Democratic Space Barometer

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Abstract

This project estimates the probability that a country will experience **at least one** opening event (a substantial increase) or **at least one** closing event (a substantial decrease) over a two-year window (2019–2020) for six indicators from the Varieties of Democracy data that capture different aspects of a country's *Democratic Space*: the formal and informal institutional environment that structures political competition within a polity.[1] While acknowledging that the *Democratic Space* captures a number of formal and informal institutions, for this project, we focus on six conceptual spaces that are particularly relevant to democracy, human rights, and governance (DRG) development programming: *associational, economic, electoral, governing, individual, and informational spaces*. This project uses a set of 12 random forest forecasting models with a vast country-year dataset with global coverage from 1970 to 2018 to estimate the probability that there will be an opening or closing event in a country within the next two years (2019–2020).

The *Democratic Space Barometer* is a tool designed to help DRG practitioners identify countries that might see an opening or closing in the conceptual spaces within a two year window. In this report, we describe the forecast component of this project. We define and then operationalize opening and closing events in these six spaces using six corresponding index variables from the Varieties of Democracy (V-Dem) project. These index variables place countries on a continuous scale for each conceptual space and year. To identify substantial opening or closing events (e.g., a large increase or decrease in the extent of horizontal government accountability as a measure of the *governing space*), we use thresholds in the extent of year-over-year changes that correspond well to several "common sense" occurrences of large movements on these indices. We then use 12 random forest models and 2018 data (the most recent available), consisting of other V-Dem version 9 indicators as well as several additional data sources, to produce two-year forecasts for 2019–2020 for the risk of *any* opening or closing events in each of the six spaces. Test forecasts that simulate forecasting with 2005, 2006, etc. to 2016 data provide some indication of the likely accuracy of the forecasts, and the overall performance matches other public forecasting projects. The forecasts and other related visualizations are presented in a publicly available dashboard available at https://www.v-dem.net/en/analysis/DemSpace.[2]

A note regarding measuring effects, causality, and interpretation

It is important to note that the output of our models are probabilities, not certainties. A high probability does not necessarily mean an event (opening or closing) will occur. Similarly, a low probability does not mean that an event will not occur. Further, with generalized linear models like logistic regression, one can make relatively simple statements about the general effects that an input variable has on the output – such as, "a one-unit increase in variable x increases the odds of an event by $Y\%$." Similarly, there are various methods for interpreting the *general association* between input variable values and predictions in random forest models. We could have shown, for example, visualizations that depict the general association between an input variable and changes in the outcome prediction on average and across cases. However, these kinds of presentations of associational effects, in our opinion, intuitively invite causal interpretations.

Unfortunately, the machine learning forecasting model we use to derive these estimates, random forest with observational data, does not lend itself to causal explanations. Movement within all dimensions of the *Democratic Space* are the product of highly complex, and often interrelated, mechanisms as well as idiosyncratic processes and conditions within specific countries, years, and spaces. Causal inference requires a research design (and corresponding theory) that can isolate distinct mechanisms. Random forest models with observational data cannot do this. Thus, we have chosen not to include such methods in the paper or dashboard and encourage readers to avoid causal interpretations of our results. The evidence needed to support causal claims require a research design that is beyond the scope of this project.

[1] Sometimes countries experience back to back opening or closing events in a two-year period, or a closing event followed immediately by an opening event (and vice versa).

[2] This project was funded by the United States Agency for International Development (USAID) through the International Republican Institute (IRI), which have legislative and institutional prohibitions on providing commentary or analysis on US domestic politics. While we use data on the US in our models, this report conforms to these legislative and institutional prohibitions.

1 Introduction

The seemingly inexorable advance of liberal democratic governance has ended, or at least encountered a serious bump in the road. In recent years, an increasing number of countries are moving to more autocratic forms of government than are democratizing (Lührmann et al. 2018, 2019, 2020). In the past, democratic erosion could be expected in young, unconsolidated democracies or autocracies with some liberalized aspects. This is still the case, but now even once-stable regimes appear to be in danger, including Hungary and Poland in Europe, and Brazil and India – two of the world's largest democracies. The specter of populist authoritarianism haunts even established democracies as well (Levitsky and Ziblatt 2018; Lührmann et al. 2020, 2019). As of 2019, more than half of the global population, across 92 countries, live under some form of autocratic rule. More striking, over one-third of the world's population live in countries that are part of the *current* wave of autocratization (Lührmann et al. 2020). That's to say, roughly 2.6 billion people *currently* live in a country where political actors are eroding core features of democratic governance.

Meaningful checks on executive power and political corruption as well as individual, political and media freedoms are under attack; polarization is on the rise, and technology has provided new opportunities for political actors to manipulate and control traditional media, social media, and civil society – all at a global scale. Indeed, three of four major democracy-measuring projects record decreases in the global average of democratic governance. The Varieties of Democracy Institute's Liberal Democracy Index has been declining since 2014 (Lührmann et al. 2018, 2019, 2020). Freedom House has been recording declines since 2005 (Freedom House 2019), and the Economist Intelligence Unit's democracy index has been stagnant or decreasing in 4 out of the 5 past years (Economist Intelligence Unit 2019). Only the Polity project (Marshall, Gurr, and Jaggers 2018) has not identified a global decline; however, it has registered decreases in major democracies.

While still unfolding, researchers have begun to identify general trends in this autocratization wave. Namely, empirical evidence suggests that the gradual and subtle nature of the tactics used to erode democratic freedoms sets this wave of autocratization apart from historical cases (Lührmann and Lindberg 2019). Historically, autocratization events tended to be quick – the numerous coups d'état that plagued many South American countries throughout the 1960s and 70s, for example. However, these brash tactics – quickly consolidating political power through force and coercion – are being replaced by more subtle means. Rather than swift, decisive blows at democratic freedoms, political actors are using "salami tactics" – distinct democratic principles, whether media freedoms or something else, are slowly eliminated "slice by slice" until they are rendered meaningless. The idea is that the public will be less shocked by these gradual restrictions, not realizing the harm until it is too late. The slow erosion of democratic freedoms in Hungary, Turkey, and Poland help illustrate this point.

There appears to be a broad consensus, supported by data, that democracy and more democratic forms of government in general, are under threat, and that wannabe autocrats are adopting more subtle tactics to avoid domestic and international scrutiny. What is less clear is which countries are at the highest risk for continuing declines, and what to do about it. To address the former, the Varieties of Democracy Institute (V-Dem) introduced the Predicting Adverse Regime Transitions (PART) project in 2019. PART provides public forecasts of the two-year risk of adverse regime transition – categorical changes in a country's regime type from more democratic governance to a more autocratic form (Morgan, Beger, and Glynn 2019). To our knowledge this is the only open, public, global mapping of democratic erosion risk currently available.

The *Democratic Space Barometer*, which we describe here, improves on PART in several ways. First, instead of a single index to describe the continuum from democratic to autocratic governance, this project focuses on six distinct spaces of the so called *Democratic Space – associational, economic, electoral, governing, individual,* and *informational spaces*.[3] Second, we introduce quantitative indicators that capture substantial shifts towards autocratic governance (i.e., "closing events") and substantial shifts towards democratic governance (i.e., "opening events"). Third, we introduce two-year forecasts for both opening and closing events in these six democratic spaces.

[3]These conceptual spaces are based on the International Republican Institute's (IRI) *Closing Space Barometer*, which includes an analytical framework for assessing the processes that facilitate a substantial reduction (closing) within these six spaces. This framework was developed based on a series of workshops conducted with DRG donors and implementing partners in 2016 and represent the conceptual features of democratic space which are most amenable to interventions.

Empirically, there is evidence that downward shifts (i.e., "closing events") can occur in different ways. Coppedge (2017) identifies two distinct routes for democratic erosion – one based on repression of speech, media, assembly, and other political rights, and the other more recent alternative path featuring concentration of power in the executive at the expense of the legislative and judicial branches. The conceptual spaces of the *Democratic Space* that we identify and our measurement strategy capture these and other autocratization tactics. Further, by splitting the broad concept of *democratic erosion* into substantive movements within distinct spaces, we provide a more fine-grained view of factors that the literature suggests can contribute to the broader and more drastic phenomena of adverse regime transitions.

We envision this tool as serving three related purposes for democracy support organizations, as well as other scholars and practitioners. First, by identifying the probability of opening and closing events across countries, these forecasts will provide practitioners with more systematic information to guide strategic resource allocation. In other words, the forecasts can help identify countries, regional, or global "hot spots" – countries with pronounced risk of movement in one direction or the other. Second, our goal is to inform program design by providing practitioners and others more concrete information about potential opportunities and risks *between* specific conceptual spaces. That is, the forecasts will help program designers identify what types of activities or interventions (e.g., civic, informational, political, institutional, economic, or rights-based) will be most likely to mitigate risks or capitalize on opportunities over the course of a program cycle. To these ends, we also provide an interactive dashboard at https://www.v-dem.net/en/analysis/DemSpace which presents our 2020–2021 forecasts.[4]

In short, this project estimates the probability that a country will experience **at least one** opening event (a substantial increase on a respective index) or **at least one** closing event (a substantial decrease on a respective index) over a two-year window (2019–2020) for each of the six democratic spaces.[5] We derive these forecasts using series of random forest machine learning models and a vast country-year dataset with global coverage from 1970 to 2018. This paper describes the technical details of this project.

In section 2, we provide definitions for each democratic space concept and identify and provide a brief description of the V-Dem index we use to measure each space. We cover how we turn these continuous indexes into discrete, single-year events that correspond to instances of substantial opening and closing events in a country as well as the data we use to derive our forecasts in Section 3.

To estimate the probability that a country will experience an opening or closing event within a two-year window in one or more of the six constituent space (12 different potential outcomes), we use the increasingly common random forest model (Muchlinski et al. 2016). We provide a brief introduction to this kind of model, and the simpler decision tree models that they are composed of, in Section 4, where we also discuss the test forecasts we used to assess the model's performance (Section 4.3) and notes on interpreting the model output predictions (Section 4.4).

The results section, Section 5, introduces the top ten 2019–2020 forecasts for each direction (opening and closing) in each space and discusses several different ways of placing these forecasts into context, e.g. how accurate any specific country forecast is likely to be, based on past performance, and how well the aggregate forecasts map on to global shifts across the spaces. For the full lists of 2019–2020 forecasts for all countries, skip to Appendix B.

2 Overview & definitions of the democratic spaces

We define *Democratic Space* as the formal and informal institutional environment that structures political competition within a polity. For a given year, a country can have a narrow *Democratic Space* (e.g., North Korea at the extreme), or its *Democratic Space* can be wide (e.g., Norway and Sweden). While the *Democratic Space* captures many formal and informal institutions, for this project, we focus on six institutional spaces

[4] While we present our most recent forecasts (2020–2021) on our public dashboard, the forecasts we present in this report are for 2019–2020, as it was written before the release of V-Dem Version 10.

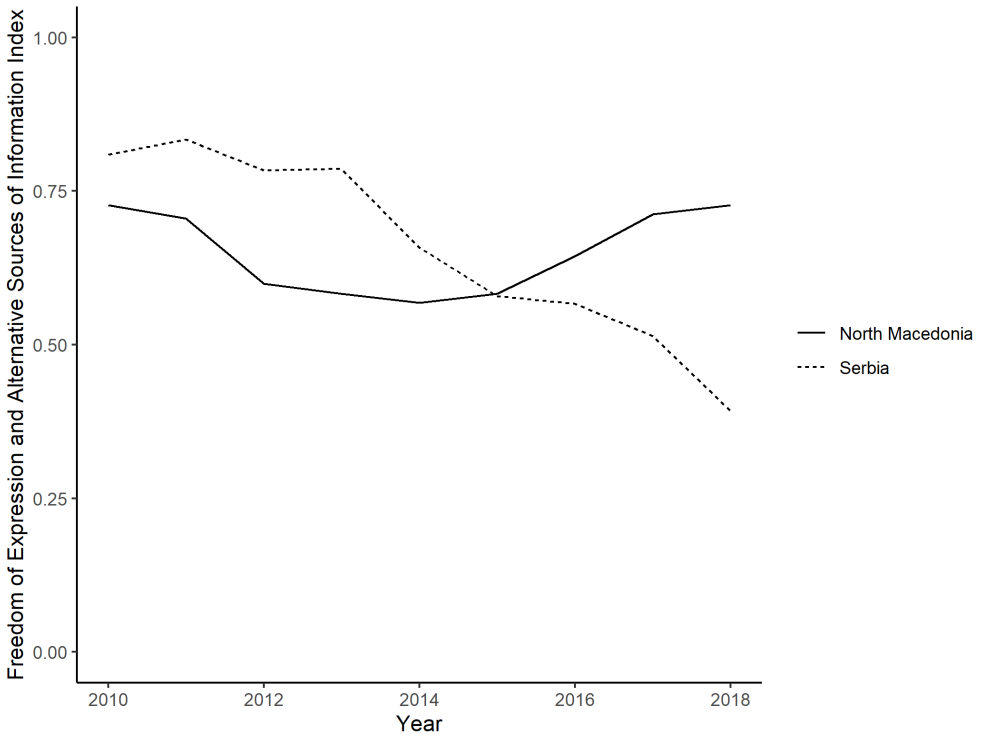
[5] Sometimes countries experience back to back opening or closing events in a two-year period, or a closing event followed immediately by an opening event (and vice versa).

that are particularly amenable to democracy, human rights, and governance (DRG) development assistance programming: *associational, economic, electoral, governing, individual, and informational conceptual spaces*.

From one year to the next, these various institutional spaces can open (*liberalize*), close (*autocratize*), or stay relatively stable. These opening and closing events can be quick and dramatic – for example, the period of quick liberalization that followed the collapse of the Soviet Union and the dramatic loss of democratic freedoms that often follow coups d'état. However, in the current global environment, the empirical evidence suggests that the institutional changes that can shift a polity towards autocracy tend to be less dramatic and accumulate over time (Lührmann and Lindberg 2019; Lührmann et al. 2020). These subtle shifts are often done with the support of a plurality of the population. They register international attention but not to the level that will necessarily trigger meaningful international collective action. The slow erosion of judicial independence and media and academic freedoms under Prime Minister Orbàn's government is a clear example of the gradual closing of both the *governing space* as well as the *informational space* in Hungary.

Likewise, there is general consensus that democratic reforms and the liberalization process also tend to occur gradually, as democratic institutions and norms are often hard to take root. The improvements in media freedoms in North Macedonia in 2016 and 2017 are examples of gradual opening events within North Macedonia's *informational space*. In fact, shown in Figure 1, a juxtaposition between the gradual improvements in the *informational space* in North Macedonia since 2015 and the closure of the *informational space* in Serbia since 2013 illustrates opening and closing events well.

Figure 1: Diverging Paths in the Informational Space in North Macedonia and Serbia



We provide concise definitions of each space and map each to a corresponding V-Dem index below. To make it easier for readers to familiarize themselves with the V-Dem indices we selected, we provide the text description from the V-Dem codebook of each of our indices in Appendix A.3.[6] All of the selected indices are on a continuous scale ranging from 0 (autocratic) to 1 (democratic).

[6]For more information on these indices and the V-Dem project in general, please see visit https://www.v-dem.net/en/about

2.1 Associational

The *associational space* is the arena in which associations of citizens meet to discuss and/or advocate for specific issues. This space corresponds to what DRG practitioners often refer to as "civic space." Civil society organizations (CSOs) are a critical actor in this regard. They help frame issues, mobilize the population, and organize collective action. Thus, limitations of the ability of CSOs to recruit, operate, and fundraise, as well as threats to the physical safety or liberties of CSO staff, are various ways different actors might try to constrain associational freedoms.

V-Dem's Core Civil Society Index (`v2xcs_ccsi`) captures this space. According to the V-Dem codebook, this index "is designed to provide a measure of a robust civil society, understood as one that enjoys autonomy from the state and in which citizens freely and actively pursue their political and civic goals, however conceived." It takes into account CSO entry and exit (`v2cseeorgs`), CSO repression (`v2cseeorgs`), and citizen participation (`v2csprtcpt`).

2.2 Economic

The *economic space* refers to the relationship between the structure of markets and political competition. We argue that public corruption, as a key mechanism through which elites influence the structure of markets to advance political goals, is an important proxy measure of a polity's economic space. We define public corruption as the extent to which public sector officials or political incumbents provide goods and services in exchange for bribes (or other material inducements), and how often they steal, embezzle, or misappropriate public funds or other state resources for personal or family use. High levels of public corruption therefore represent a relatively closed economic space, in the sense that access to both markets as well as public goods and services are restricted based on personal connections or ability to pay. Conversely, an open economic space is characterized by relatively open access to markets and the state institutions that govern markets. In an ideal-type open economic space, accumulation of resources, and any resulting access to political competition, is not constrained by personal connections, inducements, coercion, or other informal institutions.

Measuring public sector bribery (`v2excrptps`) and embezzlement (`v2exthftps`), V-Dem's Public Corruption Index (`v2x_pubcorr`) captures this space. In the V-Dem dataset, this index ranges from 0 (no corruption) to 1 (high corruption). This is the opposite of our other indices where higher scores signal a more open *democratic space*. Therefore, we invert this index to match the others.

2.3 Electoral

The *electoral space* refers to the arena for political competition. Broadly speaking, opening and closing of the *electoral space* centers around the degree of restrictions placed on a citizen's ability to participate in political processes and their ability to hold political leaders accountable. Thus, the *electoral space* captures limitations and restriction on political rallies, fundraising, and campaigning; undue and burdensome limitations on political parties, as well as fraudulent electoral processes.

V-Dem's Vertical Accountability Index (`v2x_veracc_osp`) captures this space well. It reflects "the ability of a state's population to hold its government accountable through elections and political parties" (Luhrmann et al. 2017: 7). It includes V-Dem indicators on (i) election quality; (ii) the proportion of the population that is enfranchised; (iii) whether the chief executive is subject to direct or indirect elections, as well as (iv) how free opposition parties are to operate.

2.4 Governing

The *governing space* refers to the role of state institutions, including branches of government, ministries and sub-ministerial agencies, and levels of government, in the political process. Closure in this space manifests in partisan control of government branches, the bureaucracy (agencies, commission and statutory/regulatory

bodies) and security services, as well as the weakening of institutional checks on executive power. Conversely, a relatively open governing space is characterized by checks and balances between branches; respect for jurisdictions between levels of government; and professionalized and apolitical state bureaucracies, and especially security services.

V-Dem's Horizontal Accountability Index (`v2x_horacc_osp`) captures this space. This index measures the degree to which the legislative and judicial branches can hold the executive branch accountable. It does not capture partisan control over the bureaucracy or security services; however, it does measure the extent to which there is legislative oversight of these institutions. In this sense, the Horizontal Accountability Index is the best available single proxy measure for the concept of *governing space*.

2.5 Individual

The *individual space* captures the degree to which citizens of a country are afforded basic individual freedoms: private property rights, physical integrity, freedom of movement, freedom of thought, conscience and religion, and equality under the law. In this sense, individual space refers to governmental and state respect for, and citizen freedom to exercise, fundamental human rights.

V-Dem's Equality Before the Law and Individual Liberty Index (`v2xcl_rol`) captures this space perfectly. This index measures the extent to which the laws are transparent and rigorously enforced and public administration impartial, and the extent to which citizens enjoy access to justice, secure property rights, freedom from forced labor, freedom of movement, physical integrity rights, and freedom of religion. This index takes into account indicators for rigorous and impartial public administration, transparent laws with predictable enforcement, access to justice for men/women, property rights for men/women, freedom from political killings, torture and forced labor, freedom of religion, and the freedom of foreign movement and domestic movement.

2.6 Informational

The *informational space* captures the environment in which citizens learn and apply knowledge about public affairs and public officials' performance, with the goal of holding those officials accountable for providing public goods, services, and beneficial public policies. Closure in this space may include violence or threats of violence against journalists, government influence over political coverage, censorship laws, the creation of government-run news outlets, and threats to academic freedoms and cultural expression.

V-Dem's Freedom of Expression and Alternative Sources of Information Index (`v2x_freexp_altinf`) captures this space. According to the V-Dem codebook, `v2x_freexp_altinf` measures the extent to which the government "respect[s] press and media freedom, the freedom of ordinary people to discuss political matters at home and in the public sphere, as well as the freedom of academic and cultural expression[.]" In constructing this index, V-Dem takes into account media censorship (`v2mecenefm`), harassment of journalists (`v2meharjrn)`, media bias (`v2mebias)`, media self-censorship (`v2meslfcen`), whether the media is critical (`v2mecrit`) and pluralistic (`v2merange`), as well as the freedom of discussion and academic and cultural expression (`v2cldiscm`, `v2cldiscwm`, and `v2clacfree`).

3 Measurement & Data

V-Dem provides country-year measurements for each index we use to capture our various spaces. That is, the V-Dem dataset is a spreadsheet, where columns are the reported scores for each index (e.g., the Core Civil Society Index) and each row is a country-year (e.g., there is a row for Estonia for 1991 through 2018 – $year_t$). The trio – the reported scores for country X in $year_t$ – is an observation. The dataset we use to train our models consists of yearly observations of all independent states in a given year from 1970 to 2017, reserving data from 2018 for our final predictions. To allow for the inclusion of non-V-Dem data, we reconcile the

differences between the V-Dem country-year set and the Gleditsch and Ward country-year set.[7] The number of countries in our data in a given year ranges from 137 to 169, producing 7,678 country-year observations.

We limit our sample to 1970 for two reasons. First, there is growing the evidence suggesting that the recent waves of both democratization and autocratization are different than previous waves. For a dramatic example, the factors associated with democratization in the French Revolution beginning in 1789 may not be precisely similar to those associated with the post-colonial waves of democratization in the late 20th century, or the Arab Spring in the early 21st century. We want to reduce the noise in our data and focus on the current processes that might lead to opening and closing events. The second reason is that formal recording and reporting standards for a number of important development variables (infant mortality and GDP data, among others) are relatively new, primarily starting in the 1970s. For example, as currently conceptualized and measured, GDP dates back to the 1944 Bretton Woods conference. However, accurate and comparable cross-national GDP data only becomes possible in the 1970s when more international political and financial institutions began using these quantitative data in their decision-making processes.[8]

While there are a handful of heroic data collection efforts to improve the temporal and spatial coverage of these indicators, there remains a lot of missing values in these data. It is, after all, difficult to accurately measure the GDP of Afghanistan in 1950, roughly 20 years before formal reporting standards took hold, for example. Using these data would introduce unknown bias and measurement error into our models. Nevertheless, development indicators are clearly important, and we want to include them in our models. Therefore, we limit our dataset to 1970 to help measurement error and bias as best as possible.

3.1 Operationalizing opening & closing of a space

The goal of this project is to forecast substantial opening and closing events within a two-year window across six constituent spaces of the *Democratic Space*. These *opening* and *closing* events represent *substantial year-to-year changes* in various formal and informal democratic institutions. Thus, our operationalization strategy (how we identify *opening* and *closing* events) centers around *positive* and *negative year-to-year* changes (first differences) in the V-Dem indices we identified above. The subsections below work through the specifics of our approach.

3.1.1 Identifying thresholds

This project aims to estimate the probability that a country will experience a *substantial* opening or closing event across the six constituent spaces of the *Democratic Space* within a *two-year window*. This requires defining, empirically, what constitutes a "substantial event" (whether an opening or closing event) in the V-Dem index variables we are using. We need to establish a procedure that converts year-to-year changes within an index (e.g., a country's score in $year_t$ minus its score in $year_{t-1}$). This operationalization strategy needs to be (i) universal, in that it can be applied uniformly across each distinct space, (ii) sensitive enough to capture important but potentially subtle changes but is also (iii) conservative enough to separate signal from noise, and (iv) allows for comparison across and within spaces.

We approach this empirically, defining substantial year-to-year opening and closing events uniquely for each distinct space using the following procedure:

1. Calculate the year-to-year differences for each index
    i. Index score in $year_t$ minus the score in $year_{t-1}$ for all countries in our sample (1970 to 2018)
2. Split the data into two groups:[9]
    i. All observations with year-to-year differences ≥ 0 (opening movements)

[7] For more information on the Gleditsch and Ward country-year set see http://ksgleditsch.com/data-4.html. We drop the following eight countries from the V-Dem set: São Tomé and Principe, Seychelles, Vanuatu, Palestine/West Bank, Palestine/Gaza, Somaliland, Hong Kong, and Zanzibar. And, along with all micro-states, we drop the following five countries from the GW set: Bahamas, Bahrain, Belize, Brunei, and Malta from the GW set, as they lack sufficient coverage in the V-Dem data.

[8] See https://foreignpolicy.com/2011/01/03/gdp-a-brief-history/

[9] We include all cases that saw no change (first differences = 0) in both groups to help account for extreme outliers.

   ii. All observations with year-to-year differences ≤ 0 (closing movements)
3. Calculate the standard deviation for both groups – opening movements and closing movements
4. Calculate the average these two standard deviations
5. Round this average up to the nearest 100th

- The opening event threshold for an index is this rounded average, while the closing event threshold is the rounded average multiplied by -1.

We use this procedure to establish six pairs of thresholds, one pair for each space. For each space, we code a country-year observation 1 if the year-to-year difference of the space-specific V-Dem index is greater (less) than or equal to this value, 0 otherwise.

We came to this approach through deliberation and data exploration. To help evaluate the appropriateness of this approach, Appendix A.1 provides a brief discussion about alternative strategies we considered.[10] Below we walk through the factors that we took into consideration when determining our space-specific threshold strategy and provides justifications for our decisions.

3.1.2 Justifications

It is important to note that we are developing 12 distinct models, and each model needs to be comparable to the others. This requires that we apply the same operationalization strategy for each space and direction. However, through data exploration, we found that substantial year-to-year changes (opening movements or closing movements) across each space are not necessarily the same. For example, at 0.8, the standard deviation of all year-to-year changes (opening movement, closing movement, and no movement) within V-Dem's Vertical Accountability Index (our proxy for the *electoral space*), is significantly larger than the standard deviations of year-to-year movements of the other indicators, which range from 0.04 (V-Dem's Public Corruption Index, our proxy for the *economic space*) to 0.06 (V-Dem's Horizontal Accountability Index, our proxy for the *governing space*).

Because the variances of all year-to-year movements within each space are different, using a single universal threshold would imply that we consider variation in the *relatively* fast-changing spaces (e.g., *electoral space*) more important than in relatively slower-evolving spaces (e.g., *economic space*). That is, picking a single threshold for all indices would result in uneven rates of type-I (false positives) and type-II (false negatives) errors for both opening and closing events.[11] To avoid this kind of differentiation, we chose an operationalization strategy that produces distinct thresholds for each of the six spaces.

We face a similar, if not more complicated, problem with regard to defining the event threshold *within* each space (i.e., the year-to-year change needed for an observation to register as either an opening or closing event). However, while we decided to establish distinct thresholds for each space, we also decided to establish uniform event thresholds within each space. For example, the event threshold for the *associational space* is 0.05. We measure the *associational space* using V-Dem's Core Civil Society Index, so if a country's score in the Core Civil Society Index *increases* by 0.05 points from one year to the next, we record an *opening event*. Similarly, if a country's score in the Core Civil Society Index *decreases* by 0.05 points from one year to the next, we record a *closing event*.

[10] Appendix A also contains relevant descriptive statistics concerning the cutpoint calculation, time-series plots showing the number of countries and the percentage of countries per year that experienced positive or negative substantial change, as well as country-level time-series plots that report a country's yearly level of an index and whether our threshold procedure captures the example cases IRI provided for each specific space.

[11] Type-I and type-II errors is best explained through a hypothetical. Suppose you are part of a jury in a criminal case. Your responsibility is to decide whether the defendant is innocent or guilty of the crime to which they are charged. If the defendant is indeed guilty and the majority of the jury votes to convict or if the defendant is innocent and the majority of the jury votes to acquit, all is well; justice is served. However, if the defendant is in fact innocent and the majority votes to convict, then the jury has committed a type-I error, a false positive. Conversely, if in fact the defendant is guilty and the majority votes to acquit, then the jury has committed a type-II error, a false negative. In the current context, a type-I error happens, for example, when we identify a closing event in a country when in reality the downward shift was not all that meaningful (i.e., our threshold was insufficiently strict), while a type-II error occurs when we fail to identify a meaningful downward shift (our threshold was too strict).

Ideally, we could simply take the standard deviation of all year-to-year changes as the threshold for types of events. This requires the assumption that the magnitude of year-to-year change is the same for both types of cases – opening and closing events. While the literature suggests that both autocratization and democratization processes tend to occur gradually, it does not suggest that these very different processes proceed at the same pace. We can check to see if open processes is faster than the other, however, by comparing the standard deviation of all positive year-to-year changes (opening movements) to the standard deviation of all negative year-to-year changes (closing movements). A higher standard deviation in one group relative to the other indicates that year-to-year changes within that group are larger, suggesting that that particular process, while still slow and cumulative, is nevertheless faster than the other process.

In our sample, it appears that opening events unfold quicker than closing events. When we divide the data into observations that had a positive, ≥ 0, year-to-year change (opening movements) and observations that had a negative, ≤ 0, year-to-year change (closing movements) and calculate the standard deviation of each group, we see that across all spaces, the standard deviation of opening movements is larger than the standard deviation of closing movements. While the difference between the standard deviations of these groups is small (a difference of 0.013 on average), it still suggests that there is a difference between these two processes.

Therefore, dividing the data based on positive or negative movements and taking the standard deviation of these groups helps us avoid the possibility that the relatively larger opening movements in the data might washout important information about the closing movements. This, however, complicates within-space comparability. Similar to ensuring model comparability across spaces, we want to ensure that the within space models – the opening event model and the closing event model – are comparable. Having two separate thresholds for each space (one for opening events and one for closing events) makes comparability difficult. As such, we establish a uniform threshold of positive and negative movements within each space by taking the average of these two standard deviations.

Aside from comparability, this step and the next, rounding up to the nearest 100th, helps ensure that our thresholds are stricter; we will register less opening and closing events in a given year because the event threshold is higher. Forcing a stricter threshold is important, as the value of these thresholds have clear implications concerning the usefulness of this project. Lower, less strict event thresholds would *necessarily* capture more cases relative to higher event thresholds. However, it is likely the case that the majority of the observations captured with a low event threshold are not true representations of the actual phenomena we seek to measure – there will be a lot of false positives (i.e., found guilty when in fact innocent). While we would still capture meaningful cases with a lower threshold (the year-to-year changes of meaningful events is larger by definition), we would also capture a lot of noise (i.e., a lot of the downward shifts are not all that meaningful in reality). The case we identify with smaller, less strict event thresholds, and thus our risk estimates, will be less useful, as a larger number of the events we identify will not reflect important movements in the democratic freedoms of a country. Stricter event thresholds help reduce this issue.

3.1.3 Empirical thresholds

The column labeled "Cutpoint" in Table 1 below reports our empirical thresholds for each space. Table 1 also summarizes the overall number of opening and closing events for each space. The columns, respectively, show the total number of events from 1970 to 2018 ("Total #"), the overall event rate in the data ("Total %" – total number of events/7678, the total number of country-year observations in our sample), the average number of events per year ("#/year"), and the total number of events as well as the percentage of countries that had an event in 2018 ("# 2018" and "% 2018"). For the latter, note that, with the exception of the *electoral space*, all spaces have seen an uptick in the number of positive and negative movements in recent years, suggesting more volatility in recent years across all constituent spaces of the *Democratic Space*.

Table 1: Thresholds and summary of cases and event rates for each space

Direction	Cutpoint	Total #	Total %	#/year	# 2018	% 2018
Associational						
Closing	-0.05	347	4.5	7.1	26	15.4
Opening	0.05	539	7.0	11.0	22	13.0
Economic						
Closing	-0.03	368	4.8	7.5	31	18.3
Opening	0.03	428	5.6	8.7	32	18.9
Electoral						
Closing	-0.08	158	2.1	3.2	4	2.4
Opening	0.08	241	3.1	4.9	2	1.2
Governing						
Closing	-0.06	234	3.0	4.8	16	9.5
Opening	0.06	359	4.7	7.3	13	7.7
Individual						
Closing	-0.04	312	4.1	6.4	25	14.8
Opening	0.04	489	6.4	10.0	20	11.8
Informational						
Closing	-0.05	249	3.2	5.1	15	8.9
Opening	0.05	415	5.4	8.5	12	7.1

3.1.4 Creating two-year-ahead outcome variables

While Table 1 summarizes the yearly frequencies of both opening and closing events within each space, this project is interested in estimating the risk that a country will experience at least one, but possibly two, of these events within a *two-year window*. Thus, the next challenge is how to forecast these outcomes two-years ahead. There are two ways we could do this.

The first is to forecast the risk of a year-to-year change one year and two years from now separately, and then somehow aggregate the resulting one- and two-year ahead forecasts into a single forecast for the next two years. The second approach is to first aggregate the year-to-year change variables into single two-year versions and then forecast those. We use the second approach, and *transform the yearly outcomes above into two-year version*, for these reasons:

- Forecasting the year-to-year changes two years out would require two sets of forecasting models, one forecasting one year out (i.e. use 2018 data to forecast 2019) and a second set forecasting two years out (i.e. use 2018 data to forecast 2020), and thus is more complex from a modeling and interpretation perspective.
- Since we would be using the same set of information to forecast one and two years from now, it is unlikely that we would have much traction forecasting at the yearly as opposed to two-year level. In other words, it is unlikely that we could meaningfully say that the risk of a change is higher next year than the year after that. A counterexample would be highly cyclical or seasonal data, where forecasting at a higher time resolution could add something lost when forecast directly at the lower level of time resolution.
- Forecasting at the yearly levels (first approach) is more flexible in that we could calculate the risk of various constellations of outcomes – e.g., the combined risk of no change next year followed by a change two years from now. But it is not clear (i) how well we could do this in practice (see the preceding point) nor (ii) how valuable this kind of granularity would be compared to just knowing how likely any negative or positive change is to happen at some point over the next two years.

Description of two-year outcome variables: The specific way we aggregate the year-to-year outcome variables to two-year versions is to create a variable where we record a `1` if at least one significant opening (or closing) event occurred within the next two years, and `0` otherwise for all years, 1970 to 2018. For example, the two-year opening version for one of the spaces for the year 2018 would be `1` if there was a change in either 2017, 2018, or both years, and `0` otherwise. In all, we create 12 different outcome variables, one for each of the six spaces and the two directions, modeling each separately.

For clarity, the table below shows an example of what our space-specific target data might look like for the country of "Pineland," a hypothetical case. Like in our actual dataset, here we use "up" and "down" as shorthand for opening and closing events, respectively. Each row is a country-year observation. The "space_indicator" column shows year-to-year changes in any one of the six V-Dem indices we selected. Based on the established threshold for substantial change, we record whether there was an "up" or "down" change in that year, the "year_to_year_state" column.

Country	year	space_indicator	year_to_year_state	up_next2	down_next2
Pineland	2010	0.0	same	1	0
Pineland	2011	0.0	same	1	0
Pineland	2012	0.5	up	0	0
Pineland	2013	0.5	same	0	1
Pineland	2014	0.5	same	0	1
Pineland	2015	0.0	down	0	1
Pineland	2016	-0.5	down	0	0
Pineland	2017	-0.5	same	.	.
Pineland	2018	-0.5	same	.	.
Pineland	2019	.	.	.	.
Pineland	2020	.	.	.	.

In this example, we assume that the threshold a significant opening and closing event in our space indicator is ± 0.5. Thus, in Pineland there was one year-to-year "up" movement (opening event) in 2012 and two year-to-year "down" movements (closing event) in 2015 and 2016, as shown in the "year_to_year_state" column. In the remaining years, movement within the space indicator did not exceed our empirical threshold; these country-years are thus coded as "same" in the "year_to_year_state" column.

The first event of interest in Pineland is the "up" movement in 2012. Note how the "up_next2" variable is coded based on the "year_to_year_state" column. The 2010 and 2011 values are `1` because for both the two-years-ahead window includes the 2012 "up" movement. The 2012 value of "up_next2" is `0` however, since the two-year-ahead window captures 2013 and 2014, which does not include the 2014 year-to-year "up" movement. The data end in 2018, and thus the 2017 and 2018 values for the "up_next2" outcome variable are missing – we do not know yet what happened in 2019 and 2020.

The "down_next2" outcome variable similarly shows what our models are trying to forecast for closing events. There were two year-to-year "down" movements, in 2015 and 2016. As before, the 2013 and 2014 values are `1`, but note how the 2015 value is also one. Although 2015's "down_next2" two-year-ahead window does not include the 2015 "down" movement, it does include the 2016 "down" movement. Also note how the 2014 "down_next2" two-year-ahead window includes two "down" movements, but still has only a value of `1`. This is because we code whether one or more "down" movements occurred in the two-year-ahead window, not the number of such movements.

We do not yet have values for the space indicator in 2019 and 2020. And, the "up_next2" and "down_next2" variables are also missing for 2017 and 2018. This is because they look two-years ahead, when the space indicator variable is missing values. This reflects the actual state of our data, i.e., although we do know up through 2018 what the status of the year-to-year change variables is, we do not yet know the outcome for the two-year versions. This is relevant for the test forecasts we describe below, but it does not affect our 2019–2020 forecasts.

This scheme has implications that are worth considering for interpretation of the model forecasts:

- A country can experience both a substantial "up" and "down" change in a two-year period, if they follow each other back to back.
- If the two-year version for "up" is a `1`, we do not know whether the country experienced one or two "up" changes; only that it experienced *at least one* "up" change over a two-year period. Similarly for "down" changes.

We discuss how to interpret the results of our models given these factors in Section 4.4.

3.2 Data sources

The current version of the data includes 459 predictor (independent) variables. These variables come from a number of sources or are transformations of other variables. While each predictor variable is lagged one year (e.g., the values of these variables for all 2011 observations are from 2010), we also include an un-lagged version of the outcome indicator (i.e., whether there was a closing event in a country in that specific year). For readers interested in more technical details, Appendix D provides the variable tag (the actual column name of the variable in the dataset) and sample descriptive statistics for all variables in our dataset. We detail all of our data sources below.

3.2.1 V-Dem independent variables

V-Dem version 9 (Coppedge et al. 2019) is our primary data source; 402 of our 459 variables are V-Dem indicators or are derived from these indicators.[12]

In its unaltered form, there are several missing values (labeled 'NA') throughout the V-Dem data. For the most part, this missingness is concentrated around election- and the legislative branch-specific variables, and it is the product of four V-Dem coding rules: (1) when elections are permitted, election specific variables are not scored for the years in between elections, (2) when elections are not permitted or when there is an interruption, all of a country's elections variables are recorded as NA during that period, (3) in the event of an interruption, key legislative-related variables are also recorded NA,[13] and (4) legislative-related variables are recorded as NA for the first year that institution was enacted.

When elections are permitted, we fill in NAs by carrying forward the last non-missing value. If an election-related variable is missing because elections were not permitted or because there was an interruption, we set these observations to zero and create a dummy variable indicating whether the elections were, in theory, permitted. Similarly, when legislative-related variables are missing due to an interruption, we set these

[12] For more information on the V-Dem dataset, please see https://www.v-dem.net/en/about/.

[13] According to V-Dem, an "interruption" is typically the result of a coup, declared state of emergency, or military defeat (For election variables, see: pg. 275 of the V-Dem Codebook, and for legislative variables, pg. 46 and 132-35 of the V-Dem Codebook.

observations to zero and create a dummy variable signaling this change. Finally, we back-fill all legislative variables that are NA because it is the first year of that there was a viable legislative branch.[14]

3.2.2 State age

Using the Gleditsch and Ward state list,[15] we calculate the number of years each state has been independent. This is related to things like how established the institutions and bureaucracy of a country are, and thus potentially relevant for changes in said that might influence movement on the spaces.

3.2.3 Macro-economic & social indicators

Basic macro-economic indicators are drawn from the World Bank's World Development Indicators (WDI).[16] There is a potentially enormous number of indicators that are relevant. However, missing data within all WDI data presents a serious practical limitation. We included indicators for country population, GDP, GDP per capita, and growth in GDP and GDP per capita, as well as infant mortality. These series were manually checked and augmented with several additional sources to complete data that was missing for some countries.

3.2.4 Ethnic Power Relations

The Ethnic Power Relations data (EPR) (Vogt et al. 2015) identifies politically relevant ethnic groups in a country in a given year.[17] For each group, it includes information on the group size and how much access the group has to political power. We convert this information into variables capturing the collective size and number of groups included and excluded from power. For this report, we use version 2018.1 of the EPR data.

3.2.5 Coup data

Powell and Thyne (2011) provide data for global coup d'états from 1950 forward.[18] This includes both successful and failed coup attempts. We convert these into measures of the number of (unsuccessful) coups in a country in total, in the last five years, in the last ten years, and the number of years since the last (unsuccessful) coup attempt. These are generally indicators of underdeveloped and authoritarian state institutions and thus should be related to movements in some of the democratic spaces.

3.2.6 PRIO/UCDP Armed Conflict Data

The Uppsala University Conflict Data Project (UCDP) is an extensive effort to collect and record various aspects of major violent conflict around the world, e.g. interstate wars, civil wars, and micro-data on violent events themselves.[19]

We use the main UCDP/PRIO Armed Conflict Dataset (Pettersson, Högbladh, and Öberg 2019; Gleditsch et al. 2002). This records conflicts with 25 or more battle deaths, including interstate as well as domestic (civil) conflicts. We construct various indicators from these records, e.g., whether a country experience minor (25-1,000 deaths) or major (1,000+ deaths) conflict in a year, whether it participated in a conflict in another country, and so on.

[14] We maintain annotated code for all changes made to the original V-Dem v9 data. This code can be found at https://github.com/andybega/closing-spaces/blob/master/0-outcomes/VDem_data_build.r

[15] See http://ksgleditsch.com/data-4.html

[16] See https://datacatalog.worldbank.org/dataset/world-development-indicators

[17] See https://icr.ethz.ch/data/epr/, and the EPR Core version specifically.

[18] See https://www.jonathanmpowell.com/coup-detat-dataset.html.

[19] See https://www.pcr.uu.se/research/ucdp/ for the main project site.

4 Forecast models

For each space, we estimate the probability that a country will experience an opening or closing event within a two-year window with a random forest model.[20] The random forest model is increasingly common in prediction problems centered around political phenomena. For example, it is one of the methods that the Violence Early Warning System (ViEWS) uses to predict political violence (Hegre et al. 2019).[21]

Random forest models are a combination of many relatively simple *decision tree models* and are based on the insight that many individually weak models can in combination produce forecasts that outperform that of a single strong model – in other words, a "wisdom of the crowds" approach to forecasting modeling. Therefore, to help clarify our modeling strategy, this section takes a building-block approach. It first explains the basics of decision tree models and the standard way to assess the accuracy of this class of models before expanding these principles to random forest models.

4.1 Introduction to decision tree models with binary outcomes

A decision tree for a binary outcome (e.g., the presence or absence of a closing event in a two-year window), like the one we are modeling here, is a flowchart-like model that uses *all variables (features)* in the dataset. It uses these features to successively split cases into smaller and smaller groups, so that each group leans, as much as possible, towards one of the possible outcomes we are trying to predict – e.g., whether there will be a closing event in the electoral space within a two-year window.

More specifically, decision tree models start by measuring how well *each variable, at different cut-points*, classifies observations according to the observed outcome variable. The variable and cut-point that splits the data best – the one that classifies the highest number of cases correctly – becomes the *root node*. The algorithm splits all of the observations according to the root node cut-point, creating two *branches*. At each branch, the model again assesses which of the *remaining* variables, and at what cut-point, best classifies the data in *each branch*. It repeats this process to the point in which new branches no longer improve classification – i.e., further splits classify more cases incorrectly. These end points are *terminal leafs*.

We present an example of a single decision tree model for closing events within the *electoral space* in Figure 2. The model was trained using data from 1970 to 2016. It tries to predict whether an *electoral space* closing event happened over the next two years in our entire set of country-year observations.

The first split in the tree is on whether the `lag0_diff_year_prior_v2psbars` feature was greater or equal to -0.5 for a case. This feature is the year-to-year change in V-Dem's `v2psbars` indicator, which measures how difficult it is to form a political party in the country. As long as `v2psbars` did not decrease more than -0.5 from the year prior, the model groups the case in the upper-left terminal leaf labeled `0`. The model predicts that no closing event in the *electoral space* should occur when a country's year-to-year change in the `v2psbars` indicator is greater than -0.5.

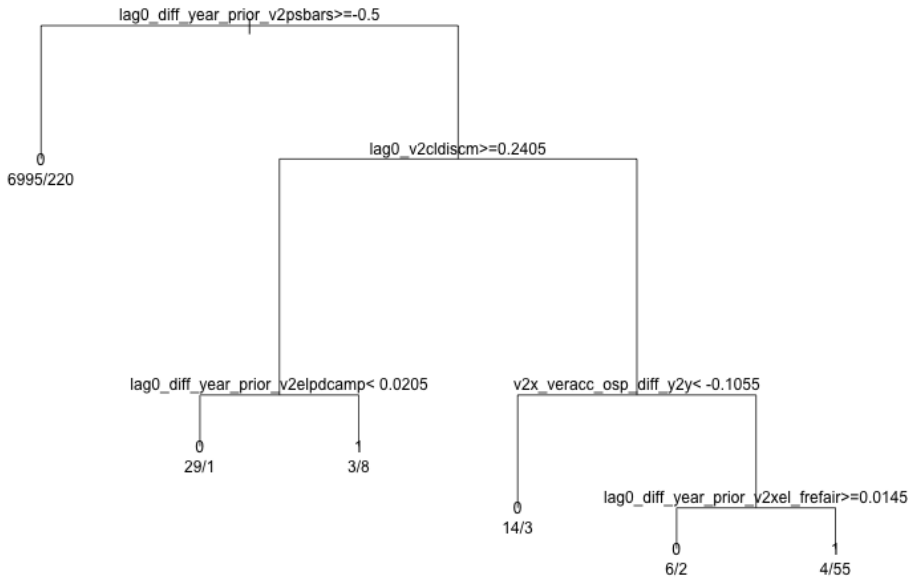
The numbers below the upper-left terminal leaf labeled `0` reflect the observed outcomes. Specifically, at the -0.5 cut-point in the `lag0_diff_year_prior_v2psbars` variable, the model predicted that 7215 cases (6995 + 220 = 7215), all with year-to-year changes in their `v2psbars` score greater than or equal to -0.5, would *not experience* a substantial closing event in the *electoral space*. It is the decision tree's best guess given year-to-year changes in the `v2psbars` index.

Ideally, the model would predict all of these 7215 cases correctly. However, while the decision tree does classify 6995 cases correctly – they had year-to-year changes in their `v2psbars` index greater than or equal to -0.5 and *did not experience* a closing event in their *electoral space*, the model classifies 220 cases incorrectly – i.e., 220 country-year observations had a year-to-year difference greater than or equal to -0.5 in their `v2psbars` indicator but *did experience* a substantial downward movement in their *electoral space*.

[20] We evaluated several different model types during development, and based on both performance and interpretability considerations we chose to focus on a single model, and specifically a random forecast model.

[21] See https://www.pcr.uu.se/research/views/

Figure 2: Example decision tree model for the risk of a closing event within the electoral space over the next two years (`dv_v2x_veracc_osp_down_next2` in the data).



Going back up to the split point, if there was a decrease less than or equal to -0.5 in a country's `v2psbars` index, we go to the right, where we are faced with another branch-split point. The decision tree model repeats this process, producing more terminal leafs where the models predicts either a `0` or `1` for whether a closing event in the *electoral space* should happened.

As one can see, decision tree models are essentially flowcharts for deciding whether to predict a "yes" or "no" on whether a significant opening or closing event will occur in a given case. These decision trees are computer-generated given the data on hand; that is, the decision points (the branch splits) in the flowchart are determined by an algorithm that seeks to maximize accuracy.

4.1.1 Assessing the performance of classification models for binary outcomes

A common way to assess the accuracy of decision tree models is with a "confusion matrix," a two-by-two table comparing the predicted outcomes to the observed outcomes. At the terminal nodes in Figure 2, the model classified cases as `1` or `0` – whether there would be a closing event in the *electoral space* within the next two years. By combining all the numbers in the terminal leafs and comparing these predictions to historical data, we can create a confusion matrix.

Table 2: Confusion matrix for decision tree example

		Actual		
		Same or up	Down	Total
Model	Same or up	$7,044$	226	$7,270$
	Down	7	63	70
	Total	70	289	$N = 7,340$

Table 2 provides a confusion matrix for our decision tree example. Rows show what the model predicted – for example, the model predicted a total of $7 + 63 = 70$ positive cases, the total number of cases under all terminal leafs labeled `1`. Columns show what actually happened – for example, we see that of those 70 cases the model classifies `1`, 63 were in fact "down" movements, but seven were not (false positives).

By comparing various combinations of cells in this table, we can calculate different aspects of the model's performance – in particular, the *true positive rate/recall*, *false positive rate*, and *precision*.[22] Since closing events are not that common – a little bit less than four percent of our country-year observations in the *electoral space* – it is common to focus on how well the model can predict positive outcomes. Most of the time the model predicted a closing event, it actually happened (precision; $63/(63+7) = 90\%$ of the time), but at the same time the model also misses many closing events (recall; $63/(63+226) = 22\%$).

4.2 Random forest models: ensembles of decision trees

Decision trees are simple but as a result also limited in their accuracy. We could make the model more complex by making the tree larger, i.e., adding more decision points. But beyond some point we would end up overfitting the data used to train (or fit) the model. The model would learn to pick up on idiosyncrasies present in the cases in the data at hand, and be able to explain those very well, but would not perform as well in predicting new cases that have their own, different, idiosyncrasies. Overfitting is a serious issue for forecasting problems, which by definition produce predictions in response to the introduction of new data.

