we can provide estimations for a range of possible scenarios.

After identifying the number of votes that the third place candidate (Gomes) attained, we established a range of possible exposure targets (from 5% to 100%) and calculated the number of voters that would have been exposed to information for each target level. We then multiplied that by the effect estimated in our models (2pp or 18%) to derive the estimated number of votes that the third place candidate would have lost from the bandwagon effect across different levels of information exposure. For example, in a scenario where only 5% of voters are exposed to information, Gomes would have lost an estimated total of 2,271 votes. If 25% of voters were exposed, then Gomes would have lost a total of 11,357 votes.

Table 11: Simulations of estimated substantive effects for the third place (first round)

Total	% exposed	# exposed	effect (pp)	effect (%)	votes lost
252386	5%	12619	2	18	2,271
252386	10%	25238	2	18	4,552
252386	25%	63096	2	18	11,357
252386	50%	126193	2	18	22,714
252386	75%	189289	2	18	34,072
252386	100%	252386	2	18	45,429

Note: Compiled by authors with data from the TSE.

J Estimates with a restricted sample without Acre-based units

We rerun our estimates without observations located in the state of Acre, where, due to time zone differences, even a 1-minute voting delay would place voting machines in the treatment condition. As shown in Tables 12 and 13, these models also produce results that are consistent with our main findings (reported in Figures 2 and 3 of the main text).

First round of elections

Table 12: The effect of information exposure on voting behavior (first round)

	(1) Frontrunner	(2) Second place	(3) Third place	(4) Blank	(5) Null
Treated (>1900h)	6.380***	-4.836***	-3.751***	0.321***	-1.335***
	(0.211)	(0.260)	(0.156)	(0.0242)	(0.0539)
Closure delay (in min.)	-0.0663***	0.0609***	0.0202***	-0.00460***	0.00792***
	(0.000710)	(0.000825)	(0.000506)	(0.0000812)	(0.000173)
% Error in biometrics	-0.112***	0.280***	0.0412***	-0.0119***	-0.0390***
	(0.00289)	(0.00318)	(0.00177)	(0.000383)	(0.000693)
Turnout	-0.178***	0.0969***	0.0624***	0.0126***	0.0450***
	(0.00361)	(0.00398)	(0.00225)	(0.000451)	(0.000833)
Time zone	9.772***	-0.951***	-4.783***	-0.857***	-1.867***
	(0.0858)	(0.0948)	(0.0236)	(0.00785)	(0.0142)
Age (avg.)	0.521***	-0.706***	0.0109***	-0.00456***	0.0169***
	(0.00404)	(0.00445)	(0.00229)	(0.000525)	(0.000894)
Women voters	-4.701***	-7.225***	6.161***	1.195***	3.565***
	(0.239)	(0.252)	(0.150)	(0.0289)	(0.0529)
Years of schooling (avg.)	12.95***	-16.46***	2.500***	-0.460***	-1.302***
	(0.0288)	(0.0318)	(0.0169)	(0.00342)	(0.00614)
Constant	-39.24***	147.5***	-10.26***	3.041***	2.441***
	(0.835)	(0.904)	(0.506)	(0.102)	(0.187)
R^2	0.437	0.539	0.103	0.067	0.139
Observations	450735	451379	449866	436850	449662
N.Clusters	450735	451379	449866	436850	449662

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-5) at the level of voting machine (where the treatment occurred).

Second round of elections

Table 13: The effect of information exposure on voting behavior (second round)

	(1) Frontrunner	(2) Second place	(3) Blank	(4) Null
Treated (>1900h)	49.89***	-31.20***	-1.088***	-17.78***
	(4.151)	(3.889)	(0.273)	(1.259)
Closure delay (in min.)	-0.225***	0.149***	0.00478***	0.0738***
	(0.0118)	(0.0104)	(0.000772)	(0.00355)
% Error in biometrics	-0.307***	0.470***	-0.0248***	-0.137***
	(0.00324)	(0.00355)	(0.000298)	(0.000781)
Turnout	-0.0738***	0.0295***	0.00458***	0.0373***
	(0.00380)	(0.00409)	(0.000324)	(0.000876)
Time zone	9.673***	-7.002***	-0.541***	-2.029***
	(0.0957)	(0.0973)	(0.00630)	(0.0162)
Age (avg.)	0.770***	-0.883***	0.0158***	0.0886***
	(0.00428)	(0.00462)	(0.000387)	(0.00102)
Women voters	-7.737***	3.444***	0.333***	3.467***
	(0.265)	(0.283)	(0.0225)	(0.0603)
Years of schooling (avg.)	15.02***	-14.84***	0.132***	-0.451***
	(0.0317)	(0.0350)	(0.00255)	(0.00682)
Constant	-50.25***	152.6***	1.327***	-1.217***
	(0.908)	(0.969)	(0.0774)	(0.207)
R^2	0.445	0.427	0.048	0.132
Observations	451095	451396	431240	450386
N.Clusters	451095	451396	431240	450386

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-4) at the level of voting machine (where the treatment occurred).

K Estimates with a restricted sample of units with biometrics

We rerun our estimates on a restricted sample composed only of units where at least one biometric-related technical issue occurred. Tables 14 and 15 report our results and show that they are consistent with our main findings reported in Figures 1 and 2 in the main text.

First round of elections

Table 14: The effect of information exposure on voting behavior (first round)

	(1) Frontrunner	(2) Second place	(3) Third place	(4) Blank	(5) Null
Treated (>1900h)	4.551***	-4.901***	-1.160***	0.0795***	-1.110***
	(0.179)	(0.218)	(0.130)	(0.0204)	(0.0444)
Closure delay (in min.)	-0.0580***	0.0561***	0.0128***	-0.00362***	0.00760***
	(0.000667)	(0.000775)	(0.000480)	(0.0000759)	(0.000162)
% Error in biometrics	-0.111***	0.203***	-0.0390***	-0.00292***	-0.0387***
	(0.00355)	(0.00392)	(0.00228)	(0.000457)	(0.000856)
Turnout	-0.235***	0.128***	0.0593***	0.0130***	0.0418***
	(0.00424)	(0.00466)	(0.00286)	(0.000516)	(0.000950)
Time zone	10.76***	-4.424***	-4.949***	-0.614***	-1.164***
	(0.0815)	(0.0882)	(0.0339)	(0.00806)	(0.0151)
Age (avg.)	0.503***	-0.693***	0.0592***	0.00356***	0.0313***
	(0.00517)	(0.00569)	(0.00320)	(0.000634)	(0.00110)
Women voters	-4.662***	-8.329***	7.866***	1.222***	3.517***
	(0.312)	(0.330)	(0.214)	(0.0359)	(0.0662)
Years of schooling (avg.)	13.64***	-16.33***	2.331***	-0.484***	-1.411***
	(0.0343)	(0.0371)	(0.0215)	(0.00389)	(0.00704)
Constant	-40.24***	159.0***	-14.81***	1.774***	0.535**
	(1.044)	(1.130)	(0.707)	(0.122)	(0.225)
R^2	0.455	0.523	0.081	0.067	0.153
Observations	324633	325037	324045	314748	323880
N.Clusters	324633	325037	324045	314748	323880

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-5) at the level of voting machine (where the treatment occurred).

Second round of elections

Table 15: The effect of information exposure on voting behavior (second round)

	(1) Frontrunner	(2) Second place	(3) Blank	(4) Null
Treated (>1900h)	8.399***	-7.393***	0.384***	-1.373***
	(0.426)	(0.417)	(0.0337)	(0.0645)
Closure delay (in min.)	-0.0962***	0.0677***	-0.00240***	0.0319***
	(0.00856)	(0.00845)	(0.000736)	(0.00337)
% Error in biometrics	-0.175***	0.296***	-0.0100***	-0.108***
	(0.00408)	(0.00448)	(0.000361)	(0.000949)
Turnout	-0.108***	0.0861***	0.00242***	0.0176***
	(0.00442)	(0.00474)	(0.000362)	(0.000983)
Time zone	12.04***	-10.39***	-0.308***	-1.345***
	(0.0970)	(0.0960)	(0.00714)	(0.0168)
Age (avg.)	0.711***	-0.843***	0.0188***	0.105***
	(0.00552)	(0.00600)	(0.000472)	(0.00123)
Women voters	-8.374***	4.361***	0.227***	3.348***
	(0.346)	(0.371)	(0.0274)	(0.0721)
Years of schooling (avg.)	15.38***	-15.06***	0.114***	-0.543***
	(0.0375)	(0.0409)	(0.00291)	(0.00752)
Constant	-53.72***	157.3***	0.856***	-2.076***
	(1.138)	(1.217)	(0.0911)	(0.243)
R^2	0.441	0.410	0.022	0.108
Observations	324561	324711	309575	323913
N.Clusters	324561	324711	309575	323913

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-4) at the level of voting machine (where the treatment occurred).