Random forests improve on the performance of a single decision tree by combining the predictions from many different decision trees that are each trained using a randomized subset of the data (Ho 1995, 1998; Breiman 1996, 2001). Rather than growing a single strong decision tree, the idea is to grow a large number of individually weak decision trees that together become strong; in essence a wisdom of the crowds for models. Randomizing the data ensures that the large number of decision trees that go into the random forest are slightly different from each other, so that they reduce the worst errors other models might make.

The process for fitting one of the decision trees that make up the random forest starts by drawing a *random bootstrapped (with replacement) dataset*. That is, it randomly draws observations from the entire dataset, allowing for the possibility that an observation can be selected more than once. In contrast, a regular decision tree like above is fitted using all of the data.

Using this randomized sample, the random forest model then trains a decision tree. However, while the basic decision tree model has access to *all* of the variables in the dataset, the random forest model randomly selects a *subset* of variables. It then builds a decision tree using the random bootstrapped (with replacement) dataset and only these randomly selected variables.

The model repeats these steps hundreds of times, growing a diverse forest of random decision trees. Each of these decision trees are unique both with regards to the observations used to train the decision tree and the variables that the model can take into consideration when defining each branch-split.

Finally, the observations that were excluded from each bootstrapped sample are then fed into each randomized tree for classification, and the mean prediction error (or out-of-bag error) is calculated. This is an important metric for model tuning – determining the optimum number of variables to use in each decision tree as well as the number of trees to grow.[23]

Once the random forest model is tuned, new data is fed into the model and each distinct decision trees classifies each observation. The average of these classifications – the percentage of times the decision trees classified the observation as a `1` – is returned as an observation's predicted probability. This random forest process – training a lot of trees on slightly different subsets of both observations and variables, procedures called "bagging" and "feature sampling" – and then combining the predictions from all of these distinct decision trees helps reduce issues related to model fit as well as a model's variance – how far predicted values deviate from observed values, out-of-sample error.

[22] True Positive Rate/Recall= True Positives / (True Positives + False Negatives); False Positive Rate = False Positives / (False Positives + True Negatives); Precision = True Positives / (True Positives + False Positives).

[23] We use the out-of-bag prediction error to tune the `mtry` hyperparameter (the number of features sampled as candidates for each split) for each outcome model separately. Prior testing showed that the optimal values for the number of trees (`num.trees`) and minimum node size (`min.node.size`) were similar enough across outcomes and directions that we set them to the same value for all models in order to reduce estimation time. All other hyperparameters were left at the default values for the `ranger()` function from R's **ranger** package.

4.2.1 Assessing the performance of probabilistic models with binary outcomes

The fact that the output of our random forest models are estimated probabilities complicates model assessment. In our decision tree example, we summarized the model's predictions in a confusion matrix (Table 2). When we have probabilistic predictions, where forecasts range from zero to one, we can still reduce these down to `0` *or* `1` forecasts by picking an acceptance threshold, the cut-point at which point a probability is classified a `1`. This allows us to assign a `1` (the model predicts an event will occur) for all probabilities above this acceptance threshold, `0` otherwise (the model predicts that an event will not occur). We can use this information to build a confusion matrix.

One can think of the acceptance threshold as a slider that trades one aspect of the model's performance for another. For example, we can make a model more conservative by increasing the acceptance threshold, which converts less estimated probabilities into a `1`. This high acceptance threshold will result in a lower *true positive rate*, a lower *false positive rate*, and lower *precision*.

However, assessing a probabilistic model by looking at only *one specific* acceptance threshold is less than ideal; it masks important information about model performance across the complete range of estimates and acceptance thresholds. Thankfully, others have solved this problem for us. Indeed, to assess the accuracy of our estimated probabilities, we rely on two industry standard performance metrics: Area Under the Curve-Receiver/Operating Characteristic (AUC-ROC) and Area Under the Curve-Precision/Recall (AUC-PR) scores. Both of these standard metrics summarize a model's performance across a continuous range of acceptance thresholds, zero to one.

The AUC-ROC metric summarizes the trade-off between *true positive rate/recall* and the *false positive rate*, while the AUC-PR metric summarizes the trade-off between the model's *precision*, and *recall* – the *true positive rate* across a range of acceptance thresholds. For both metrics, higher values suggest better model performance. While an AUC-ROC score above 0.5 indicates that the model is preforming better than random chance, a (soft) industry standard is that AUC-ROC scores above 0.8 suggest that the model is performing well. Further, an AUC-PR score that is higher than the observed frequency of events in the data is a signal that the model is an improvement over random chance.

For class-imbalanced prediction problems – when the outcome variable is a rare event like the one currently under consideration, the AUC-PR measure is a better performance measure since it is more sensitive to how well a model predicts positive cases. Thus, the AUC-PR is our preferred metric of assessment performance; nonetheless, we report both, as is standard practice.

4.3 Test and validation strategy

All models require a test and validation strategy – a method of assessing how well the model should perform given new data. Here, again, overfitting is a problem. In brief, assessing the accuracy of a model's predictions with the data that the model was trained is likely make us overconfident of the accuracy of our models. The usual practice to overcome this is to reserve a portion of the data and, after a model is trained with the non-reserved data, have the model to predict the reserved data (validation set) and examine the accuracy. For example, common strategies are a single training and test split where we reserve, say, 20% of the data for evaluating the model's out-of-sample accuracy, or k-fold cross-validation, where we randomly split the available data into a number of "folds", e.g., 5 folds, and then iteratively hold back one of the folds while training the model on the other 4 folds, using the data in the reserved fold as test data.

While these validation strategies work well when we can reasonably assume that each row in the data is independent from others (i.e. when all of observations, in this case country-years, are unrelated to all others), they have a number of drawbacks when applied to structured data like ours. For example, we should not expect that the state of civic space in a country in 2020 is not related to the state of civic space in that country in 2019. In other words, it is strange to train a model on data for 1980-2000 and then use it to predict an outcome in out-of-sample data for 1970-1979. This requires the assumption that the processes that led to an opening or closing event remains constant over time. Thus, it is important to check how well a

model performs under conditions that mimic current conditions. In short, our strategy uses a series of 12 yearly test forecasts (2005 to 2016) to mimic the process we use to generate our "live" 2019–2020 forecasts with data from 2018.

Since we ultimately want to have a measure of accuracy for our live forecasts (e.g., 2019–2020), our yearly test forecast strategy allows us to recreate several waves of historic forecasts from 2005 to 2016. We use the output of these 12 test forecast years to assess model performance, in general, and to assess how much the performance of our models changes from year-to-year due to randomness or other fluctuations as well as how conservative our models are.

To do this, we discard data after 2005, fit the models using the available data (1970 to 2004), and then use our model and data from 2005 to forecast for the 2006–2007 window. Essentially, we try to move the clock back and recreate the conditions under which we would have forecasted in 2005. Then we set the clock to 2006, train a new set of models, produce forecasts for 2007–2008, and so on for our 12 waves of yearly test forecasts. Because these are "historical" forecasts, we know the actual outcomes – for example, we know which countries had a closing event in the *electoral space* in 2006 and 2007 – and can use this information to assess the performance of our models.

We use the estimated probabilities from our models for all 12 yearly test forecast and the observed outcomes from the data to calculate our high-level performance metrics – AUC-ROC and AUC-PR scores. Further, our yearly test forecast approach allows us to run a simulation exercise that helps us evaluate how well these yearly tests match the real-world outcome we observed in a given year. Visually, our simulation exercise allows us to assess whether are models are more or less conservative.

To do this we can take all of the model's forecasts for a year, and then we "simulate" the world by drawing hypothetical opening (or closing) events for each country in accordance with the respective probabilities for a given space, direction, and test year forecast. Explained in more detail in Section 5.4, this simulation exercise allows us to derive statistically how many opening and closing events we would expected to occur versus how many actually did occur in a test window two-year window.

4.4 The output of our random forest models & how to interpret these results

The output of a trained random forest classification model is an estimated probability for all observations – the probability that a country will experience *at least one, but possibly two* "down" movement(s) in the *electoral space* within the next two years, for example. Within the current context, however, we are interested in estimating three probabilities: (1) opening, (2) closing, and (3) no substantial change within the next two years. Rather than directly modeling the probability that no change, in either direction, will occur in the next two years, we calculate this probability from the outputs from the models for opening and closing events:

Pr(no change) = (1 - Pr(any up next two years)) * (1 - Pr(any down next two years))

Relationship between these probabilities:. The three probabilities above (for any up, any down, or no change) *do not* sum up to one. The occurrence of a substantial opening event and a substantial closing event over a two-year span *are not mutually exclusive events*. Sometimes, though relatively rare, a country can experience back-to-back opening and closing events within the same space. The estimated probability for "any up next two years" really captures three distinct combinations of events: one up and no down, two up and no down, and also one up and one down. Similarly, this is the case for "any down next two years". The probability for "no change" on the other only captures one scenario: no up or down events in the two-year window.

As a result of these relationships, it is sometimes the case that the forecast models produce relatively large probabilities for both opening and closing events in a country for a given two-year window. This can be seen in some of the charts that follow. This is not incorrect; one way to think of these instances is that the situation in that country in that space is very fluid, indicating a need for a programmatic intervention to be prepared for several potential contingencies. This, of course, requires more case- and space-specific evidence than our models can provide, and we encourage readers to investigate these cases, and to consider these forecasts in the context of their own deep context knowledge.

Additionally, it is important to note that the output of our models are probabilities, not certainties. That is, a high probability does not necessarily mean an event (opening or closing) will occur. Similarly, a low probability does not mean that an event will not occur. For example, the probability of rolling a 12 with two six-sided dice is 2.78%, but every once in a while this occurs in a game of *Monopoly*.

Further, the machine learning forecasting model we use to derive these estimates, random forest with observational data, does not lend itself to causal explanations. Movement within all constituent spaces of the *Democratic Space* are the product of highly complex, and often interrelated, mechanisms as well as idiosyncratic processes and conditions within specific countries, years, and spaces. Causal inference requires a research design (and corresponding theory) that can isolate distinct mechanisms. Random forest models with observational data cannot do this. Nevertheless, as we discuss below, our models perform relatively well and can be helpful for identifying potential opportunities for policy interventions that might help stave off potential closing events or promote potential opening events. With these caveats in mind, we now focus on the performance and results of our models.

5 Results

The first subsection below centers on the performance of our model with regard to our high-level metrics – the AUC-ROC and AUC-PR scores for all 12 of our models. The second subsection presents our 2019–2020 forecasts for each space and direction. For space considerations, we only present the top ten forecasts for each model in this section; however, we provide all of our 2019–2020 forecasts in Appendix B below.[24] After presenting the top ten forecasts for each space and direction, we use our set of 12 test year forecasts to assess the past performance of our models as well as the number of events we would expect to occur given our simulation exercise.

5.1 High-level metrics of model performance

Table 3 provides the AUC-ROC and AUC-PR scores for each of our models, which serve as high-level summary statistics for the overall performance of our models. These are aggregate performance metrics, calculated using the estimated probabilities from our 12 waves of yearly test forecasts (2005-2016, $n = 2,018$). They provide insights into the general performance of our models over the last decade or so, as we are more concerned with recent performance than we are about the "historical" performance of our models.

From the table, we see that all of our models have relatively high AUC-ROC scores. Each is above 0.5, with most surpassing 0.8; even our poorest performing models – those for the *economic space* – have respectable AUC-ROC scores, hovering just below the standard 0.8 benchmark. Nevertheless, because our outcome variables are class-imbalanced (i.e., opening and closing events are relatively rare events), the AUC-PR metric is a better measure of model performance. Here too, we see that all of our models have AUC-PR scores higher than the observed rate within our data (the 'Rate' column in Table 3). These scores indicate that our models at or above industry standards.

[24] Aside from the 2019–2020 forecasts, the tables in Appendix B also list the rank and risk category for each estimate. This is helpful for interpretation, as it is difficult to assess whether an estimated risk of 0.369 for a closing event in the *electoral space* is high or low, for example. The rank and risk category columns in the tables in Appendix B make it easier to compare, at a glance, whether a specific country's estimated probability is high or low *relative* to other countries. Further, we encourage readers to visit our interactive dashboard that compliments this report at https://www.v-dem.net/en/analysis/DemSpace/.

Table 3: Summary of random forest test forecast performance by outcome and direction of change. For AUC-ROC, randomly guessing will on average achieve a value of 0.5; for AUC-PR, randomly guessing will on average achieve a value equal to the positive rate in the data, which is shown in the 'Rate' column.

Indicator	Direction	AUC-ROC	AUC-PR	Rate
Associational				
v2xcs_ccsi	Opening	0.80	0.30	0.11
	Closing	0.81	0.39	0.15
	Stable	0.79	0.93	0.77
Economic				
v2x_pubcorr	Opening	0.75	0.35	0.15
	Closing	0.77	0.35	0.13
	Stable	0.76	0.89	0.74
Electoral				
v2x_veracc_osp	Opening	0.89	0.43	0.03
	Closing	0.86	0.35	0.02
	Stable	0.85	0.99	0.95
Governing				
v2x_horacc_osp	Opening	0.84	0.38	0.07
	Closing	0.82	0.32	0.07
	Stable	0.81	0.96	0.87
Individual				
v2xcl_rol	Opening	0.83	0.35	0.11
	Closing	0.83	0.40	0.13
	Stable	0.83	0.95	0.78
Informational				
v2x_freexp_altinf	Opening	0.83	0.32	0.07
	Closing	0.82	0.35	0.10
	Stable	0.79	0.95	0.83

5.2 Overview of the 2019–2020 forecasts for opening & closing in each space

Figures 3 to 8 present the ten highest estimated probabilities for both opening and closing events in each space within the 2019–2020 forecast window. There is no inherent reason to focus only on the ten highest probability forecasts. We do so here for space considerations, and because it is more manageable and easier to digest. Again, in Appendix B and on the interactive dashboard we developed for this project, we provide all of the estimated probabilities from our models for the 2019–2020 forecast window.

Each of the figures below show two charts. The top chart shows the highest probability forecasts in a specific space for opening events – i.e., countries where there is a good chance, according to our models, of experiencing an opening event over the 2019-2020 period. The bottom chart, correspondingly, shows the ten cases with the highest forecasted risk of a closing event within a specific space – i.e., countries which are most likely to experience a closing event over the 2019-2020 period.

Within each chart, there are three bars for each country. There bars show the estimated probability of closing or opening events or of there being no event in either direction. We show all three pieces of information for each country because a high opportunity for an opening event does not necessarily mean a low risk for

a closing event. As we discussed in Section 4.4, this is not a mistake. It suggests that the situation in a country is fluid and that the country context may present both opportunities and risks for programmatic interventions. The results tables in Appendix B report the estimated probabilities for both closing and events for each country, allowing for easier identification of these fluid cases.

Providing the in-depth case-specific research needed to fully evaluate the situation in a country is beyond the scope of this project. However, providing a brief example of how the results of our models seem to map to important events in a country at a crossroads provides some clarity. For example, Figures 3, 6, 7, and 8 depict the top ten estimated probabilities that an opening or closing event will occur in the *associational, governing, individual,* and *informational spaces*, respectively, within the 2019–2020 forecast window. Having relatively high estimates for both opening and closing events across these four spaces, Zimbabwe stands out.

Uncertainty around the what direction Zimbabwe's political institutions might take has its origins in 2017, when Zimbabwe's longtime ruler, Robert Mugabe, was forced to resign after a military uprising. Mugabe's successor, Emmerson Mnangagwa, promised a new dawn for Zimbabwe – economic and political reforms, in particular. These reforms, however, have been slow to develop. The 2018 elections offered an opportunity for an opening event in Zimbabwe's *electoral space*, but unfortunately, there was widespread allegations of election irregularities, ranging from voter intimidation and biased media coverage of opposition candidates.

Nevertheless, new elections in and of themselves tend to either provide an opportunity for institutional improvement, greater checks and balances, in particular, or they can help fledgling rulers consolidate their grip on power.[25] The uncertainty in the direction that Zimbabwe's *governing space* might take in 2019–2020 reflects the fluid situation surrounding the 2018 election and new governing elites. Sadly, the events on the ground suggest that we will see a closing event in Zimbabwe's *governing space*, as Mnangagwa's ruling party, ZANU-PF, seems to be consolidating rule, effectively limiting checks on Mnangagwa's power.

Nevertheless, by 2018, the situation in Zimbabwe still showed signs of promise across a number of spaces. Improvement in civil society, physical integrity rights, and media freedoms all looked possible, as there was still a lot of uncertainty around Mnangagwa's hold on power. Unfortunately, when citizens took to the streets to protest increased fuel prices, Mnangagwa relied on the military to violently suppress the protester.[26] Further, there has been widespread harassment of opposition media as well as civil society organizations.

The data that we use to produce our 2019–2020 estimates end in 2018, so these events, which occurred in 2019, are not captured our data. Thus, while our models suggest that either an opening or a closing event was likely across these space in the 2019–2020 forecast window, a brief review of the events on the ground in 2019 suggest we are more likely to see closing events within these spaces once the V-Dem releases their 2019 data.

While this brief case study is by no means comprehensive, it is instructive in how a reader can use the results for our models to identify cases that might be ripe for policy interventions.

[25] See https://wapo.st/2RVUaRp (shortened URL for formatting)

[26] See https://www.nytimes.com/2019/08/10/world/africa/zimbabwe-president-emmerson-mnangagwa-mugabe.html and https://www.foreignaffairs.com/articles/zimbabwe/2019-02-21/whats-driving-crisis-zimbabwe.

Figure 3: Final estimates for the associational space.

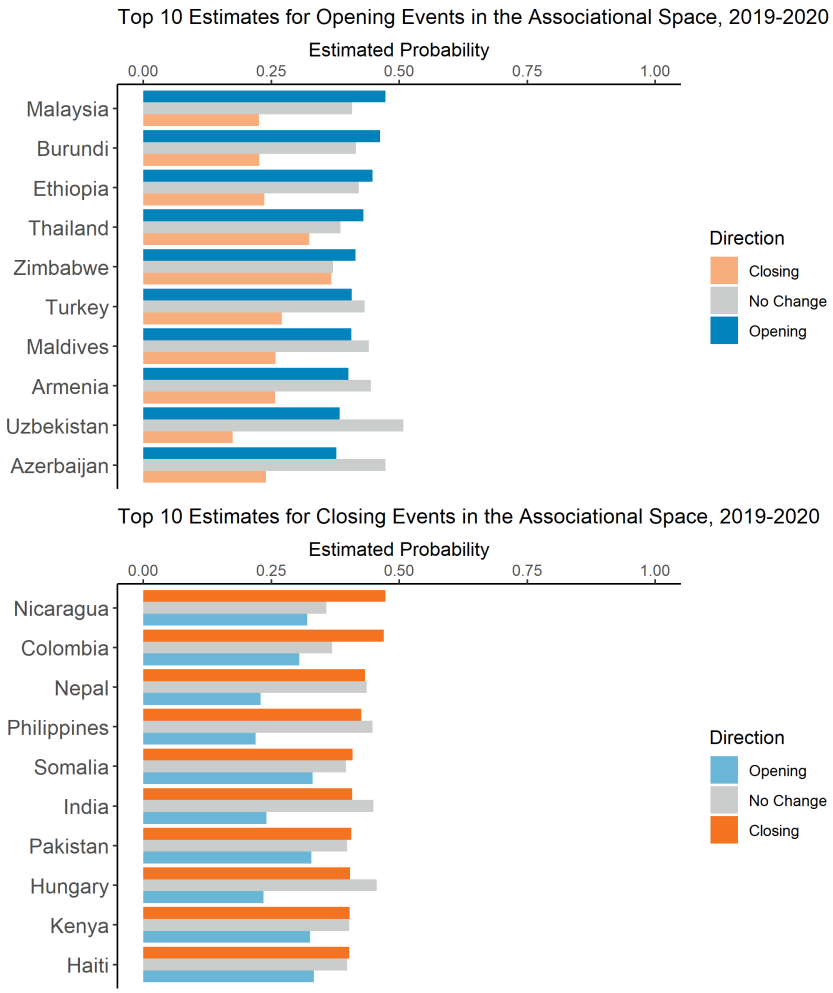


Figure 4: Final estimates for the economic space.

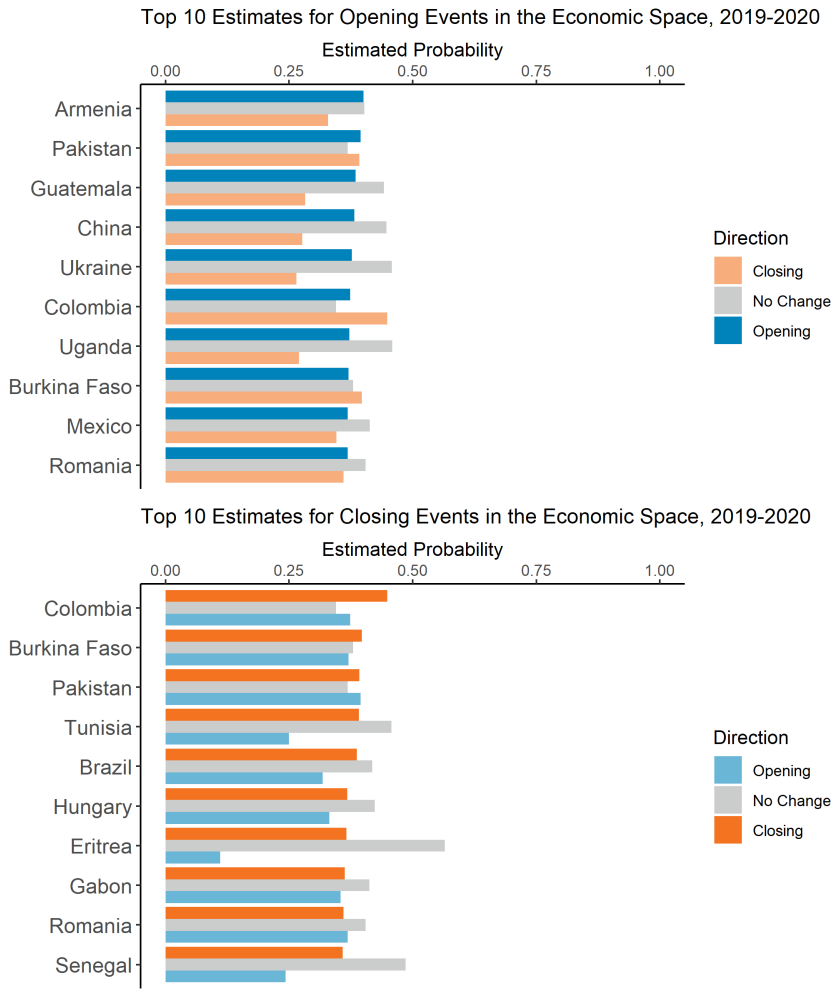


Figure 5: Final estimates for the electoral space.

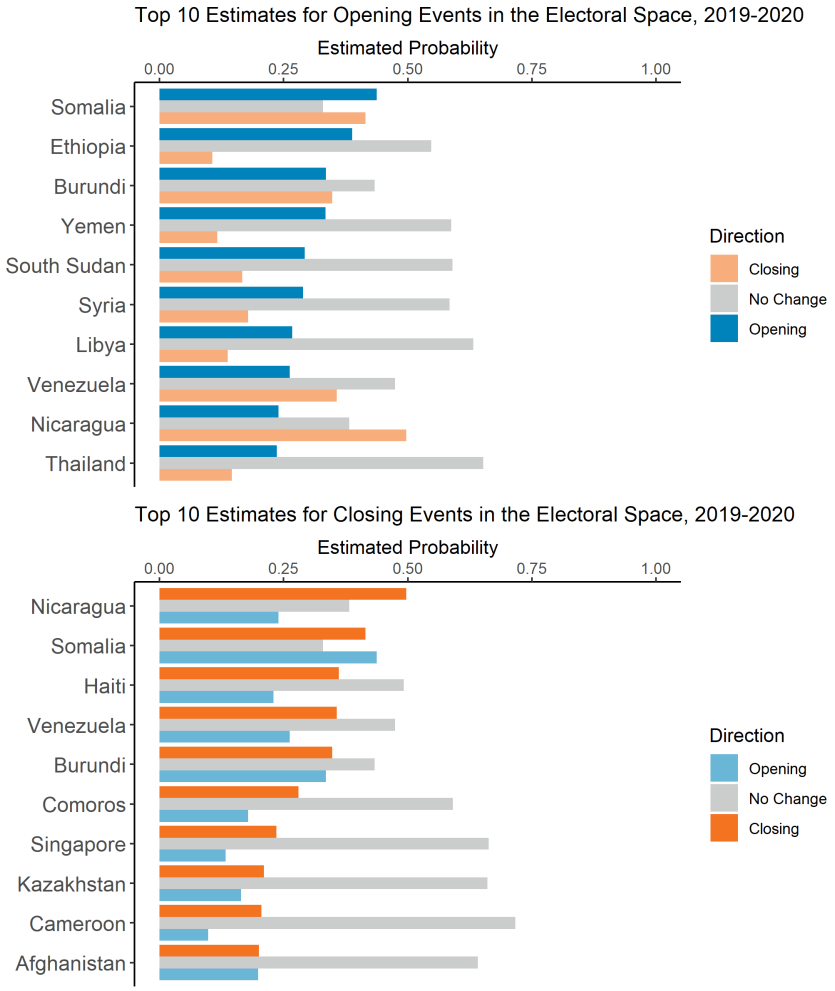


Figure 6: Final estimates for the governing space.

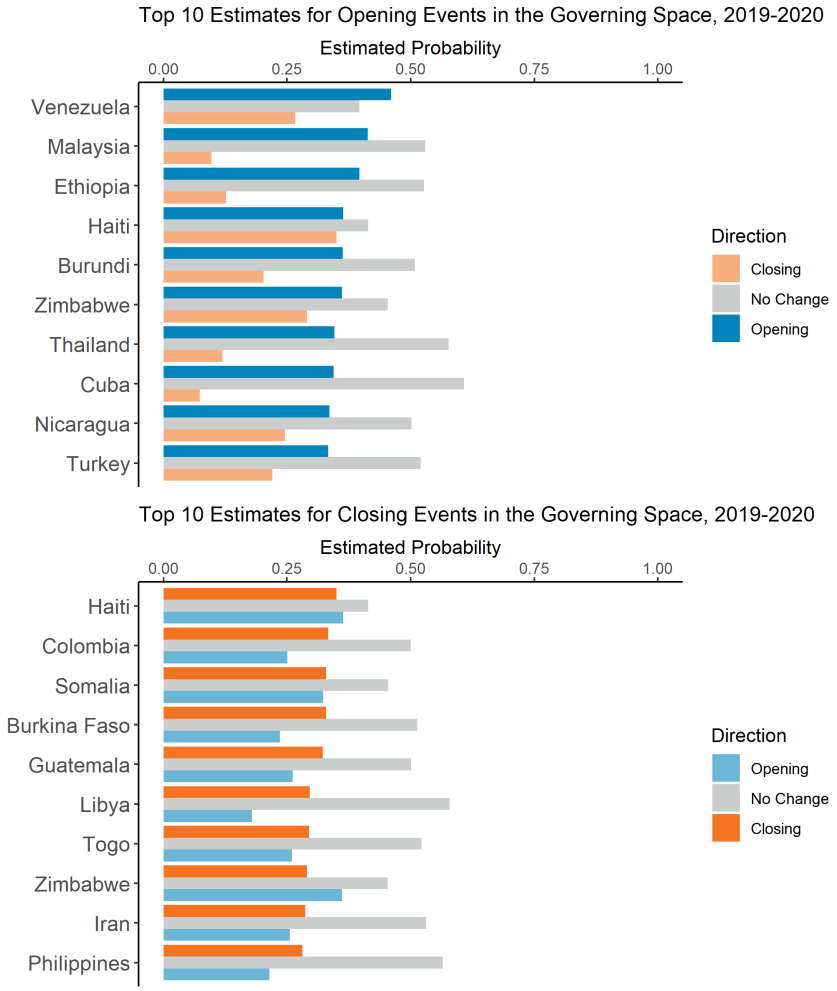


Figure 7: Final estimates for the individual space.

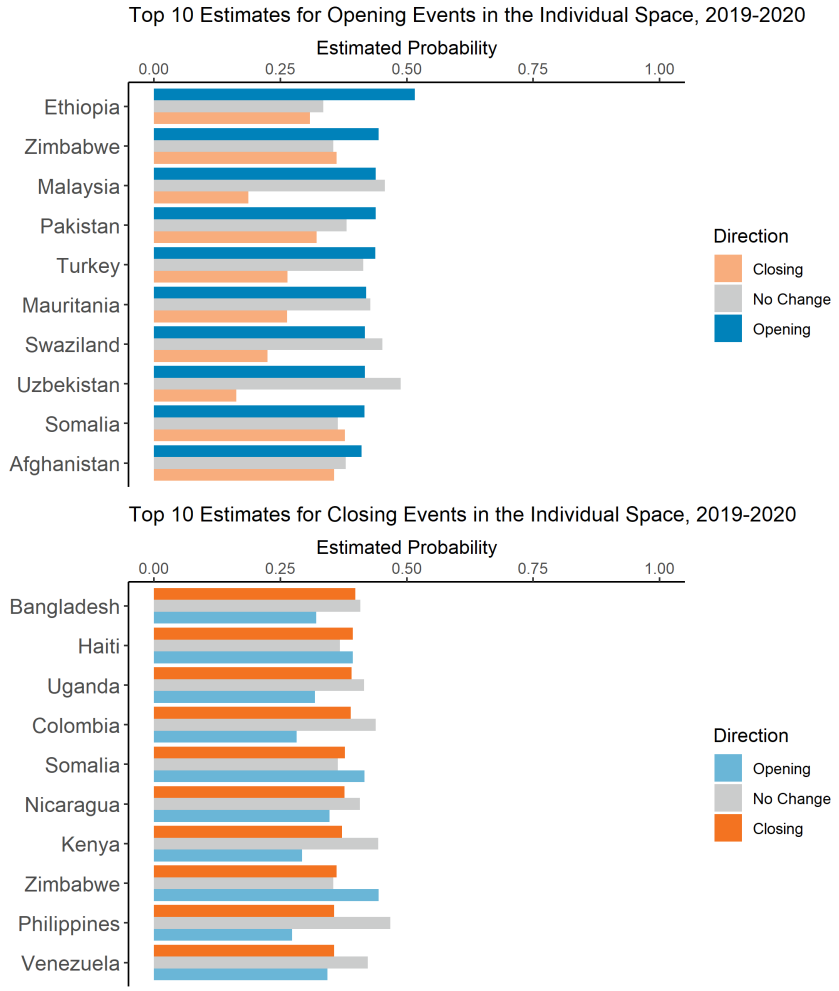
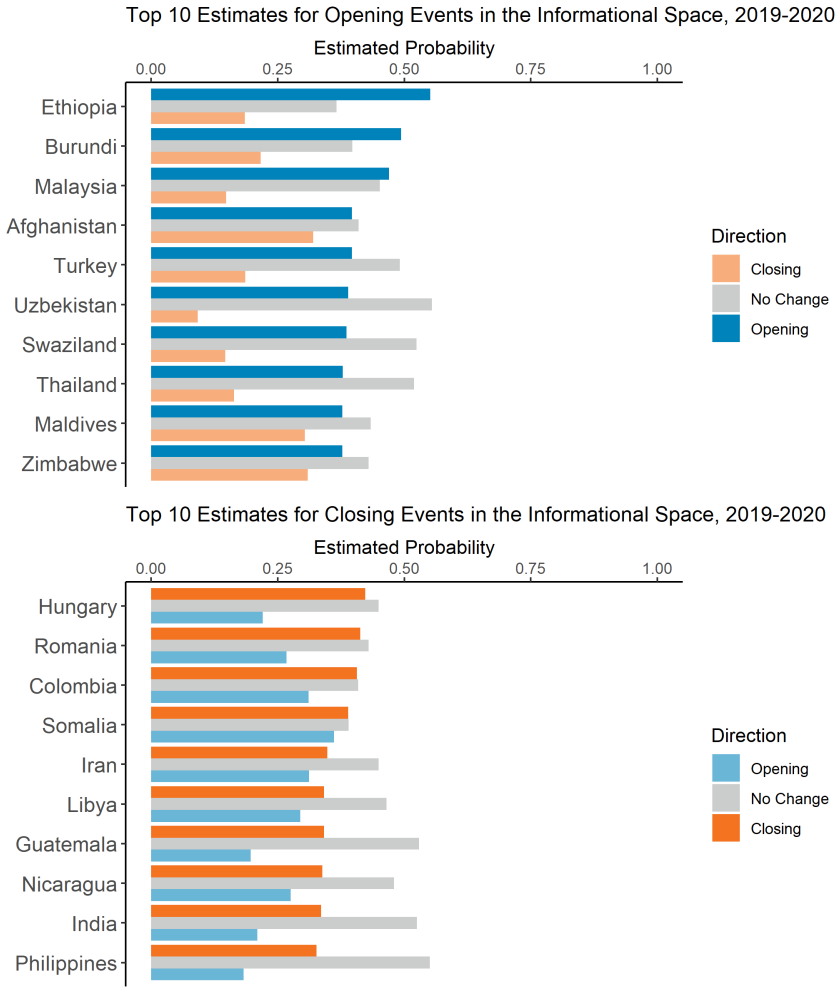


Figure 8: Final estimates for the informational space.

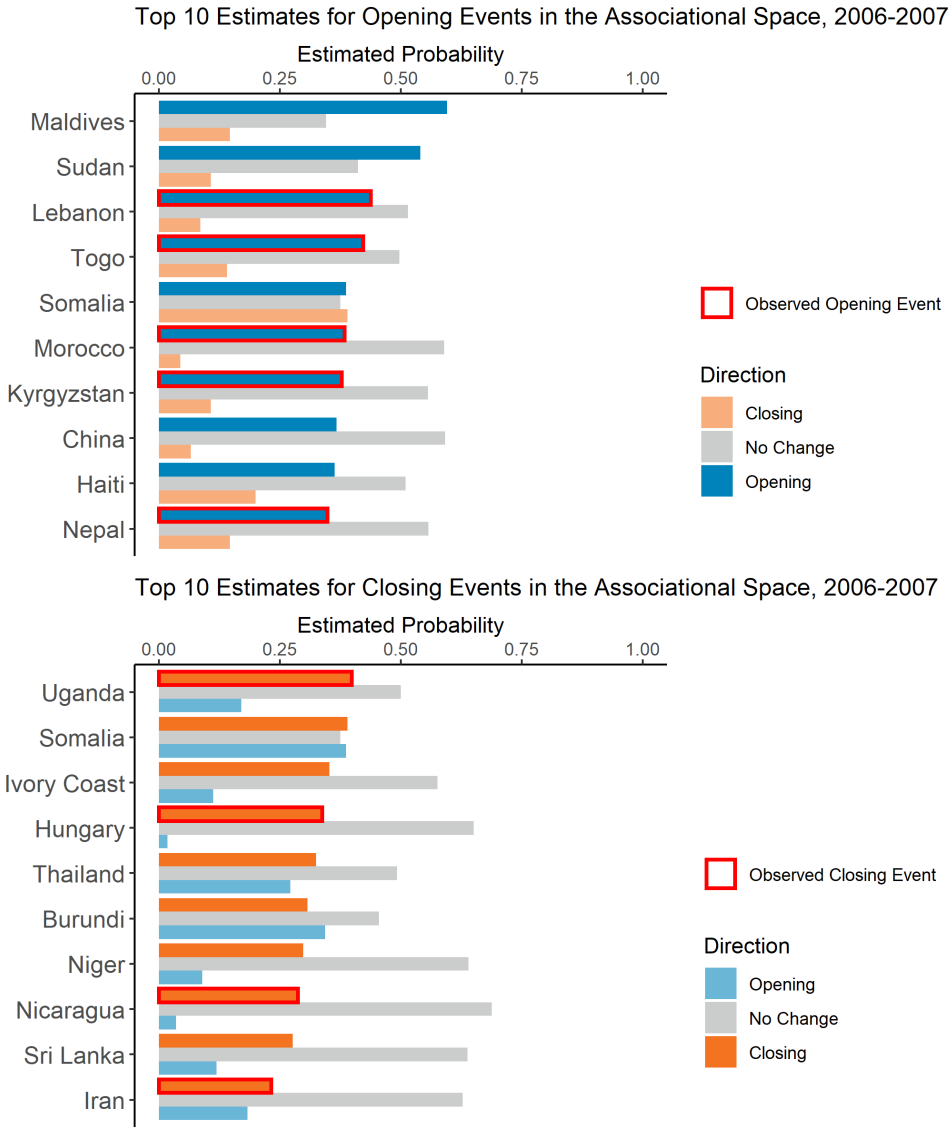


5.3 How accurate are these top ten forecasts? An assessment of past performance

Since we do not yet have data for 2019 and 2020, we cannot assess the accuracy of the forecasts shown in the figures above. Nonetheless, we can use our series of test year forecasts (2005-2016) as a guide. Figures 22 to 93 in Appendix C show similar plots to those we presented in Section 5.2. These figures focus on each of our 12 test year forecasts. While similar to our 2019–2020 top ten forecasts figures, the figures in Appendix C provide an extra piece of information: we highlight in red cases in which a closing or opening event actually occurred within a specified test forecast window.

As an example, we include one of these figures below. Using data from 2005 to forecast opening and closing events in 2006–2007, the top chart in Figure 9 tells us that Lebanon, Togo, Morocco, Kyrgyzstan, and Nepal were among the top ten estimates for 2006–2007 and had an opening event in the *associational space*. Thus, of the ten cases with the highest opening forecasts, five did experience an opening event. Further, from the bottom chart in Figure 9, we can see that four of the top ten – Uganda, Hungary, Nicaragua, and Iran – had closing events in the *associational space*.

Figure 9: Test year estimates for the associational space, 2006–2007.



This percentage of observed events (opening and closing) that are captured within the top ten forecasts for each test year as well as the percentage of observed events that are not captured within the top ten predictions provides us with a general sense of the *precision* of our models – proportion of positive identifications that were actually correct within the top ten forecasts. Table 4 and Table 5 presents this information for all of our 12 test year forecasts for both opening and closing events within each space.

With respect to the 2019–2020 forecast charts we presented in Section 5.2, these tables can give us some hint as to how many of the countries in the top ten forecasts are likely to be in the set that experience an event. For example, looking at the first row in Table 4, the top ten test forecasts for the *associational space* included anywhere from two to seven actual observed instances of an opening event, with an average of about five. We can thus expect that of the ten countries shown in the top chart in Figure 3, roughly four or five will *probably* experience an opening event in the *associational space*, if past relationships and patterns continue to hold.[27]

Looking at the results in both Table 4 and Table 5, we see that our models for the *electoral space* capture the least amount of observed events within the top ten forecasts. However, they also show that our *electoral space* models have the lowest percentage of observed events that occur within the bottom 159 forecasts. This is because the *electoral space* has the lowest observed event rate of all six spaces. As we noted elsewhere in this report, this is consistent with the fact that the *electoral space* captures a number of election-specific components that are slow to change from one year to the next.

Further, within our set of yearly test forecasts, our *economic space* models perform relatively well. They capture more observed events in the top ten for both opening and closing than any of our other models. That said, our *economic space* models also tend to capture more observed events in the bottom-159 forecasts than our other models – hence, the lower overall AUC-ROC and AUC-PR scores found in Table 3. This makes sense, given the fact that the *economic space* has the highest observed events across all six distinct spaces. In any case, the remained of our models – *associational, governing, individual,* and *informational* – all preform at or above traditional performance benchmarks.

[27] That is, our models use historical relationships between the model inputs (predictors) and outcomes, so to the extent these past relationships continue to hold, we can use the test forecasts as a guide.

Table 4: The percentage of cases that experienced an **opening event** that were in the top-10 yearly test forecasts (precision) and the percentage of events that were not in the top-10 (they were in the remaining 159 estimates) yearly test forecasts for each two-year test window.

	All Years	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17	2017-18
Associational													
Top-10	**46.67%**	50%	30%	40%	40%	70%	50%	50%	70%	20%	40%	40%	60%
Bottom-159	**8.91%**	3.14%	3.77%	3.14%	7.55%	9.43%	6.29%	18.24%	16.35%	3.77%	5.03%	11.95%	18.24%
Economic													
Top-10	**44.17%**	40%	30%	40%	20%	30%	40%	70%	100%	10%	30%	60%	60%
Bottom-159	**13.57%**	6.29%	3.77%	3.14%	8.18%	11.95%	6.92%	24.53%	23.27%	13.21%	15.72%	18.24%	27.67%
Electoral													
Top-10	**29.75%**	50%	40%	60%	20%	20%	40%	40%	40%	30%	10%	0%	10%
Bottom-159	**1.89%**	2.52%	3.14%	1.89%	1.89%	3.14%	1.89%	1.89%	1.26%	1.26%	0.63%	1.26%	1.89%
Governing													
Top-10	**48.33%**	60%	40%	30%	60%	50%	50%	50%	70%	30%	20%	50%	70%
Bottom-159	**4.25%**	1.89%	3.14%	3.14%	1.89%	2.52%	3.77%	7.55%	6.92%	3.14%	3.77%	5.03%	8.18%
Individual													
Top-10	**43.33%**	40%	60%	40%	50%	60%	20%	40%	70%	20%	30%	40%	50%
Bottom-159	**9.28%**	5.03%	3.14%	3.77%	8.18%	11.32%	8.18%	14.47%	12.58%	8.18%	6.29%	12.58%	17.61%
Informational													
Top-10	**40.83%**	50%	50%	60%	20%	40%	40%	60%	70%	20%	20%	20%	40%
Bottom-159	**5.29%**	3.14%	2.52%	1.26%	5.03%	4.4%	3.77%	11.95%	11.32%	3.14%	3.14%	5.03%	8.81%

Note: The 'All Years' column provides the percentage of opening events that are or are not captured within the entire set of of top-10 predictions for all 12 test year forecasts (2005-2016). For the 'Top-10' rows under the 'All Years' column, the denominator is 120 (top-10 predictions * 12 test year forecasts), while the numerator is the total number of observed events that are captured within this set of top-10 predictions. For the 'Bottom-159' rows under the 'All Years' column, the denominator is 1908 (the bottom 159 predictions * 12 test-year forecasts), while the numerator is the total number of observed events that are captured within the bottom-159 predictions. The remaining columns provide this information for each specific test-year forecast, where 10 is the denominator for the 'Top-10' rows and 159 is the denominator for the 'Bottom-159' rows.

Table 5: The percentage of cases that experienced an **closing event** that were in the top-10 yearly test forecasts (precision) and the percentage of events that were not in the top-10 (they were in the remaining 159 estimates) yearly test forecasts for each two-year test window.

	All Years	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17	2017-18
Associational													
Top-10	**46.67%**	40%	50%	10%	30%	60%	40%	60%	50%	40%	50%	80%	50%
Bottom-159	**12.95%**	7.55%	5.66%	5.66%	7.55%	6.29%	6.29%	20.13%	19.5%	11.95%	18.24%	23.27%	23.27%
Economic													
Top-10	**43.8%**	10%	20%	40%	30%	50%	50%	60%	70%	20%	50%	60%	70%
Bottom-159	**10.9%**	3.14%	5.03%	3.77%	6.29%	3.77%	7.55%	19.5%	13.84%	8.18%	11.32%	19.5%	28.93%
Electoral													
Top-10	**22.31%**	0%	40%	10%	10%	40%	0%	10%	50%	40%	20%	10%	40%
Bottom-159	**1.15%**	2.52%	0.63%	1.26%	2.52%	0%	0%	0.63%	1.26%	1.89%	0.63%	1.26%	1.26%
Governing													
Top-10	**41.67%**	30%	40%	70%	40%	40%	20%	20%	80%	20%	30%	50%	60%
Bottom-159	**5.29%**	1.89%	3.14%	3.14%	2.52%	1.89%	2.52%	13.84%	10.06%	2.52%	5.03%	6.29%	10.69%
Individual													
Top-10	**45.83%**	40%	30%	30%	40%	40%	20%	50%	60%	50%	40%	80%	70%
Bottom-159	**10.53%**	3.77%	3.77%	3.77%	4.4%	4.4%	7.55%	20.13%	15.72%	5.66%	12.58%	19.5%	25.16%
Informational													
Top-10	**46.67%**	20%	30%	40%	40%	70%	0%	50%	90%	50%	40%	80%	50%
Bottom-159	**7.91%**	3.14%	2.52%	2.52%	6.29%	3.77%	4.4%	12.58%	9.43%	4.4%	11.32%	16.35%	18.24%

Note: The 'All Years' column provides the percentage of opening events that are or are not captured within the entire set of of top-10 predictions for all 12 test year forecasts (2005-2016). For the 'Top-10' rows under the 'All Years' column, the denominator is 120 (top-10 predictions * 12 test year forecasts), while the numerator is the total number of observed events that are captured within this set of top-10 predictions. For the 'Bottom-159' rows under the 'All Years' column, the denominator is 1908 (the bottom 159 predictions * 12 test-year forecasts), while the numerator is the total number of observed events that are captured within the bottom-159 predictions. The remaining columns provide this information for each specific test-year forecast, where 10 is the denominator for the 'Top-10' rows and 159 is the denominator for the 'Bottom-159' rows.

5.4 How consistent & conservative are our models? Simulation performance

Above we looked at the forecasts for small sets of cases – top ten estimated probabilities of opening or closing events. We can also use the model forecasts to compare, at a global level, how many opening and closing events we *expected* to occur in total versus how many actually did occur in a two-year window. This gives us a sense of how conservative our models are – i.e., how well do our estimates reflect what actually occurred.

To do this we can simulate potential outcomes using the nearly 200 forecasts we have from any given year of our test forecasts. In short, our simulation exercise uses the outputs from our set of yearly test forecasts to "simulate" hypothetical worlds in which opening and closing events take place, given the forecasts produced by our models. It is as if we had a set of coins, each representing a country. With these "country coins", heads represents an event and tails represents no event. By flipping these "country coins" and counting the number of heads we get, we can create hypothetical cases – either an event occurs (heads) or it does not (tails). However, in our simulation exercise, each "county coin" is weighted according to the model's predictions for each test year forecast. For example, if the model estimated that country X had a 30% probability of an opening event in a test year forecast, then in our simulation the "country coin" for country X would be weighted such that there was a 30% chance its "country coin" would come up heads.

With a perfect model, we would expect that the number of hypothetical opening (or closing) events we get in this simulation to match, more or less, the number of opening (or closing) events in a given space that we observe in reality. However, there is a lot of randomness here: one simulation will likely be different from another. So, we run 30,000 simulations per county. After running these 30,000 simulations, we then count up how many opening (or closing) events each simulated world gave us, repeating this process for all test year forecasts for each respective space and directional move. Figures 10 to 21 show the results of these simulations. To help clarify the interpretation of these figures, we walk through the first below.

Figure 10 is for opening events in the *associational space*. The top row in the chart shows the simulation output for the forecasts for 2006–2007 that we generated using 2005 data in models trained on data from 1970 to 2004. The density ridge summarizes the number of events we obtained in each of the 30,000 simulations for opening events in the *associational space* within the 2006–2007 window. Higher levels in this density indicate that more simulated worlds had the corresponding y-axis number of simulated opening events.

For this first density, the average across all simulations was around 17. The black point marks how many events actually happened that year, which in this case was nine. Thus the model forecasts overall were too high for the 2006–2007 *associational space* forecast window. Conversely, if we look at the row for the 2010–2011 forecast window, which uses data from 2009, there were more observed opening events than we simulated, meaning the model forecasts overall were too low for that year. In fact, in the 2010–2011 forecast window, the average across all simulations was around 15; however, there were 22 observed opening events in the *associational space* in the 2010–2011 forecast window.

Thus, generally, if a dot falls to the right of the distribution (beyond the high density areas in the plot), our model is *more conservative* – our simulation predicted that *fewer events* would occur than what actually occurred. However, if a dot falls to the left of the distribution, our model is *less conservative* – our simulation predicted *more events* would occur then what actually occurred. When a dot falls within the high density areas of the plot, this suggests that the model is, in general, fairly accurate.

Figure 10: Simulated distributions of **opening** events in the **associational** space for each test year forecast.

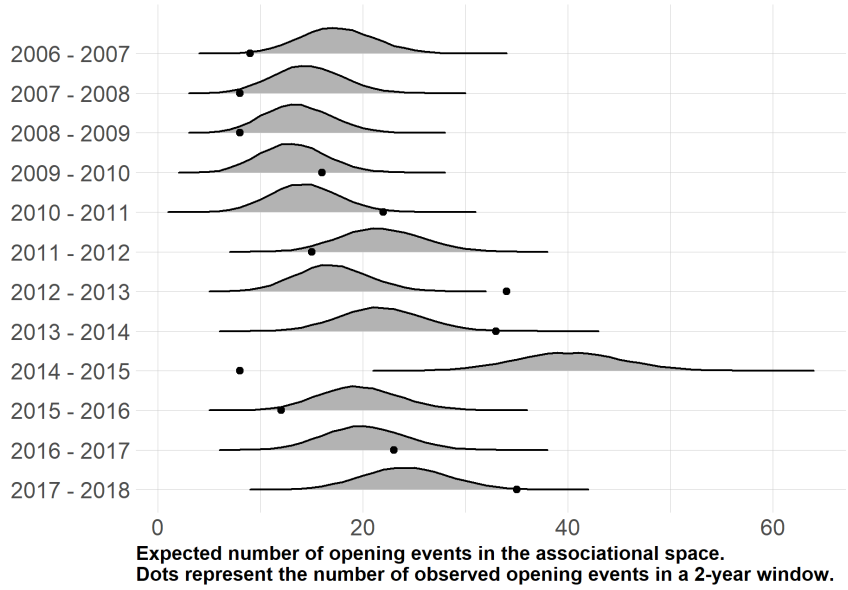


Figure 11: Simulated distributions of **closing** events in the **associational** space for each test year forecast.