L Results according to the number of voters (by quartiles)

We rerun our estimates on samples restricted to voting stations of different sizes. Tables 16-21 report our results and show that they are consistent with our main findings (from Table 1 in the main text).

First round of elections

Quartile 25 (0-220 voters)

Table 16: The effect of information exposure on voting behavior (first round)

	(1) Frontrunner	(2) Second place	(3) Third place	(4) Blank	(5) Null
Treated (>1900h)	7.823***	-20.07***	2.443***	0.502***	1.262***
	(1.000)	(1.175)	(0.320)	(0.0858)	(0.172)
Closure delay (in min.)	-0.108***	0.155***	-0.00214	-0.00873***	0.00220
	(0.00716)	(0.00791)	(0.00477)	(0.000841)	(0.00179)
% Error in biometrics	-0.0790***	0.140***	0.0281***	0.00322**	-0.0157***
	(0.00751)	(0.00875)	(0.00479)	(0.00126)	(0.00178)
Turnout	-0.137***	0.145***	0.0165**	-0.00505***	-0.0108***
	(0.00979)	(0.0116)	(0.00680)	(0.00159)	(0.00259)
Time zone	10.20***	-2.972***	-4.899***	-0.792***	-1.536***
	(0.288)	(0.340)	(0.0902)	(0.0296)	(0.0474)
Age (avg.)	0.789***	-0.971***	-0.122***	0.00884***	0.0468***
	(0.0111)	(0.0133)	(0.00681)	(0.00175)	(0.00271)
Women voters	-14.19***	3.883***	6.398***	-0.0176	3.400***
	(0.824)	(0.920)	(0.479)	(0.108)	(0.173)
Years of schooling (avg.)	15.28***	-19.00***	1.676***	-0.219***	-0.776***
	(0.0867)	(0.0994)	(0.0515)	(0.0113)	(0.0187)
Constant	-39.52***	142.9***	3.114**	6.131***	2.129***
	(2.687)	(3.086)	(1.550)	(0.370)	(0.595)
R^2	0.514	0.553	0.054	0.025	0.078
Observations	44829	45321	44069	38825	44081
N.Clusters	44829	45321	44069	38825	44081

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-5) at the level of voting machine (where the treatment occurred).

Quartile 50 (220-339 voters)

Table 17: The effect of information exposure on voting behavior (first round)

	(1) Frontrunner	(2) Second place	(3) Third place	(4) Blank	(5) Null
Treated (>1900h)	7.570***	-10.96***	-2.138***	0.527***	0.439***
	(0.300)	(0.356)	(0.240)	(0.0323)	(0.0710)
Closure delay (in min.)	-0.0953***	0.0970***	0.0287***	-0.00699***	-0.00000663
	(0.00118)	(0.00145)	(0.00111)	(0.000140)	(0.000302)
% Error in biometrics	-0.137***	0.237***	0.0403***	-0.00584***	-0.0129***
	(0.00434)	(0.00471)	(0.00290)	(0.000540)	(0.00101)
Turnout	-0.118***	-0.0166***	0.0838***	0.0228***	0.0486***
	(0.00541)	(0.00591)	(0.00370)	(0.000645)	(0.00124)
Time zone	11.93***	-5.250***	-4.168***	-0.684***	-1.771***
	(0.111)	(0.122)	(0.0427)	(0.0103)	(0.0194)
Age (avg.)	0.626***	-0.852***	-0.0202***	0.0171***	0.0331***
	(0.00642)	(0.00710)	(0.00391)	(0.000789)	(0.00140)
Women voters	-9.689***	-1.189***	7.380***	0.775***	2.819***
	(0.375)	(0.394)	(0.256)	(0.0423)	(0.0803)
Years of schooling (avg.)	14.08***	-16.89***	1.786***	-0.376***	-1.320***
	(0.0452)	(0.0490)	(0.0275)	(0.00513)	(0.00936)
Constant	-45.95***	161.4***	-12.89***	1.391***	3.224***
	(1.282)	(1.381)	(0.851)	(0.147)	(0.279)
R^2	0.513	0.571	0.081	0.054	0.138
Observations	182692	182805	182562	177070	182460
N.Clusters	182692	182805	182562	177070	182460

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-5) at the level of voting machine (where the treatment occurred).

Quartile 75 (>339 voters)

Table 18: The effect of information exposure on voting behavior (first round)

	(1) Frontrunner	(2) Second place	(3) Third place	(4) Blank	(5) Null
Treated (>1900h)	7.472***	-8.215***	-2.638***	0.422***	-1.033***
	(0.244)	(0.291)	(0.149)	(0.0263)	(0.0577)
Closure delay (in min.)	-0.0908***	0.0934***	0.0214***	-0.00655***	0.00532***
	(0.000916)	(0.00102)	(0.000523)	(0.0000981)	(0.000209)
% Error in biometrics	0.113***	0.118***	0.00548**	-0.00427***	-0.0441***
	(0.00488)	(0.00479)	(0.00242)	(0.000568)	(0.00121)
Turnout	-0.0966***	0.00433	0.0239***	0.0209***	0.0815***
	(0.00546)	(0.00569)	(0.00290)	(0.000648)	(0.00121)
Time zone	6.260***	2.856***	-4.162***	-0.999***	-1.694***
	(0.119)	(0.137)	(0.0377)	(0.0109)	(0.0204)
Age (avg.)	0.395***	-0.554***	0.0704***	-0.0192***	0.00145
	(0.00566)	(0.00582)	(0.00297)	(0.000722)	(0.00123)
Women voters	-5.245***	-6.663***	7.214***	1.231***	3.009***
	(0.323)	(0.317)	(0.192)	(0.0391)	(0.0731)
Years of schooling (avg.)	9.629***	-13.21***	3.691***	-0.734***	-1.706***
	(0.0425)	(0.0449)	(0.0223)	(0.00496)	(0.00890)
Constant	-11.69***	117.9***	-20.64***	4.805***	3.583***
	(1.144)	(1.172)	(0.649)	(0.140)	(0.257)
R^2	0.347	0.492	0.182	0.136	0.188
Observations	225135	225175	225132	222644	225033
N.Clusters	225135	225175	225132	222644	225033

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-5) at the level of voting machine (where the treatment occurred).

Second round of elections

Quartile 25 (0-220 voters)

Table 19: The effect of information exposure on voting behavior (second round)

	(1) Frontrunner	(2) Second place	(3) Blank	(4) Null
Treated (>1900h)	15.05***	-15.98***	0.508***	-0.305*
	(1.330)	(1.350)	(0.117)	(0.183)
Closure delay (in min.)	-0.114***	0.114***	-0.00458**	0.00928**
	(0.0125)	(0.0139)	(0.00184)	(0.00412)
% Error in biometrics	-0.151***	0.245***	-0.00672***	-0.0905***
	(0.00892)	(0.00977)	(0.00106)	(0.00221)
Turnout	0.0106	0.00102	-0.000120	-0.0190***
	(0.0103)	(0.0112)	(0.00122)	(0.00264)
Time zone	11.79***	-9.481***	-0.456***	-1.667***
	(0.321)	(0.333)	(0.0233)	(0.0497)
Age (avg.)	1.055***	-1.194***	0.0132***	0.0955***
	(0.0120)	(0.0130)	(0.00136)	(0.00321)
Women voters	-16.84***	13.74***	-0.488***	2.661***
	(0.920)	(0.973)	(0.0925)	(0.198)
Years of schooling (avg.)	16.83***	-17.28***	0.117***	-0.00406
	(0.0976)	(0.105)	(0.00952)	(0.0211)
Constant	-58.93***	159.5***	4.147***	1.589**
	(2.957)	(3.142)	(0.305)	(0.652)
R^2	0.516	0.498	0.013	0.092
Observations	45121	45347	36603	44452
N.Clusters	45121	45347	36603	44452

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-4) at the level of voting machine (where the treatment occurred).

Quartile 50 (220-339 voters)

Table 20: The effect of information exposure on voting behavior (second round)

	(1) Frontrunner	(2) Second place	(3) Blank	(4) Null
Treated (>1900h)	6.707***	-7.244***	0.536***	-0.136*
	(0.546)	(0.542)	(0.0422)	(0.0789)
Closure delay (in min.)	-0.161***	0.124***	0.00163	0.0327***
	(0.0195)	(0.0161)	(0.00122)	(0.00499)
% Error in biometrics	-0.316***	0.445***	-0.0204***	-0.109***
	(0.00485)	(0.00530)	(0.000419)	(0.00113)
Turnout	-0.0276***	-0.0178***	0.00689***	0.0342***
	(0.00557)	(0.00598)	(0.000459)	(0.00130)
Time zone	14.06***	-11.85***	-0.351***	-1.796***
	(0.126)	(0.128)	(0.00868)	(0.0204)
Age (avg.)	0.892***	-1.041***	0.0258***	0.117***
	(0.00680)	(0.00736)	(0.000587)	(0.00158)
Women voters	-11.96***	9.120***	0.229***	2.459***
	(0.423)	(0.450)	(0.0329)	(0.0914)
Years of schooling (avg.)	16.44***	-16.46***	0.202***	-0.263***
	(0.0489)	(0.0532)	(0.00379)	(0.0101)
Constant	-67.19***	169.7***	-0.0193	-1.231***
	(1.411)	(1.503)	(0.111)	(0.308)
R^2	0.510	0.490	0.060	0.122
Observations	182739	182792	173859	182649
N.Clusters	182739	182792	173859	182649