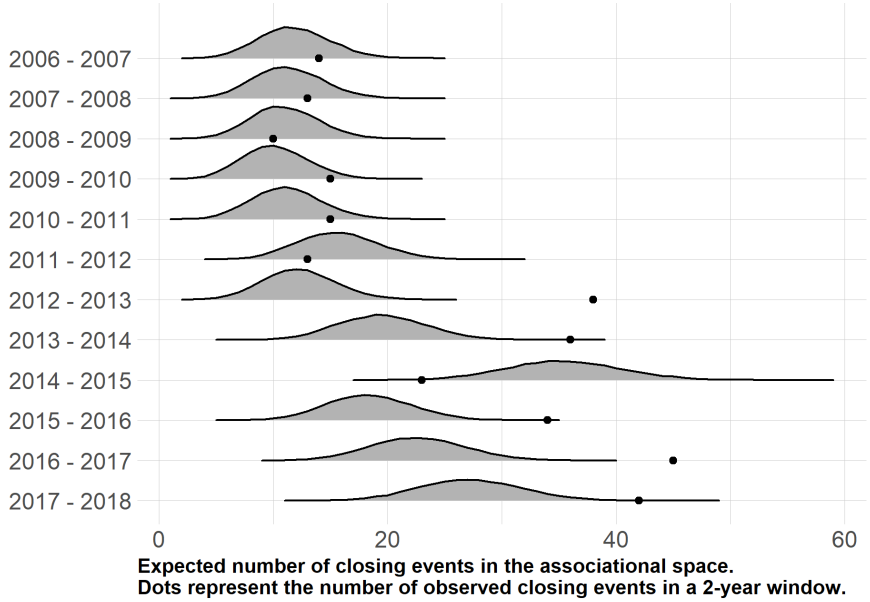


Figure 12: Simulated distributions of **opening** events in the **economic** space for each test year forecast.

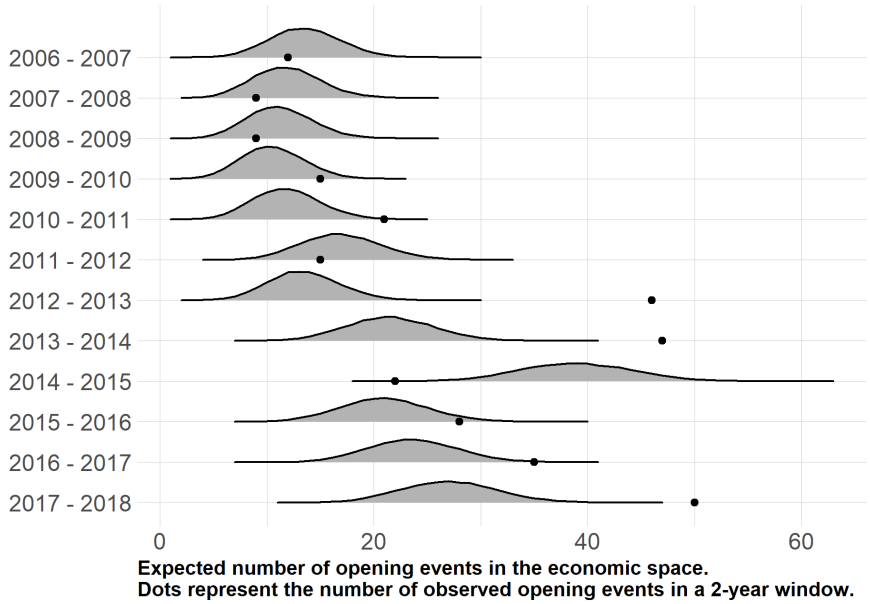


Figure 13: Simulated distributions of **closing** events in the **economic** space for each test year forecast.

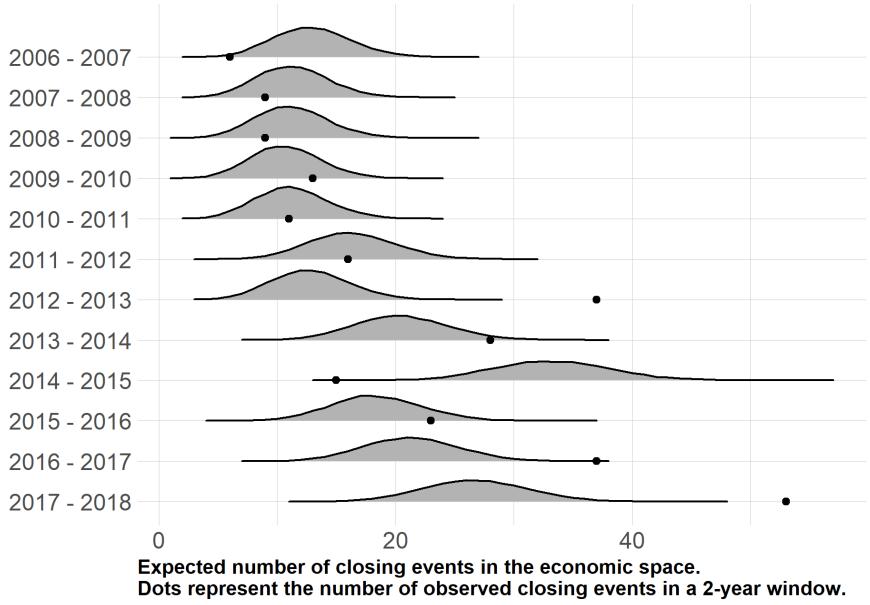


Figure 14: Simulated distributions of **opening** events in the **electoral** space for each test year forecast.

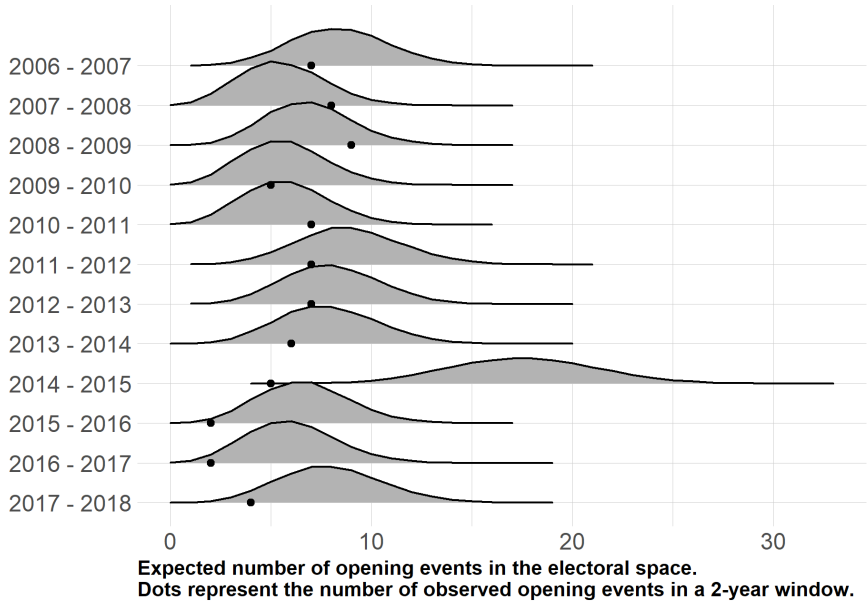


Figure 15: Simulated distributions of **closing** events in the **electoral** space for each test year forecast.

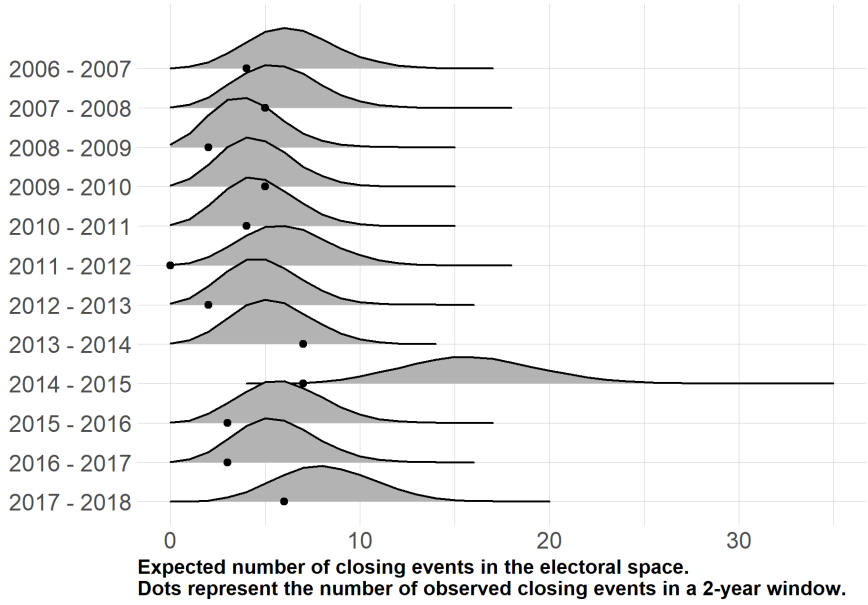


Figure 16: Simulated distributions of **opening** events in the **governing** space for each test year forecast.

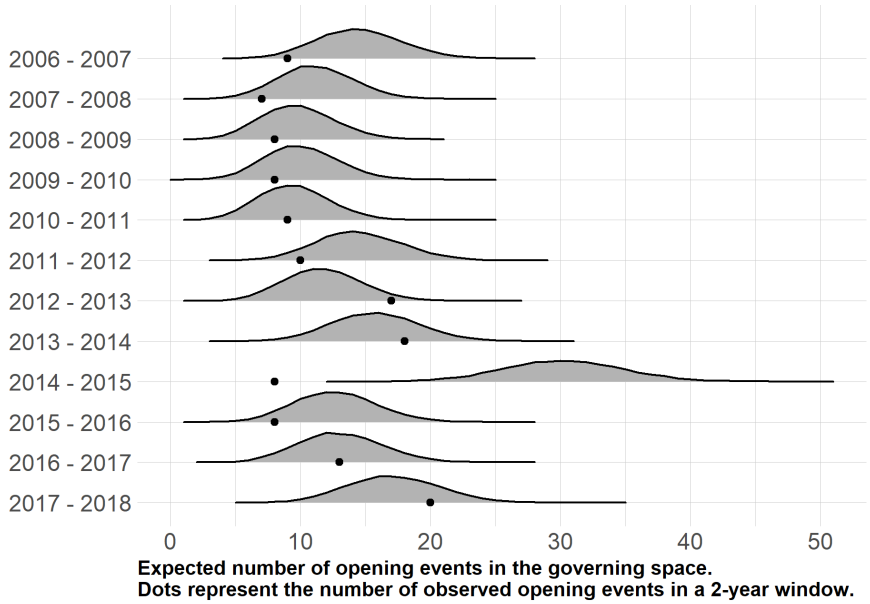


Figure 17: Simulated distributions of **closing** events in the **governing** space for each test year forecast.

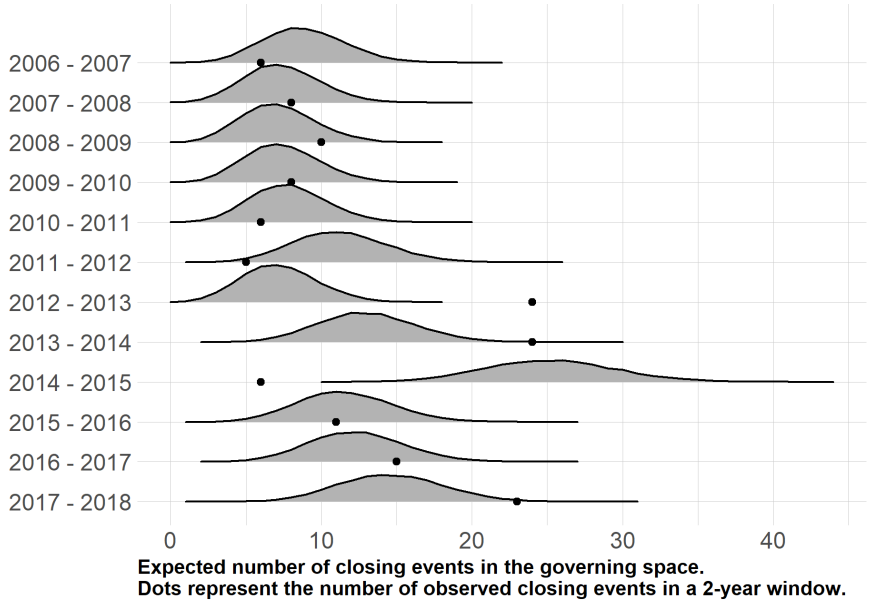


Figure 18: Simulated distributions of **opening** events in the **individual** space for each test year forecast.

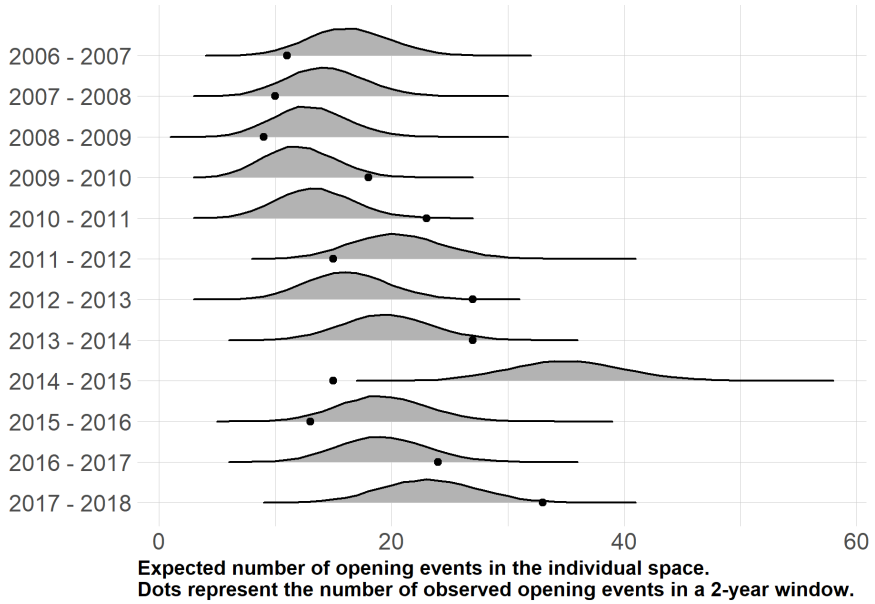


Figure 19: Simulated distributions of **closing** events in the **individual** space for each test year forecast.

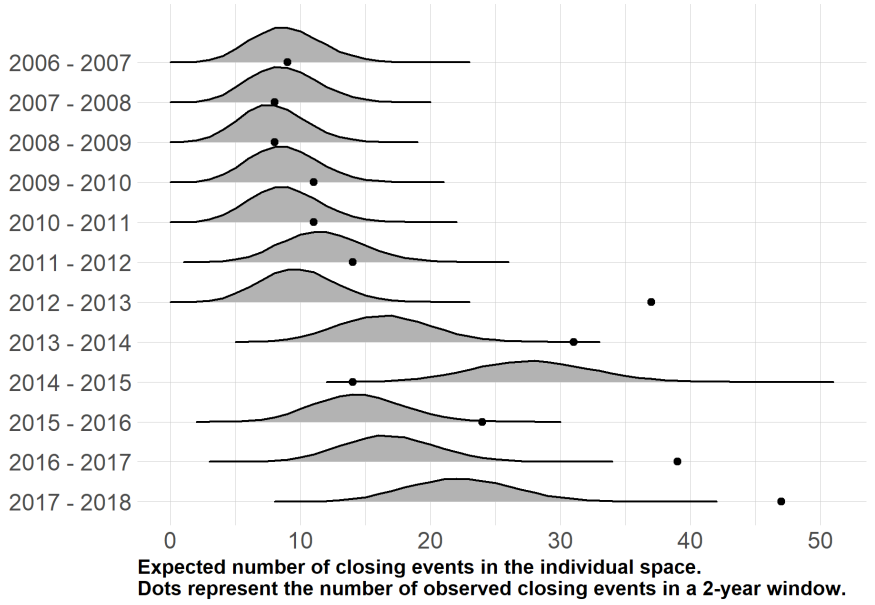


Figure 20: Simulated distributions of **opening** events in the **informational** space for each test year forecast.

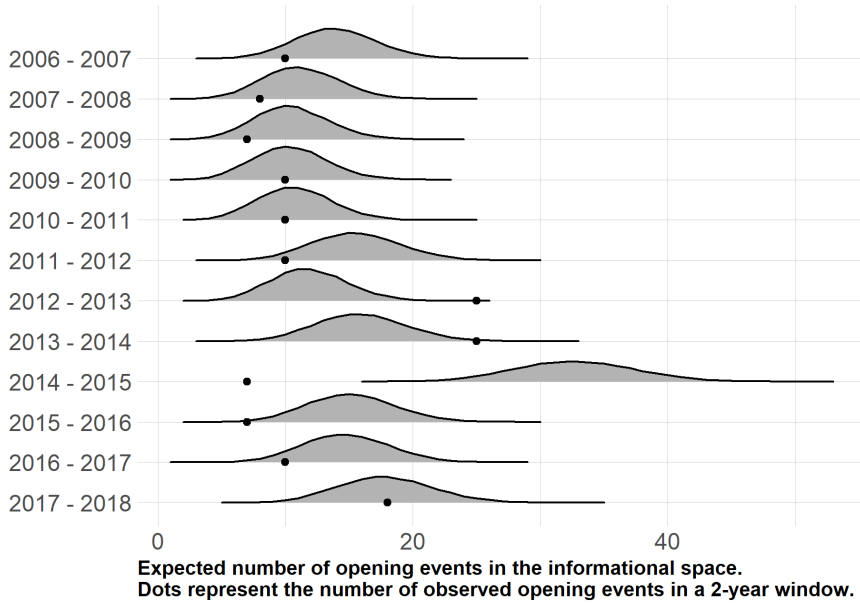
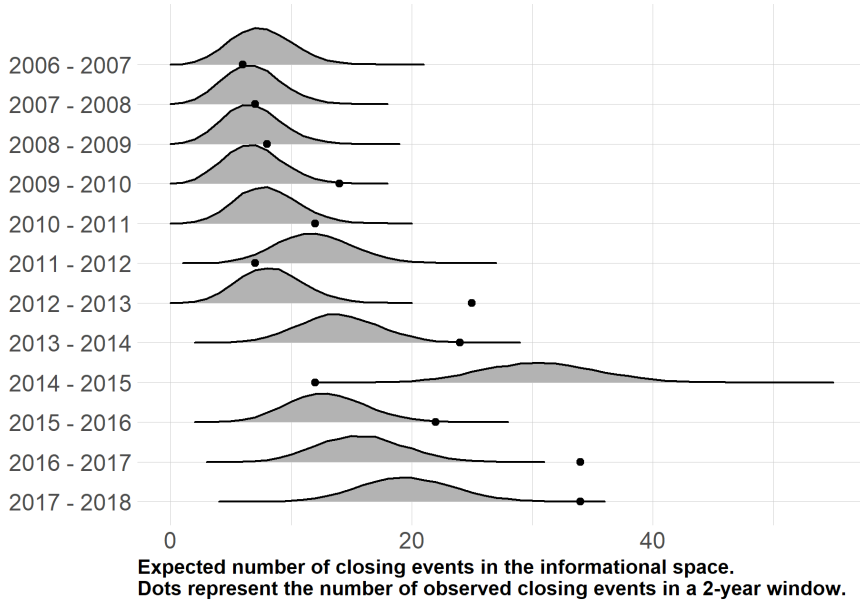


Figure 21: Simulated distributions of **closing** events in the **informational** space for each test year forecast.



While the focus here is on space-specific performance, we do see some general trends across each space. In particular, our simulation exercise suggests that, with the exception of our 2013 test year forecasts (the forecasts for the 2014–2015 window) which will discuss shortly, our models are fairly conservative and consistent. All of the density distributions of our simulations are, for the most part, in line with previous years – we can draw a straight line through the center these distributions. Further, especially in the more recent years and for closing events, the observed number of events is either to the right of the distribution or solidly within the highest density areas.

Nevertheless, for both opening and closing events, our models tend to miss the mark for our 2013 test year forecasts (those that provide estimates for the 2014–2015 two-year test window). While it is difficult to identify the exact cause of this result, the fact that we see it across all space and for both directions suggest that it is an artifact of the data not necessarily our measurement or modeling strategies. And, there is a well-known issue with the V-Dem data that might help explain these results.

The output of the V-Dem measurement model shows a number of small increases in country scores in 2012 followed by a number of small decreases in 2013. The V-Dem teams argues that these changes do not appear to be the result of actual changes in a country. Rather, they suggest that the increases in 2012 and the subsequent decreases in 2013 are the artifact of initial issues related to their lateral coding rules and other issues related to their ability to retain experts in their early data collection efforts (the first public release of the V-Dem dataset, version 5, was not until early 2016).[28] These small swings could be a contributing factor in the performance of our forecasting models for the 2013 test-year forecasts. Be that as it may, this data anomaly occurs in only one of the nearly 50 years of country-year data. That is, in aggregate, our simulation exercise suggests that this issue gets washed-out. In any case, V-Dem addresses this issue in their Version 10 data, which will be publicly available in March 2020.

6 Conclusion

There is broad concern about the apparent wave of autocratization that has occurred in several democratic countries in the past few years (Economist Intelligence Unit 2019; Freedom House 2019; Lührmann et al. 2019). Notable examples include Poland and Hungary in Europe, Brazil and India – two of the world's largest democracies. Although today more people live in democracies than ever before, this is also the first time since World War Two that there has been a persistent decline in the quality of democracy. Overall, close to one-third of the world's population is impacted by the current wave of autocratization (Lührmann et al. 2019).

Last year, the V-Dem Institute initiated the Predicting Adverse Regime Change (PART) project, an effort to predict adverse regime transitions – movement towards more authoritarianism in a country's regime (Morgan, Beger, and Glynn 2019)[29]. Declines in the quality of governance in democracies make up a large segment of these adverse transitions. The PART project uses V-Dem's Regimes of the World (RoW) index to identify adverse regime transitions. The RoW index groups countries into four categories ranging from liberal democracy to closed autocracy, and adverse regime transitions are operationalized as shifts from one category to a lower one. Similar to this project, PART then produces forecasts over a two-year window using the latest available V-Dem data.

The PART project focused on large shifts in a country's general regime type. These shifts are often monumental is scope. However, these large changes are often proceeded by small, but still significant shifts within distinct political institutions. The PART project misses these critically important changes. Thus, using IRI's *Democratic Space* framework, this project expands on the PART project. We mapped IRI's six conceptual spaces of the *Democratic Space* to appropriate V-Dem indices, took a data-driven approach to identify thresholds for both opening and closing events within each space, we used an increasingly common

[28]The V-Dem team discusses this issue in detail in their methodology working paper – WP 21-2019v4, page 23 in particular, which can be found at https://www.v-dem.net/media/filer_public/60/a5/60a52aaf-008c-4d80-82ca-3bca827fbeb9/v-dem_working_paper_2019_21_4.pdf.

[29]The dashboard is available at https://www.v-dem.net/en/analysis/Forecast.

machine learning algorithm – the random forest model – to derive our two-year ahead forecasts for each of the six spaces, and we are making our final predictions publicly available through an interactive dashboard.

The forecasts are created using random forest models, which we described in brief in Section 4. Important for interpretation but also accuracy is that random forest models allow input variables to have potentially complicated and interrelated (to other input variables) relationships with the risk of an outcome event, unlike simpler generalized linear models like logistic regression. This makes it harder to interpret how an input is related to an output risk, but it also allows the models to achieve greater predictive accuracy than simpler alternatives. That is to say, assessing *what exactly* is driving our forecasts, including what variables or combinations of variables might be the *cause* of either an opening or closing event requires an entirely different research design.

Using test forecasts from 2005 to 2016, where we try to replicate the data that would have been available had we forecasted two-years ahead from 2005, etc., we can evaluate how accuracy the models' predictions are. Through this procedure we found that the accuracy is at levels similar to those in other public forecasting projects in the realm of political conflict. The PART project had AUC-PR and AUC-ROC values that averaged roughly 0.35 and 0.84, using an ensemble model that includes a random forest as one of three components. Our test forecasts average 0.35 and 0.83 for the same metrics.

In closing, we should note that while this report is framed around producing risk estimates for the 2019–2020 forecast window, we plan to update our models to forecast the 2020–2021 window in late March 2020 when V-Dem releases the version 10 data. We plan to archive our 2019–2020 forecasts for later assessment and publicly display the 2020–2021 on our public-facing dashboard.

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Lührmann, Anna, Valeriya Mechkova, Sirianne Dahlum, Laura Maxwell, Moa Olin, Constanza Sanhueza Petrarca, Rachel Sigman, Matthew C Wilson, and Staffan I Lindberg. 2018. "State of the World 2017: Autocratization and Exclusion?" *Democratization* 25 (8): 1321–40.

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Appendices

A Outcome variable Appendix

A.1 Alternative thresholding strategies

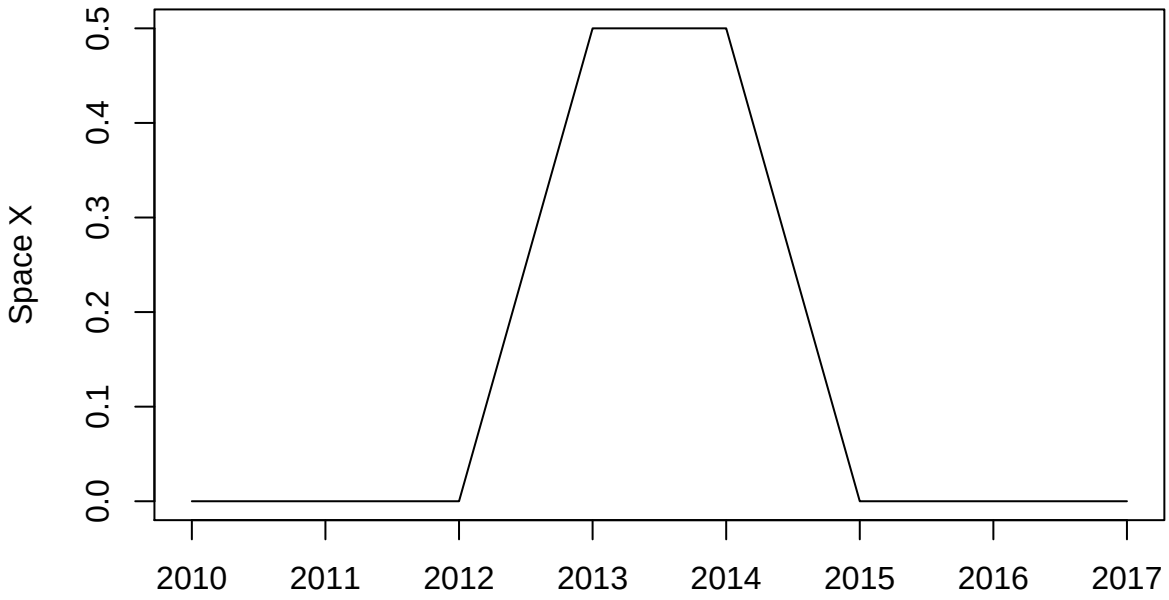
This section provides additional reasoning for the thresholding strategy we chose, i.e. using 6 distinct thresholds, with one each for the 6 spaces.

The simplest strategy is to use a single global threshold for demarcating significant movements in each space. However, the six spaces do not all fluctuate equally over time. Some like the electoral space involve relatively large changes, while others fluctuate more gradually. Using a single threshold would potentially weigh the rapidly changing spaces more than the slow changing spaces, which implies that the rapidly changing one are essentially more important or at least would be more prominent in our outcome data. To avoid this we instead use space-specific thresholds.

Through similar reasoning, one could argue that we should also separate thresholds for upwards and downwards changes. And it is the case, in the data, that the amount of variation and general direction of movement in the spaces falls more towards upwards movement over time. We decided against threshold-specific for two reasons.

First, while we cannot make clear statements about the substantive significance of a 0.05 or 0.04 movement on the electoral space compared to the informational space, absolute movements upwards or downwards within each space are meaningful. Specifically, if we use the same threshold for upwards and downwards movements and we see that overall there have been more upwards movements, we know that conditions in that space are getting better. Conversely, if we see more changes in the electoral space than in the informational space, it's not clear what that means. By separating thresholds for upwards and downwards movements in each space we would essentially be normalizing out global movements that happen in the background.

Using separate up and down thresholds also has strange implications when we look at the data for specific countries. The plot below illustrates a hypothetical example of the values for a space in some country of interest over time.



There is a large increase in 2013 but then an equivalent drop in 2015. If we were to use separate thresholds for those up and down movements we could end up in a situation where we consider the increase to not be significant but the down movement to be significant. Even though the country overall in 2015 is exactly back where it was in 2012.

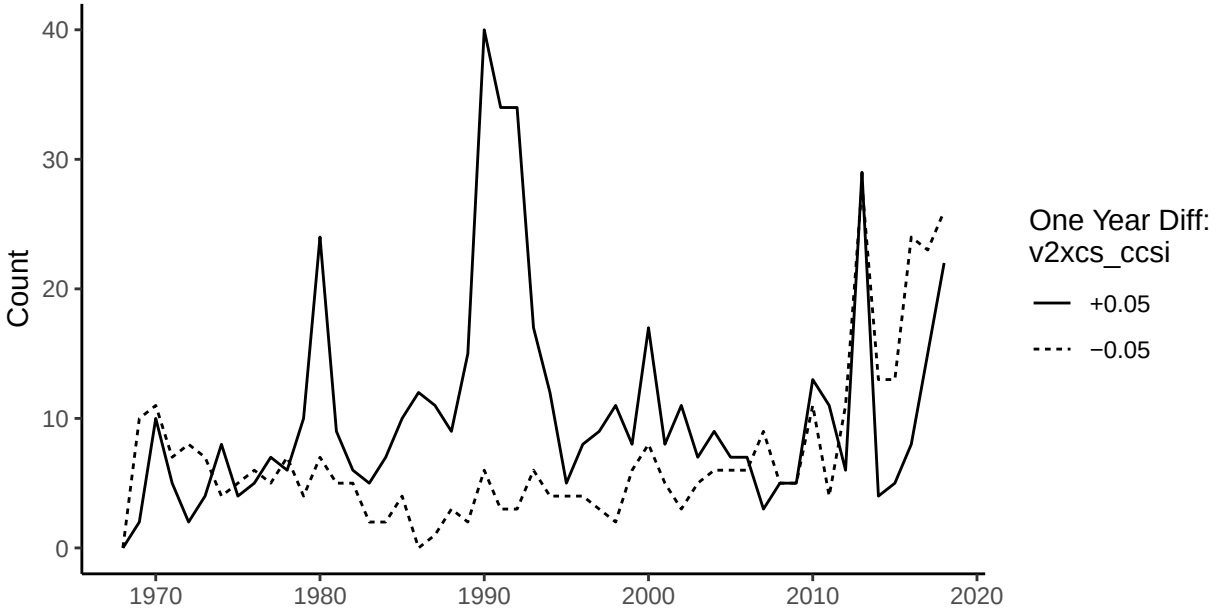
A.2 Descriptive statistics and case examples

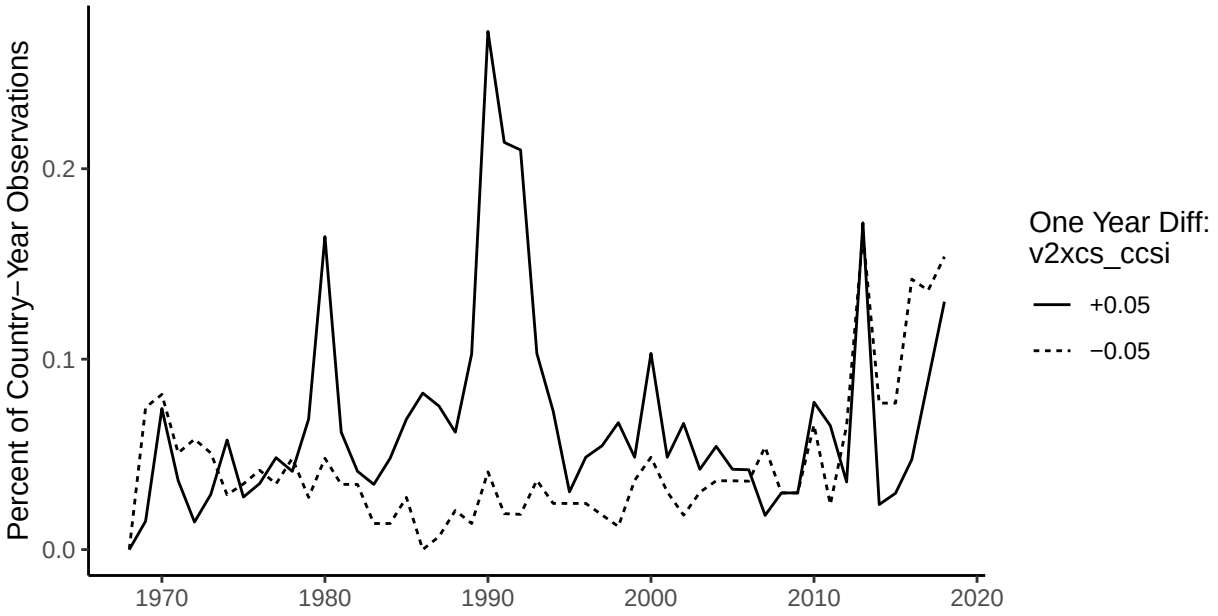
For each of our six spaces, this section provides summary statistics for all observations (pooled), all observations with a first difference greater than or equal to zero (up), and all observations with a first difference less than or equal to zero (down). For each of these distinct sets of observations, we provide the minimum, maximum, mean and standard deviation for the observed first differences, the proposed positive and negative threshold (Pos Cutoff and Neg Cutoff), the number of observed opening and closing events (#-Pos and #-Neg), and the percentage of observed opening and closing events (%-Pos and %-Neg). We also provide two time series plots that reflect the number and frequency of opening and closing events in each year of our dataset. Finally, we provide country-level time series plots that report a country's yearly level of an index and whether our threshold procedure captures the example cases IRI provided.

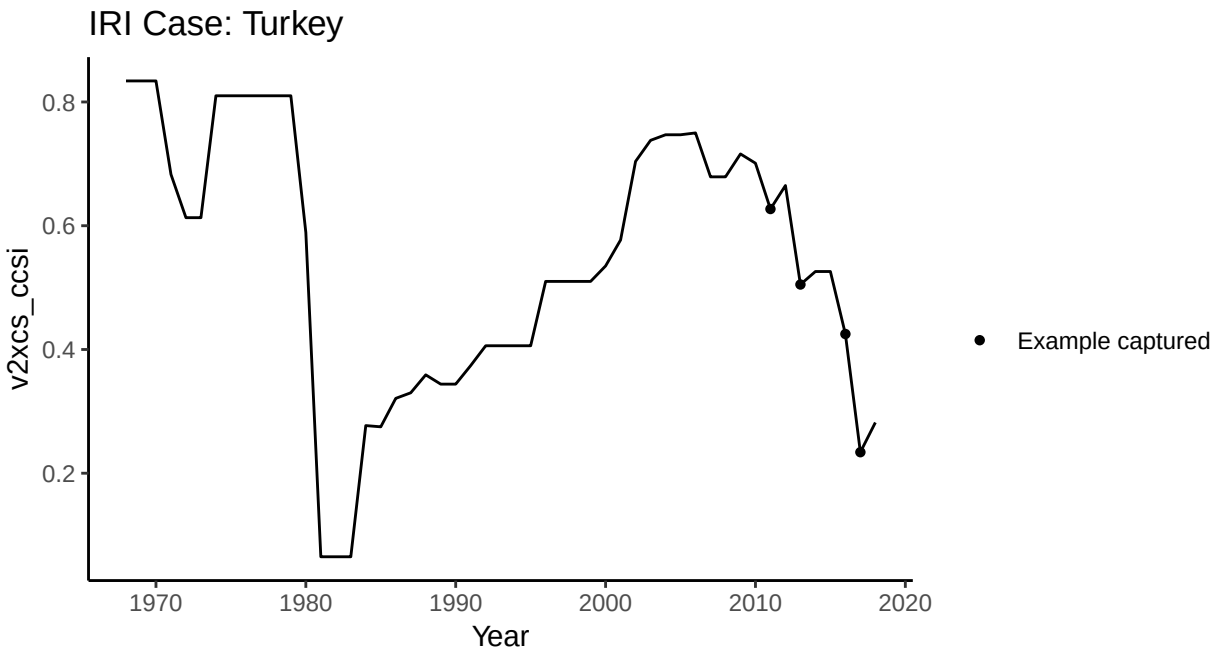
A.2.1 Associational – Core civil society index (v2xcs_ccsi)

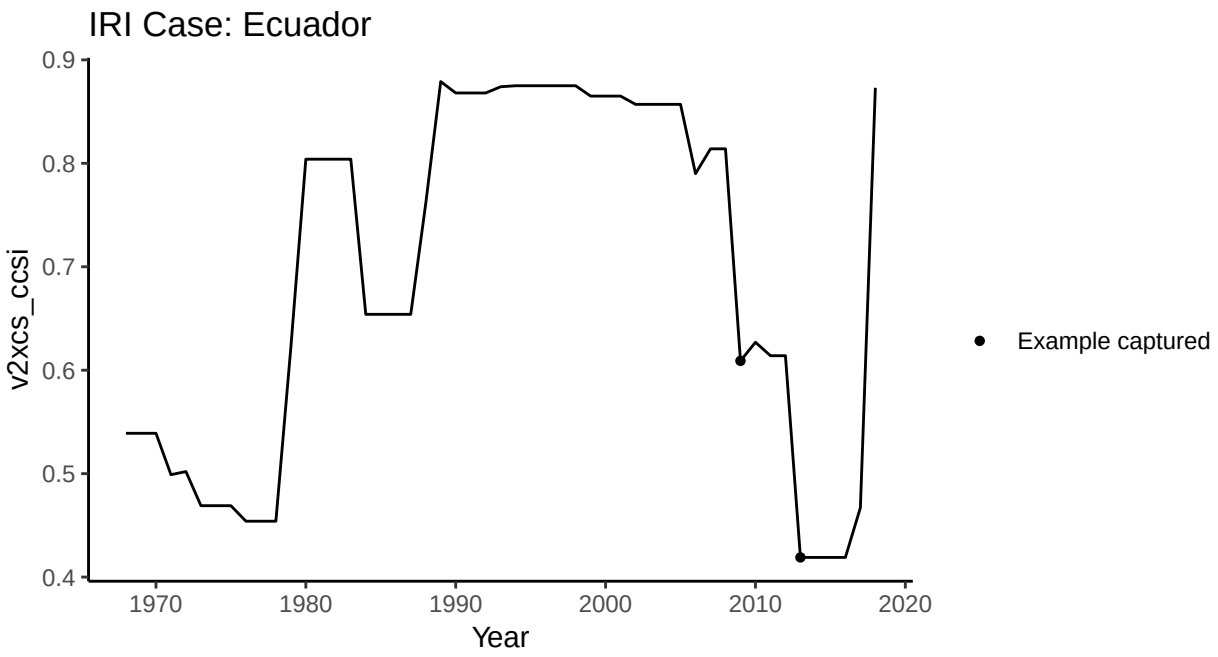
Table 6: Summary Statistics for Different Directional Samples – 1970-2018 (v2xcs_ccsi)

Sample	Min	Max	Mean	SD	Pos Cutoff	Neg Cutoff	#-Pos	#-Neg	%-Pos	%-Neg
Pooled	-0.524	0.767	0.005	0.056	0.056	-0.056	490	303	0.062	0.038
Up	0.000	0.767	0.015	0.051	0.050		541		0.068	
Down	-0.524	0.000	-0.009	0.032		-0.050		357		0.045





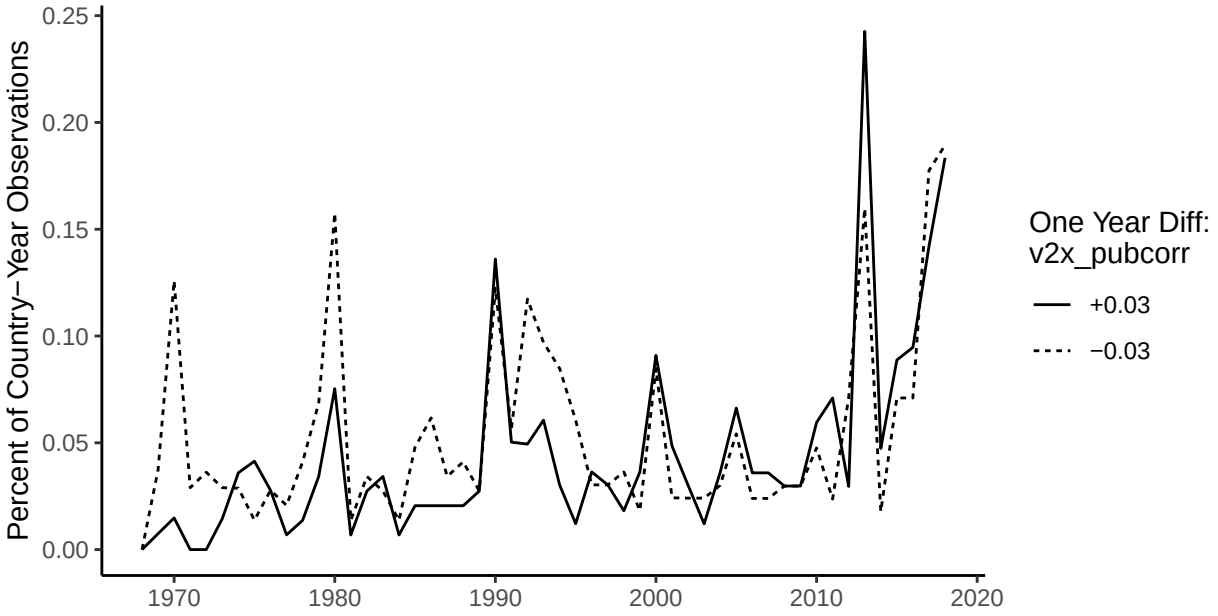

IRI Case: Turkey
v2xcs_ccsi
0.8
0.6
0.4
0.2
1970
1980
1990
2000
2010
2020
Year
Example captured

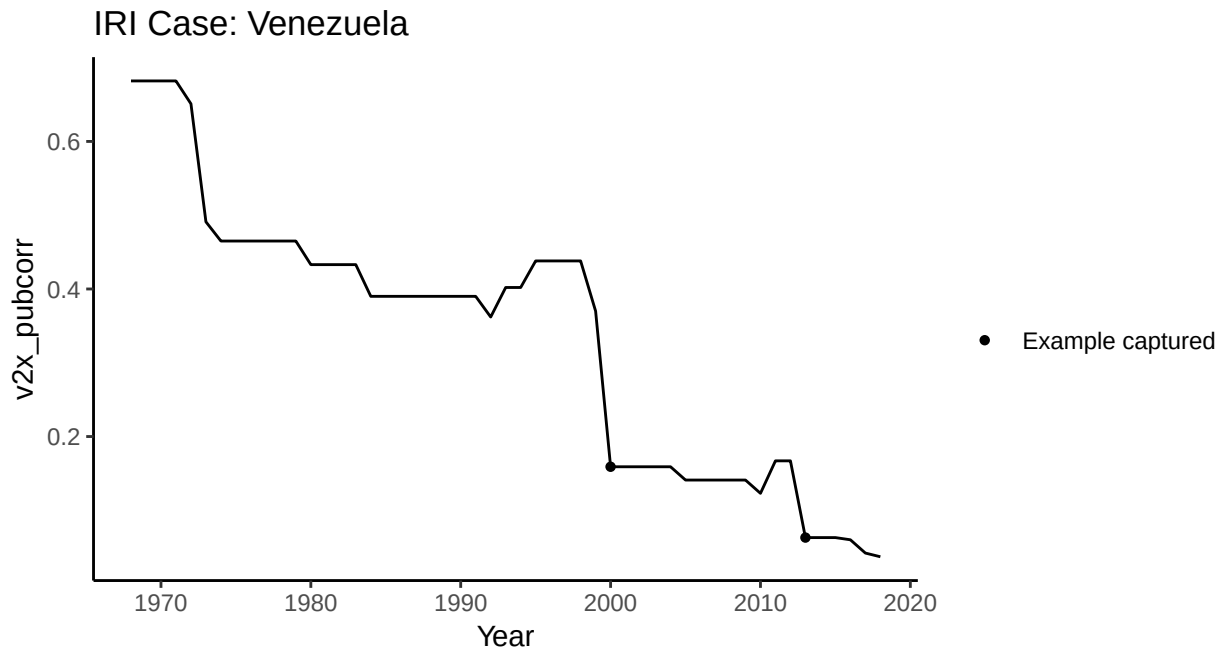

IRI Case: Ecuador
v2xcs_ccsi
0.9
0.8
0.7
0.6
0.5
0.4
1970
1980
1990
2000
2010
2020
Year
Example captured

A.2.2 Economic – Public Corruption Index (v2x_pubcorr)

Table 7: Summary Statistics for Different Directional Samples – 1970-2018 (v2x_pubcorr)

Sample	Min	Max	Mean	SD	Pos Cutoff	Neg Cutoff	#-Pos	#-Neg	%-Pos	%-Neg
Pooled	-0.562	0.679	-0.001	0.040	0.04	-0.04	308	358	0.039	0.045
Up	0.000	0.679	0.005	0.028	0.03		370		0.047	
Down	-0.562	0.000	-0.007	0.030		-0.03		434		0.055

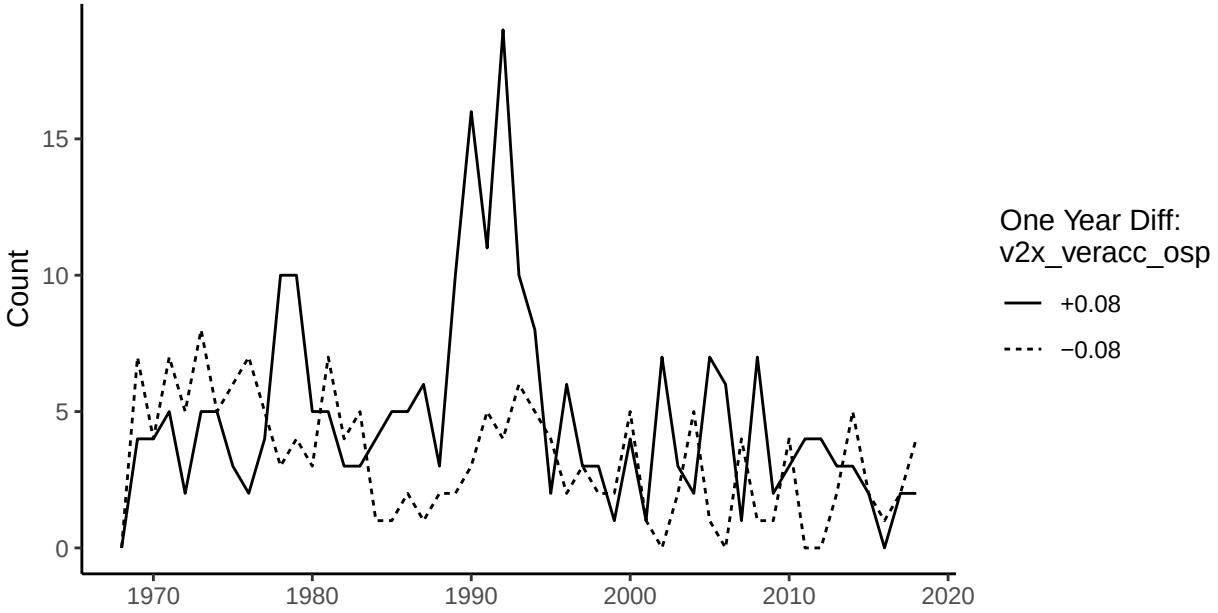


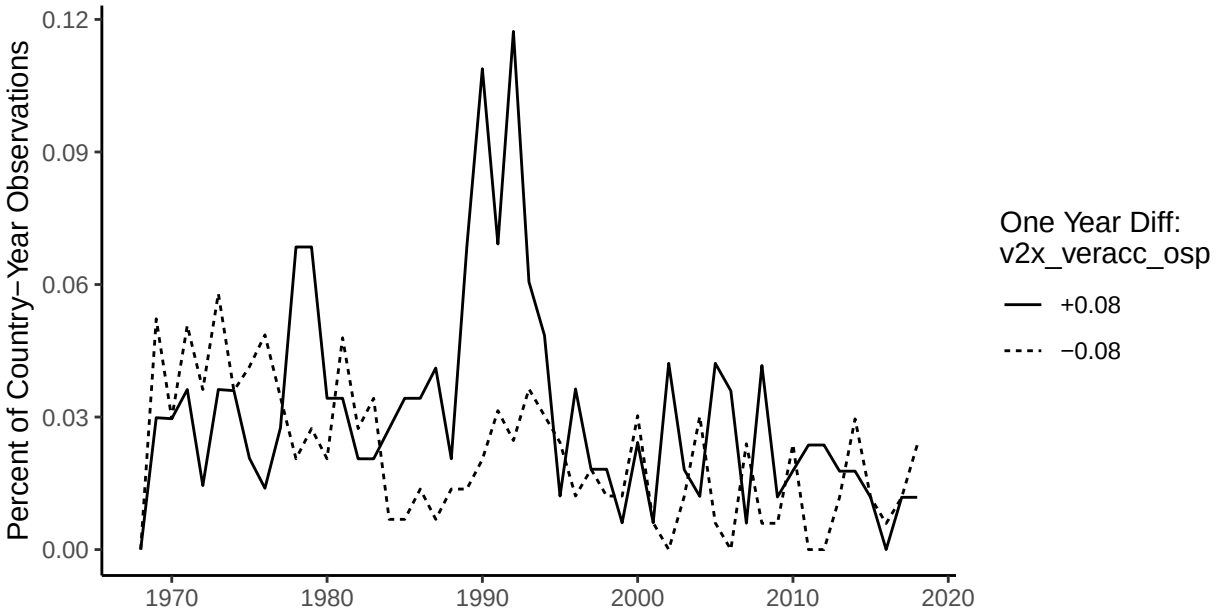

IRI Case: Venezuela
v2x_pubcorr
0.6
0.4
0.2
1970
1980
1990
2000
2010
2020
Year
Example captured

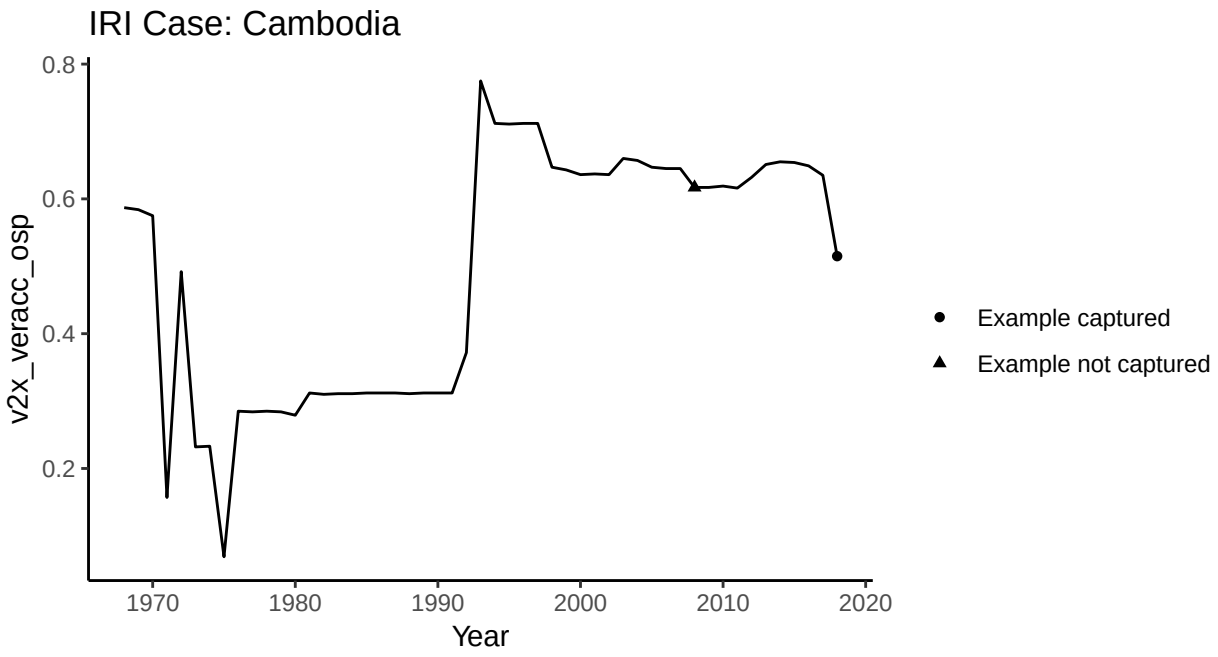
A.2.3 Electoral – Vertical accountability index (v2x_veracc_osp)

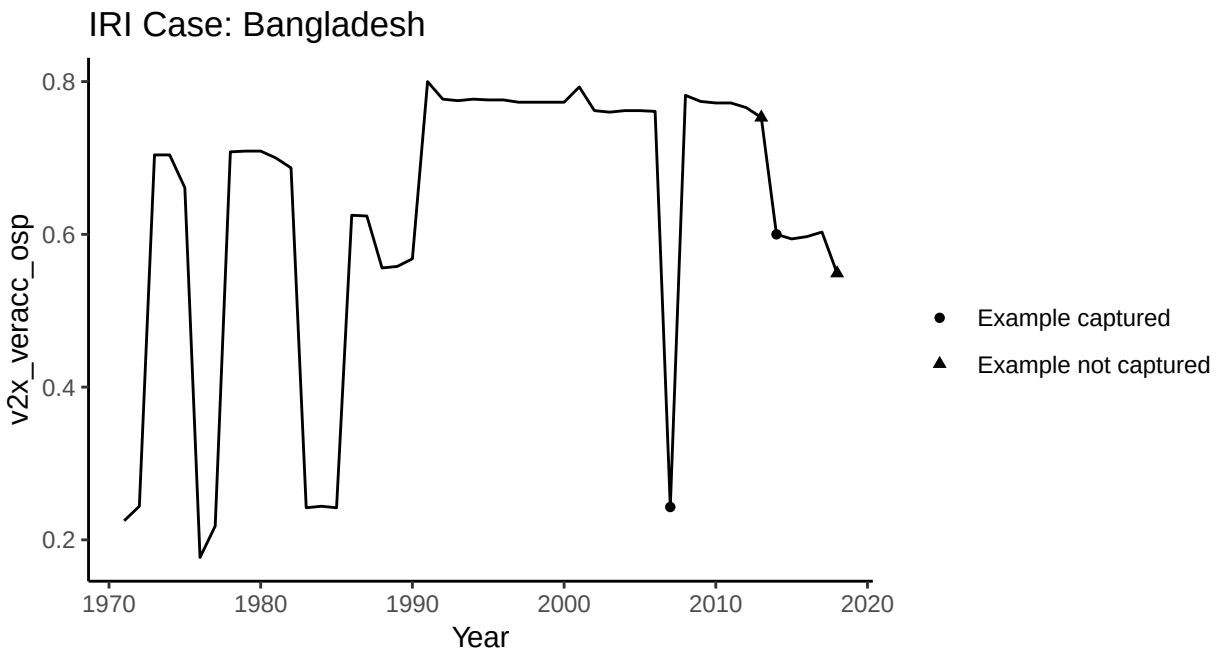
Table 8: Summary Statistics for Different Directional Samples – 1970-2018 (v2x_veracc_osp)

Sample	Min	Max	Mean	SD	Pos Cutoff	Neg Cutoff	#-Pos	#-Neg	%-Pos	%-Neg
Pooled	-0.762	0.802	0.004	0.084	0.084	-0.084	241	157	0.030	0.020
Up	0.000	0.802	0.020	0.078	0.080		245		0.031	
Down	-0.762	0.000	-0.015	0.068		-0.080		165		0.021





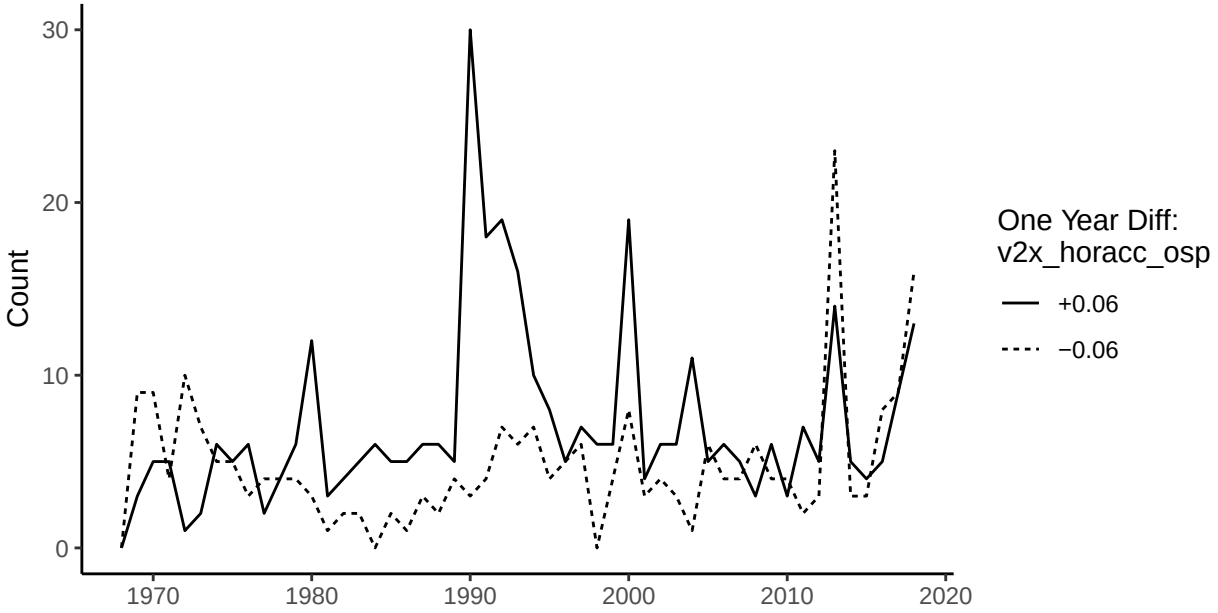

IRI Case: Cambodia
v2x_veracc_osp
0.8
0.6
0.4
0.2
1970
1980
1990
2000
2010
2020
Year
Example captured
Example not captured

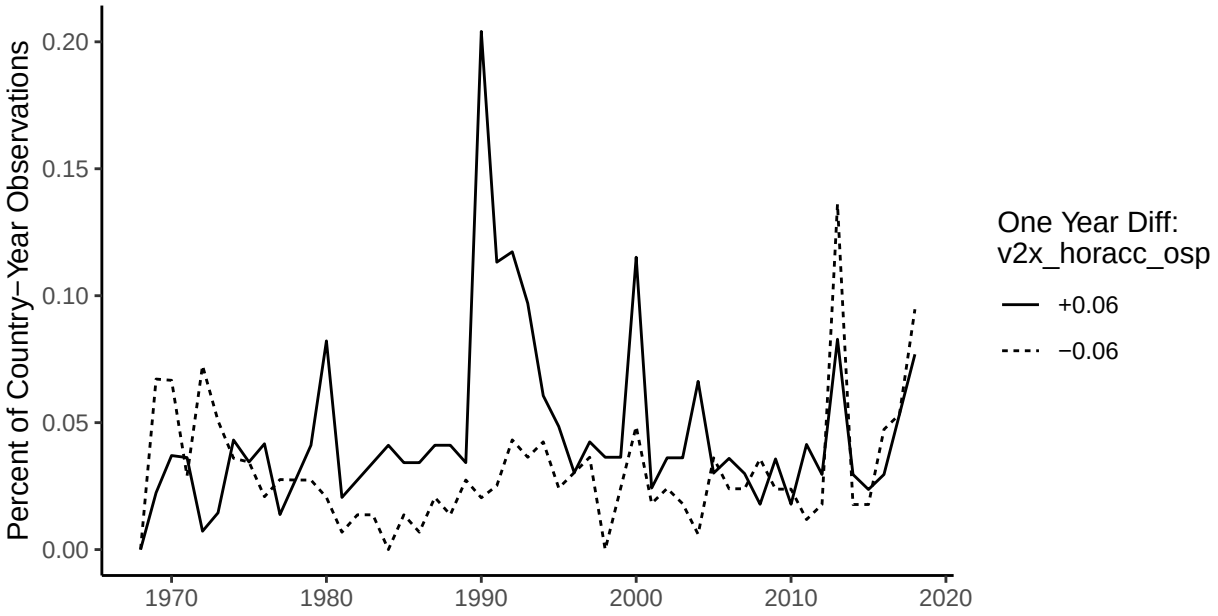

IRI Case: Bangladesh
v2x_veracc_osp
0.8
0.6
0.4
0.2
1970
1980
1990
2000
2010
2020
Year
Example captured
Example not captured

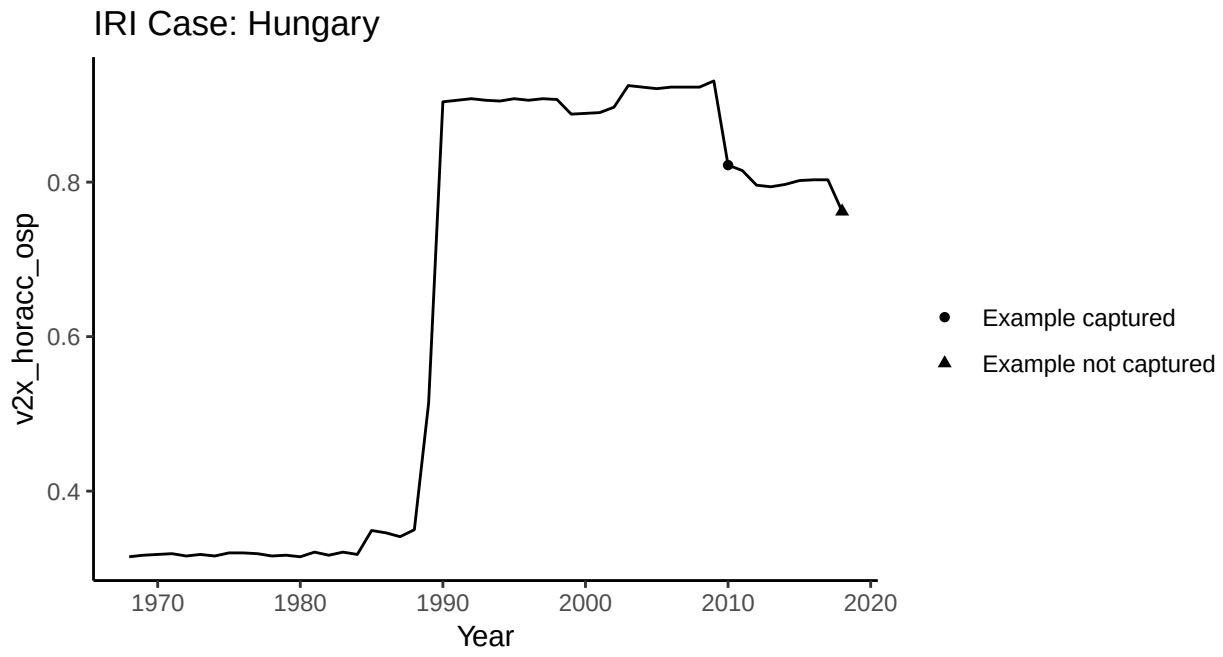
A.2.4 Governing – Horizontal Accountability Index (v2x_horacc_osp)

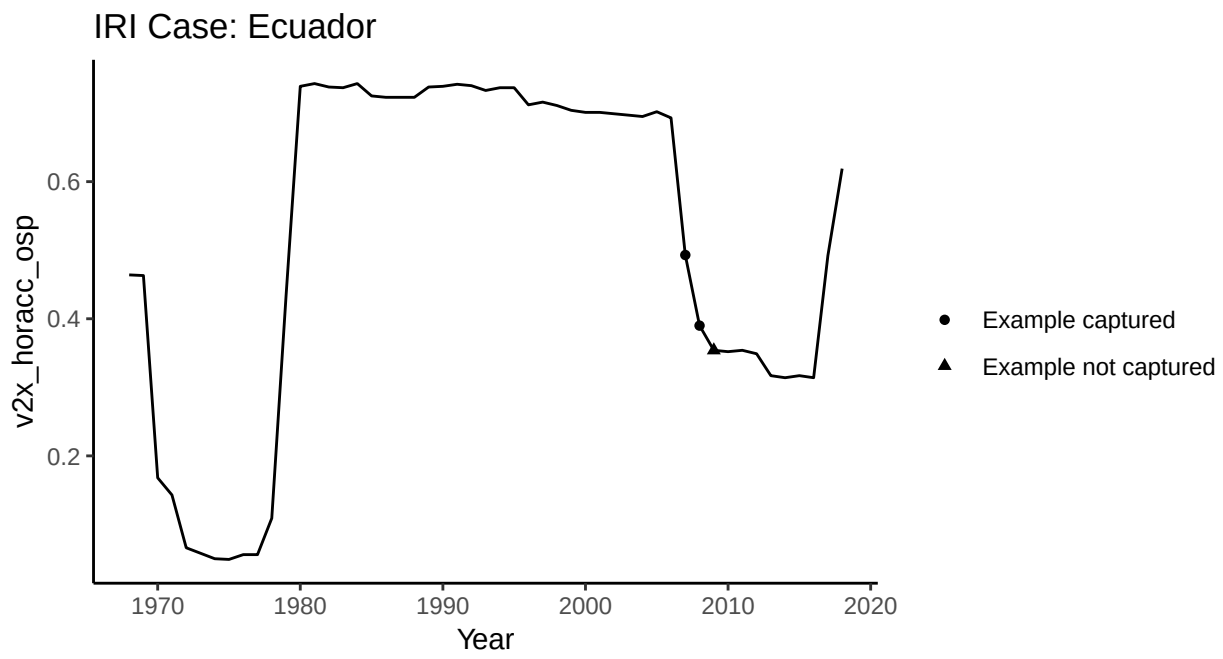
Table 9: Summary Statistics for Different Directional Samples – 1970-2018 (v2x_horacc_osp)

Sample	Min	Max	Mean	SD	Pos Cutoff	Neg Cutoff	#-Pos	#-Neg	%-Pos	%-Neg
Pooled	-0.715	0.839	0.004	0.060	0.06	-0.06	359	241	0.045	0.030
Up	0.000	0.839	0.018	0.059	0.06		363		0.046	
Down	-0.715	0.000	-0.013	0.044		-0.06		244		0.031





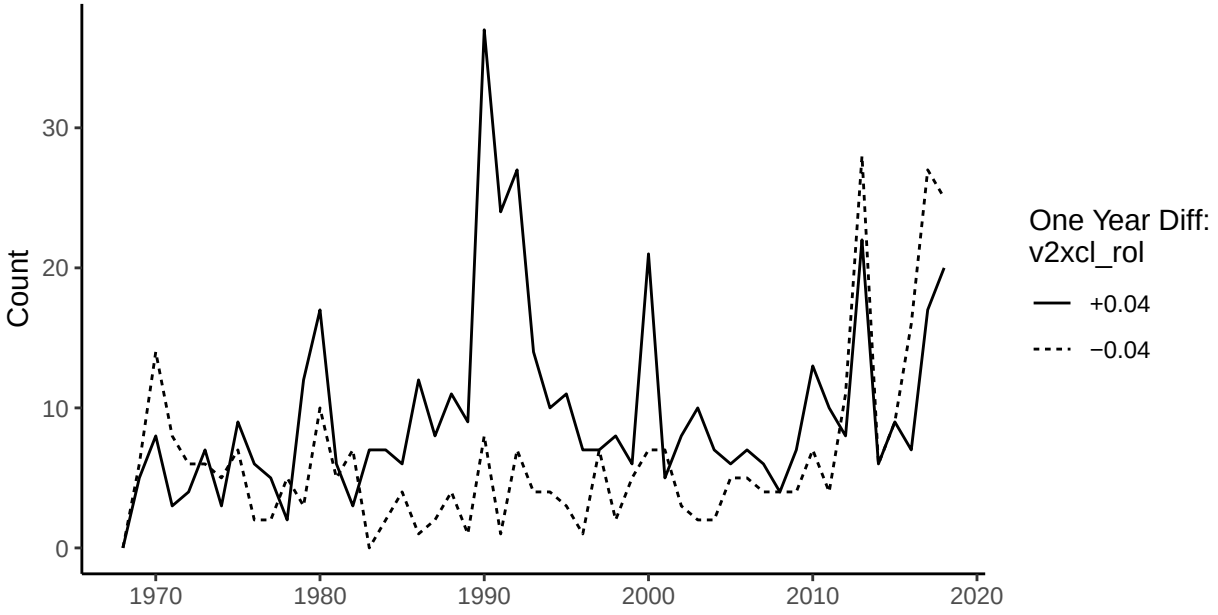

IRI Case: Hungary
v2x_horacc_osp
0.8
0.6
0.4
1970
1980
1990
2000
2010
2020
Year
Example captured
Example not captured

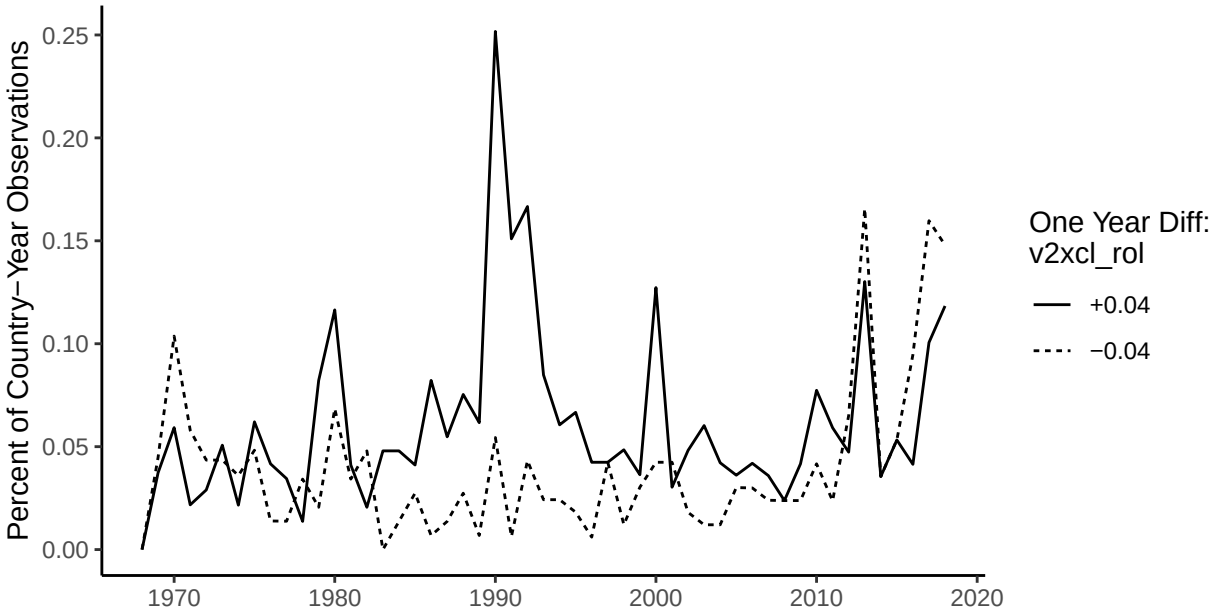

IRI Case: Ecuador
v2x_horacc_osp
0.6
0.4
0.2
1970
1980
1990
2000
2010
2020
Year
Example captured
Example not captured

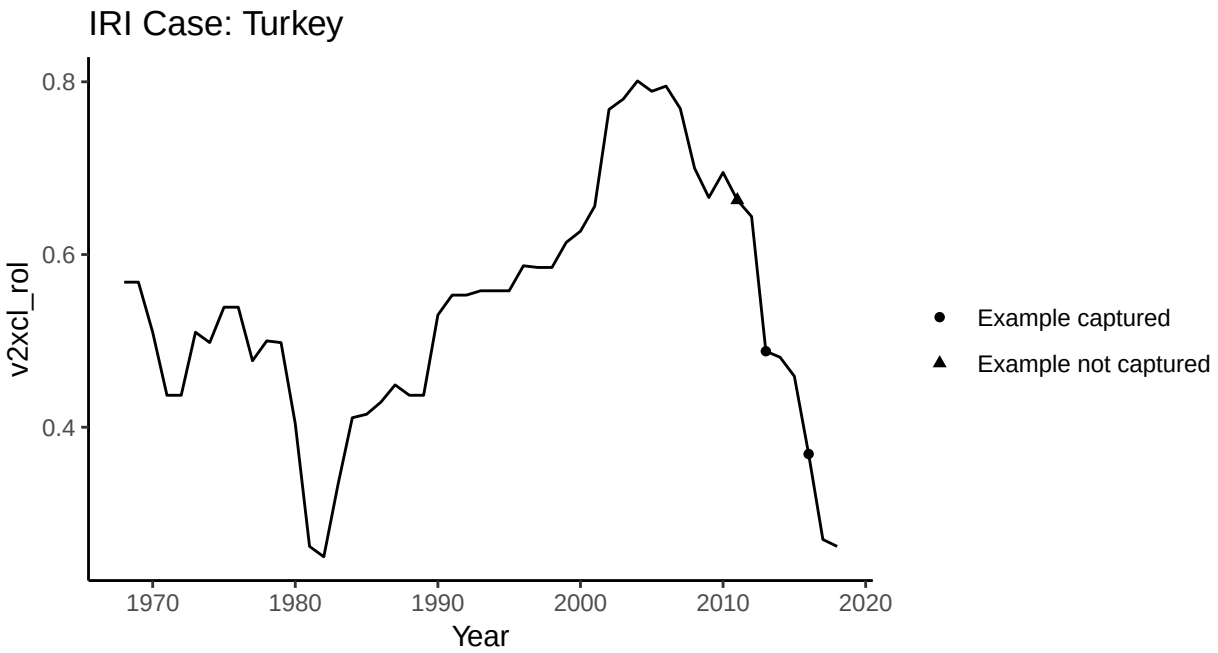
A.2.5 Individual – Equality Before the Law and Individual Liberty Index (v2xcl_rol)

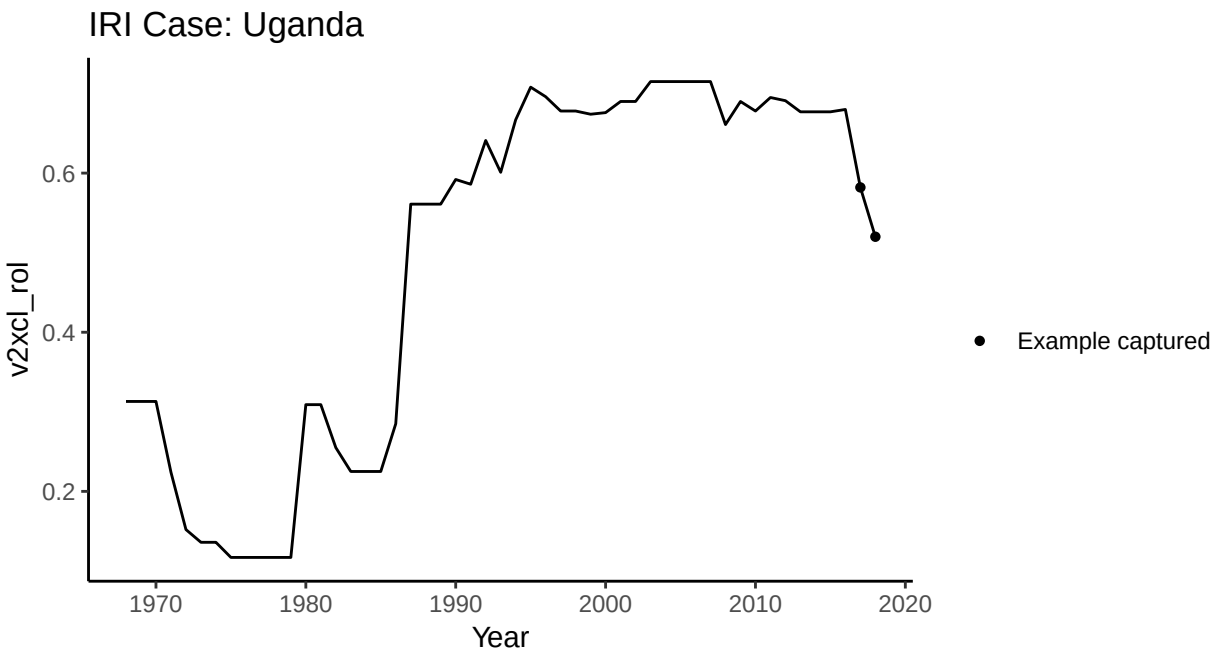
Table 10: Summary Statistics for Different Directional Samples – 1970-2018 (v2xcl_rol)

Sample	Min	Max	Mean	SD	Pos Cutoff	Neg Cutoff	#-Pos	#-Neg	%-Pos	%-Neg
Pooled	-0.532	0.75	0.004	0.045	0.045	-0.045	416	269	0.052	0.034
Up	0.000	0.75	0.013	0.043	0.040		494		0.062	
Down	-0.532	0.00	-0.009	0.026		-0.040		318		0.040





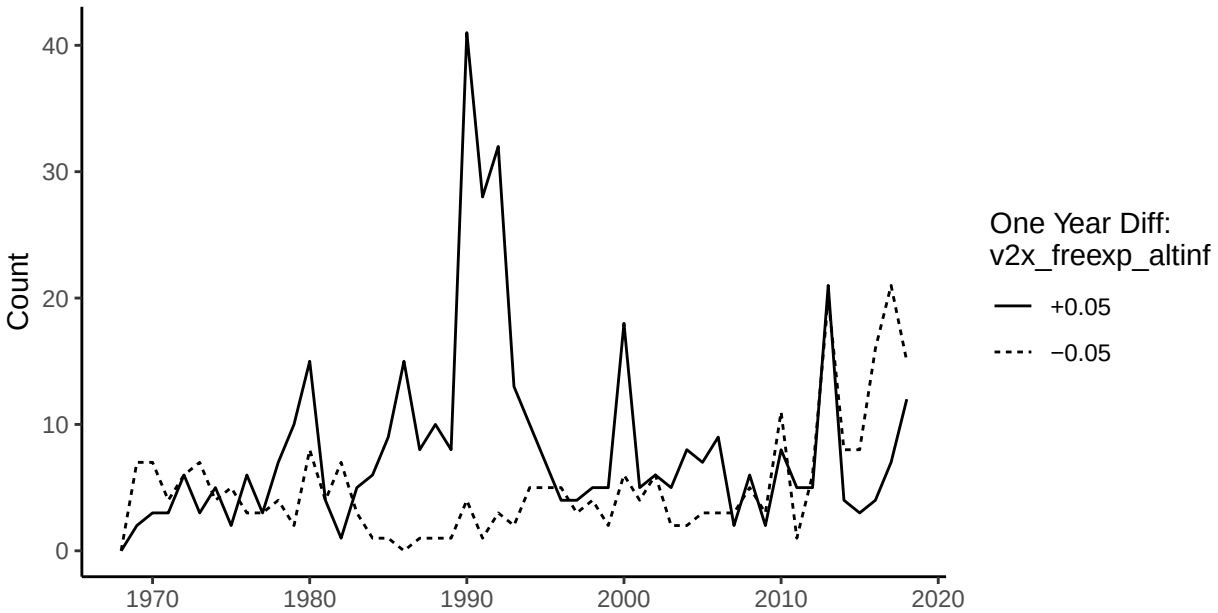

IRI Case: Turkey
0.8
0.6
0.4
v2xcl_rol
1970
1980
1990
2000
2010
2020
Year
Example captured
Example not captured

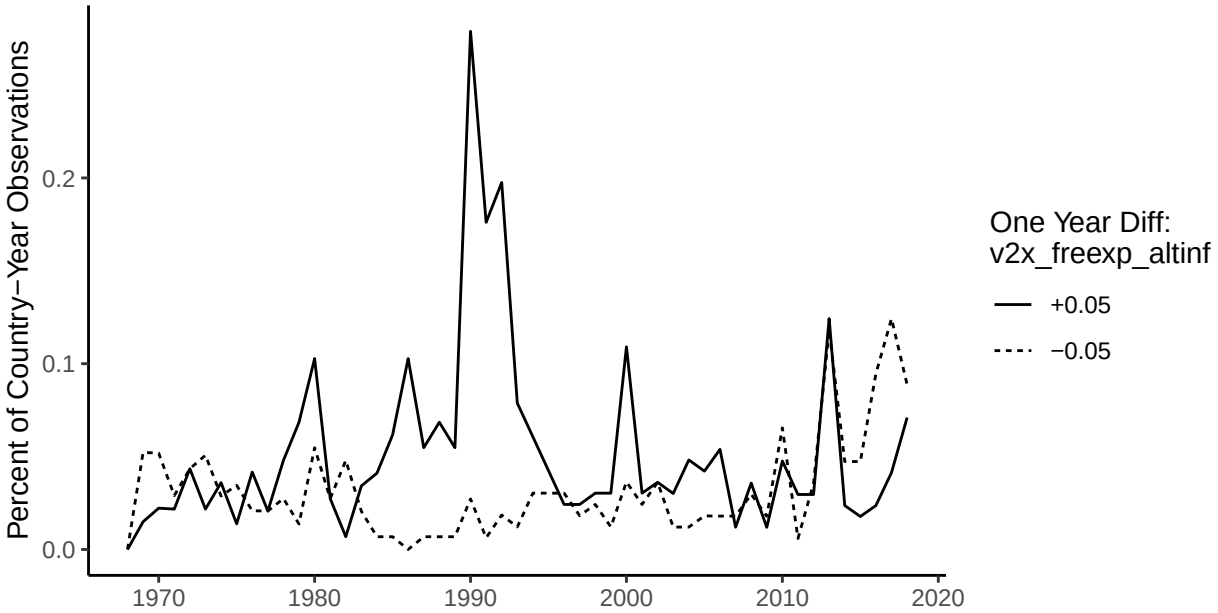

IRI Case: Uganda
0.6
0.4
0.2
v2xcl_rol
1970
1980
1990
2000
2010
2020
Year
Example captured

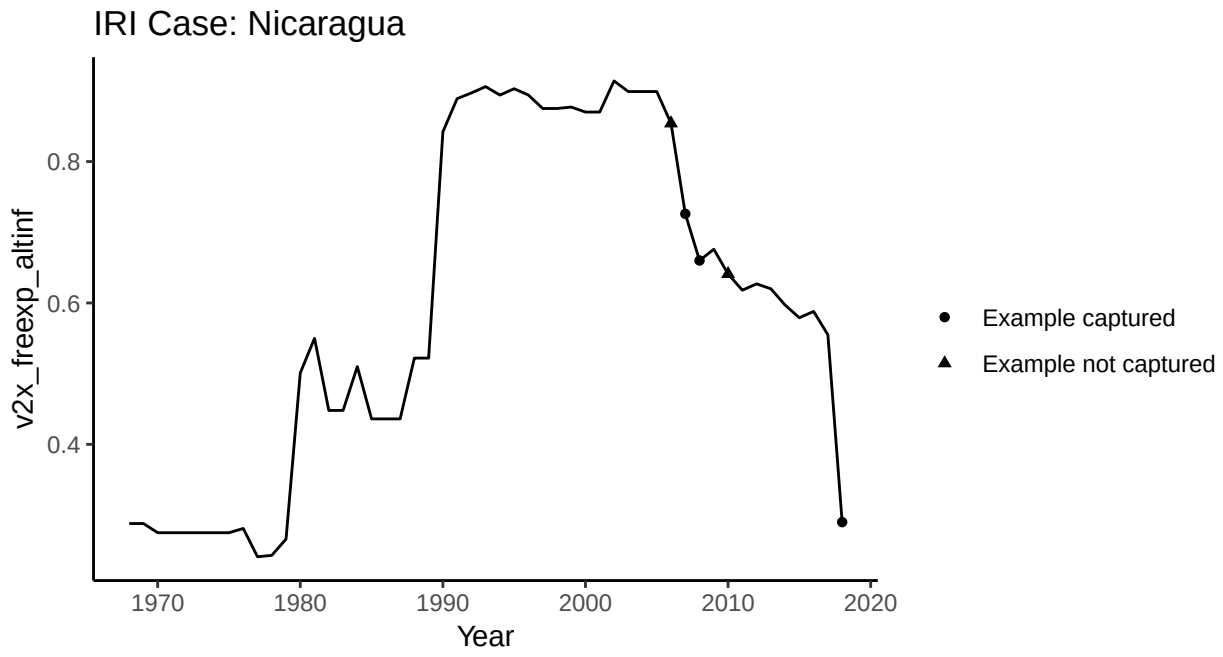
A.2.6 Informational – Freedom of Expression and Alternative Sources of Information index (v2x_freexp_altinf)

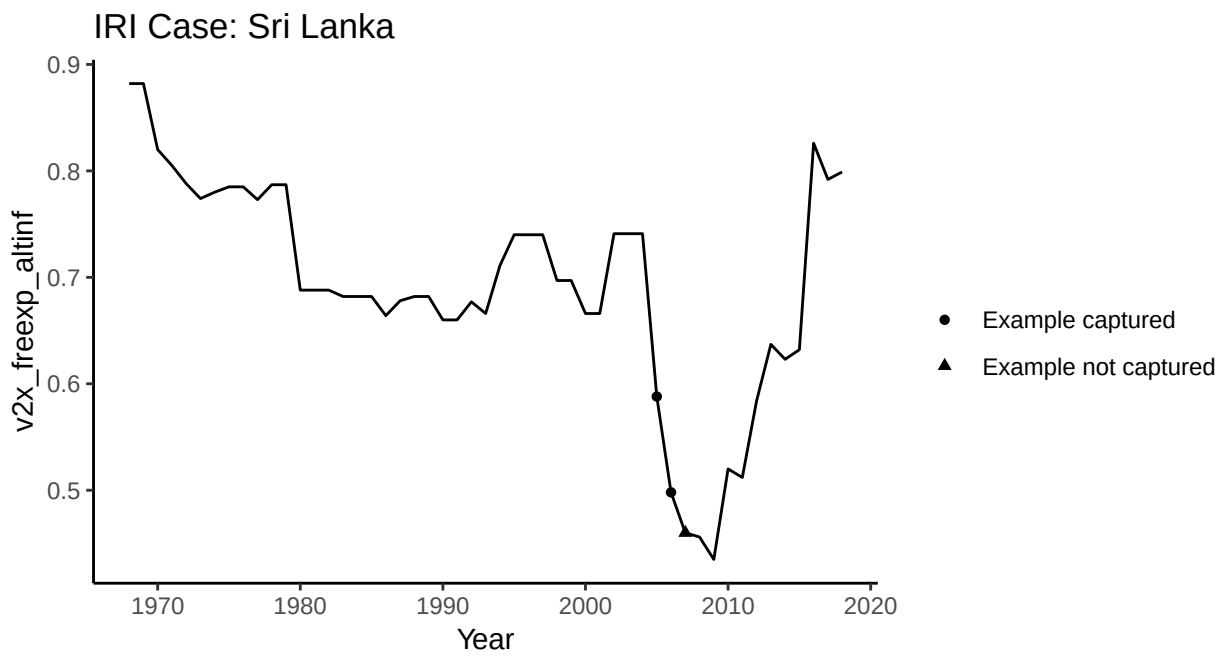
Table 11: Summary Statistics for Different Directional Samples – 1970-2018 (v2x_freexp_altinf)

Sample	Min	Max	Mean	SD	Pos Cutoff	Neg Cutoff	#-Pos	#-Neg	%-Pos	%-Neg
Pooled	-0.571	0.862	0.005	0.057	0.057	-0.057	360	213	0.045	0.027
Up	0.000	0.862	0.016	0.055	0.050		417		0.052	
Down	-0.571	0.000	-0.010	0.032		-0.050		256		0.032






IRI Case: Nicaragua
v2x_freexp_altinf
0.8
0.6
0.4
1970
1980
1990
2000
2010
2020
Year
Example captured
Example not captured


IRI Case: Sri Lanka
v2x_freexp_altinf
0.9
0.8
0.7
0.6
0.5
1970
1980
1990
2000
2010
2020
Year
Example captured
Example not captured

A.3 V-Dem codebook entries

This section provides information on the construction of the V-Dem indices we use are proxies for each space. We copied this information directly from the V-Dem codebook.

Associational – Core Civil Society Index - v2xcs_ccsi

V-Dem Codebook Entry:

Question: How robust is civil society?

Clarification: The sphere of civil society lies in the public space between the private sphere and the state. Here, citizens organize in groups to pursue their collective interests and ideals. We call these groups civil society organizations CSOs. CSOs include, but are by no means limited to, interest groups, labor unions, spiritual organizations if they are engaged in civic or political activities, social movements, professional associations, charities, and other non-governmental organizations. The core civil society index CCSI is designed to provide a measure of a robust civil society, understood as one that enjoys autonomy from the state and in which citizens freely and actively pursue their political and civic goals, however conceived.

Scale: Interval, from low to high (0-1).

Source(s): v2cseeorgs v2csreprss v2csprtcpt

Aggregation: The index is formed by taking the point estimates from a Bayesian factor analysis model of the indicators for CSO entry and exit (v2cseeorgs), CSO repression (v2csreprss) and CSO participatory environment (v2csprtcpt).

Economic – Public Sector Corruption Index - v2x_pubcorr[30]

V-Dem Codebook Entry:

Question: To what extent do public sector employees grant favors in exchange for bribes, kickbacks, or other material inducements, and how often do they steal, embezzle, or misappropriate public funds or other state resources for personal or family use?

Clarification: The directionality of the V-Dem corruption index runs from less corrupt to more corrupt unlike the other V-Dem variables that generally run from less democratic to more democratic situation.

Scale: low to high (0-1).

Source(s): v2excrptps v2exthftps

Aggregation: The index is formed by taking the average of the point estimates from a Bayesian factor analysis model of the indicators for public sector bribery v2excrptps and embezzlement v2exthftps.

Electoral – Vertical Accountability Index - v2x_veracc_osp

V-Dem Codebook Entry:

Question: To what extent is the ideal of vertical government accountability achieved?

Clarification: Vertical accountability captures the extent to which citizens have the power to hold the government accountable. The mechanisms of vertical accountability include formal political participation on part of the citizens — such as being able to freely organize in political parties — and participate in free and fair elections, including for the chief executive.

[30] Note that in its original construction of this index `0` means no corruption and `1` means a lot of corruption. This is the opposite of the other indices, where low scores represent more "autocratic" and high scores more "democratic". As such, we rescale this variable.

Scale: low to high (0-1).

Source(s): v2x_elecreg v2elembaut v2elembcap v2elrgstry v2elirreg v2elintim v2elmulpar v2elfrfair v2elsuffrage v2expathhs v2ex_legconhos v2expathhg v2exaphogp v2ex_hosw v2psparban v2psbars v2psoppaut

Aggregation: Vertical accountability consists of two main components: elections and political parties. We operationalize electoral accountability with three components: 1) an aggregate measure the quality of elections; 2) the percent of enfranchised population and 3) whether the chief executive is directly or indirectly elected. We model non-electoral regimes as having no suffrage and the quality of elections as a function of having an electoral regime (v2x_elecreg). Quality of elections consists of seven variables measuring different aspects of national elections for the executive and legislature. Specifically, we include autonomy and capacity of the electoral management body (v2elembaut) and (v2elembcap); accuracy of the voter registry (v2elrgstry), intentional irregularities conducted by the government and opposition (v2elirreg); intimidation and harassment by the government and its agents (v2elintim); to what extent the elections were multi-party in practice (v2elmulpar); and an overall measure for the freedom and fairness of elections (v2elfrfair). This is a modified version of the V-Dem Clean elections index (v2xel_frefair). We added the variable v2elmulpar, which is theoretically important for accountability, and we removed v2elvotbuy and v2elpeace, as they have low loadings. We measure suffrage as the percentage of people that have the legal right to vote (v2elsuffrage) to proxy the inclusivity of the exercise of electoral accountability. To account for the differences between states which have an executive subject to elections, we include a dichotomous indicator of whether or not the head of the executive either the head of state or head of government - whoever has more relative power over the appointment and dismissal of cabinet ministers as measured by v2ex_hosw is subjected to direct or indirect elections (v2expathhs v2ex_legconhos v2expathhg v2exaphogp). The second form of vertical accountability focuses on political parties, which we model as a hierarchical node. This node includes variables that capture whether there are barriers to forming a party and how restrictive they are (v2psparban) and (v2psbars), as well as the degree to which opposition parties are independent of the ruling regime (v2psoppaut).

Governing – Horizontal Accountability Index – v2x_horacc_osp

V-Dem Codebook Entry:

Question: To what extent is the ideal of horizontal government accountability achieved?

Clarification: Horizontal accountability concerns the power of state institutions to oversee the government by demanding information, questioning officials and punishing improper behavior. This form of accountability ensures checks between institutions and prevents the abuse of power. The key agents in horizontal government accountability are: the legislature; the judiciary; and specific oversight agencies such as ombudsmen, prosecutor and comptroller generals.

Scale: low to high (0-1).

Source(s): v2juhcind v2juncind v2juhccomp v2jucomp v2exrescon v2lgotovst v2lginvstp v2lgbicam v2lgotovst

Aggregation: We capture the extent to which the judiciary, the legislature and other oversight agencies hold the government to account by modeling each of these factors as separate hierarchical nodes. The judiciary node speaks to the degree to which members of the executive compromise horizontal accountability by "unlawfully encroaching" on the legitimate authority of the judiciary branch. To capture that we use the indicators from the V-Dem judicial constraints on the executive index (v2x_jucon). To model the degree to which a legislature facilitates horizontal accountability we model whether or not a legislature exists a dichotomized version of v2lgbicam, and legislature activities as a function of this variable. The key function of a legislature in terms of horizontal accountability is to scrutinize government officials' potential misconduct by demanding information for their policies and decisions, and taking specific actions in case of irregularities. We use as baseline the indicators from the V-Dem legislative constraints on the executive index (v2xlg_legcon): the degree to which: 1 the legislature routinely questions the executive (v2lgotovst); and 2 a legislature is likely to investigate and produce a decision unfavorable to the executive, if the latter were engaged in an illegal or unethical activity (v2lginvstp). We exclude the legislature opposition parties (v2lgoppart) as this aspect is part of vertical accountability. Finally, we include a variable regarding the degree to which other

state bodies comptroller general, general prosecutor, or ombudsman are likely to investigate and report on potential illegal or unethical activities on part of the executive (v2lgotovst).

Individual – Equality Before the Law and Individual Liberty Index - v2xcl_rol

Question: To what extent are laws transparent and rigorously enforced and public administration impartial, and to what extent do citizens enjoy access to justice, secure property rights, freedom from forced labor, freedom of movement, physical integrity rights, and freedom of religion?

Scale: low to high (0-1).

Source(s): v2clrspct v2cltrnslw v2clacjstm v2clacjstw v2clprptym v2clprptyw v2cltort v2clkill v2clslavem v2clslavef v2clrelig v2clfmove v2cldmovem v2cldmovew

Aggregation: The index is formed by taking the point estimates from a Bayesian factor analysismodel of the indicators for rigorous and impartial public administration (v2clrspct), transparent laws with predictable enforcement (v2cltrnslw), access to justice for men/women (v2clacjstm, v2clacjstw), property rights for men/women (v2clprptym, v2clprptyw), freedom from torture (v2cltort), freedom from political killings (v2clkill), from forced labor for men/women (v2clslavem v2clslavef), freedom of religion (v2clrelig), freedom of foreign movement (v2clfmove), and freedom of domestic movement for men/women (v2cldmovem, v2cldmovew).

Informational – Freedom of Expression and Alternative Sources of Information Index - v2x_freexp_altinf

Question: To what extent does government respect press and media freedom, the freedom of ordinary people to discuss political matters at home and in the public sphere, as well as the freedom of academic and cultural expression?

Clarification: This index includes all variables in the two indices v2x_freexp and v2xme_altinf.

Scale: Interval, from low to high (0-1).

Source(s): v2mecenefm v2meharjrn v2meslfcen v2mebias v2mecrit v2merange v2cldiscm v2cldiscw v2clacfree

Aggregation: The index is formed by taking the point estimates from a Bayesian factor analysis model of the indicators for media censorship effort (v2mecenefm), harassment of journalists (v2meharjrn), media bias (v2mebias), media self-censorship (v2meslfcen), print/broadcast media critical (v2mecrit), and print/broadcast media perspectives (v2merange), freedom of discussion for men/women (v2cldiscm, v2cldiscw), and freedom of academic and cultural expression (v2clacfree).

B 2019–2020 estimated probabilities for all countries, spaces, and directions

Each table below lists the estimated risk of an opening or closing for all countries covered by the forecasts. Along with the estimated probability ("Prob." in the tables), there are extra columns for the opening or closing rank and risk category ("Cat.") that a country has. We have included these since it can be hard to place a raw probability forecast into context, e.g., is a value of 0.319 high or low? The rank and risk category columns make it possible to compare, at a glance, whether such a value is high or low *relative* to other countries.

The rank column is the order of a country when we sort all countries by the probability estimate in descending order. A value of "1" indicates the country that had the highest estimated probability, and high values, e.g., "150" indicate a country with a low estimated probability.[31]

The risk category column maps countries into five equally sized groups based on how high their risk probability is. E.g., countries in the "Highest" category include the fifth of all countries for which we have forecasts and which had the correspondingly highest probabilities.

B.1 Associational

Table 12: Associational Space: 2019-2020 forecasts for all countries

	Opening			Closing		
Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Afghanistan	0.336	18	Highest	0.349	19	Highest
Albania	0.222	81	Medium	0.276	50	High
Algeria	0.256	65	High	0.239	77	Medium
Angola	0.370	11	Highest	0.233	82	Medium
Argentina	0.077	132	Low	0.222	93	Medium
Armenia	0.401	8	Highest	0.258	65	High
Australia	0.017	157	Lowest	0.034	167	Lowest
Austria	0.100	126	Low	0.180	110	Low
Azerbaijan	0.377	10	Highest	0.240	75	Medium
Bangladesh	0.288	51	High	0.396	11	Highest
Barbados	0.116	118	Low	0.162	118	Low
Belarus	0.367	12	Highest	0.186	107	Low
Belgium	0.011	163	Lowest	0.030	168	Lowest
Benin	0.102	124	Low	0.231	85	Medium
Bhutan	0.249	67	High	0.127	132	Low
Bolivia	0.149	107	Low	0.315	36	High
Bosnia & Herz.	0.206	87	Medium	0.344	21	Highest
Botswana	0.159	105	Low	0.210	96	Medium
Brazil	0.163	103	Low	0.317	35	High
Bulgaria	0.113	119	Low	0.186	107	Low
Burkina Faso	0.201	88	Medium	0.395	12	Highest
Burundi	0.463	2	Highest	0.227	88	Medium

[31] Sometimes there are ties, when two or more countries have near-identical risk estimates. In those cases, all countries will get the highest rank possible from the group, and the next rank will resume at the number we get when accounting for the number of tied countries. E.g. if we have five countries with Prob = 0.5 and 1 country with Prob = 0.4, the first five countries will have rank = 1, and the last country will have rank = 6.