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-4) at the level of voting machine (where the treatment occurred).

Quartile 75 (>339)

Table 21: The effect of information exposure on voting behavior (second round)

	(1) Frontrunner	(2) Second place	(3) Blank	(4) Null
Treated (>1900h)	17.77***	-17.60***	0.705***	-1.061***
	(0.756)	(0.675)	(0.0563)	(0.198)
Closure delay (in min.)	-0.229***	0.150***	0.00346***	0.0759***
	(0.0163)	(0.0125)	(0.000892)	(0.00637)
% Error in biometrics	-0.269***	0.459***	-0.0334***	-0.157***
	(0.00504)	(0.00543)	(0.000426)	(0.00126)
Turnout	-0.119***	0.0466***	0.00285***	0.0671***
	(0.00585)	(0.00619)	(0.000451)	(0.00124)
Time zone	5.574***	-2.765***	-0.592***	-2.125***
	(0.141)	(0.143)	(0.00919)	(0.0242)
Age (avg.)	0.579***	-0.658***	0.00904***	0.0685***
	(0.00605)	(0.00642)	(0.000528)	(0.00138)
Women voters	-6.611***	2.745***	0.645***	3.112***
	(0.359)	(0.379)	(0.0300)	(0.0841)
Years of schooling (avg.)	12.63***	-11.80***	0.0705***	-0.940***
	(0.0468)	(0.0518)	(0.00358)	(0.00998)
Constant	-17.17***	114.9***	1.341***	1.428***
	(1.263)	(1.334)	(0.105)	(0.292)
R^2	0.340	0.313	0.052	0.157
Observations	225156	225178	222503	225159
N.Clusters	225156	225178	222503	225159

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-4) at the level of voting machine (where the treatment occurred).

M Results using data from the 2014 Brazilian presidential elections

It is also possible that voters in treated units were already more prone to supporting the frontrunner, Bolsonaro, than voters in untreated units. To account for this, we examine the electoral preferences of treated and untreated units in the 2014 presidential elections. As Tables 22 and 23 show, units exposed to information in 2018 were more prone supporting the left-wing PT and less supportive of the centre-right PSDB. That is, there is no evidence to suggest that units treated in 2018 were already more predisposed to supporting Bolsonaro.

Table 22: Voter behaviour in the first round of the 2014 elections according to the treatment in the 2018 presidential elections

	(1) Frontrunner (PT)	(2) Second place (PSDB)	(3) Third place (PSB)
Treated (>1900h)	4.755***	-7.974***	2.734***
	(0.204)	(0.150)	(0.173)
Time zone	-2.452***	7.288***	-1.271***
	(0.108)	(0.107)	(0.0917)
Age (avg.)	-0.736***	0.893***	-0.184***
	(0.00430)	(0.00436)	(0.00322)
Women voters	-7.875***	-17.50***	16.17***
	(0.253)	(0.266)	(0.203)
Years of schooling (avg.)	-16.33***	11.53***	4.009***
	(0.0277)	(0.0280)	(0.0222)
R^2	0.544	0.390	0.129
Observations	349751	349203	348471
N.Clusters	349751	349203	348471

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-3) at the level of voting machine (where the treatment occurred).

Table 23: Voter behaviour in the first round of the 2014 elections according to the treatment in the 2018 presidential elections

	(1) Frontrunner (PT)	(2) Second place (PSDB)	(3) Third place (PSB)
Treated (>1900h)	0.865***	-4.639***	2.630***
	(0.0537)	(0.0554)	(0.0384)
Time zone	-1.813***	5.759***	-0.595***
	(0.104)	(0.112)	(0.106)
Age (avg.)	-0.737***	0.880***	-0.176***
	(0.00430)	(0.00433)	(0.00320)
Women voters	-7.986***	-16.54***	15.60***
	(0.253)	(0.264)	(0.202)
Years of schooling (avg.)	-16.37***	11.56***	4.018***
	(0.0277)	(0.0278)	(0.0219)
R^2	0.543	0.399	0.138
Observations	349751	349203	348471
N.Clusters	349751	349203	348471

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-3) at the level of voting machine (where the treatment occurred).