Table 12: Associational Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
C.A.R.	0.310	35	High	0.279	47	High
Cambodia	0.284	56	High	0.245	72	Medium
Cameroon	0.308	37	High	0.321	33	Highest
Canada	0.017	157	Lowest	0.068	154	Lowest
Cape Verde	0.059	139	Lowest	0.084	148	Lowest
Chad	0.233	76	Medium	0.236	79	Medium
Chile	0.077	132	Low	0.238	78	Medium
China	0.187	97	Medium	0.252	69	Medium
Colombia	0.305	39	High	0.469	2	Highest
Comoros	0.277	58	High	0.288	44	High
Costa Rica	0.035	147	Lowest	0.146	124	Low
Croatia	0.169	101	Medium	0.242	74	Medium
Cuba	0.354	14	Highest	0.105	138	Lowest
Cyprus	0.077	132	Low	0.108	137	Lowest
Czech Republic	0.057	142	Lowest	0.140	129	Low
D.R.C.	0.285	55	High	0.269	58	High
Denmark	0.007	166	Lowest	0.039	165	Lowest
Djibouti	0.301	42	High	0.198	100	Medium
Dominican Rep.	0.160	104	Low	0.168	117	Low
Ecuador	0.201	88	Medium	0.276	50	High
Egypt	0.305	39	High	0.142	128	Low
El Salvador	0.155	106	Low	0.286	46	High
Equatorial Guinea	0.245	69	Medium	0.091	143	Lowest
Eritrea	0.279	57	High	0.041	164	Lowest
Estonia	0.013	162	Lowest	0.052	161	Lowest
Ethiopia	0.448	3	Highest	0.236	79	Medium
Fiji	0.309	36	High	0.333	25	Highest
Finland	0.020	156	Lowest	0.145	126	Low
France	0.059	139	Lowest	0.221	95	Medium
Gabon	0.195	94	Medium	0.341	23	Highest
Georgia	0.175	100	Medium	0.233	82	Medium
Germany	0.015	160	Lowest	0.066	155	Lowest
Ghana	0.053	143	Lowest	0.171	115	Low
Greece	0.086	131	Low	0.202	99	Medium
Guatemala	0.184	98	Medium	0.390	14	Highest
Guinea	0.290	48	High	0.319	34	High
Guinea-Bissau	0.286	54	High	0.225	91	Medium
Guyana	0.145	109	Low	0.248	71	Medium
Haiti	0.333	21	Highest	0.402	10	Highest
Honduras	0.217	84	Medium	0.257	67	High
Hungary	0.235	74	Medium	0.404	8	Highest
Iceland	0.008	165	Lowest	0.036	166	Lowest
India	0.241	72	Medium	0.408	6	Highest
Indonesia	0.180	99	Medium	0.392	13	Highest
Iran	0.289	49	High	0.277	49	High

Table 12: Associational Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Iraq	0.358	13	Highest	0.340	24	Highest
Ireland	0.043	144	Lowest	0.097	142	Lowest
Israel	0.241	72	Medium	0.198	100	Medium
Italy	0.103	123	Low	0.188	104	Low
Ivory Coast	0.247	68	Medium	0.270	56	High
Jamaica	0.031	150	Lowest	0.120	135	Low
Japan	0.029	151	Lowest	0.086	147	Lowest
Jordan	0.221	82	Medium	0.126	133	Low
Kazakhstan	0.317	32	Highest	0.307	39	High
Kenya	0.326	29	Highest	0.403	9	Highest
Kosovo	0.260	64	High	0.263	61	High
Kuwait	0.328	25	Highest	0.177	113	Low
Kyrgyzstan	0.267	63	High	0.313	37	High
Laos	0.235	74	Medium	0.053	160	Lowest
Latvia	0.032	149	Lowest	0.064	156	Lowest
Lebanon	0.201	88	Medium	0.301	41	High
Lesotho	0.198	92	Medium	0.256	68	Medium
Liberia	0.124	115	Low	0.326	29	Highest
Libya	0.289	49	High	0.349	19	Highest
Lithuania	0.101	125	Low	0.131	131	Low
Luxembourg	0.003	168	Lowest	0.017	169	Lowest
Macedonia	0.254	66	High	0.240	75	Medium
Madagascar	0.212	85	Medium	0.210	96	Medium
Malawi	0.136	112	Low	0.223	92	Medium
Malaysia	0.473	1	Highest	0.226	90	Medium
Maldives	0.406	7	Highest	0.258	65	High
Mali	0.268	62	High	0.387	15	Highest
Mauritania	0.339	17	Highest	0.331	26	Highest
Mauritius	0.145	109	Low	0.179	112	Low
Mexico	0.232	78	Medium	0.233	82	Medium
Moldova	0.233	76	Medium	0.243	73	Medium
Mongolia	0.076	135	Lowest	0.186	107	Low
Montenegro	0.293	47	High	0.306	40	High
Morocco	0.269	61	High	0.222	93	Medium
Mozambique	0.296	45	High	0.270	56	High
Myanmar	0.343	16	Highest	0.263	61	High
Namibia	0.120	117	Low	0.251	70	Medium
Nepal	0.230	79	Medium	0.434	3	Highest
Netherlands	0.014	161	Lowest	0.121	134	Low
New Zealand	0.022	154	Lowest	0.077	151	Lowest
Nicaragua	0.320	30	Highest	0.473	1	Highest
Niger	0.191	95	Medium	0.273	52	High
Nigeria	0.138	111	Low	0.206	98	Medium
North Korea	0.129	114	Low	0.043	163	Lowest
Norway	0.006	167	Lowest	0.063	157	Lowest

Table 12: Associational Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Oman	0.208	86	Medium	0.077	151	Lowest
Pakistan	0.328	25	Highest	0.407	7	Highest
Panama	0.098	127	Low	0.230	86	Medium
Papua New Guinea	0.133	113	Low	0.149	121	Low
Paraguay	0.122	116	Low	0.187	105	Low
Peru	0.106	122	Low	0.267	60	High
Philippines	0.220	83	Medium	0.426	4	Highest
Poland	0.244	71	Medium	0.309	38	High
Portugal	0.027	152	Lowest	0.112	136	Lowest
Qatar	0.245	69	Medium	0.088	146	Lowest
Rep. of Congo	0.302	41	High	0.288	44	High
Romania	0.225	80	Medium	0.374	17	Highest
Russia	0.327	27	Highest	0.299	42	High
Rwanda	0.334	19	Highest	0.228	87	Medium
Saudi Arabia	0.113	119	Low	0.056	159	Lowest
Senegal	0.088	130	Low	0.196	102	Low
Serbia	0.295	46	High	0.322	32	Highest
Sierra Leone	0.168	102	Low	0.260	63	High
Singapore	0.189	96	Medium	0.146	124	Low
Slovakia	0.112	121	Low	0.150	120	Low
Slovenia	0.039	146	Lowest	0.081	150	Lowest
Solomon Islands	0.064	137	Lowest	0.091	143	Lowest
Somalia	0.331	23	Highest	0.409	5	Highest
South Africa	0.076	135	Low	0.269	58	High
South Korea	0.058	141	Lowest	0.104	139	Lowest
South Sudan	0.287	53	High	0.273	52	High
Spain	0.010	164	Lowest	0.180	110	Low
Sri Lanka	0.196	93	Medium	0.292	43	High
Sudan	0.299	43	High	0.272	54	High
Suriname	0.064	137	Lowest	0.137	130	Low
Swaziland	0.352	15	Highest	0.235	81	Medium
Sweden	0.016	159	Lowest	0.147	123	Low
Switzerland	0.001	169	Lowest	0.046	162	Lowest
Syria	0.332	22	Highest	0.100	141	Lowest
Taiwan	0.042	145	Lowest	0.059	158	Lowest
Tajikistan	0.313	33	Highest	0.227	88	Medium
Tanzania	0.299	43	High	0.342	22	Highest
Thailand	0.430	4	Highest	0.324	31	Highest
The Gambia	0.201	88	Medium	0.149	121	Low
Timor-Leste	0.149	107	Low	0.170	116	Low
Togo	0.334	19	Highest	0.326	29	Highest
Trinidad and Tobago	0.033	148	Lowest	0.077	151	Lowest
Tunisia	0.095	128	Low	0.145	126	Low
Turkey	0.407	6	Highest	0.271	55	High
Turkmenistan	0.274	60	High	0.089	145	Lowest

Table 12: Associational Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
U.A.E.	0.306	38	High	0.161	119	Low
Uganda	0.327	27	Highest	0.382	16	Highest
Ukraine	0.288	51	High	0.279	47	High
United Kingdom	0.022	154	Lowest	0.082	149	Lowest
Uruguay	0.026	153	Lowest	0.102	140	Lowest
Uzbekistan	0.384	9	Highest	0.175	114	Low
Venezuela	0.329	24	Highest	0.330	27	Highest
Vietnam	0.275	59	High	0.259	64	High
Yemen	0.320	30	Highest	0.187	105	Low
Zambia	0.312	34	High	0.328	28	Highest
Zimbabwe	0.414	5	Highest	0.367	18	Highest

B.2 Economic

Table 13: Economic Space: 2019-2020 forecasts for all countries

	Opening			Closing		
Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Afghanistan	0.353	14	Highest	0.234	94	Medium
Albania	0.354	12	Highest	0.341	17	Highest
Algeria	0.169	128	Low	0.194	116	Low
Angola	0.288	55	High	0.153	134	Low
Argentina	0.278	64	High	0.296	44	High
Armenia	0.400	1	Highest	0.329	22	Highest
Australia	0.049	159	Lowest	0.041	161	Lowest
Austria	0.149	137	Lowest	0.160	130	Low
Azerbaijan	0.243	90	Medium	0.164	128	Low
Bangladesh	0.287	57	High	0.232	96	Medium
Barbados	0.191	120	Low	0.227	99	Medium
Belarus	0.212	111	Low	0.196	115	Low
Belgium	0.016	167	Lowest	0.024	168	Lowest
Benin	0.353	14	Highest	0.336	18	Highest
Bhutan	0.141	140	Lowest	0.154	133	Low
Bolivia	0.238	97	Medium	0.168	126	Low
Bosnia & Herz.	0.289	54	High	0.320	30	Highest
Botswana	0.241	94	Medium	0.230	97	Medium
Brazil	0.318	33	High	0.387	6	Highest
Bulgaria	0.288	55	High	0.299	43	High
Burkina Faso	0.370	8	Highest	0.397	3	Highest
Burundi	0.216	110	Low	0.208	109	Low
C.A.R.	0.233	99	Medium	0.258	74	Medium
Cambodia	0.200	116	Low	0.229	98	Medium
Cameroon	0.244	88	Medium	0.099	148	Lowest
Canada	0.027	165	Lowest	0.036	164	Lowest
Cape Verde	0.169	128	Low	0.258	74	Medium
Chad	0.165	133	Low	0.051	158	Lowest
Chile	0.211	113	Low	0.261	70	Medium
China	0.382	4	Highest	0.277	59	High
Colombia	0.374	6	Highest	0.449	2	Highest
Comoros	0.272	65	High	0.252	77	Medium
Costa Rica	0.223	103	Low	0.203	112	Low
Croatia	0.265	70	Medium	0.324	26	Highest
Cuba	0.212	111	Low	0.267	64	High
Cyprus	0.222	104	Low	0.203	112	Low
Czech Republic	0.228	102	Low	0.226	101	Medium
D.R.C.	0.169	128	Low	0.061	155	Lowest
Denmark	0.031	163	Lowest	0.029	166	Lowest
Djibouti	0.170	127	Low	0.156	132	Low
Dominican Rep.	0.297	47	High	0.188	120	Low
Ecuador	0.317	36	High	0.320	30	Highest
Egypt	0.189	121	Low	0.140	140	Lowest

Table 13: Economic Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
El Salvador	0.319	31	Highest	0.330	21	Highest
Equatorial Guinea	0.110	147	Lowest	0.138	141	Lowest
Eritrea	0.110	147	Lowest	0.366	8	Highest
Estonia	0.076	154	Lowest	0.088	150	Lowest
Ethiopia	0.338	22	Highest	0.301	42	High
Fiji	0.262	72	Medium	0.289	51	High
Finland	0.059	156	Lowest	0.057	157	Lowest
France	0.117	144	Lowest	0.151	135	Low
Gabon	0.354	12	Highest	0.362	9	Highest
Georgia	0.266	67	Medium	0.346	14	Highest
Germany	0.024	166	Lowest	0.037	163	Lowest
Ghana	0.210	114	Low	0.235	93	Medium
Greece	0.283	59	High	0.313	36	High
Guatemala	0.385	3	Highest	0.282	57	High
Guinea	0.221	106	Low	0.249	81	Medium
Guinea-Bissau	0.220	108	Low	0.128	145	Lowest
Guyana	0.262	72	Medium	0.259	73	Medium
Haiti	0.346	18	Highest	0.261	70	Medium
Honduras	0.296	49	High	0.192	117	Low
Hungary	0.331	26	Highest	0.368	7	Highest
Iceland	0.036	162	Lowest	0.043	159	Lowest
India	0.262	72	Medium	0.312	39	High
Indonesia	0.315	39	High	0.296	44	High
Iran	0.358	11	Highest	0.322	28	Highest
Iraq	0.298	46	High	0.269	63	High
Ireland	0.063	155	Lowest	0.131	143	Lowest
Israel	0.263	71	Medium	0.248	82	Medium
Italy	0.241	94	Medium	0.293	48	High
Ivory Coast	0.313	40	High	0.288	53	High
Jamaica	0.195	117	Low	0.267	64	High
Japan	0.078	153	Lowest	0.061	155	Lowest
Jordan	0.244	88	Medium	0.182	123	Low
Kazakhstan	0.316	37	High	0.272	60	High
Kenya	0.329	27	Highest	0.309	41	High
Kosovo	0.279	63	High	0.284	55	High
Kuwait	0.177	125	Low	0.247	83	Medium
Kyrgyzstan	0.291	52	High	0.207	111	Low
Laos	0.088	152	Lowest	0.161	129	Low
Latvia	0.144	139	Lowest	0.176	124	Low
Lebanon	0.206	115	Low	0.219	103	Low
Lesotho	0.318	33	High	0.318	32	Highest
Liberia	0.318	33	Highest	0.313	36	High
Libya	0.312	41	High	0.233	95	Medium
Lithuania	0.173	126	Low	0.295	46	High
Luxembourg	0.014	168	Lowest	0.032	165	Lowest

Table 13: Economic Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Macedonia	0.243	90	Medium	0.244	84	Medium
Madagascar	0.282	60	High	0.236	92	Medium
Malawi	0.352	16	Highest	0.356	12	Highest
Malaysia	0.325	30	Highest	0.239	89	Medium
Maldives	0.309	43	High	0.333	19	Highest
Mali	0.348	17	Highest	0.271	61	High
Mauritania	0.328	28	Highest	0.240	86	Medium
Mauritius	0.261	77	Medium	0.279	58	High
Mexico	0.369	9	Highest	0.346	14	Highest
Moldova	0.309	43	High	0.289	51	High
Mongolia	0.231	100	Medium	0.239	89	Medium
Montenegro	0.301	45	High	0.310	40	High
Morocco	0.292	50	High	0.292	50	High
Mozambique	0.312	41	High	0.192	117	Low
Myanmar	0.336	23	Highest	0.252	77	Medium
Namibia	0.231	100	Medium	0.293	48	High
Nepal	0.319	31	Highest	0.284	55	High
Netherlands	0.056	157	Lowest	0.062	154	Lowest
New Zealand	0.090	149	Lowest	0.069	153	Lowest
Nicaragua	0.245	86	Medium	0.333	19	Highest
Niger	0.297	47	High	0.294	47	High
Nigeria	0.326	29	Highest	0.211	107	Low
North Korea	0.159	134	Low	0.165	127	Low
Norway	0.031	163	Lowest	0.041	161	Lowest
Oman	0.270	66	High	0.110	147	Lowest
Pakistan	0.394	2	Highest	0.392	4	Highest
Panama	0.220	108	Low	0.213	106	Low
Papua New Guinea	0.150	135	Lowest	0.219	103	Low
Paraguay	0.248	83	Medium	0.169	125	Low
Peru	0.266	67	Medium	0.286	54	High
Philippines	0.280	62	High	0.326	24	Highest
Poland	0.266	67	High	0.314	35	High
Portugal	0.246	85	Medium	0.186	121	Low
Qatar	0.193	119	Low	0.321	29	Highest
Rep. of Congo	0.238	97	Medium	0.264	67	Medium
Romania	0.368	10	Highest	0.360	10	Highest
Russia	0.254	78	Medium	0.220	102	Low
Rwanda	0.254	78	Medium	0.241	85	Medium
Saudi Arabia	0.089	150	Lowest	0.143	139	Lowest
Senegal	0.243	90	Medium	0.358	11	Highest
Serbia	0.339	21	Highest	0.266	66	High
Sierra Leone	0.292	50	High	0.353	13	Highest
Singapore	0.117	144	Lowest	0.149	136	Lowest
Slovakia	0.188	122	Low	0.237	91	Medium
Slovenia	0.120	143	Lowest	0.136	142	Lowest

Table 13: Economic Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Solomon Islands	0.133	141	Lowest	0.183	122	Low
Somalia	0.342	19	Highest	0.240	86	Medium
South Africa	0.248	83	Medium	0.324	26	Highest
South Korea	0.149	137	Lowest	0.130	144	Lowest
South Sudan	0.150	135	Low	0.192	117	Low
Spain	0.054	158	Lowest	0.028	167	Lowest
Sri Lanka	0.250	80	Medium	0.344	16	Highest
Sudan	0.291	52	High	0.252	77	Medium
Suriname	0.242	93	Medium	0.210	108	Low
Swaziland	0.286	58	High	0.327	23	Highest
Sweden	0.043	161	Lowest	0.076	152	Lowest
Switzerland	0.009	169	Lowest	0.013	169	Lowest
Syria	0.181	123	Low	0.147	138	Lowest
Taiwan	0.167	132	Low	0.227	99	Medium
Tajikistan	0.281	61	High	0.160	130	Low
Tanzania	0.342	19	Highest	0.318	32	Highest
Thailand	0.262	72	Medium	0.313	36	High
The Gambia	0.222	104	Low	0.240	86	Medium
Timor-Leste	0.181	123	Low	0.208	109	Low
Togo	0.262	72	Medium	0.262	69	Medium
Trinidad and Tobago	0.130	142	Lowest	0.113	146	Lowest
Tunisia	0.250	80	Medium	0.391	5	Highest
Turkey	0.335	25	Highest	0.326	24	Highest
Turkmenistan	0.221	106	Low	0.149	136	Lowest
U.A.E.	0.111	146	Lowest	0.093	149	Lowest
Uganda	0.372	7	Highest	0.270	62	High
Ukraine	0.377	5	Highest	0.264	67	High
United Kingdom	0.048	160	Lowest	0.043	159	Lowest
Uruguay	0.089	150	Lowest	0.088	150	Lowest
Uzbekistan	0.245	86	Medium	0.219	103	Low
Venezuela	0.250	80	Medium	0.198	114	Low
Vietnam	0.240	96	Medium	0.252	77	Medium
Yemen	0.168	131	Low	0.256	76	Medium
Zambia	0.316	37	High	0.317	34	High
Zimbabwe	0.336	23	Highest	0.261	70	Medium

B.3 Electoral

Table 14: Electoral Space: 2019-2020 forecasts for all countries

	Opening			Closing		
Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Afghanistan	0.199	15	Highest	0.200	10	Highest
Albania	0.059	74	Medium	0.058	65	High
Algeria	0.093	56	High	0.034	98	Medium
Angola	0.170	23	Highest	0.048	77	Medium
Argentina	0.007	122	Low	0.001	160	Lowest
Armenia	0.177	22	Highest	0.044	80	Medium
Australia	0.000	154	Lowest	0.001	160	Lowest
Austria	0.003	131	Lowest	0.021	111	Low
Azerbaijan	0.153	30	Highest	0.194	12	Highest
Bangladesh	0.200	14	Highest	0.149	21	Highest
Barbados	0.006	125	Low	0.019	115	Low
Belarus	0.100	50	High	0.028	103	Low
Belgium	0.003	131	Lowest	0.003	151	Lowest
Benin	0.054	77	Medium	0.081	47	High
Bhutan	0.024	102	Low	0.057	66	High
Bolivia	0.011	115	Low	0.041	83	Medium
Bosnia & Herz.	0.036	90	Medium	0.091	45	High
Botswana	0.002	138	Lowest	0.014	125	Low
Brazil	0.017	111	Low	0.039	90	Medium
Bulgaria	0.001	146	Lowest	0.012	132	Low
Burkina Faso	0.030	95	Medium	0.101	37	High
Burundi	0.336	3	Highest	0.348	5	Highest
C.A.R.	0.096	55	High	0.106	36	High
Cambodia	0.139	34	High	0.068	60	High
Cameroon	0.098	54	High	0.206	9	Highest
Canada	0.000	154	Lowest	0.001	160	Lowest
Cape Verde	0.002	138	Lowest	0.011	133	Low
Chad	0.128	42	High	0.154	19	Highest
Chile	0.099	52	High	0.041	83	Medium
China	0.066	68	Medium	0.023	108	Low
Colombia	0.022	106	Low	0.136	26	Highest
Comoros	0.179	21	Highest	0.280	6	Highest
Costa Rica	0.008	119	Low	0.053	73	Medium
Croatia	0.004	126	Low	0.054	70	Medium
Cuba	0.231	11	Highest	0.022	110	Low
Cyprus	0.001	146	Lowest	0.008	138	Lowest
Czech Republic	0.000	154	Lowest	0.001	160	Lowest
D.R.C.	0.083	59	High	0.077	52	High
Denmark	0.001	146	Lowest	0.004	150	Lowest
Djibouti	0.130	41	High	0.040	86	Medium
Dominican Rep.	0.049	80	Medium	0.019	115	Low
Ecuador	0.031	94	Medium	0.036	95	Medium
Egypt	0.163	26	Highest	0.036	95	Medium

Table 14: Electoral Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
El Salvador	0.017	111	Low	0.077	52	High
Equatorial Guinea	0.043	85	Medium	0.040	86	Medium
Eritrea	0.186	19	Highest	0.026	106	Low
Estonia	0.003	131	Low	0.009	136	Lowest
Ethiopia	0.388	2	Highest	0.107	35	High
Fiji	0.062	73	Medium	0.100	41	High
Finland	0.008	119	Low	0.010	134	Low
France	0.004	126	Low	0.040	86	Medium
Gabon	0.124	43	High	0.101	37	High
Georgia	0.024	102	Low	0.006	147	Lowest
Germany	0.000	154	Lowest	0.002	155	Lowest
Ghana	0.000	154	Lowest	0.021	111	Low
Greece	0.032	92	Medium	0.014	125	Low
Guatemala	0.032	92	Medium	0.100	41	High
Guinea	0.110	47	High	0.173	16	Highest
Guinea-Bissau	0.044	83	Medium	0.108	34	High
Guyana	0.030	95	Medium	0.020	113	Low
Haiti	0.230	12	Highest	0.361	3	Highest
Honduras	0.114	45	High	0.036	95	Medium
Hungary	0.066	68	Medium	0.068	60	High
Iceland	0.000	154	Lowest	0.002	155	Lowest
India	0.063	71	Medium	0.080	49	High
Indonesia	0.009	118	Low	0.056	67	Medium
Iran	0.078	60	High	0.134	27	Highest
Iraq	0.069	65	High	0.070	58	High
Ireland	0.007	122	Low	0.003	151	Lowest
Israel	0.008	119	Low	0.027	105	Low
Italy	0.000	154	Lowest	0.014	125	Low
Ivory Coast	0.063	71	Medium	0.101	37	High
Jamaica	0.001	146	Lowest	0.000	169	Lowest
Japan	0.004	126	Low	0.013	131	Low
Jordan	0.023	105	Low	0.031	100	Medium
Kazakhstan	0.164	25	Highest	0.210	8	Highest
Kenya	0.108	48	High	0.118	31	Highest
Kosovo	0.034	91	Medium	0.046	79	Medium
Kuwait	0.037	89	Medium	0.073	56	High
Kyrgyzstan	0.058	75	Medium	0.039	90	Medium
Laos	0.077	61	High	0.020	113	Low
Latvia	0.000	154	Lowest	0.008	138	Lowest
Lebanon	0.024	102	Low	0.038	94	Medium
Lesotho	0.028	99	Medium	0.076	54	High
Liberia	0.046	82	Medium	0.054	70	Medium
Libya	0.267	7	Highest	0.138	25	Highest
Lithuania	0.001	146	Lowest	0.002	155	Lowest
Luxembourg	0.000	154	Lowest	0.007	144	Lowest

Table 14: Electoral Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Macedonia	0.013	114	Low	0.014	125	Low
Madagascar	0.067	67	High	0.061	63	High
Malawi	0.030	95	Medium	0.029	102	Low
Malaysia	0.199	15	Highest	0.076	54	High
Maldives	0.137	36	High	0.093	44	High
Mali	0.163	26	Highest	0.079	50	High
Mauritania	0.113	46	High	0.099	43	High
Mauritius	0.011	115	Low	0.007	144	Lowest
Mexico	0.027	100	Medium	0.040	86	Medium
Moldova	0.030	95	Medium	0.030	101	Medium
Mongolia	0.003	131	Low	0.002	155	Lowest
Montenegro	0.131	40	High	0.056	67	Medium
Morocco	0.042	86	Medium	0.052	75	Medium
Mozambique	0.054	77	Medium	0.044	80	Medium
Myanmar	0.048	81	Medium	0.078	51	High
Namibia	0.002	138	Lowest	0.018	119	Low
Nepal	0.068	66	High	0.070	58	High
Netherlands	0.007	122	Low	0.008	138	Lowest
New Zealand	0.002	138	Lowest	0.002	155	Lowest
Nicaragua	0.240	9	Highest	0.497	1	Highest
Niger	0.074	63	High	0.081	47	High
Nigeria	0.020	107	Low	0.063	62	High
North Korea	0.139	34	High	0.024	107	Low
Norway	0.000	154	Lowest	0.010	134	Low
Oman	0.064	70	Medium	0.017	120	Low
Pakistan	0.158	28	Highest	0.168	17	Highest
Panama	0.002	138	Lowest	0.008	138	Lowest
Papua New Guinea	0.119	44	High	0.042	82	Medium
Paraguay	0.002	138	Lowest	0.016	121	Low
Peru	0.001	146	Lowest	0.008	138	Lowest
Philippines	0.041	88	Medium	0.119	30	Highest
Poland	0.010	117	Low	0.101	37	High
Portugal	0.000	154	Lowest	0.001	160	Lowest
Qatar	0.100	50	High	0.039	90	Medium
Rep. of Congo	0.149	32	Highest	0.130	28	Highest
Romania	0.057	76	Medium	0.054	70	Medium
Russia	0.084	58	High	0.016	121	Low
Rwanda	0.132	39	High	0.056	67	High
Saudi Arabia	0.044	83	Medium	0.007	144	Lowest
Senegal	0.014	113	Low	0.014	125	Low
Serbia	0.070	64	High	0.084	46	High
Sierra Leone	0.027	100	Medium	0.028	103	Low
Singapore	0.133	38	High	0.235	7	Highest
Slovakia	0.002	138	Lowest	0.039	90	Medium
Slovenia	0.000	154	Lowest	0.003	151	Lowest

Table 14: Electoral Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Solomon Islands	0.018	110	Low	0.006	147	Lowest
Somalia	0.438	1	Highest	0.414	2	Highest
South Africa	0.003	131	Low	0.019	115	Low
South Korea	0.004	126	Low	0.009	136	Lowest
South Sudan	0.292	5	Highest	0.167	18	Highest
Spain	0.003	131	Low	0.001	160	Lowest
Sri Lanka	0.053	79	Medium	0.023	108	Low
Sudan	0.152	31	Highest	0.181	13	Highest
Suriname	0.020	107	Low	0.041	83	Medium
Swaziland	0.196	17	Highest	0.179	14	Highest
Sweden	0.002	138	Lowest	0.014	125	Low
Switzerland	0.000	154	Lowest	0.001	160	Lowest
Syria	0.289	6	Highest	0.179	14	Highest
Taiwan	0.000	154	Lowest	0.003	151	Lowest
Tajikistan	0.146	33	Highest	0.120	29	Highest
Tanzania	0.019	109	Low	0.048	77	Medium
Thailand	0.237	10	Highest	0.146	22	Highest
The Gambia	0.136	37	High	0.008	138	Lowest
Timor-Leste	0.004	126	Low	0.016	121	Low
Togo	0.099	52	High	0.199	11	Highest
Trinidad and Tobago	0.000	154	Lowest	0.016	121	Low
Tunisia	0.003	131	Low	0.019	115	Low
Turkey	0.219	13	Highest	0.061	63	High
Turkmenistan	0.186	19	Highest	0.033	99	Medium
U.A.E.	0.042	86	Medium	0.053	73	Medium
Uganda	0.104	49	High	0.146	22	Highest
Ukraine	0.076	62	High	0.072	57	High
United Kingdom	0.001	146	Lowest	0.001	160	Lowest
Uruguay	0.000	154	Lowest	0.001	160	Lowest
Uzbekistan	0.170	23	Highest	0.052	75	Medium
Venezuela	0.262	8	Highest	0.357	4	Highest
Vietnam	0.092	57	High	0.116	33	Highest
Yemen	0.334	4	Highest	0.117	32	Highest
Zambia	0.154	29	Highest	0.139	24	Highest
Zimbabwe	0.191	18	Highest	0.154	19	Highest

B.4 Individual

Table 15: Individual Space: 2019-2020 forecasts for all countries

	Opening			Closing		
Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Afghanistan	0.411	10	Highest	0.356	10	Highest
Albania	0.152	107	Low	0.237	61	High
Algeria	0.267	65	High	0.245	53	High
Angola	0.398	12	Highest	0.199	76	Medium
Argentina	0.079	124	Low	0.086	124	Low
Armenia	0.309	43	High	0.199	76	Medium
Australia	0.010	148	Lowest	0.004	168	Lowest
Austria	0.012	146	Lowest	0.094	120	Low
Azerbaijan	0.278	60	High	0.268	45	High
Bangladesh	0.321	34	High	0.398	1	Highest
Barbados	0.038	134	Low	0.070	136	Lowest
Belarus	0.358	21	Highest	0.245	53	High
Belgium	0.003	164	Lowest	0.004	168	Lowest
Benin	0.094	120	Low	0.177	87	Medium
Bhutan	0.159	106	Low	0.067	139	Lowest
Bolivia	0.137	111	Low	0.160	98	Medium
Bosnia & Herz.	0.262	66	High	0.316	24	Highest
Botswana	0.116	113	Low	0.114	115	Low
Brazil	0.195	95	Medium	0.243	57	High
Bulgaria	0.088	121	Low	0.141	106	Low
Burkina Faso	0.205	91	Medium	0.351	14	Highest
Burundi	0.401	11	Highest	0.240	60	High
C.A.R.	0.386	17	Highest	0.216	71	Medium
Cambodia	0.320	35	High	0.224	66	Medium
Cameroon	0.305	44	High	0.296	32	Highest
Canada	0.009	151	Lowest	0.032	149	Lowest
Cape Verde	0.032	137	Lowest	0.049	141	Lowest
Chad	0.195	95	Medium	0.189	82	Medium
Chile	0.055	131	Low	0.146	105	Low
China	0.214	87	Medium	0.229	64	High
Colombia	0.282	56	High	0.389	4	Highest
Comoros	0.292	53	High	0.331	19	Highest
Costa Rica	0.029	138	Lowest	0.064	140	Lowest
Croatia	0.124	112	Low	0.139	108	Low
Cuba	0.387	16	Highest	0.185	84	Medium
Cyprus	0.036	135	Lowest	0.042	143	Lowest
Czech Republic	0.009	151	Lowest	0.072	134	Low
D.R.C.	0.271	64	High	0.269	44	High
Denmark	0.004	161	Lowest	0.009	165	Lowest
Djibouti	0.291	54	High	0.169	89	Medium
Dominican Rep.	0.289	55	High	0.301	31	Highest
Ecuador	0.238	80	Medium	0.165	93	Medium
Egypt	0.381	18	Highest	0.209	72	Medium

Table 15: Individual Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
El Salvador	0.275	62	High	0.310	29	Highest
Equatorial Guinea	0.233	82	Medium	0.082	129	Low
Eritrea	0.241	77	Medium	0.082	129	Low
Estonia	0.003	164	Lowest	0.012	161	Lowest
Ethiopia	0.516	1	Highest	0.309	30	Highest
Fiji	0.258	68	Medium	0.243	57	High
Finland	0.007	157	Lowest	0.036	146	Lowest
France	0.021	142	Lowest	0.073	133	Low
Gabon	0.232	83	Medium	0.284	37	High
Georgia	0.078	125	Low	0.125	111	Low
Germany	0.007	157	Lowest	0.016	159	Lowest
Ghana	0.059	128	Low	0.140	107	Low
Greece	0.058	129	Low	0.126	110	Low
Guatemala	0.296	50	High	0.311	28	Highest
Guinea	0.246	75	Medium	0.333	18	Highest
Guinea-Bissau	0.303	45	High	0.244	55	High
Guyana	0.177	101	Medium	0.229	64	High
Haiti	0.393	13	Highest	0.394	2	Highest
Honduras	0.296	50	High	0.235	62	High
Hungary	0.178	100	Medium	0.313	27	Highest
Iceland	0.002	166	Lowest	0.007	166	Lowest
India	0.325	32	Highest	0.323	22	Highest
Indonesia	0.192	97	Medium	0.243	57	High
Iran	0.343	25	Highest	0.353	12	Highest
Iraq	0.388	15	Highest	0.257	51	High
Ireland	0.013	143	Lowest	0.029	151	Lowest
Israel	0.103	117	Low	0.098	119	Low
Italy	0.027	140	Lowest	0.070	136	Lowest
Ivory Coast	0.257	69	Medium	0.222	69	Medium
Jamaica	0.027	140	Lowest	0.070	136	Lowest
Japan	0.010	148	Lowest	0.029	151	Lowest
Jordan	0.254	74	Medium	0.123	112	Low
Kazakhstan	0.311	42	High	0.329	20	Highest
Kenya	0.293	52	High	0.372	7	Highest
Kosovo	0.282	56	High	0.222	69	Medium
Kuwait	0.169	102	Low	0.162	96	Medium
Kyrgyzstan	0.281	59	High	0.179	86	Medium
Laos	0.228	84	Medium	0.072	134	Low
Latvia	0.007	157	Lowest	0.013	160	Lowest
Lebanon	0.317	38	High	0.285	36	High
Lesotho	0.257	69	Medium	0.268	45	High
Liberia	0.236	81	Medium	0.280	39	High
Libya	0.366	20	Highest	0.352	13	Highest
Lithuania	0.029	138	Lowest	0.046	142	Lowest
Luxembourg	0.001	168	Lowest	0.006	167	Lowest

Table 15: Individual Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Macedonia	0.255	72	Medium	0.192	79	Medium
Madagascar	0.332	29	Highest	0.231	63	High
Malawi	0.192	97	Medium	0.190	81	Medium
Malaysia	0.439	3	Highest	0.186	83	Medium
Maldives	0.391	14	Highest	0.315	25	Highest
Mali	0.314	40	High	0.324	21	Highest
Mauritania	0.419	6	Highest	0.263	49	High
Mauritius	0.084	122	Low	0.078	131	Low
Mexico	0.261	67	High	0.166	92	Medium
Moldova	0.163	104	Low	0.169	89	Medium
Mongolia	0.075	126	Low	0.100	118	Low
Montenegro	0.277	61	High	0.259	50	High
Morocco	0.224	85	Medium	0.153	101	Medium
Mozambique	0.208	90	Medium	0.277	41	High
Myanmar	0.375	19	Highest	0.224	66	High
Namibia	0.112	114	Low	0.176	88	Medium
Nepal	0.211	88	Medium	0.345	15	Highest
Netherlands	0.010	148	Lowest	0.012	161	Lowest
New Zealand	0.009	151	Lowest	0.023	156	Lowest
Nicaragua	0.347	24	Highest	0.377	5	Highest
Niger	0.100	119	Low	0.192	79	Medium
Nigeria	0.201	94	Medium	0.169	89	Medium
North Korea	0.142	108	Low	0.033	148	Lowest
Norway	0.002	166	Lowest	0.011	163	Lowest
Oman	0.328	30	Highest	0.083	127	Low
Pakistan	0.438	4	Highest	0.321	23	Highest
Panama	0.112	114	Low	0.164	94	Medium
Papua New Guinea	0.211	88	Medium	0.154	100	Medium
Paraguay	0.162	105	Low	0.149	103	Low
Peru	0.111	116	Low	0.148	104	Low
Philippines	0.273	63	High	0.357	9	Highest
Poland	0.139	109	Low	0.183	85	Medium
Portugal	0.004	161	Lowest	0.029	151	Lowest
Qatar	0.255	72	Medium	0.197	78	Medium
Rep. of Congo	0.326	31	Highest	0.272	42	High
Romania	0.242	76	Medium	0.314	26	Highest
Russia	0.302	46	High	0.343	16	Highest
Rwanda	0.320	35	High	0.244	55	High
Saudi Arabia	0.138	110	Low	0.102	116	Low
Senegal	0.056	130	Low	0.151	102	Low
Serbia	0.299	48	High	0.282	38	High
Sierra Leone	0.241	77	Medium	0.162	96	Medium
Singapore	0.166	103	Low	0.118	114	Low
Slovakia	0.044	133	Low	0.077	132	Low
Slovenia	0.009	151	Lowest	0.022	157	Lowest

Table 15: Individual Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Solomon Islands	0.083	123	Low	0.085	125	Low
Somalia	0.416	9	Highest	0.377	5	Highest
South Africa	0.101	118	Low	0.255	52	High
South Korea	0.012	146	Lowest	0.032	149	Lowest
South Sudan	0.239	79	Medium	0.200	75	Medium
Spain	0.007	157	Lowest	0.018	158	Lowest
Sri Lanka	0.224	85	Medium	0.203	74	Medium
Sudan	0.314	40	High	0.280	39	High
Suriname	0.062	127	Low	0.083	127	Low
Swaziland	0.417	7	Highest	0.224	66	High
Sweden	0.008	156	Lowest	0.038	144	Lowest
Switzerland	0.000	169	Lowest	0.010	164	Lowest
Syria	0.298	49	High	0.123	112	Low
Taiwan	0.013	143	Lowest	0.025	155	Lowest
Tajikistan	0.348	23	Highest	0.205	73	Medium
Tanzania	0.257	69	Medium	0.288	34	High
Thailand	0.343	25	Highest	0.268	45	High
The Gambia	0.203	92	Medium	0.101	117	Low
Timor-Leste	0.187	99	Medium	0.155	99	Medium
Togo	0.335	28	Highest	0.335	17	Highest
Trinidad and Tobago	0.013	143	Lowest	0.037	145	Lowest
Tunisia	0.053	132	Low	0.085	125	Low
Turkey	0.438	4	Highest	0.264	48	High
Turkmenistan	0.349	22	Highest	0.092	121	Low
U.A.E.	0.203	92	Medium	0.089	123	Low
Uganda	0.318	37	High	0.391	3	Highest
Ukraine	0.317	38	High	0.290	33	Highest
United Kingdom	0.004	161	Lowest	0.027	154	Lowest
Uruguay	0.009	151	Lowest	0.036	146	Lowest
Uzbekistan	0.417	7	Highest	0.163	95	Medium
Venezuela	0.343	25	Highest	0.356	10	Highest
Vietnam	0.300	47	High	0.288	34	High
Yemen	0.282	56	High	0.137	109	Low
Zambia	0.322	33	Highest	0.270	43	High
Zimbabwe	0.444	2	Highest	0.361	8	Highest

B.5 Informational

Table 16: Informational Space: 2019-2020 forecasts for all countries

	Opening			Closing		
Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Afghanistan	0.397	4	Highest	0.320	13	Highest
Albania	0.174	79	Medium	0.243	35	High
Algeria	0.200	65	High	0.224	47	High
Angola	0.346	15	Highest	0.123	115	Low
Argentina	0.021	143	Lowest	0.124	113	Low
Armenia	0.267	45	High	0.174	78	Medium
Australia	0.006	162	Lowest	0.022	164	Lowest
Austria	0.059	116	Low	0.191	66	Medium
Azerbaijan	0.326	19	Highest	0.236	38	High
Bangladesh	0.278	38	High	0.286	22	Highest
Barbados	0.058	117	Low	0.107	123	Low
Belarus	0.246	51	High	0.172	80	Medium
Belgium	0.002	167	Lowest	0.016	166	Lowest
Benin	0.127	98	Medium	0.223	49	High
Bhutan	0.197	68	Medium	0.232	41	High
Bolivia	0.076	109	Low	0.125	111	Low
Bosnia & Herz.	0.183	74	Medium	0.310	15	Highest
Botswana	0.063	112	Low	0.156	91	Medium
Brazil	0.163	85	Medium	0.299	19	Highest
Bulgaria	0.151	89	Medium	0.266	28	Highest
Burkina Faso	0.101	104	Low	0.274	26	Highest
Burundi	0.493	2	Highest	0.216	54	High
C.A.R.	0.251	49	High	0.178	76	Medium
Cambodia	0.264	46	High	0.191	66	Medium
Cameroon	0.312	22	Highest	0.227	45	High
Canada	0.003	165	Lowest	0.042	154	Lowest
Cape Verde	0.033	132	Low	0.084	133	Low
Chad	0.341	16	Highest	0.159	89	Medium
Chile	0.054	118	Low	0.137	103	Low
China	0.166	84	Medium	0.142	100	Medium
Colombia	0.311	23	Highest	0.406	3	Highest
Comoros	0.262	47	High	0.267	27	Highest
Costa Rica	0.013	153	Lowest	0.110	120	Low
Croatia	0.222	57	High	0.262	29	Highest
Cuba	0.347	14	Highest	0.076	134	Low
Cyprus	0.026	140	Lowest	0.097	129	Low
Czech Republic	0.022	142	Lowest	0.144	98	Medium
D.R.C.	0.285	35	High	0.153	92	Medium
Denmark	0.003	165	Lowest	0.013	167	Lowest
Djibouti	0.304	28	Highest	0.113	119	Low
Dominican Rep.	0.118	101	Medium	0.210	55	High
Ecuador	0.149	90	Medium	0.185	73	Medium
Egypt	0.256	48	High	0.125	111	Low

Table 16: Informational Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
El Salvador	0.130	97	Medium	0.286	22	Highest
Equatorial Guinea	0.204	63	High	0.047	149	Lowest
Eritrea	0.163	85	Medium	0.054	145	Lowest
Estonia	0.020	144	Lowest	0.024	163	Lowest
Ethiopia	0.551	1	Highest	0.185	73	Medium
Fiji	0.244	52	High	0.235	39	High
Finland	0.006	162	Lowest	0.058	143	Lowest
France	0.023	141	Lowest	0.124	113	Low
Gabon	0.188	72	Medium	0.232	41	High
Georgia	0.041	125	Low	0.193	64	High
Germany	0.029	136	Lowest	0.044	152	Lowest
Ghana	0.020	144	Lowest	0.110	120	Low
Greece	0.033	132	Low	0.175	77	Medium
Guatemala	0.197	68	Medium	0.341	6	Highest
Guinea	0.222	57	High	0.240	37	High
Guinea-Bissau	0.243	53	High	0.225	46	High
Guyana	0.106	103	Low	0.191	66	High
Haiti	0.366	11	Highest	0.325	11	Highest
Honduras	0.179	77	Medium	0.187	71	Medium
Hungary	0.220	59	High	0.423	1	Highest
Iceland	0.002	167	Lowest	0.026	162	Lowest
India	0.210	60	High	0.336	9	Highest
Indonesia	0.066	111	Low	0.304	17	Highest
Iran	0.311	23	Highest	0.348	5	Highest
Iraq	0.306	27	Highest	0.141	101	Medium
Ireland	0.007	159	Lowest	0.071	137	Lowest
Israel	0.141	92	Medium	0.201	60	High
Italy	0.030	135	Low	0.129	109	Low
Ivory Coast	0.200	65	High	0.173	79	Medium
Jamaica	0.016	149	Lowest	0.076	134	Low
Japan	0.034	130	Low	0.034	160	Lowest
Jordan	0.204	63	High	0.101	127	Low
Kazakhstan	0.279	37	High	0.233	40	High
Kenya	0.209	61	High	0.299	19	Highest
Kosovo	0.181	76	Medium	0.203	58	High
Kuwait	0.179	77	Medium	0.232	41	High
Kyrgyzstan	0.131	95	Medium	0.165	85	Medium
Laos	0.167	81	Medium	0.047	149	Lowest
Latvia	0.008	157	Lowest	0.038	157	Lowest
Lebanon	0.167	81	Medium	0.167	84	Medium
Lesotho	0.131	95	Medium	0.202	59	High
Liberia	0.120	99	Medium	0.217	52	High
Libya	0.294	32	Highest	0.341	6	Highest
Lithuania	0.048	122	Low	0.107	123	Low
Luxembourg	0.008	157	Lowest	0.012	168	Lowest

Table 16: Informational Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Macedonia	0.172	80	Medium	0.193	64	High
Madagascar	0.149	90	Medium	0.196	62	High
Malawi	0.062	113	Low	0.147	96	Medium
Malaysia	0.470	3	Highest	0.148	95	Medium
Maldives	0.378	9	Highest	0.303	18	Highest
Mali	0.200	65	High	0.277	24	Highest
Mauritania	0.341	16	Highest	0.223	49	High
Mauritius	0.033	132	Low	0.121	116	Low
Mexico	0.157	87	Medium	0.159	89	Medium
Moldova	0.152	88	Medium	0.229	44	High
Mongolia	0.034	130	Low	0.133	104	Low
Montenegro	0.208	62	High	0.206	56	High
Morocco	0.167	81	Medium	0.140	102	Low
Mozambique	0.120	99	Medium	0.168	83	Medium
Myanmar	0.310	25	Highest	0.172	80	Medium
Namibia	0.037	129	Low	0.191	66	High
Nepal	0.047	124	Low	0.258	32	Highest
Netherlands	0.019	146	Lowest	0.020	165	Lowest
New Zealand	0.016	149	Lowest	0.040	155	Lowest
Nicaragua	0.276	40	High	0.338	8	Highest
Niger	0.062	113	Low	0.164	86	Medium
Nigeria	0.040	126	Low	0.133	104	Low
North Korea	0.101	104	Low	0.029	161	Lowest
Norway	0.012	154	Lowest	0.036	158	Lowest
Oman	0.191	70	Medium	0.049	147	Lowest
Pakistan	0.336	18	Highest	0.318	14	Highest
Panama	0.050	120	Low	0.152	93	Medium
Papua New Guinea	0.133	94	Medium	0.110	120	Low
Paraguay	0.090	106	Low	0.144	98	Medium
Peru	0.039	127	Low	0.130	107	Low
Philippines	0.182	75	Medium	0.326	10	Highest
Poland	0.292	34	High	0.262	29	Highest
Portugal	0.014	151	Lowest	0.051	146	Lowest
Qatar	0.184	73	Medium	0.060	142	Lowest
Rep. of Congo	0.310	25	Highest	0.189	70	Medium
Romania	0.268	44	High	0.413	2	Highest
Russia	0.274	41	High	0.162	88	Medium
Rwanda	0.303	29	Highest	0.172	80	Medium
Saudi Arabia	0.076	109	Low	0.043	153	Lowest
Senegal	0.048	122	Low	0.151	94	Medium
Serbia	0.278	38	High	0.325	11	Highest
Sierra Leone	0.089	108	Low	0.130	107	Low
Singapore	0.190	71	Medium	0.121	116	Low
Slovakia	0.029	136	Lowest	0.223	49	High
Slovenia	0.010	155	Lowest	0.071	137	Lowest

Table 16: Informational Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Solomon Islands	0.039	127	Low	0.056	144	Lowest
Somalia	0.361	12	Highest	0.390	4	Highest
South Africa	0.054	118	Low	0.182	75	Medium
South Korea	0.027	139	Lowest	0.092	130	Low
South Sudan	0.272	43	High	0.204	57	High
Spain	0.007	159	Lowest	0.036	158	Lowest
Sri Lanka	0.137	93	Medium	0.224	47	High
Sudan	0.319	20	Highest	0.195	63	High
Suriname	0.019	146	Lowest	0.092	130	Low
Swaziland	0.386	7	Highest	0.147	96	Medium
Sweden	0.009	156	Lowest	0.048	148	Lowest
Switzerland	0.001	169	Lowest	0.007	169	Lowest
Syria	0.247	50	High	0.068	139	Lowest
Taiwan	0.017	148	Lowest	0.062	140	Lowest
Tajikistan	0.285	35	High	0.199	61	High
Tanzania	0.228	56	High	0.246	34	High
Thailand	0.379	8	Highest	0.164	86	Medium
The Gambia	0.090	106	Low	0.106	125	Low
Timor-Leste	0.061	115	Low	0.115	118	Low
Togo	0.314	21	Highest	0.254	33	Highest
Trinidad and Tobago	0.014	151	Lowest	0.103	126	Low
Tunisia	0.028	138	Lowest	0.098	128	Low
Turkey	0.397	4	Highest	0.186	72	Medium
Turkmenistan	0.234	54	High	0.062	140	Lowest
U.A.E.	0.107	102	Low	0.072	136	Lowest
Uganda	0.303	29	Highest	0.291	21	Highest
Ukraine	0.232	55	High	0.241	36	High
United Kingdom	0.004	164	Lowest	0.040	155	Lowest
Uruguay	0.007	159	Lowest	0.045	151	Lowest
Uzbekistan	0.389	6	Highest	0.092	130	Low
Venezuela	0.358	13	Highest	0.276	25	Highest
Vietnam	0.273	42	High	0.262	29	Highest
Yemen	0.293	33	Highest	0.133	104	Low
Zambia	0.297	31	Highest	0.217	52	High
Zimbabwe	0.378	9	Highest	0.309	16	Highest

B.6 Governing

Table 17: Governing Space: 2019-2020 forecasts for all countries

	Opening			Closing		
Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Afghanistan	0.293	17	Highest	0.211	35	High
Albania	0.096	103	Low	0.191	41	High
Algeria	0.137	88	Medium	0.076	116	Low
Angola	0.289	19	Highest	0.115	88	Medium
Argentina	0.079	109	Low	0.106	93	Medium
Armenia	0.286	20	Highest	0.171	52	High
Australia	0.002	158	Lowest	0.016	161	Lowest
Austria	0.007	151	Lowest	0.074	119	Low
Azerbaijan	0.229	41	High	0.087	109	Low
Bangladesh	0.239	36	High	0.197	40	High
Barbados	0.023	131	Low	0.078	115	Low
Belarus	0.158	82	Medium	0.066	127	Low
Belgium	0.001	162	Lowest	0.009	165	Lowest
Benin	0.129	90	Medium	0.157	61	High
Bhutan	0.068	112	Low	0.055	130	Low
Bolivia	0.113	97	Medium	0.138	72	Medium
Bosnia & Herz.	0.187	69	Medium	0.217	32	Highest
Botswana	0.038	122	Low	0.069	125	Low
Brazil	0.192	63	High	0.267	14	Highest
Bulgaria	0.033	124	Low	0.120	86	Medium
Burkina Faso	0.236	38	High	0.328	5	Highest
Burundi	0.362	5	Highest	0.202	38	High
C.A.R.	0.203	58	High	0.182	47	High
Cambodia	0.191	64	High	0.091	106	Low
Cameroon	0.227	43	High	0.145	69	Medium
Canada	0.001	162	Lowest	0.020	159	Lowest
Cape Verde	0.002	158	Lowest	0.051	135	Lowest
Chad	0.178	74	Medium	0.080	114	Low
Chile	0.032	127	Low	0.128	77	Medium
China	0.174	77	Medium	0.143	70	Medium
Colombia	0.251	35	High	0.333	3	Highest
Comoros	0.308	14	Highest	0.263	16	Highest
Costa Rica	0.009	145	Lowest	0.082	113	Low
Croatia	0.064	114	Low	0.087	109	Low
Cuba	0.344	8	Highest	0.073	121	Low
Cyprus	0.003	156	Lowest	0.050	137	Lowest
Czech Republic	0.008	147	Lowest	0.052	133	Low
D.R.C.	0.158	82	Medium	0.168	56	High
Denmark	0.000	167	Lowest	0.008	167	Lowest
Djibouti	0.168	79	Medium	0.071	122	Low
Dominican Rep.	0.199	60	High	0.135	74	Medium
Ecuador	0.254	32	High	0.191	41	High
Egypt	0.168	79	Medium	0.131	75	Medium

Table 17: Governing Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
El Salvador	0.208	55	High	0.254	22	Highest
Equatorial Guinea	0.129	90	Medium	0.042	143	Lowest
Eritrea	0.094	104	Low	0.054	132	Low
Estonia	0.000	167	Lowest	0.012	164	Lowest
Ethiopia	0.397	3	Highest	0.127	79	Medium
Fiji	0.188	68	Medium	0.153	64	High
Finland	0.010	143	Lowest	0.043	142	Lowest
France	0.024	130	Low	0.092	102	Low
Gabon	0.228	42	High	0.230	26	Highest
Georgia	0.033	124	Low	0.128	77	Medium
Germany	0.001	162	Lowest	0.016	161	Lowest
Ghana	0.018	134	Lowest	0.115	88	Medium
Greece	0.018	134	Low	0.087	109	Low
Guatemala	0.261	27	Highest	0.322	6	Highest
Guinea	0.223	45	High	0.188	45	High
Guinea-Bissau	0.281	23	Highest	0.202	38	High
Guyana	0.173	78	Medium	0.126	81	Medium
Haiti	0.363	4	Highest	0.350	1	Highest
Honduras	0.234	39	High	0.209	36	High
Hungary	0.176	76	Medium	0.278	12	Highest
Iceland	0.002	158	Lowest	0.004	168	Lowest
India	0.218	47	High	0.160	59	High
Indonesia	0.033	124	Low	0.177	48	High
Iran	0.256	31	Highest	0.287	10	Highest
Iraq	0.290	18	Highest	0.216	33	High
Ireland	0.007	151	Lowest	0.041	144	Lowest
Israel	0.050	118	Low	0.063	128	Low
Italy	0.018	134	Low	0.092	102	Low
Ivory Coast	0.211	53	High	0.138	72	Medium
Jamaica	0.008	147	Lowest	0.049	138	Lowest
Japan	0.008	147	Lowest	0.029	154	Lowest
Jordan	0.067	113	Low	0.055	130	Low
Kazakhstan	0.232	40	High	0.146	68	Medium
Kenya	0.138	87	Medium	0.262	17	Highest
Kosovo	0.213	52	High	0.186	46	High
Kuwait	0.089	106	Low	0.102	97	Medium
Kyrgyzstan	0.112	98	Medium	0.154	62	High
Laos	0.140	86	Medium	0.062	129	Low
Latvia	0.017	137	Lowest	0.016	161	Lowest
Lebanon	0.118	95	Medium	0.153	64	High
Lesotho	0.179	72	Medium	0.152	66	High
Liberia	0.237	37	High	0.256	21	Highest
Libya	0.179	72	Medium	0.296	7	Highest
Lithuania	0.006	153	Lowest	0.051	135	Low
Luxembourg	0.011	141	Lowest	0.002	169	Lowest

Table 17: Governing Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Macedonia	0.191	64	High	0.103	95	Medium
Madagascar	0.285	21	Highest	0.189	44	High
Malawi	0.042	119	Low	0.109	90	Medium
Malaysia	0.413	2	Highest	0.097	100	Medium
Maldives	0.310	13	Highest	0.225	28	Highest
Mali	0.207	56	High	0.258	20	Highest
Mauritania	0.283	22	Highest	0.171	52	High
Mauritius	0.040	120	Low	0.076	116	Low
Mexico	0.189	67	High	0.173	49	High
Moldova	0.177	75	Medium	0.173	49	High
Mongolia	0.071	111	Low	0.125	83	Medium
Montenegro	0.221	46	High	0.154	62	High
Morocco	0.110	99	Medium	0.100	99	Medium
Mozambique	0.154	84	Medium	0.127	79	Medium
Myanmar	0.227	43	High	0.171	52	High
Namibia	0.056	117	Low	0.101	98	Medium
Nepal	0.101	102	Low	0.261	18	Highest
Netherlands	0.001	162	Lowest	0.024	155	Lowest
New Zealand	0.008	147	Lowest	0.032	153	Lowest
Nicaragua	0.336	9	Highest	0.245	23	Highest
Niger	0.107	100	Medium	0.245	23	Highest
Nigeria	0.129	90	Medium	0.124	84	Medium
North Korea	0.093	105	Low	0.039	146	Lowest
Norway	0.004	154	Lowest	0.017	160	Lowest
Oman	0.126	94	Medium	0.047	139	Lowest
Pakistan	0.315	12	Highest	0.269	13	Highest
Panama	0.086	107	Low	0.107	92	Medium
Papua New Guinea	0.147	85	Medium	0.131	75	Medium
Paraguay	0.131	89	Medium	0.191	41	High
Peru	0.020	133	Low	0.126	81	Medium
Philippines	0.214	50	High	0.281	11	Highest
Poland	0.102	101	Medium	0.124	84	Medium
Portugal	0.004	154	Lowest	0.038	148	Lowest
Qatar	0.128	93	Medium	0.052	133	Low
Rep. of Congo	0.274	25	Highest	0.143	70	Medium
Romania	0.261	27	Highest	0.261	18	Highest
Russia	0.185	71	Medium	0.071	122	Low
Rwanda	0.262	26	Highest	0.108	91	Medium
Saudi Arabia	0.039	121	Low	0.039	146	Lowest
Senegal	0.079	109	Low	0.092	102	Low
Serbia	0.209	54	High	0.216	33	Highest
Sierra Leone	0.276	24	Highest	0.173	49	High
Singapore	0.297	15	Highest	0.089	107	Low
Slovakia	0.012	140	Lowest	0.075	118	Low
Slovenia	0.009	145	Lowest	0.040	145	Lowest

Table 17: Governing Space: 2019-2020 forecasts for all countries *(continued)*

Country	Prob.	Rank	Cat.	Prob.	Rank	Cat.
Solomon Islands	0.058	115	Low	0.092	102	Low
Somalia	0.323	11	Highest	0.329	4	Highest
South Africa	0.034	123	Low	0.106	93	Medium
South Korea	0.011	141	Lowest	0.033	152	Lowest
South Sudan	0.254	32	Highest	0.224	29	Highest
Spain	0.002	158	Lowest	0.023	158	Lowest
Sri Lanka	0.196	61	High	0.164	57	High
Sudan	0.216	49	High	0.171	52	High
Suriname	0.029	129	Low	0.069	125	Low
Swaziland	0.297	15	Highest	0.159	60	High
Sweden	0.003	156	Lowest	0.046	140	Lowest
Switzerland	0.001	162	Lowest	0.009	165	Lowest
Syria	0.214	50	High	0.071	122	Low
Taiwan	0.032	127	Low	0.024	155	Lowest
Tajikistan	0.200	59	High	0.096	101	Medium
Tanzania	0.082	108	Low	0.148	67	High
Thailand	0.346	7	Highest	0.119	87	Medium
The Gambia	0.206	57	High	0.089	107	Low
Timor-Leste	0.117	96	Medium	0.103	95	Medium
Togo	0.260	29	Highest	0.294	8	Highest
Trinidad and Tobago	0.013	139	Lowest	0.024	155	Lowest
Tunisia	0.014	138	Lowest	0.086	112	Low
Turkey	0.333	10	Highest	0.221	31	Highest
Turkmenistan	0.165	81	Medium	0.036	150	Lowest
U.A.E.	0.057	116	Low	0.044	141	Lowest
Uganda	0.190	66	High	0.230	26	Highest
Ukraine	0.194	62	High	0.238	25	Highest
United Kingdom	0.000	167	Lowest	0.036	150	Lowest
Uruguay	0.010	143	Lowest	0.037	149	Lowest
Uzbekistan	0.218	47	High	0.074	119	Low
Venezuela	0.460	1	Highest	0.266	15	Highest
Vietnam	0.187	69	Medium	0.222	30	Highest
Yemen	0.260	29	Highest	0.163	58	High
Zambia	0.254	32	Highest	0.205	37	High
Zimbabwe	0.361	6	Highest	0.290	9	Highest

C Past top 10 forecast charts

Associational

Figure 22: Test year estimates for the associational space, 2006–2007.

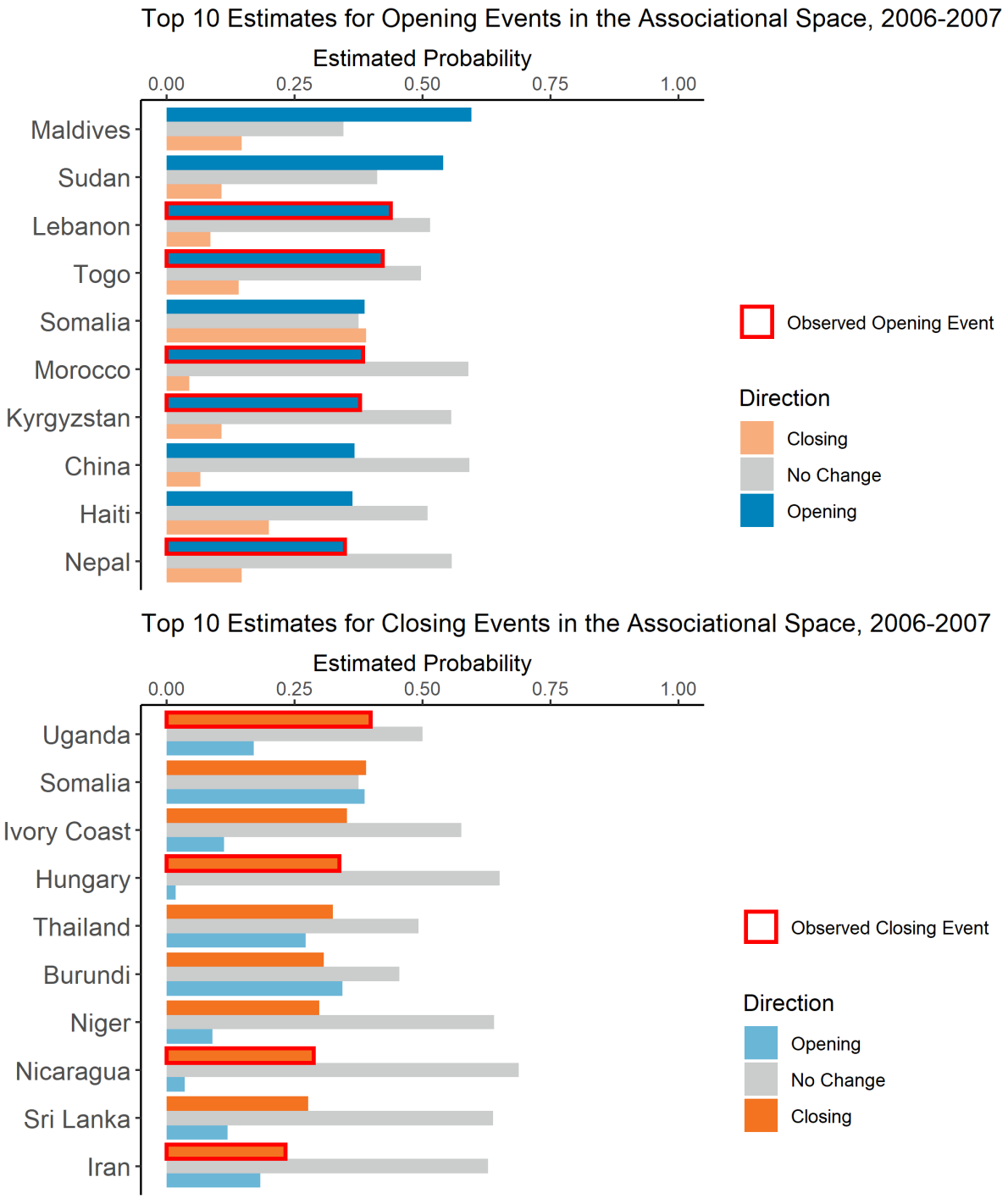


Figure 23: Test year estimates for the associational space, 2007–2008.

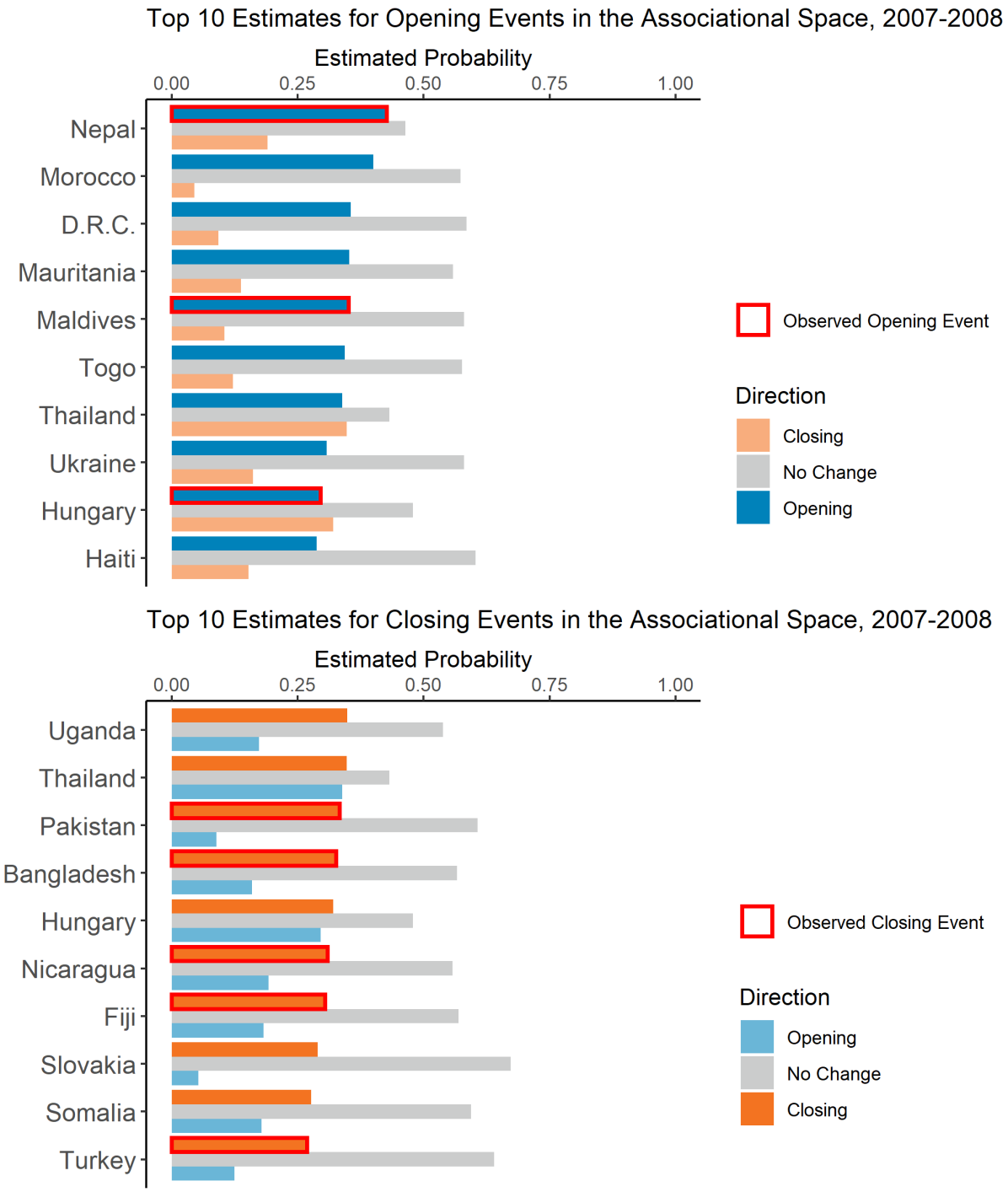


Figure 24: Test year estimates for the associational space, 2008–2009.

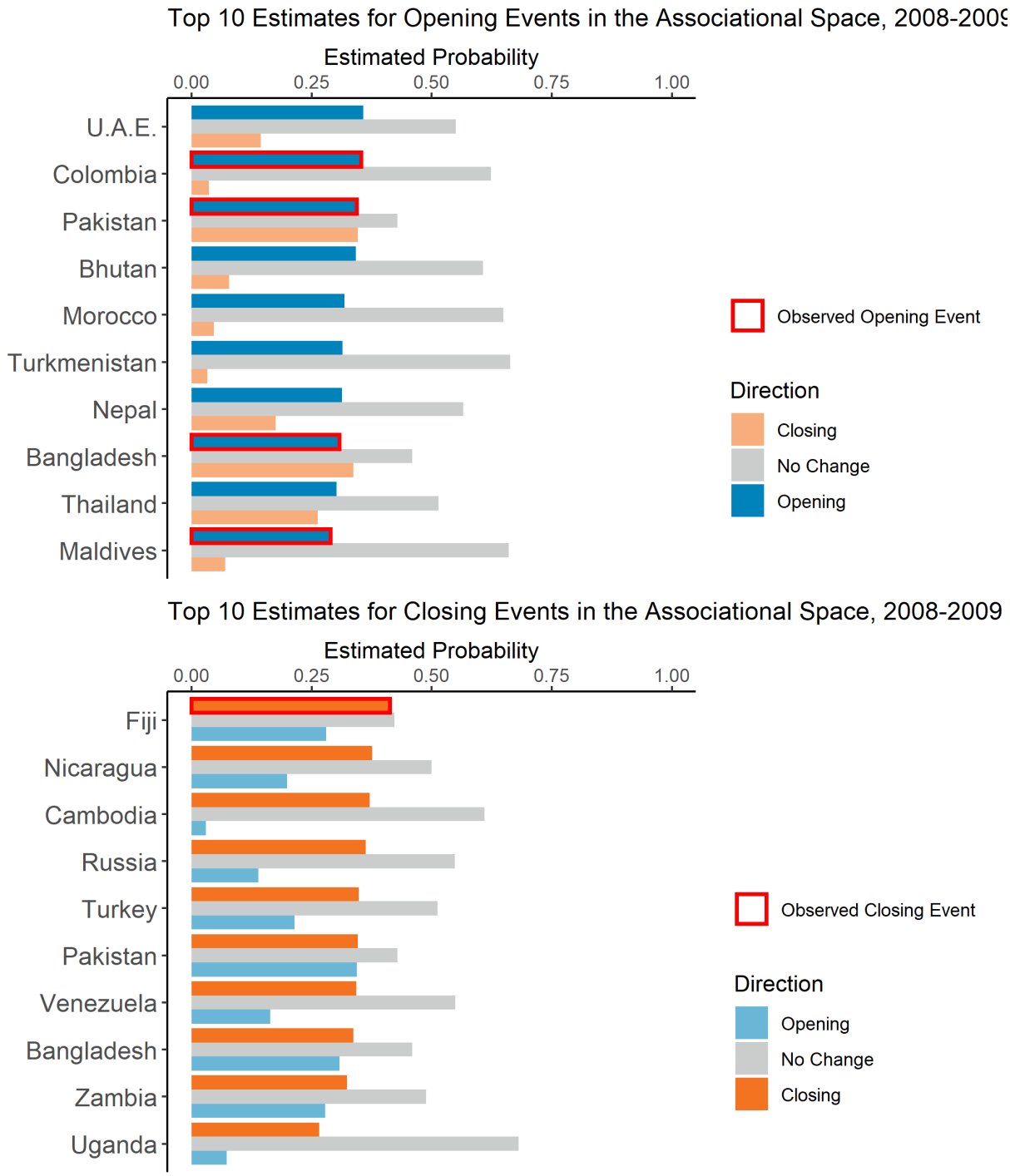


Figure 25: Test year estimates for the associational space, 2009–2010.

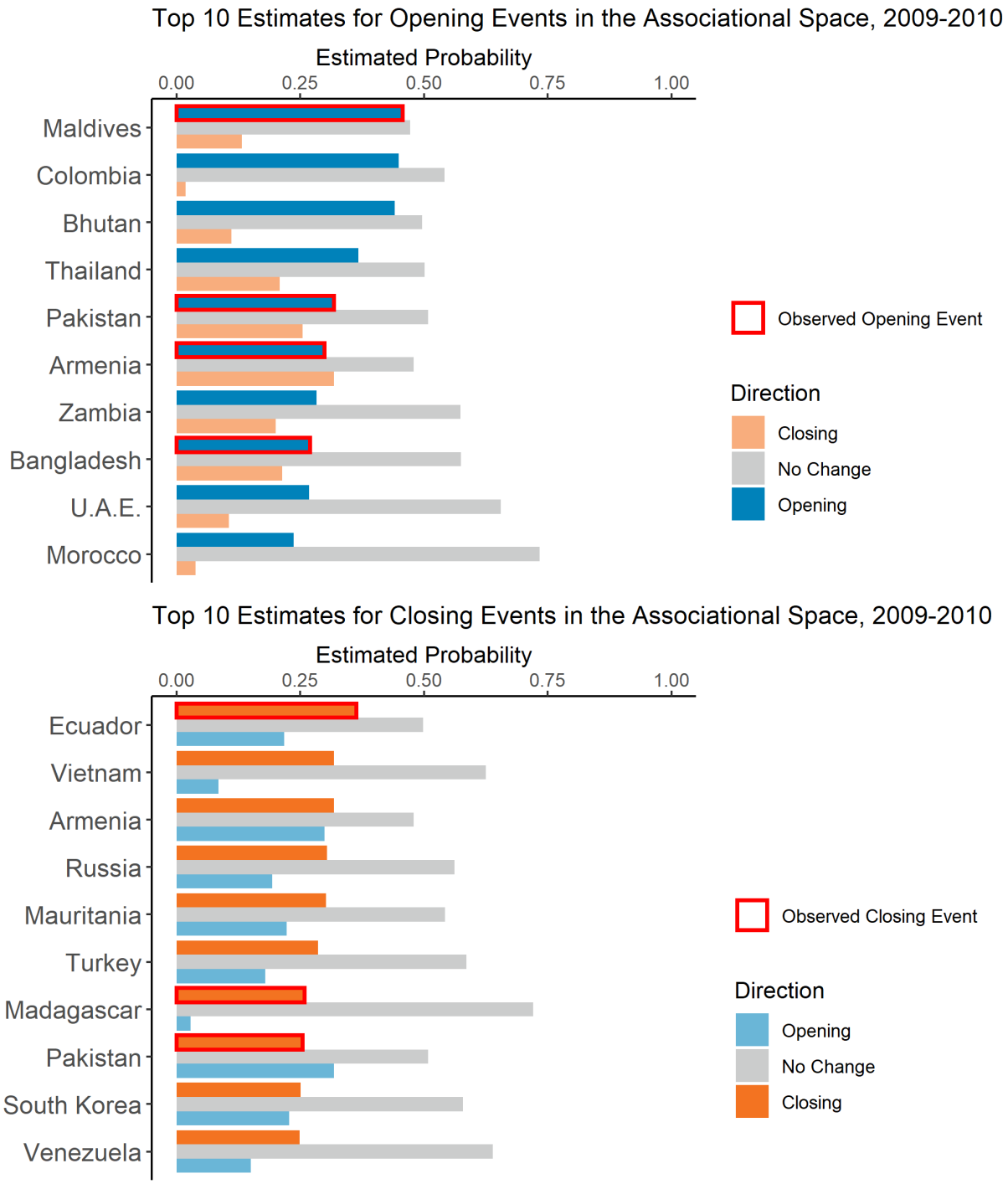


Figure 26: Test year estimates for the associational space, 2010–2011.

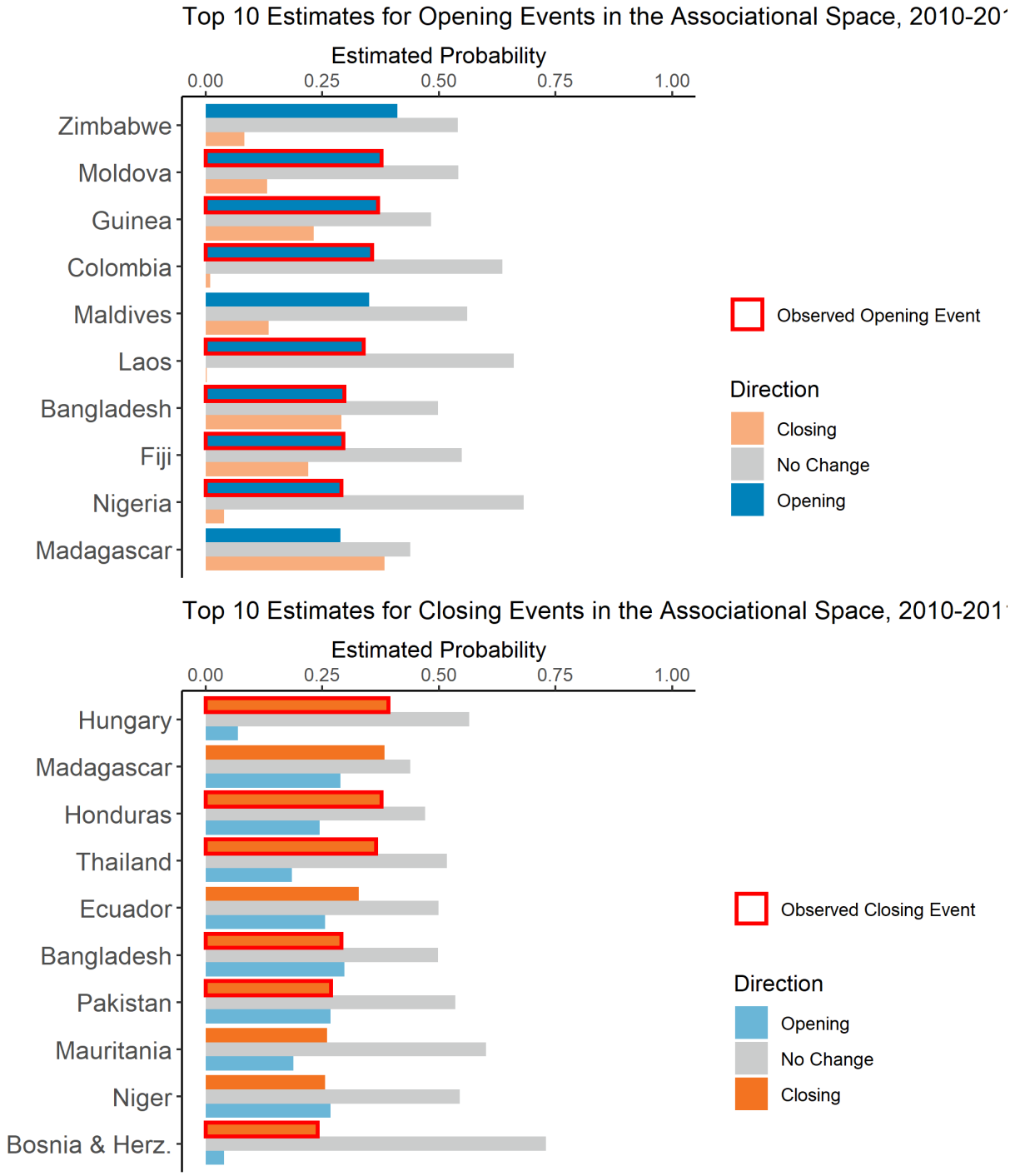


Figure 27: Test year estimates for the associational space, 2011–2012.

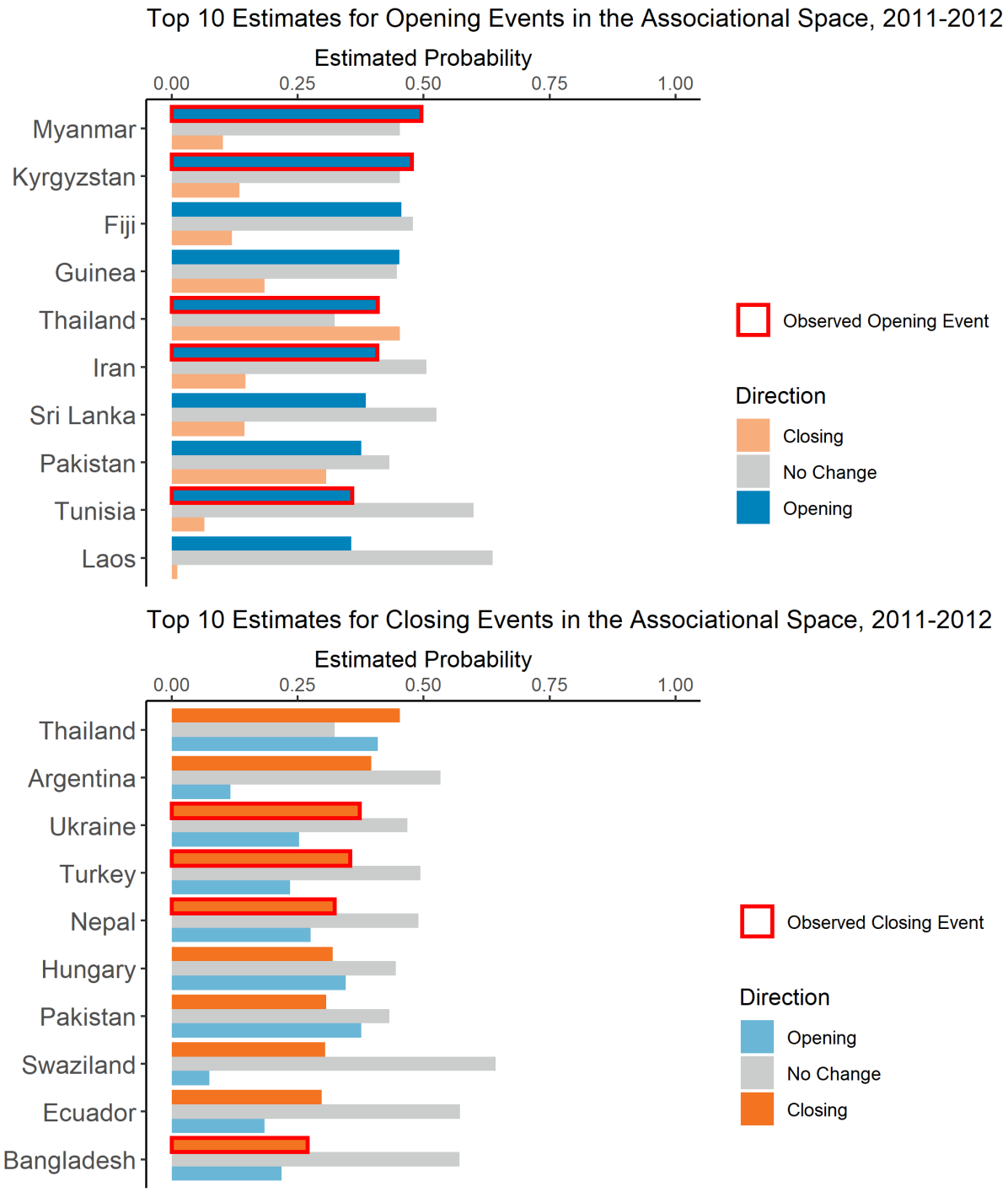


Figure 28: Test year estimates for the associational space, 2012–2013.

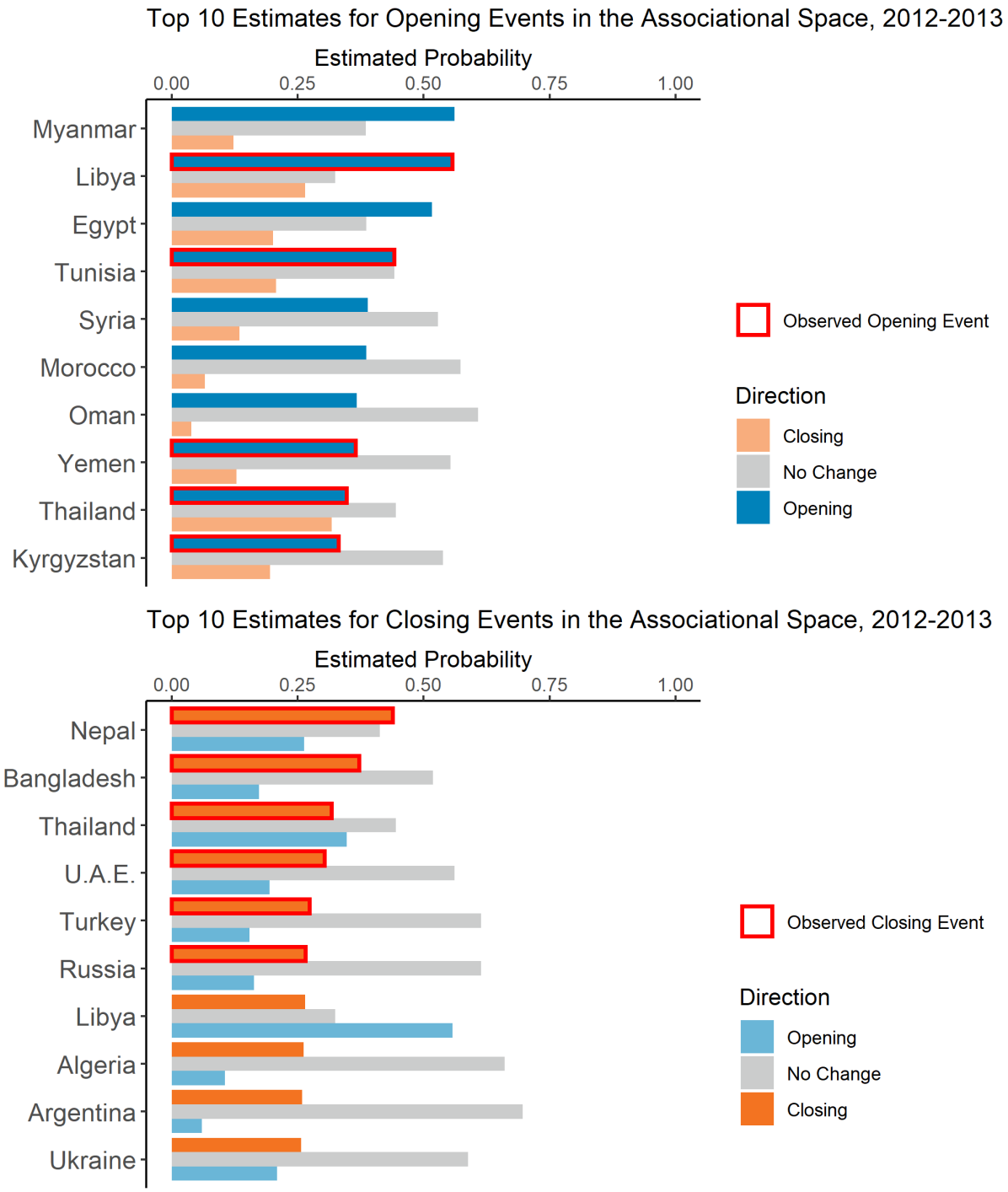


Figure 29: Test year estimates for the associational space, 2013–2014.

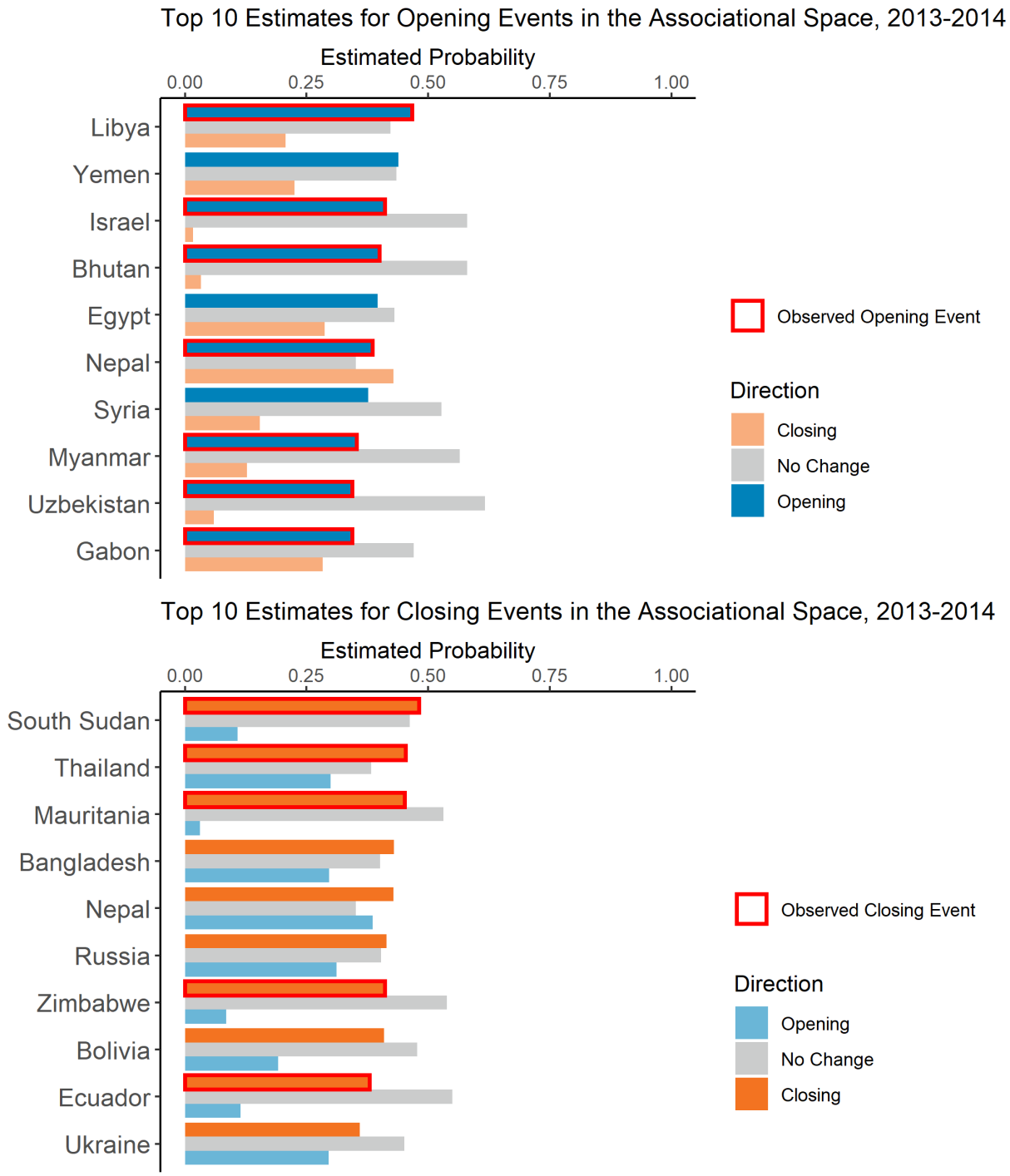


Figure 30: Test year estimates for the associational space, 2014–2015.

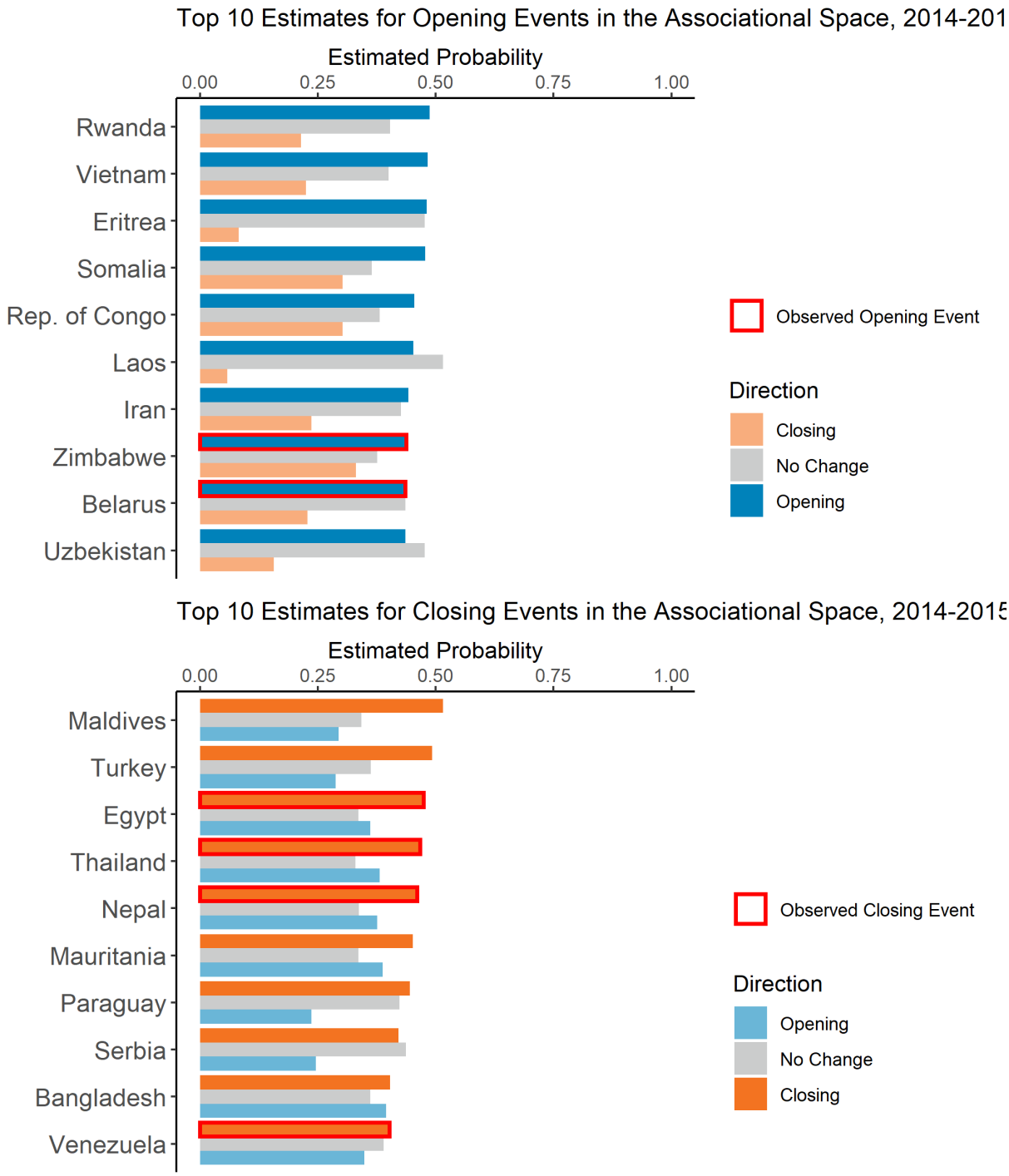


Figure 31: Test year estimates for the associational space, 2015–2016.

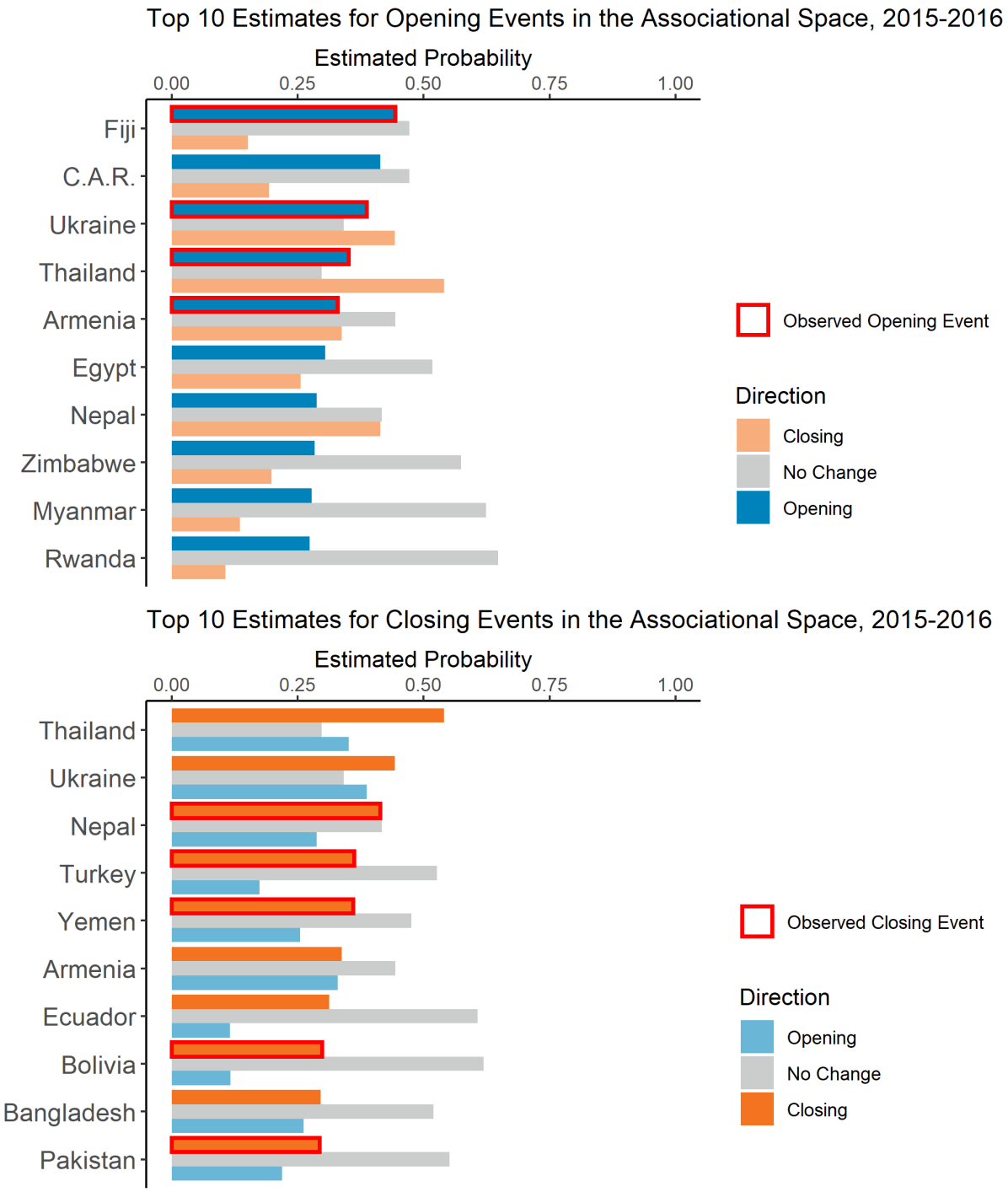


Figure 32: Test year estimates for the associational space, 2016–2017.