N Estimates with the placebo treatment

Tables 24 and 25 report the estimates for both first and second rounds of elections with a placebo treatment. To be considered treated units in our placebo analyses, voting machines would have had to close with a delay (after 17:00 local-time) but before the results started being announced (at 19:00 BRT). In other words, for these analyses, treated units encompass voting machines where voters faced delays and stayed in the queue but could not have been exposed to information.

First round of elections

Table 24: The effect of non-information exposure on voting behaviour - Placebo treatment (first round)

	(1) Frontrunner	(2) Second place	(3) Third place	(4) Blank	(5) Null
Treated (>1700h and <1900h)	-2.840***	1.771***	1.099***	0.0130**	0.593***
	(0.0492)	(0.0501)	(0.0290)	(0.00597)	(0.0104)
Closure delay (in min.)	-0.0532***	0.0507***	0.0125***	-0.00388***	0.00524***
	(0.000491)	(0.000600)	(0.000372)	(0.0000583)	(0.000127)
% Error in biometrics	-0.115***	0.281***	0.0436***	-0.0122***	-0.0382***
	(0.00286)	(0.00317)	(0.00176)	(0.000381)	(0.000686)
Turnout	-0.181***	0.0926***	0.0654***	0.0128***	0.0465***
	(0.00359)	(0.00397)	(0.00224)	(0.000449)	(0.000828)
Time zone	9.956***	-2.625***	-4.304***	-0.817***	-1.685***
	(0.0730)	(0.0853)	(0.0230)	(0.00666)	(0.0126)
Age (avg.)	0.512***	-0.703***	0.0142***	-0.00418***	0.0194***
	(0.00403)	(0.00444)	(0.00229)	(0.000523)	(0.000890)
Women voters	-4.141***	-7.814***	6.096***	1.184***	3.491***
	(0.238)	(0.252)	(0.149)	(0.0288)	(0.0525)
Years of schooling (avg.)	12.94***	-16.40***	2.475***	-0.457***	-1.307***
	(0.0286)	(0.0317)	(0.0168)	(0.00340)	(0.00611)
Constant	-38.78***	153.0***	-12.61***	2.902***	1.448***
	(0.819)	(0.895)	(0.501)	(0.101)	(0.184)
R^2	0.442	0.538	0.106	0.069	0.145
Observations	452656	453301	451763	438539	451574
N.Clusters	452656	453301	451763	438539	451574

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-5) at the level of voting machine (where the treatment occurred).

Second round of elections

Table 25: The effect of non-information exposure on voting behaviour - Placebo treatment (second round)

	(1) Frontrunner	(2) Second place	(3) Blank	(4) Null
Treated (>1700h and <1900h)	-1.144***	0.611***	0.0303***	0.496***
	(0.0491)	(0.0512)	(0.00402)	(0.0117)
Closure delay (in min.)	-0.0897***	0.0675***	0.00173***	0.0225***
	(0.00843)	(0.00788)	(0.000659)	(0.00264)
% Error in biometrics	-0.307***	0.468***	-0.0246***	-0.136***
	(0.00323)	(0.00355)	(0.000297)	(0.000777)
Turnout	-0.0762***	0.0313***	0.00456***	0.0380***
	(0.00379)	(0.00407)	(0.000322)	(0.000868)
Time zone	10.89***	-8.382***	-0.450***	-1.984***
	(0.0847)	(0.0864)	(0.00585)	(0.0136)
Age (avg.)	0.767***	-0.880***	0.0158***	0.0889***
	(0.00427)	(0.00461)	(0.000386)	(0.00101)
Women voters	-7.311***	3.056***	0.345***	3.410***
	(0.264)	(0.283)	(0.0224)	(0.0599)
Years of schooling (avg.)	14.99***	-14.80***	0.131***	-0.455***
	(0.0317)	(0.0349)	(0.00255)	(0.00679)
Constant	-54.34***	157.3***	1.008***	-1.445***
	(0.896)	(0.958)	(0.0765)	(0.204)
R^2	0.447	0.428	0.047	0.141
Observations	453016	453317	432965	452260
N.Clusters	453016	453317	432965	452260

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis is voting machine. We cluster standard errors of all OLS models (1-4) at the level of voting machine (where the treatment occurred).