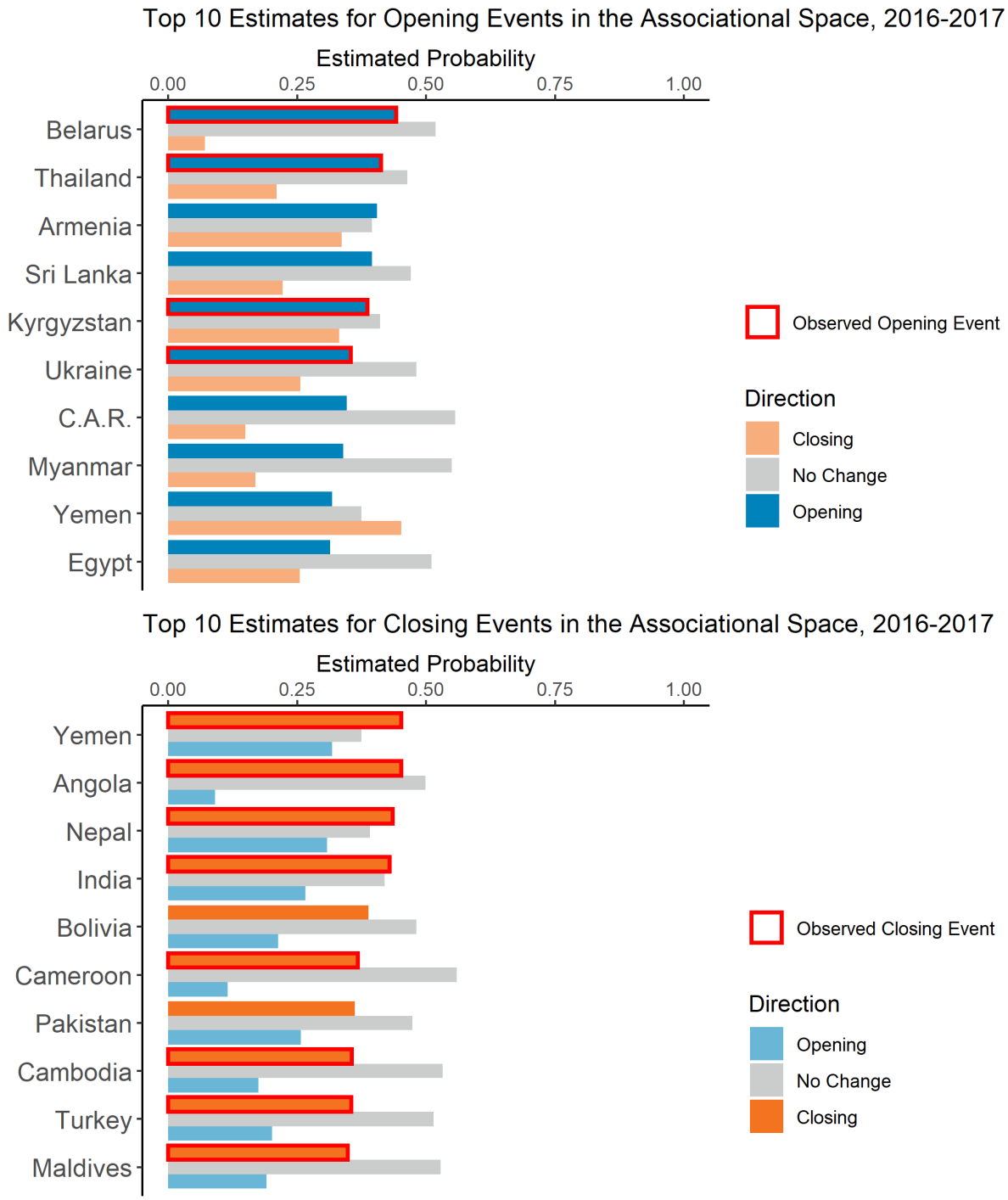
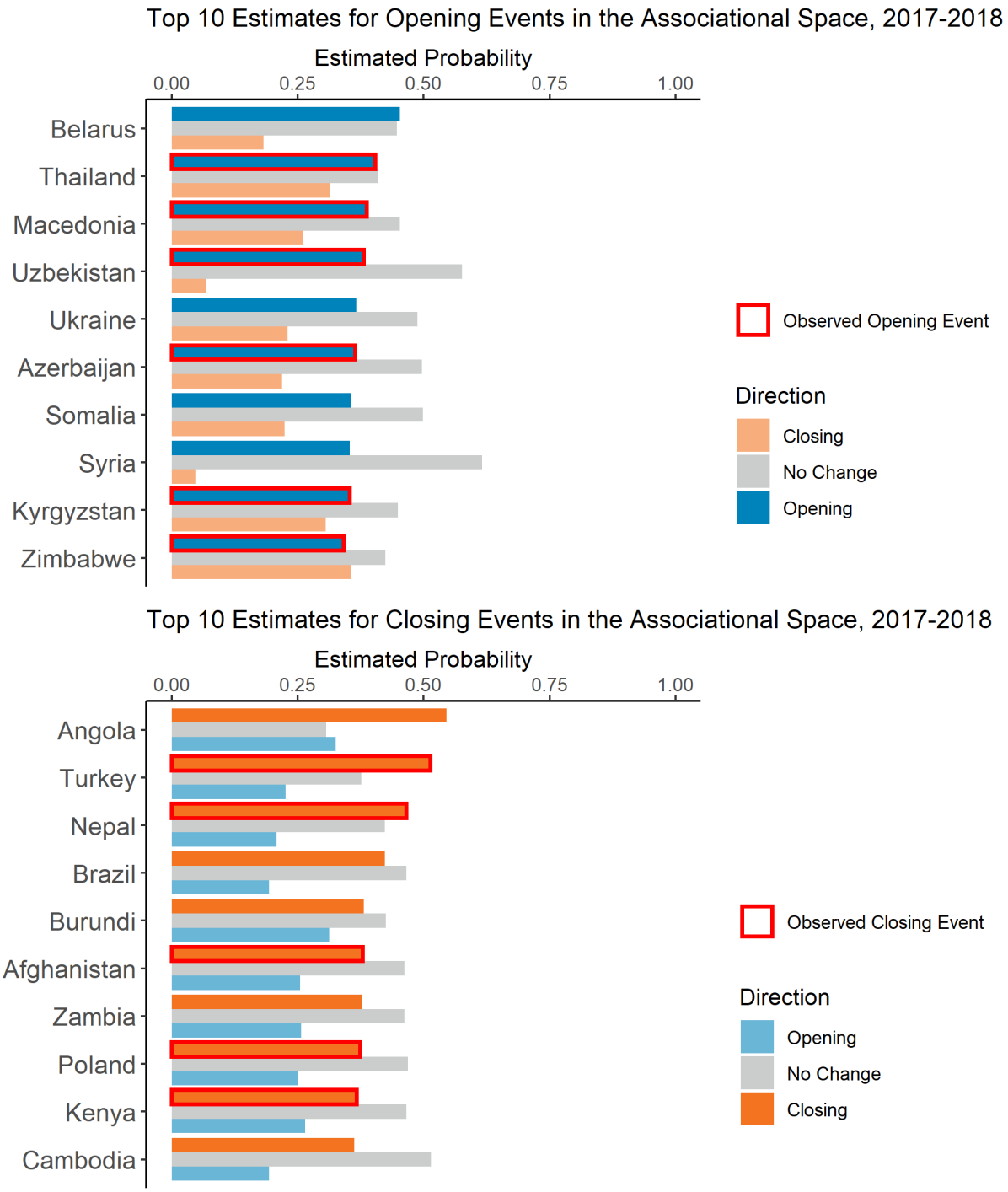


Figure 33: Test year estimates for the associational space, 2017–2018.



Economic

Figure 34: Test year estimates for the economic space, 2006–2007.

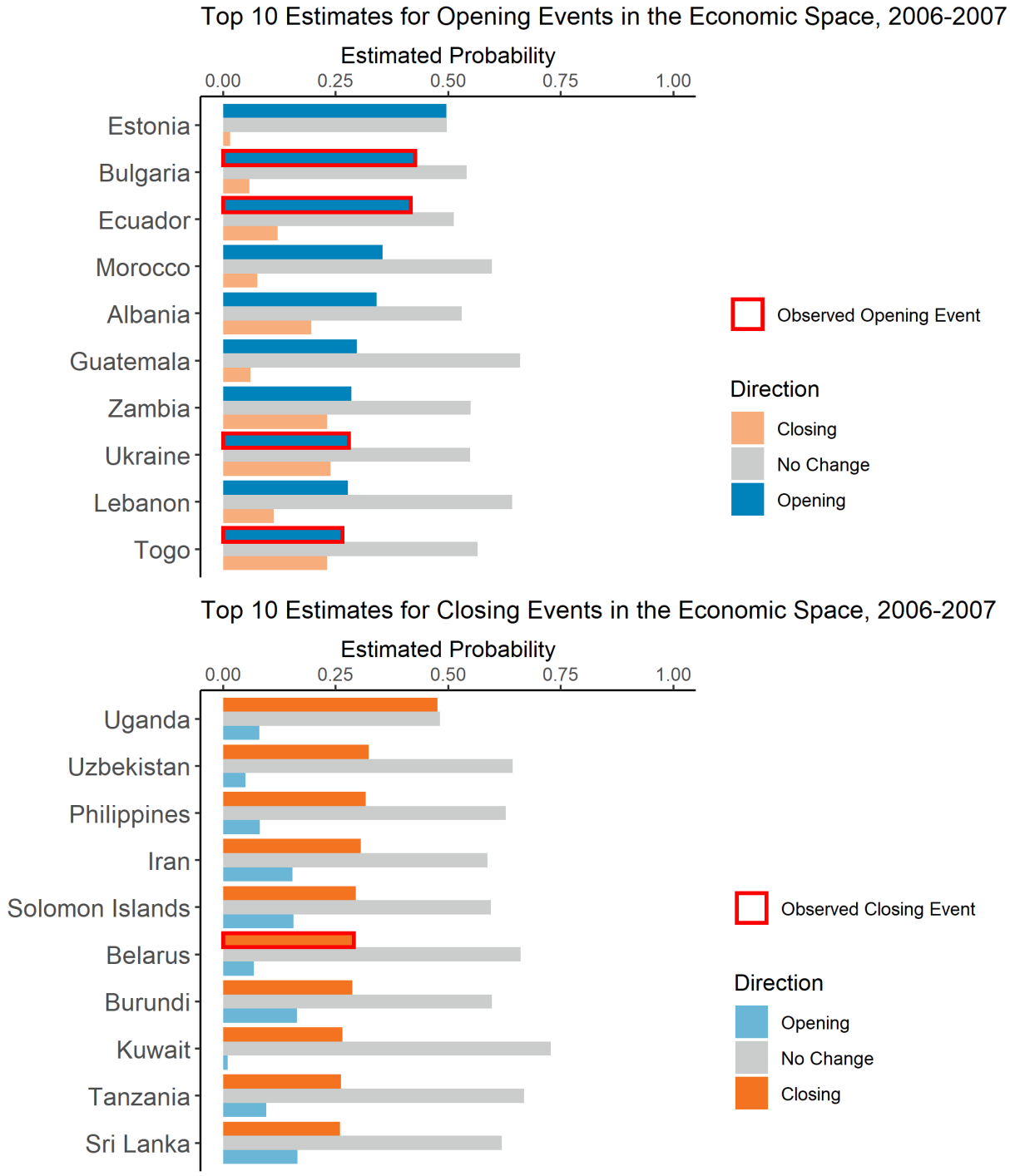


Figure 35: Test year estimates for the economic space, 2007–2008.

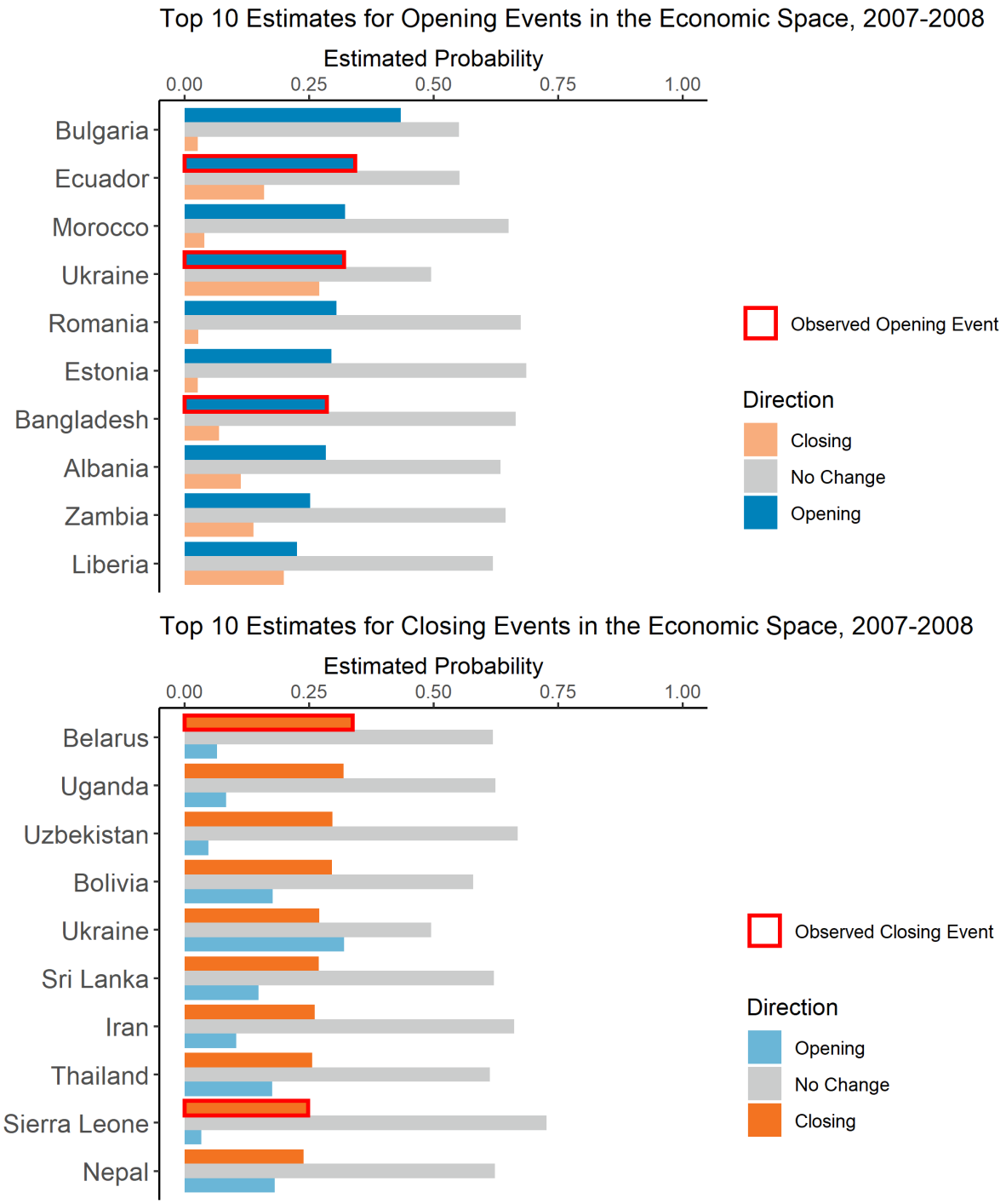


Figure 36: Test year estimates for the economic space, 2008–2009.

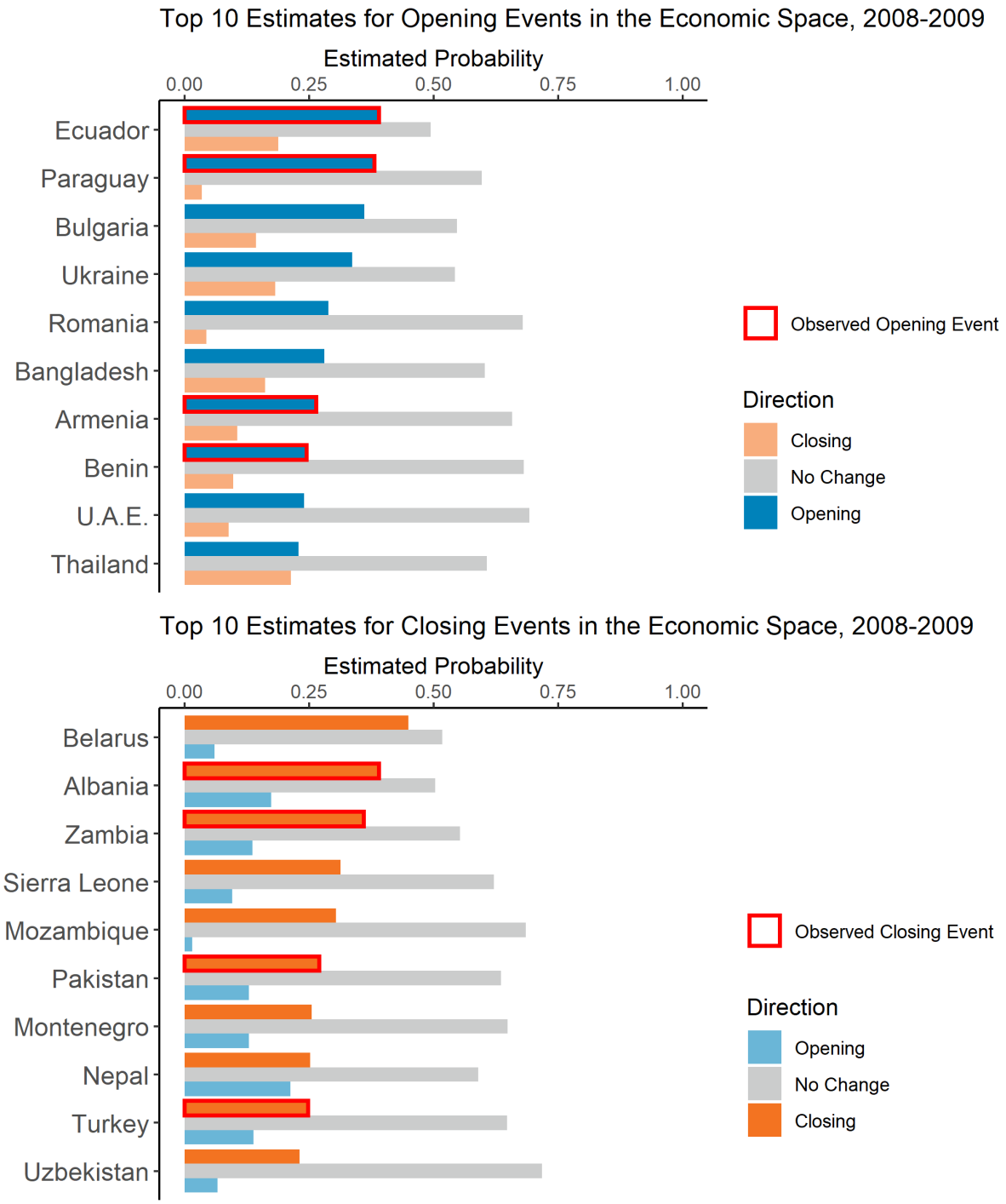


Figure 37: Test year estimates for the economic space, 2009–2010.

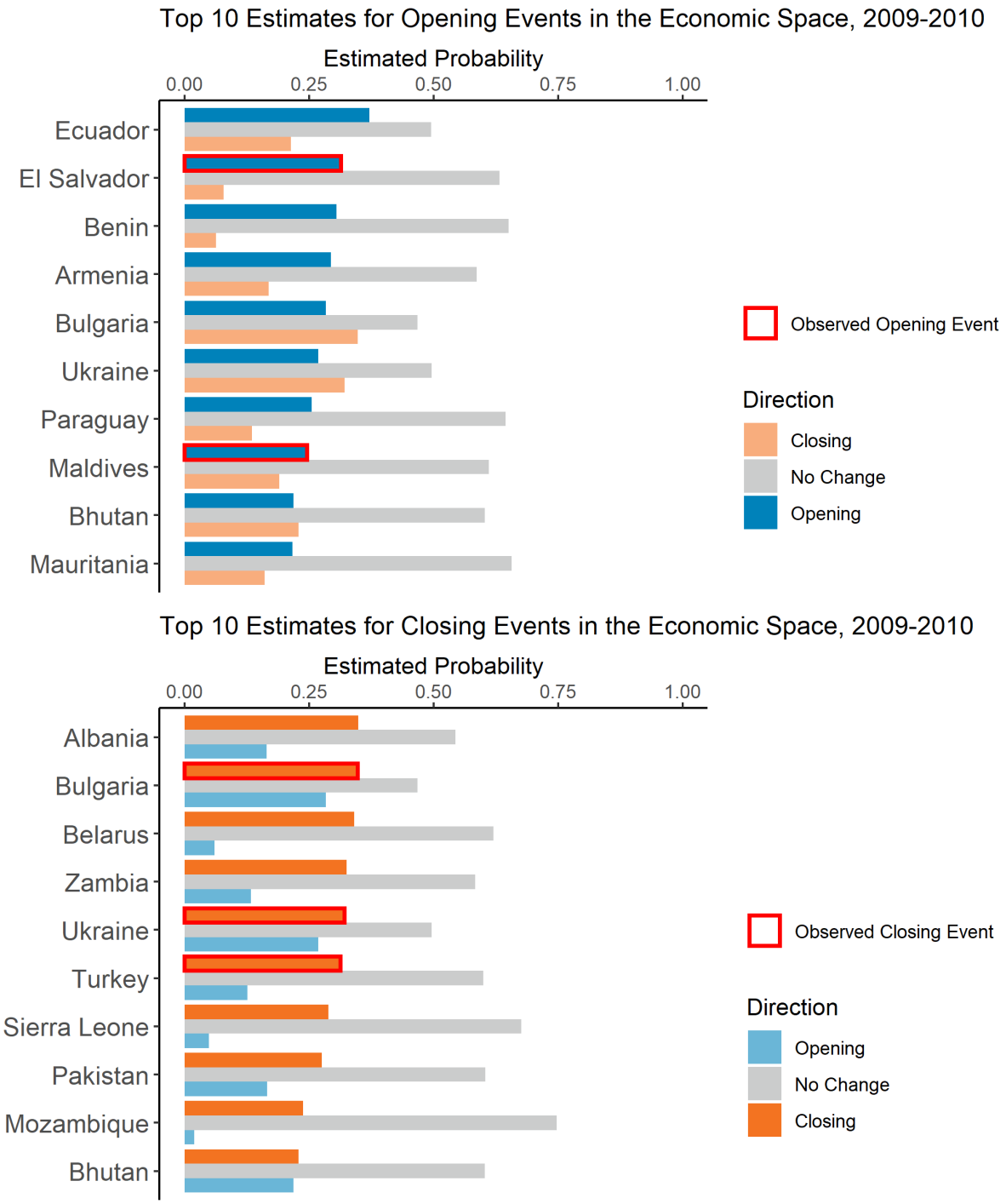


Figure 38: Test year estimates for the economic space, 2010–2011.

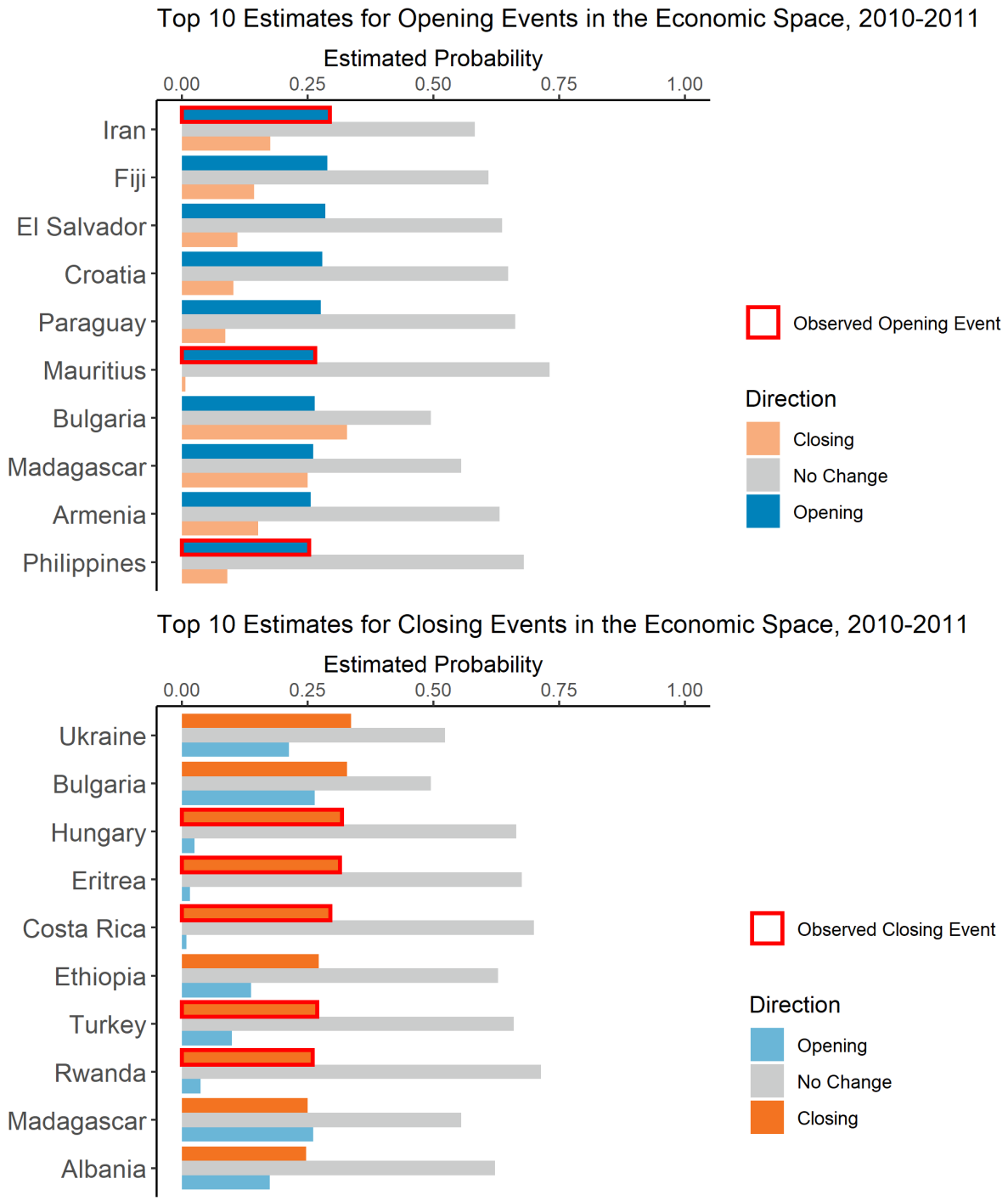


Figure 39: Test year estimates for the economic space, 2011–2012.

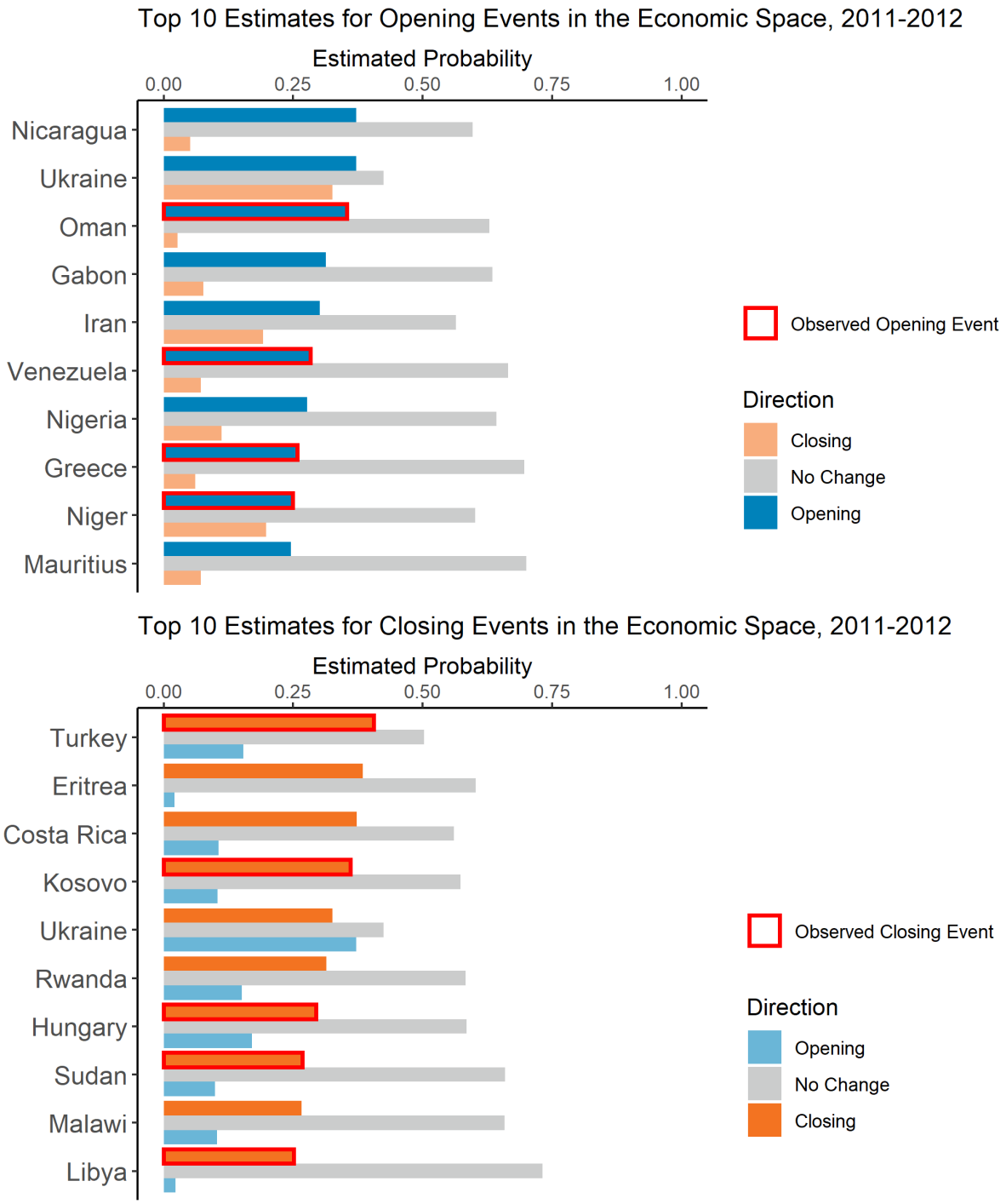


Figure 40: Test year estimates for the economic space, 2012–2013.

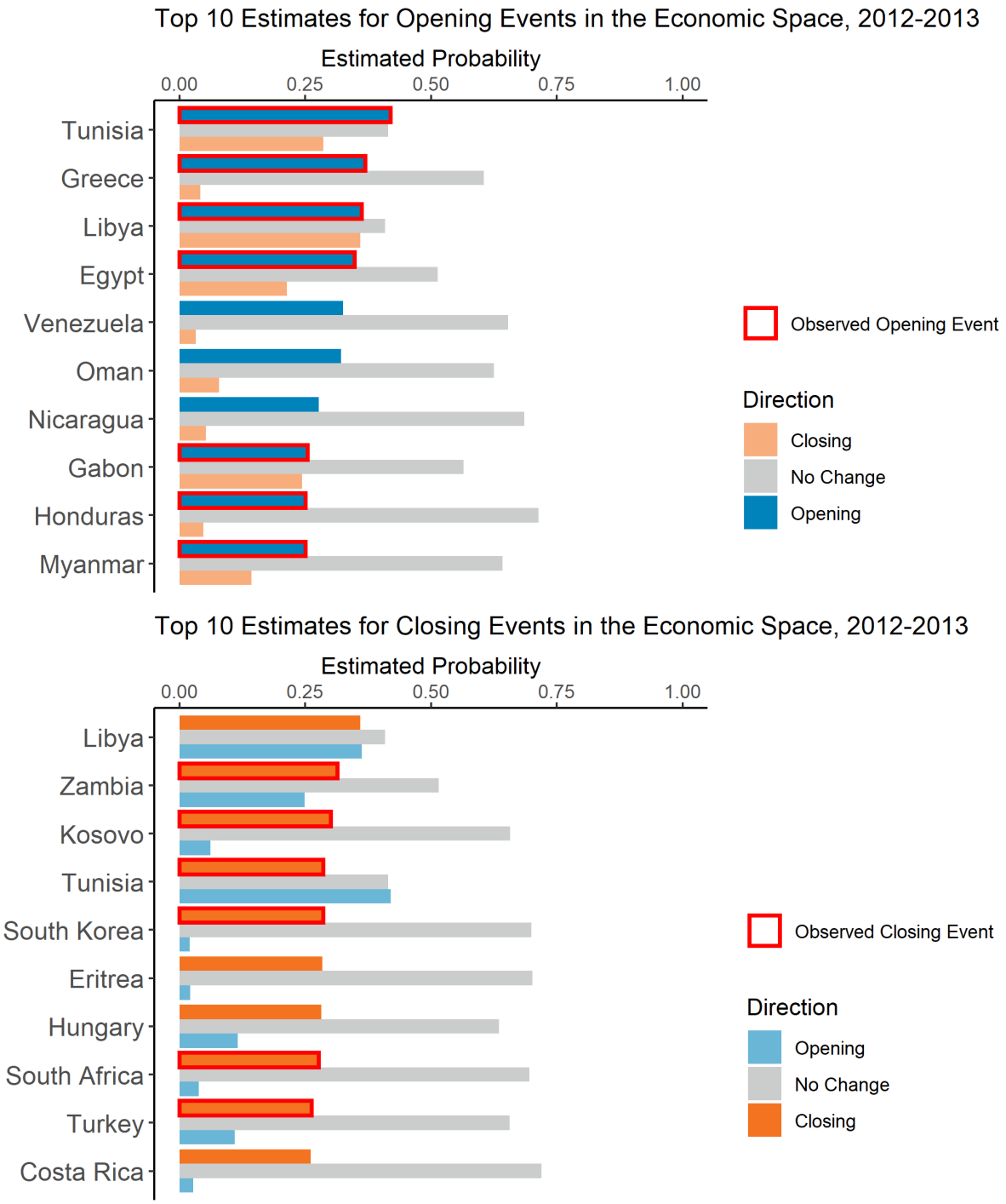


Figure 41: Test year estimates for the economic space, 2013–2014.

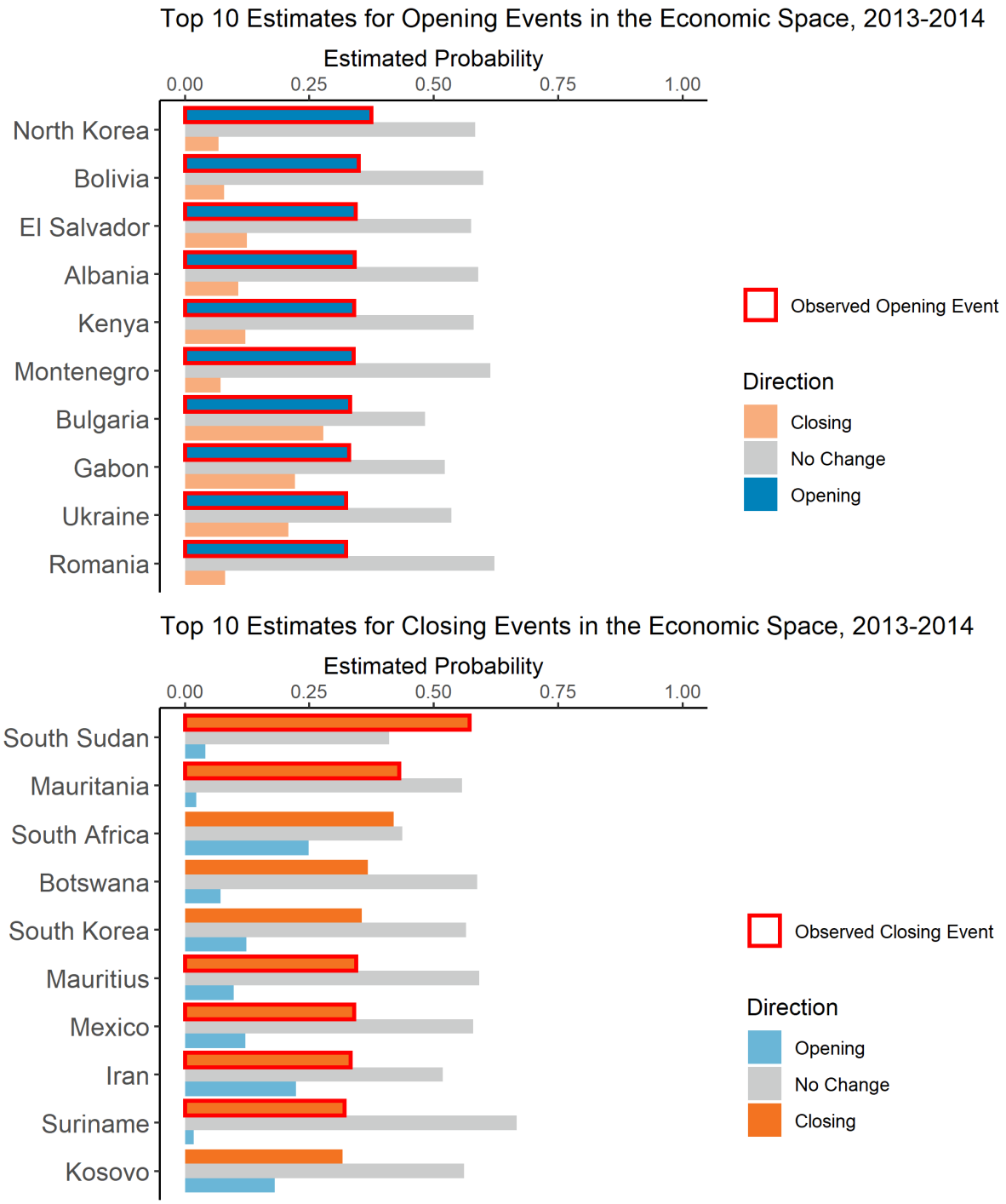


Figure 42: Test year estimates for the economic space, 2014–2015.

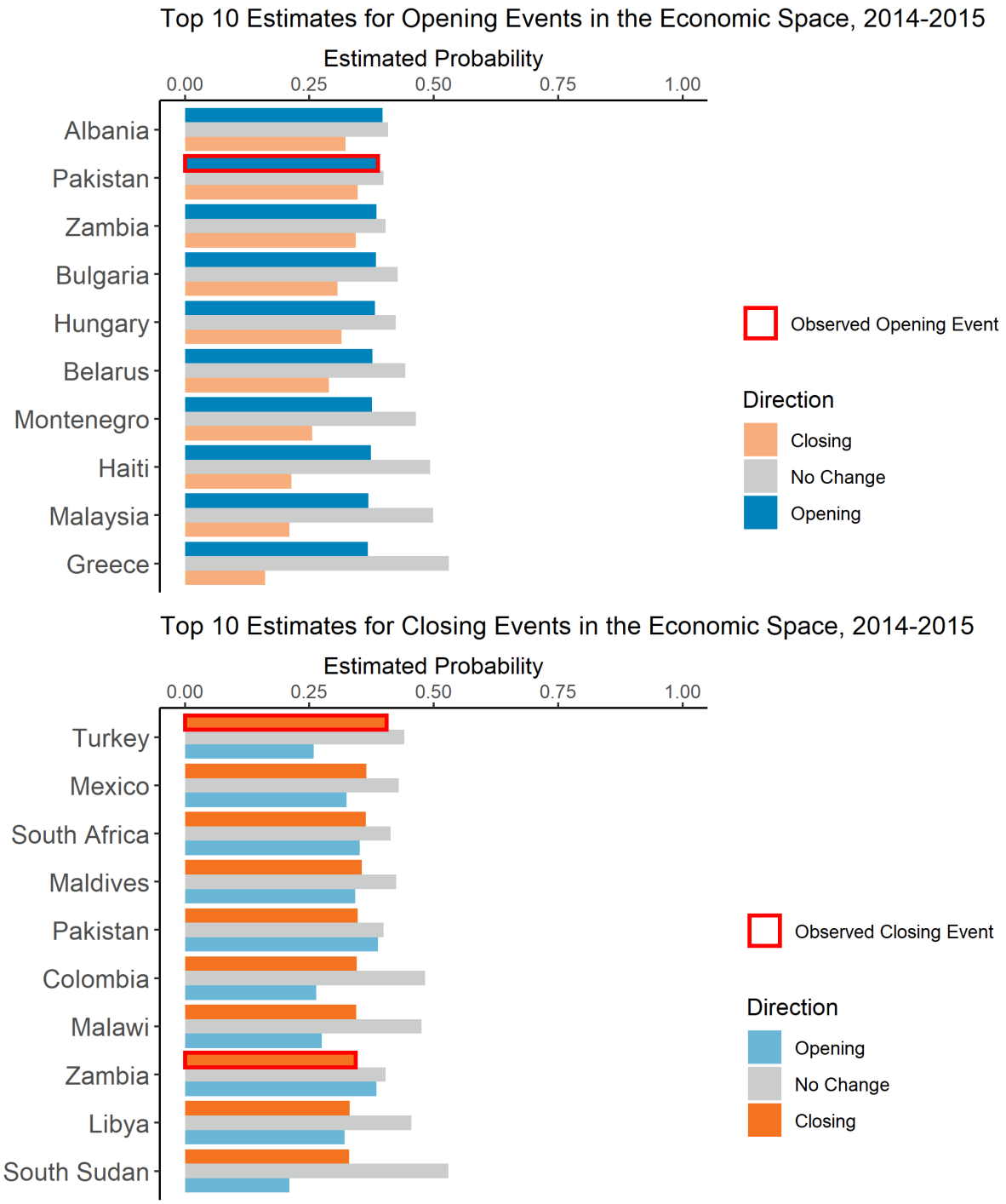


Figure 43: Test year estimates for the economic space, 2015–2016.

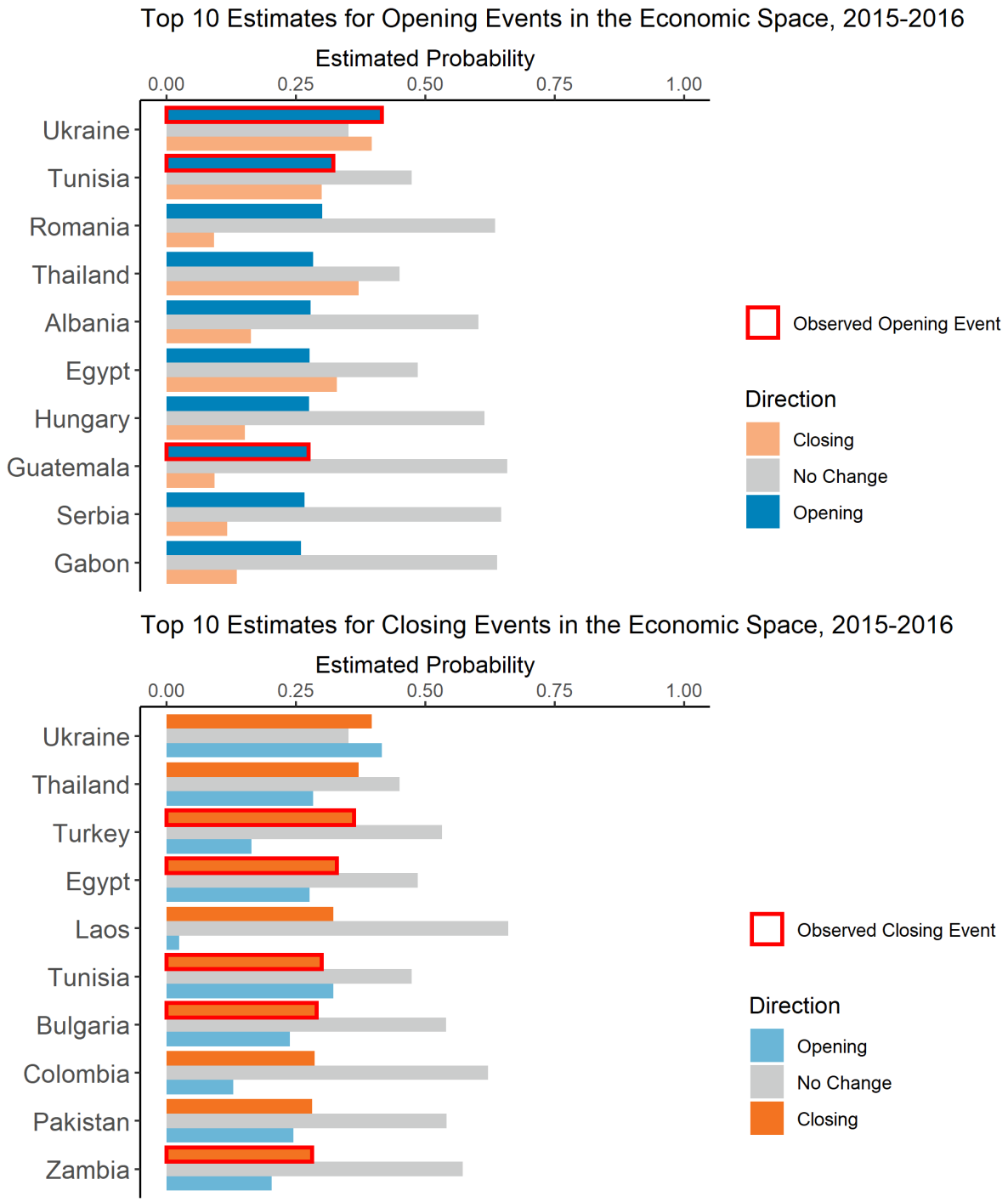


Figure 44: Test year estimates for the economic space, 2016–2017.

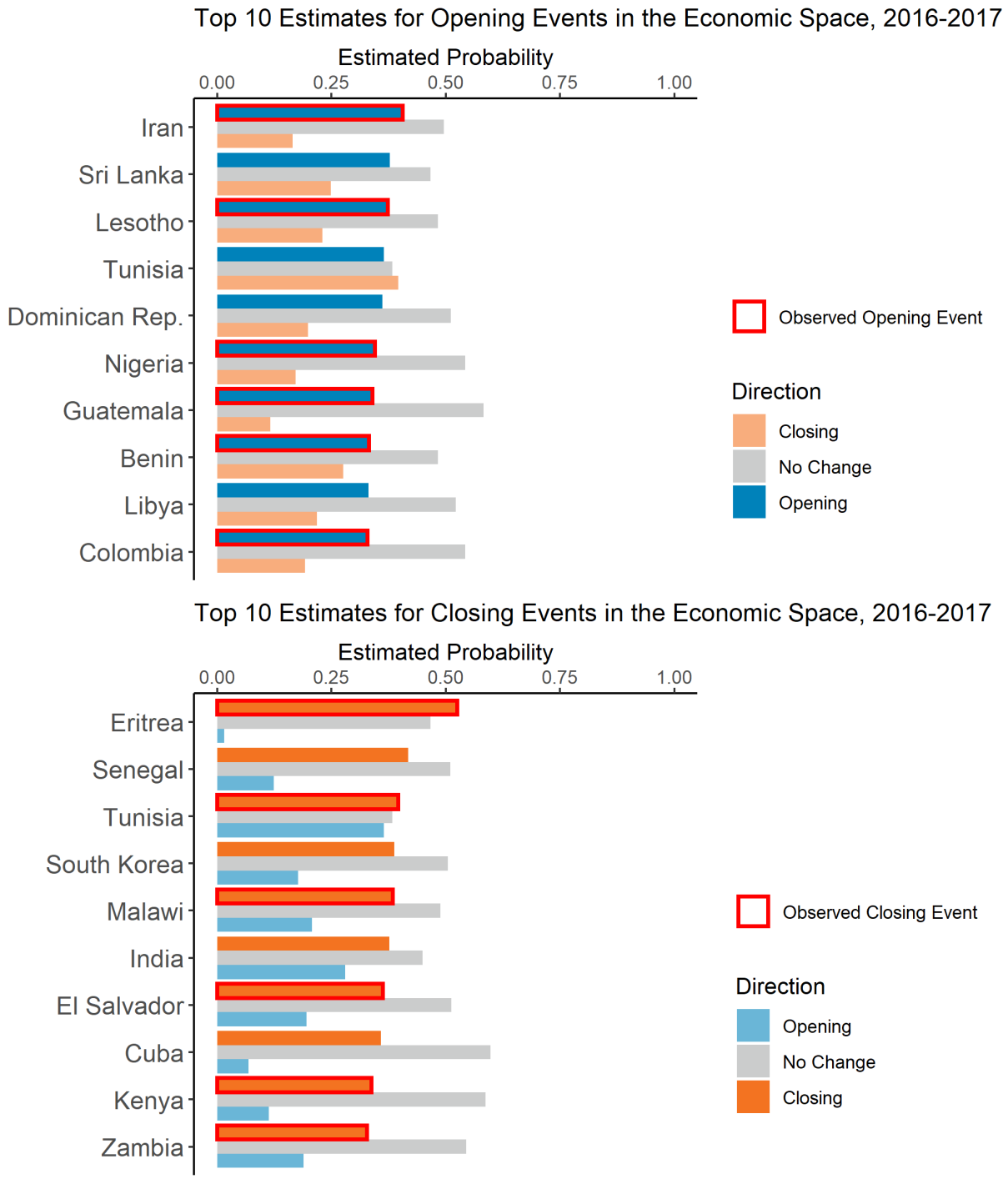
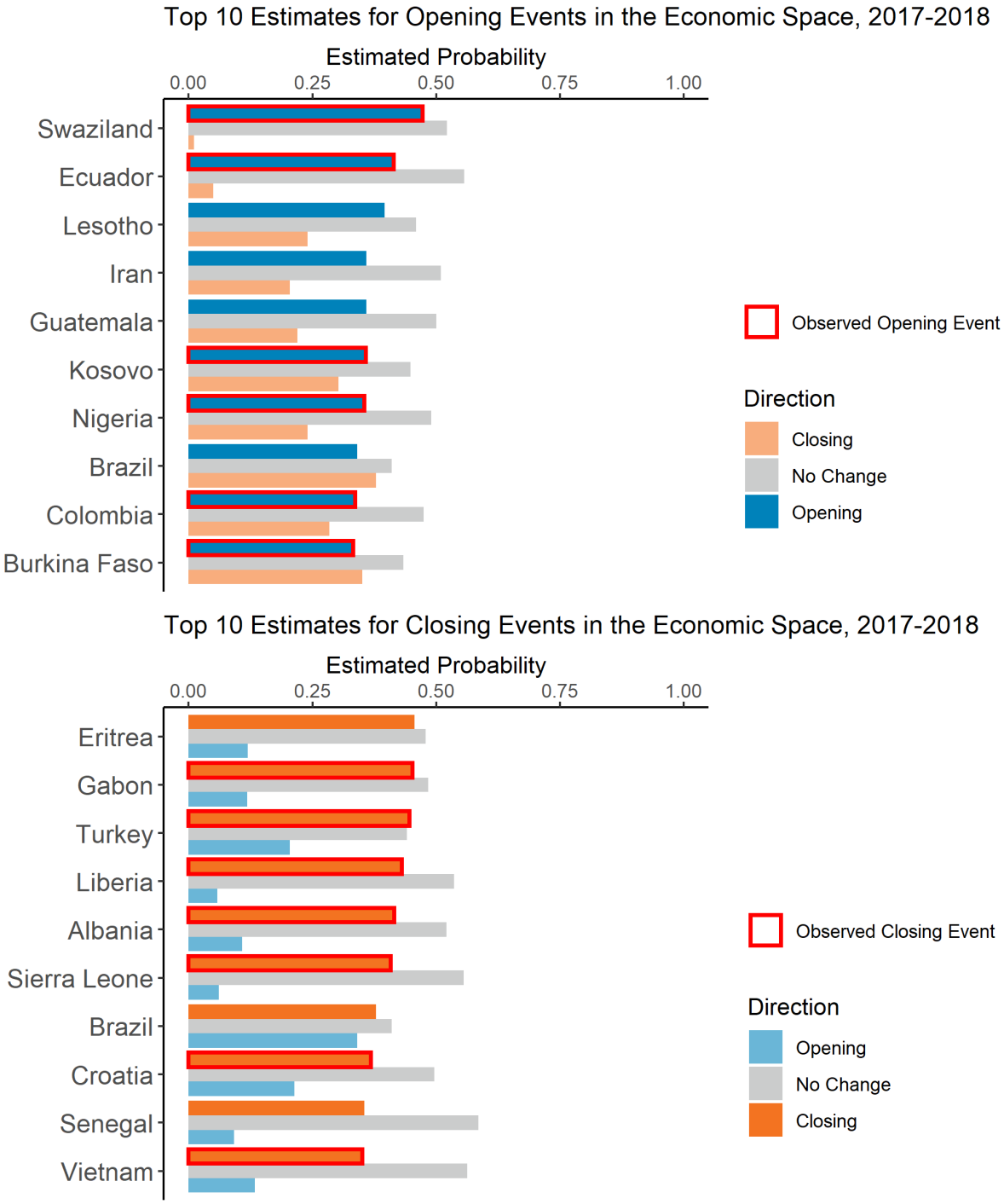


Figure 45: Test year estimates for the economic space, 2017–2018.



Electoral

Figure 46: Test year estimates for the electoral space, 2006–2007.

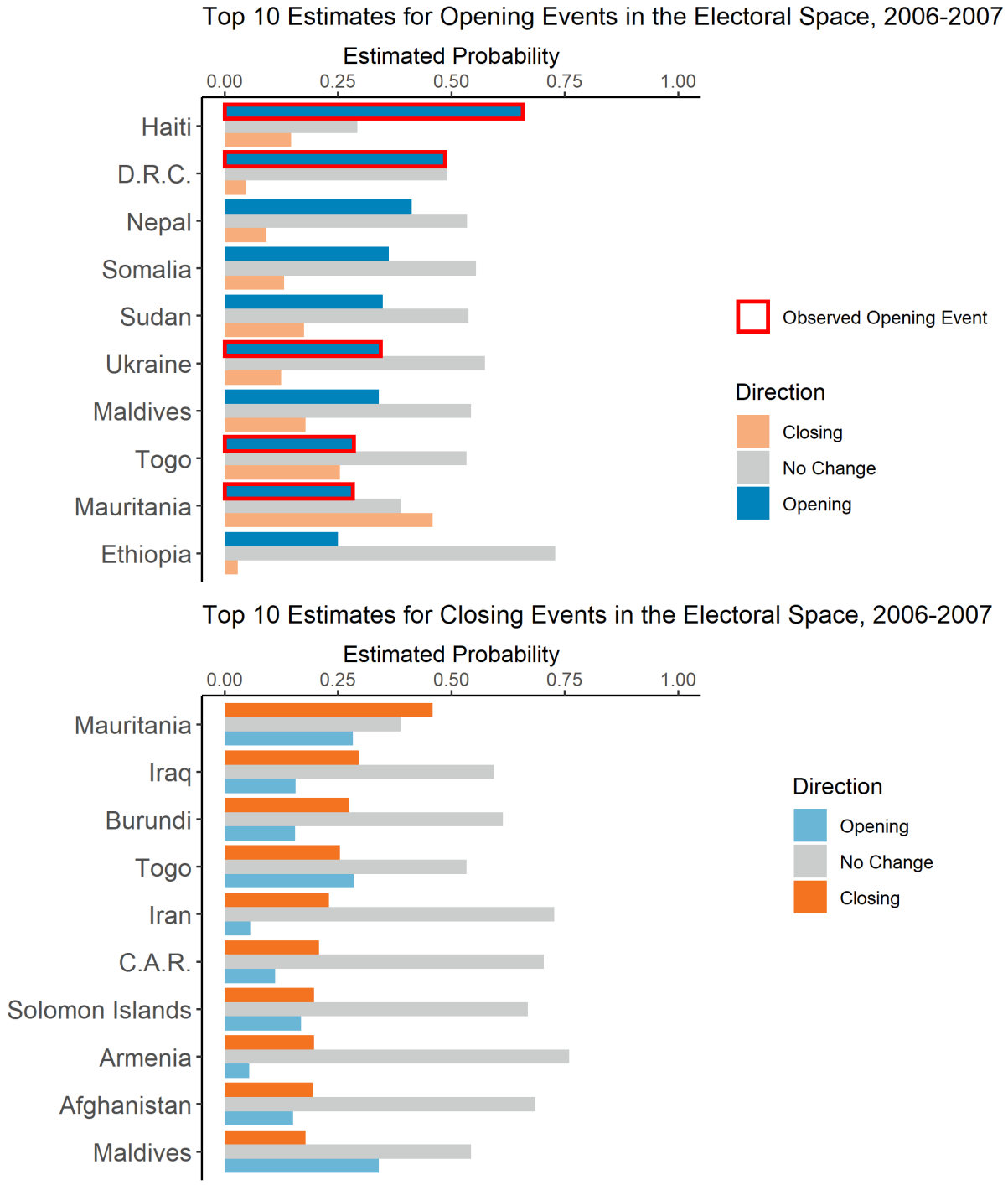


Figure 47: Test year estimates for the electoral space, 2007–2008.

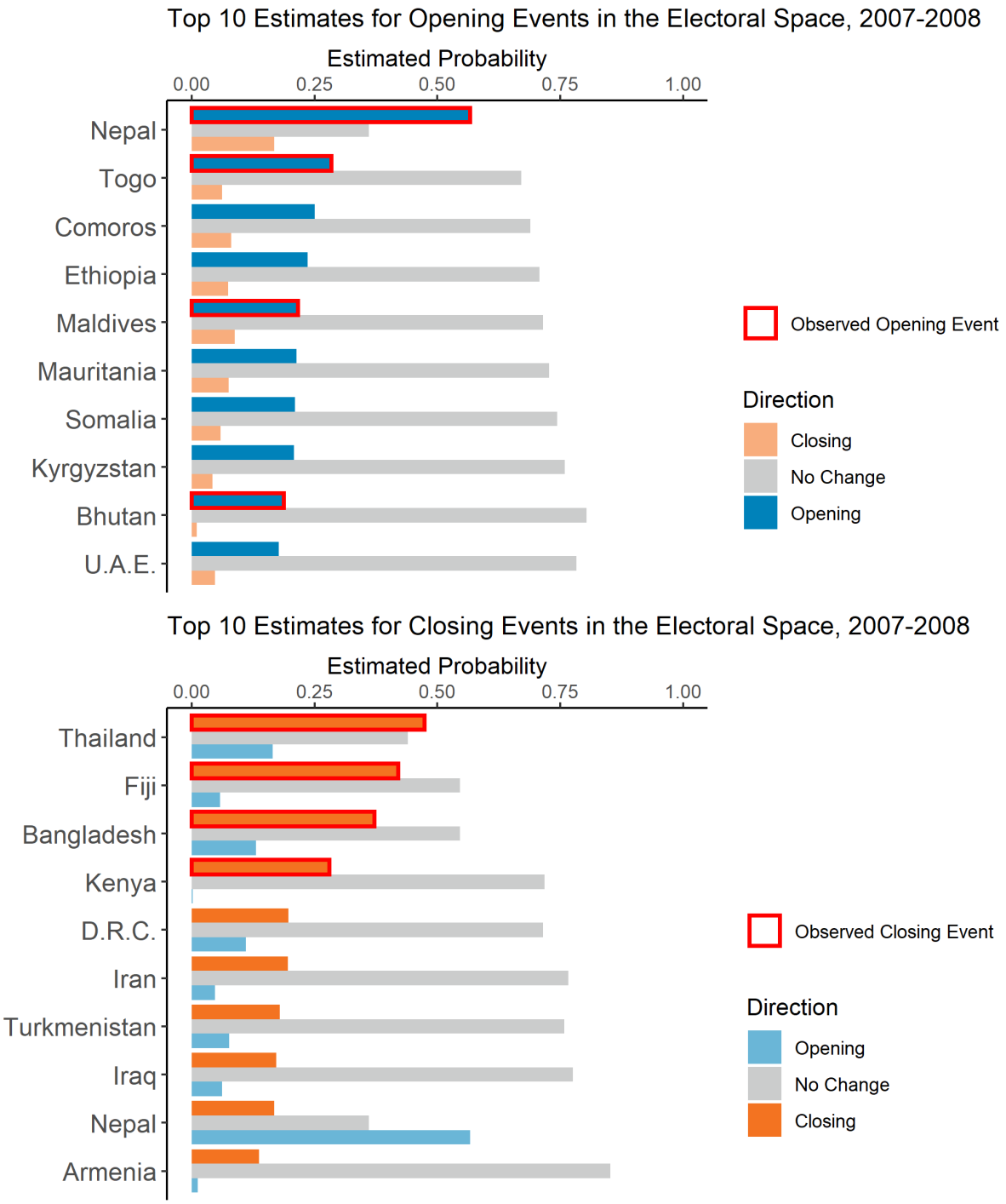


Figure 48: Test year estimates for the electoral space, 2008–2009.

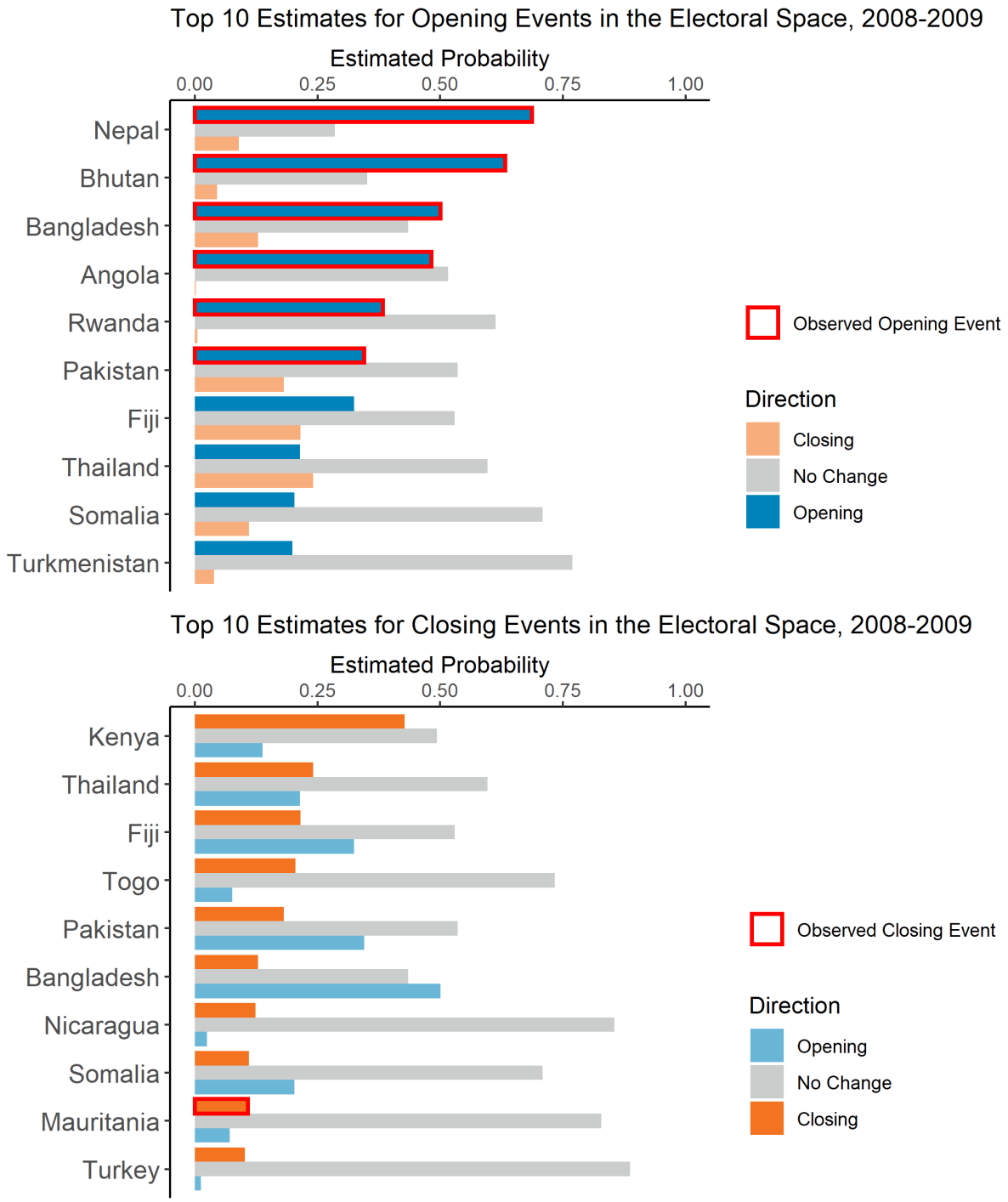


Figure 49: Test year estimates for the electoral space, 2009–2010.

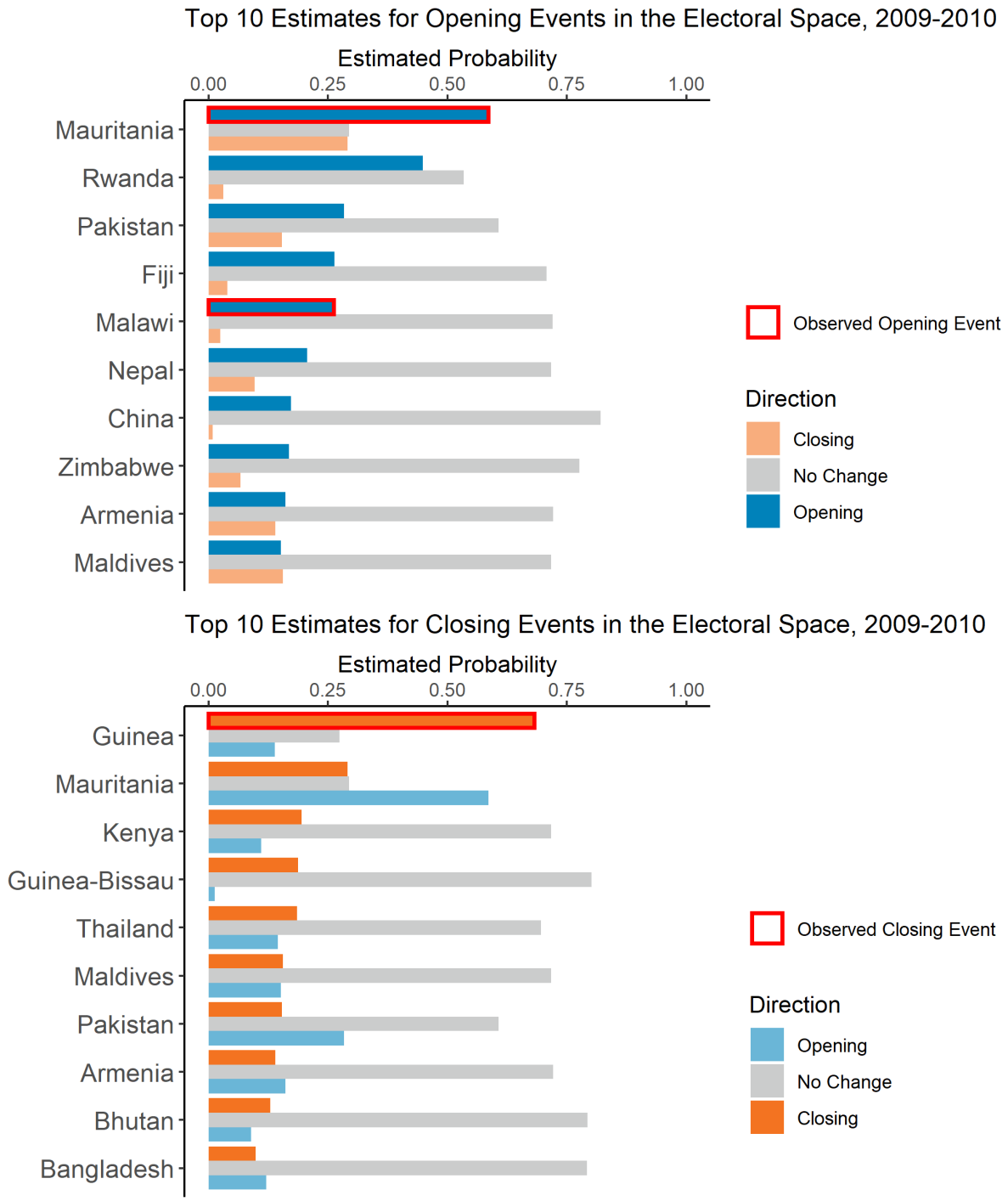


Figure 50: Test year estimates for the electoral space, 2010–2011.

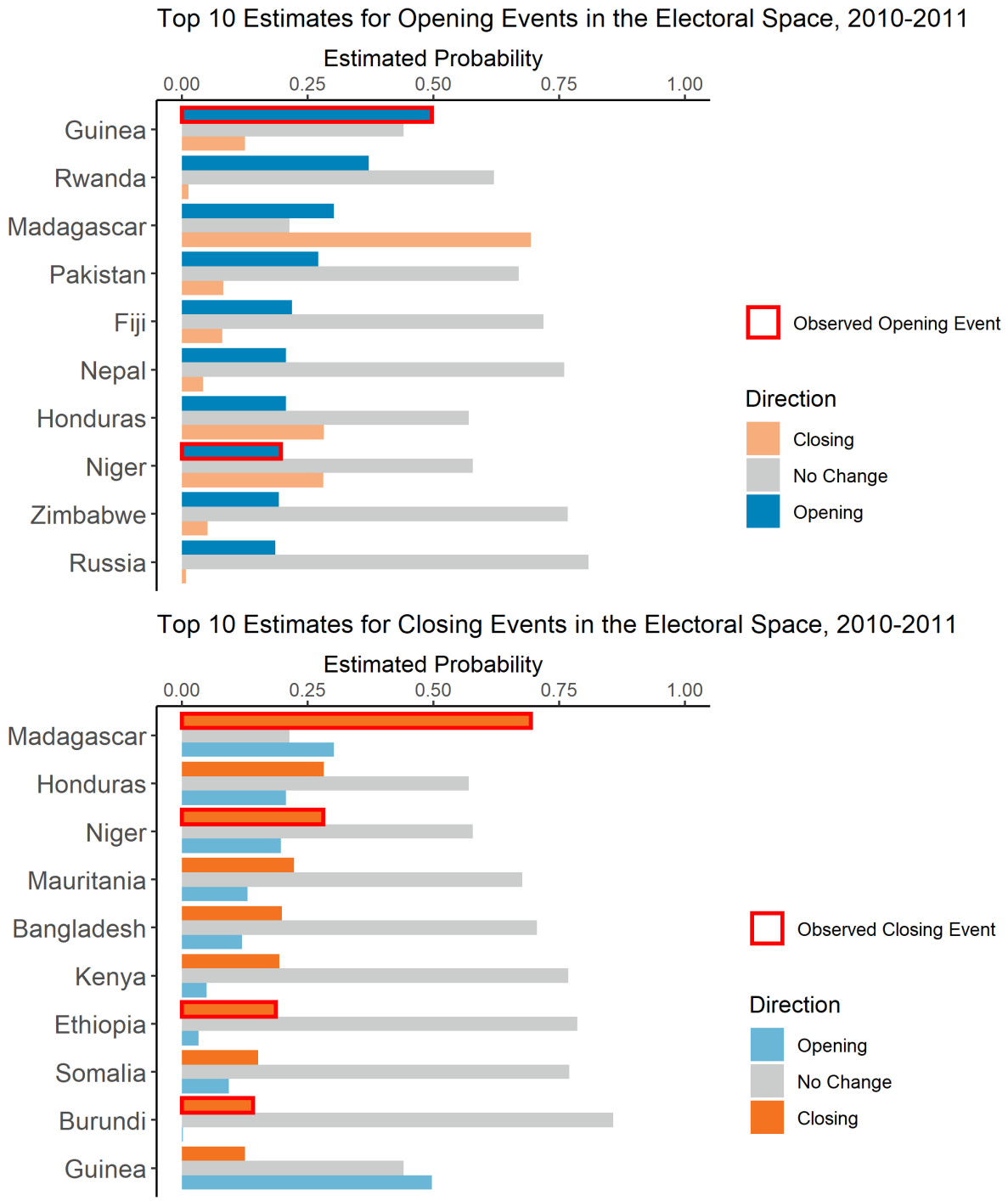


Figure 51: Test year estimates for the electoral space, 2011–2012.

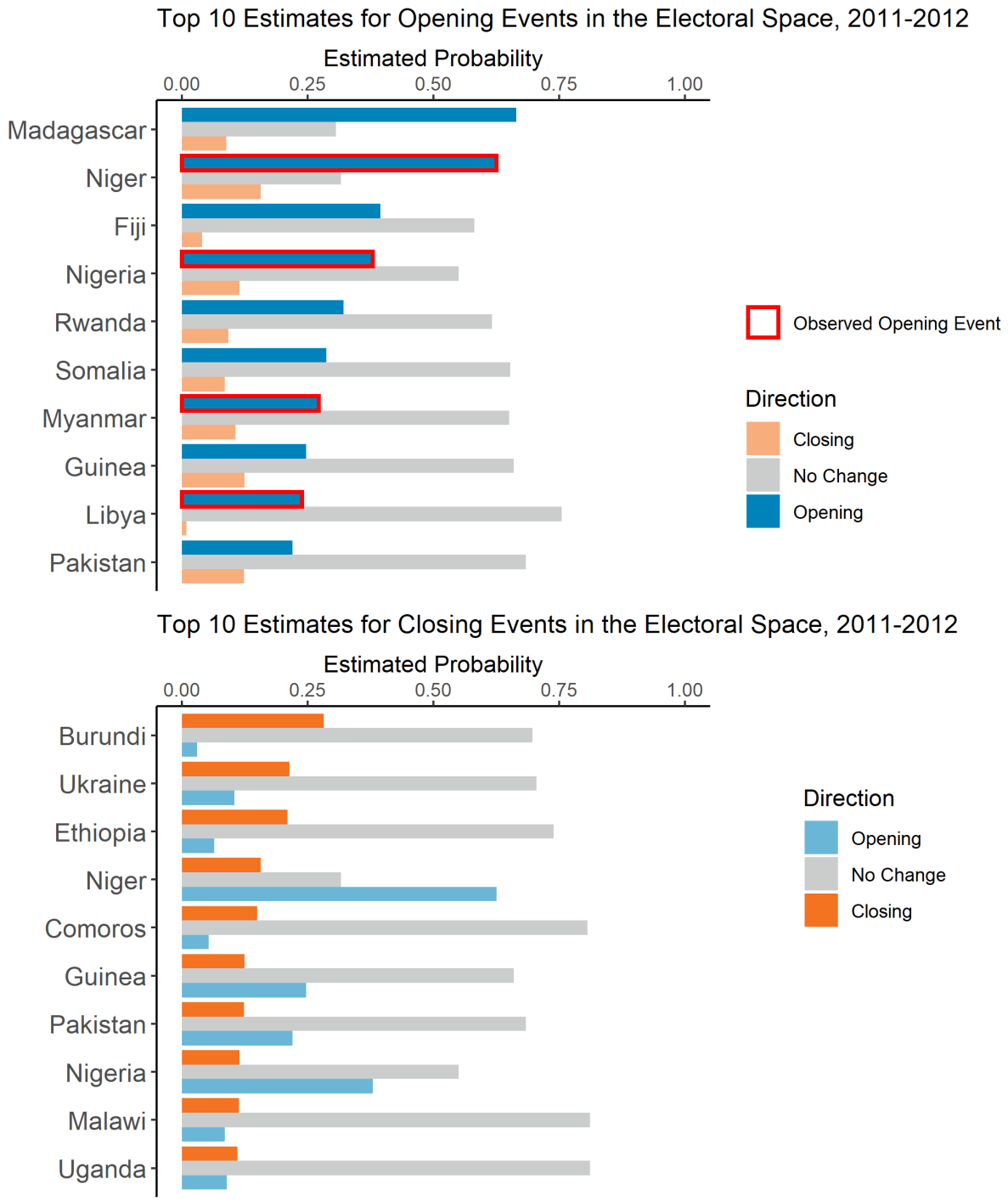


Figure 52: Test year estimates for the electoral space, 2012–2013.

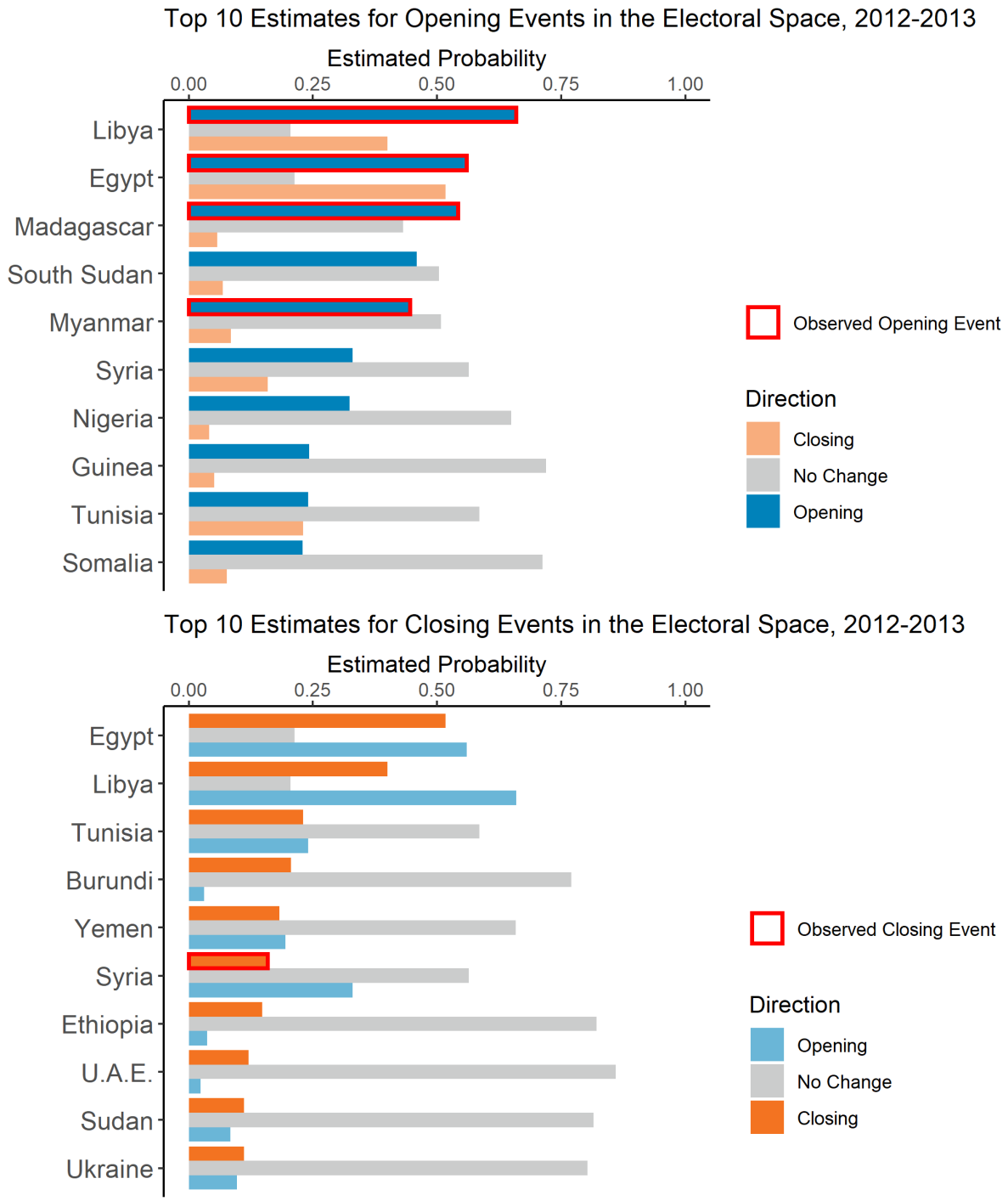


Figure 53: Test year estimates for the electoral space, 2013–2014.

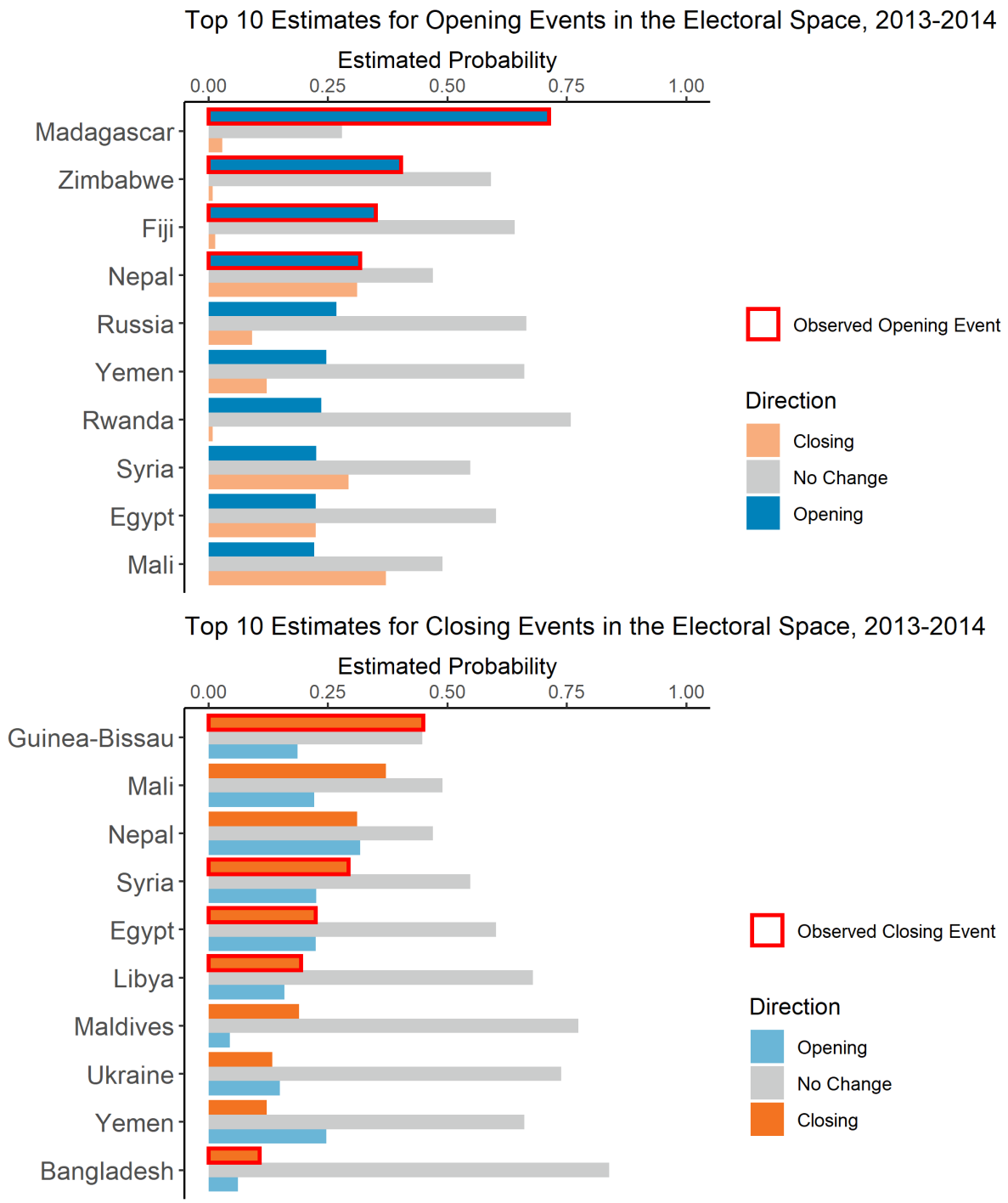


Figure 54: Test year estimates for the electoral space, 2014–2015.

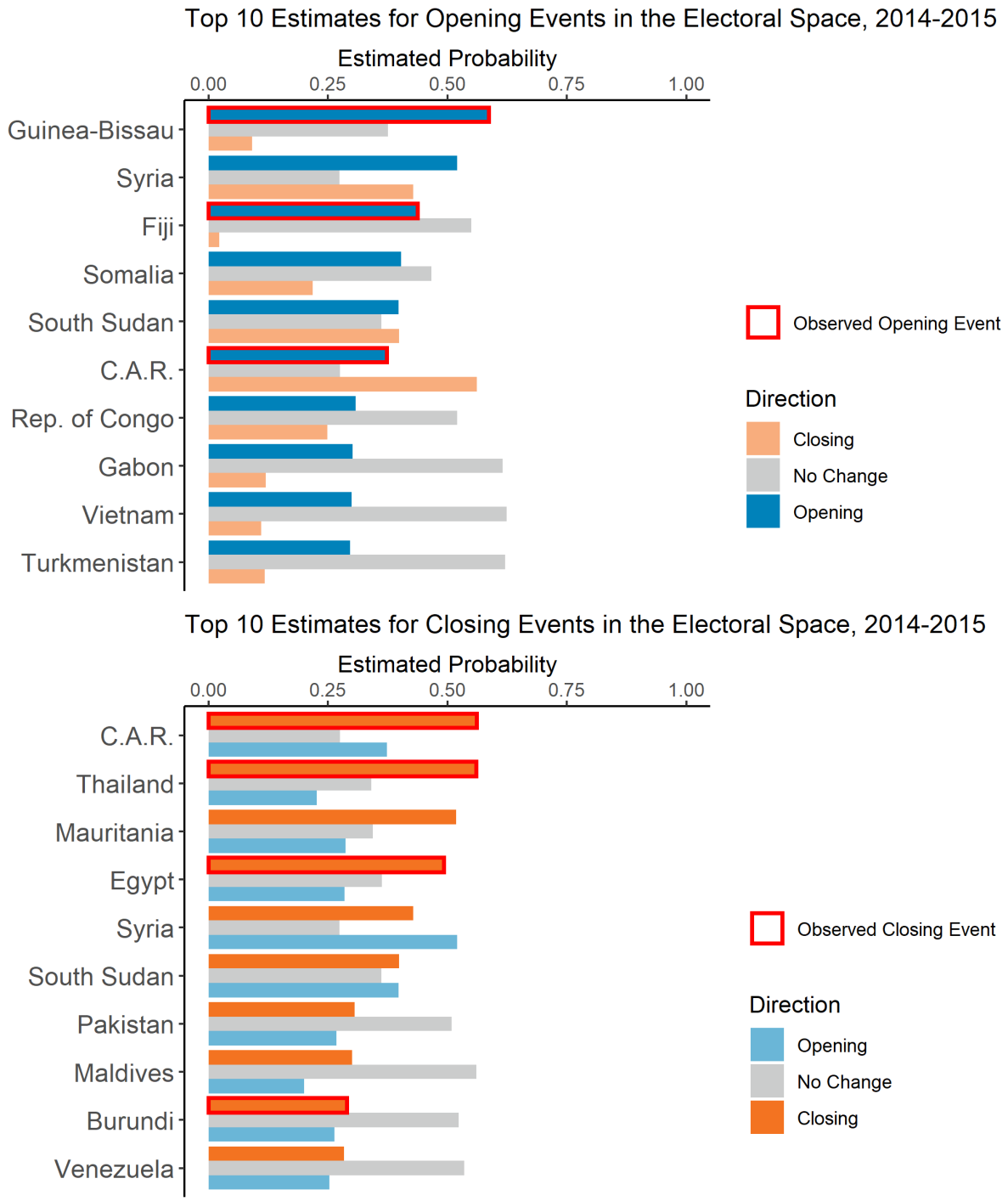


Figure 55: Test year estimates for the electoral space, 2015–2016.

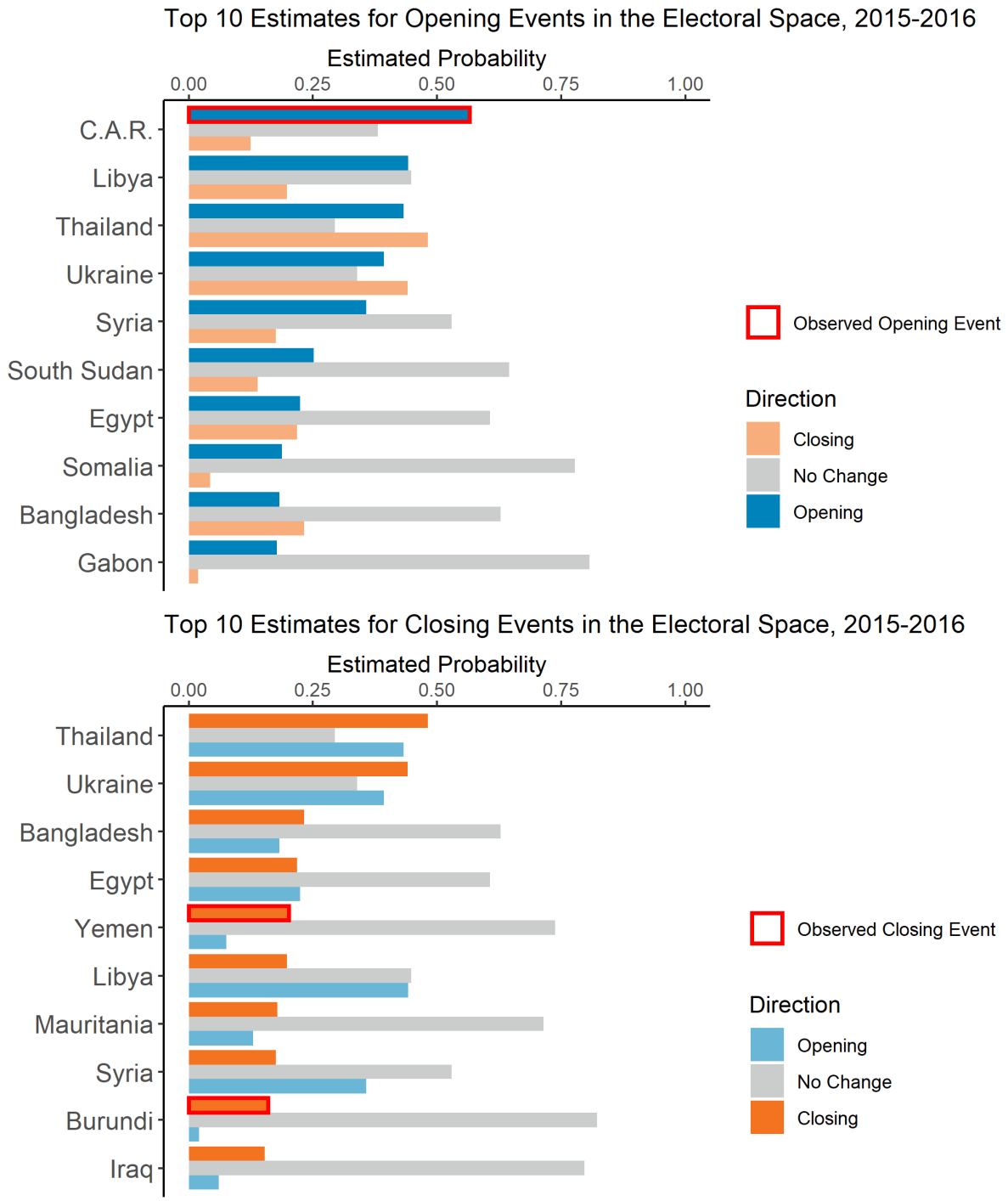


Figure 56: Test year estimates for the electoral space, 2016–2017.

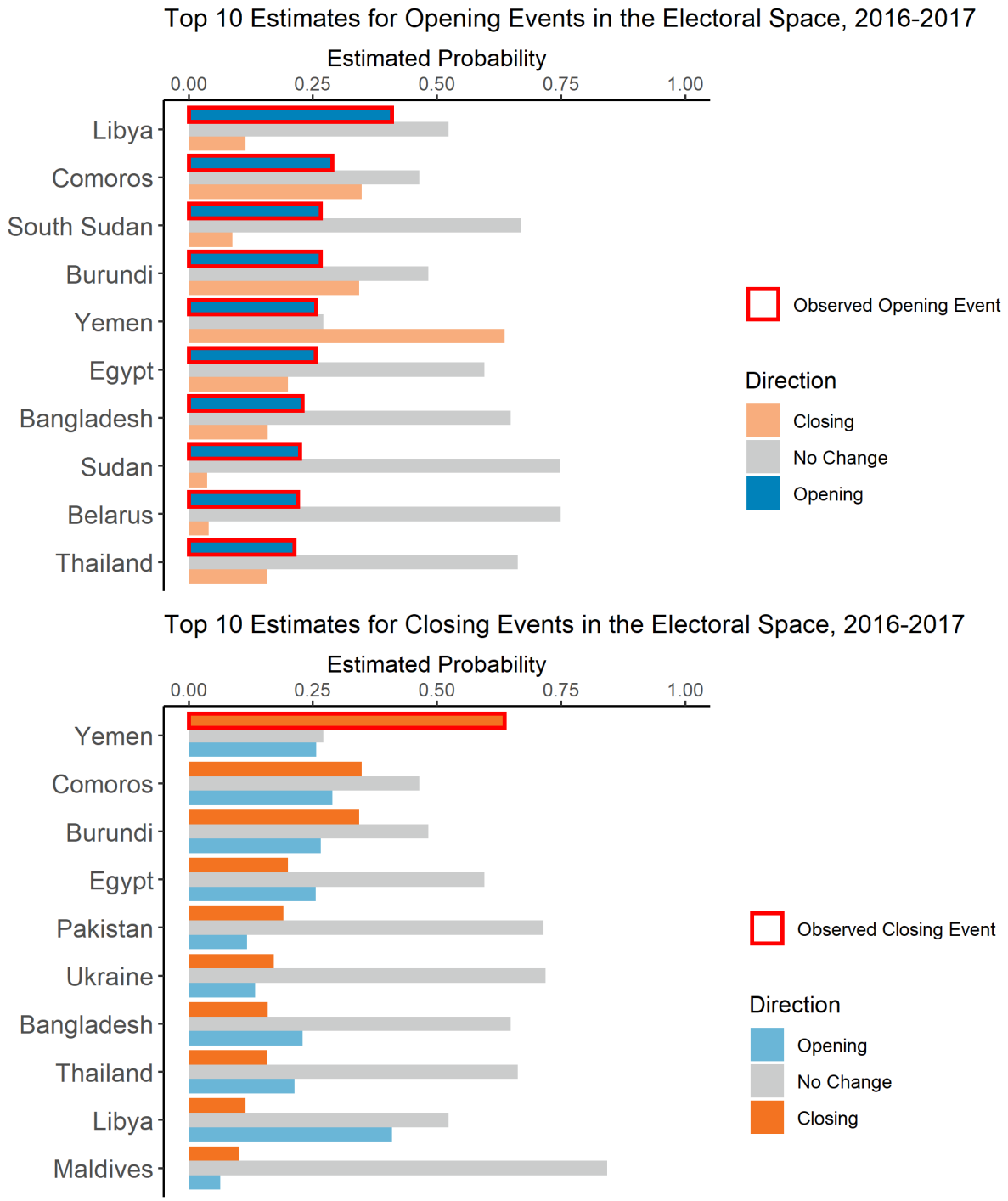
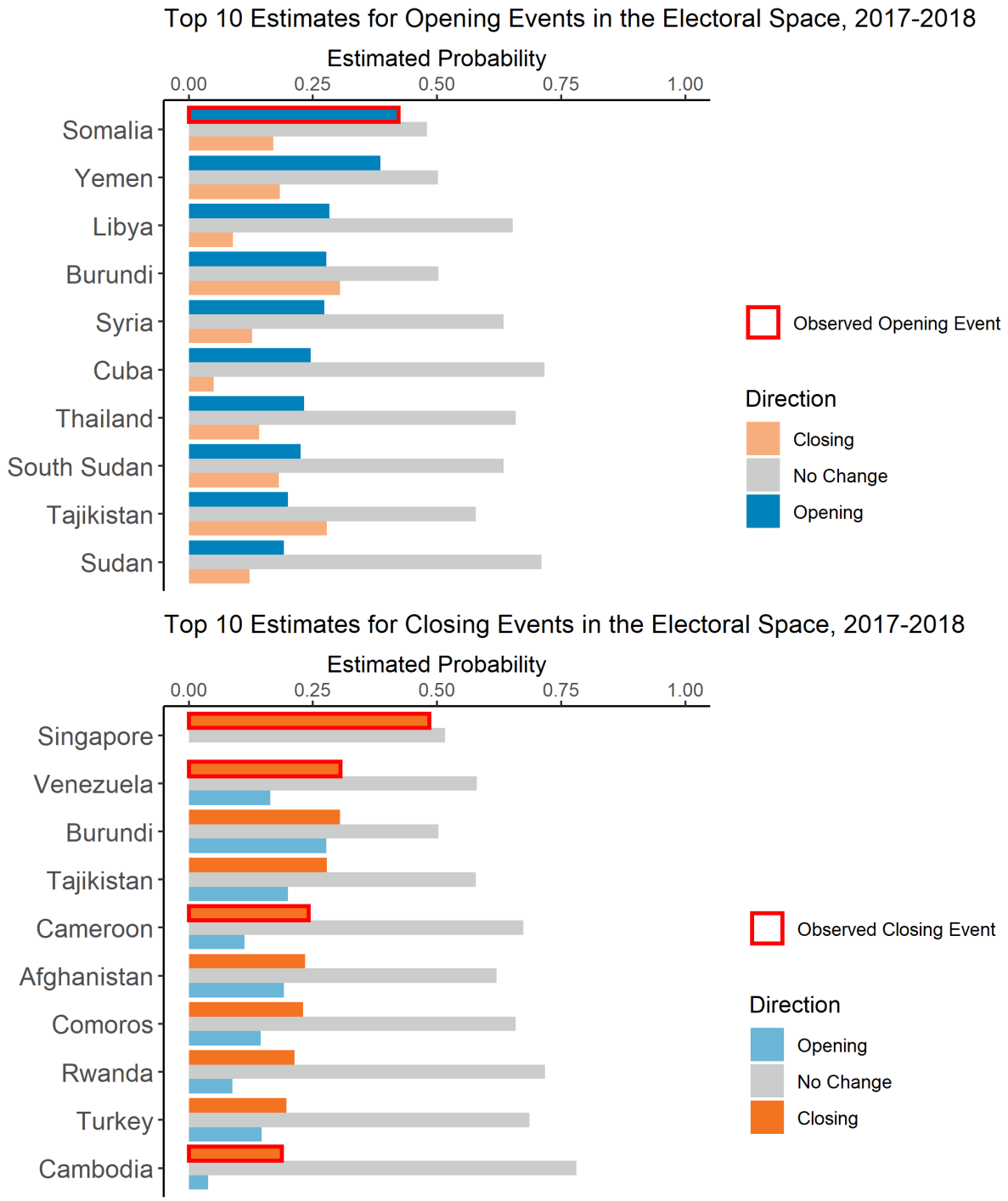


Figure 57: Test year estimates for the electoral space, 2017–2018.



Governing

Figure 58: Test year estimates for the governing space, 2006–2007.

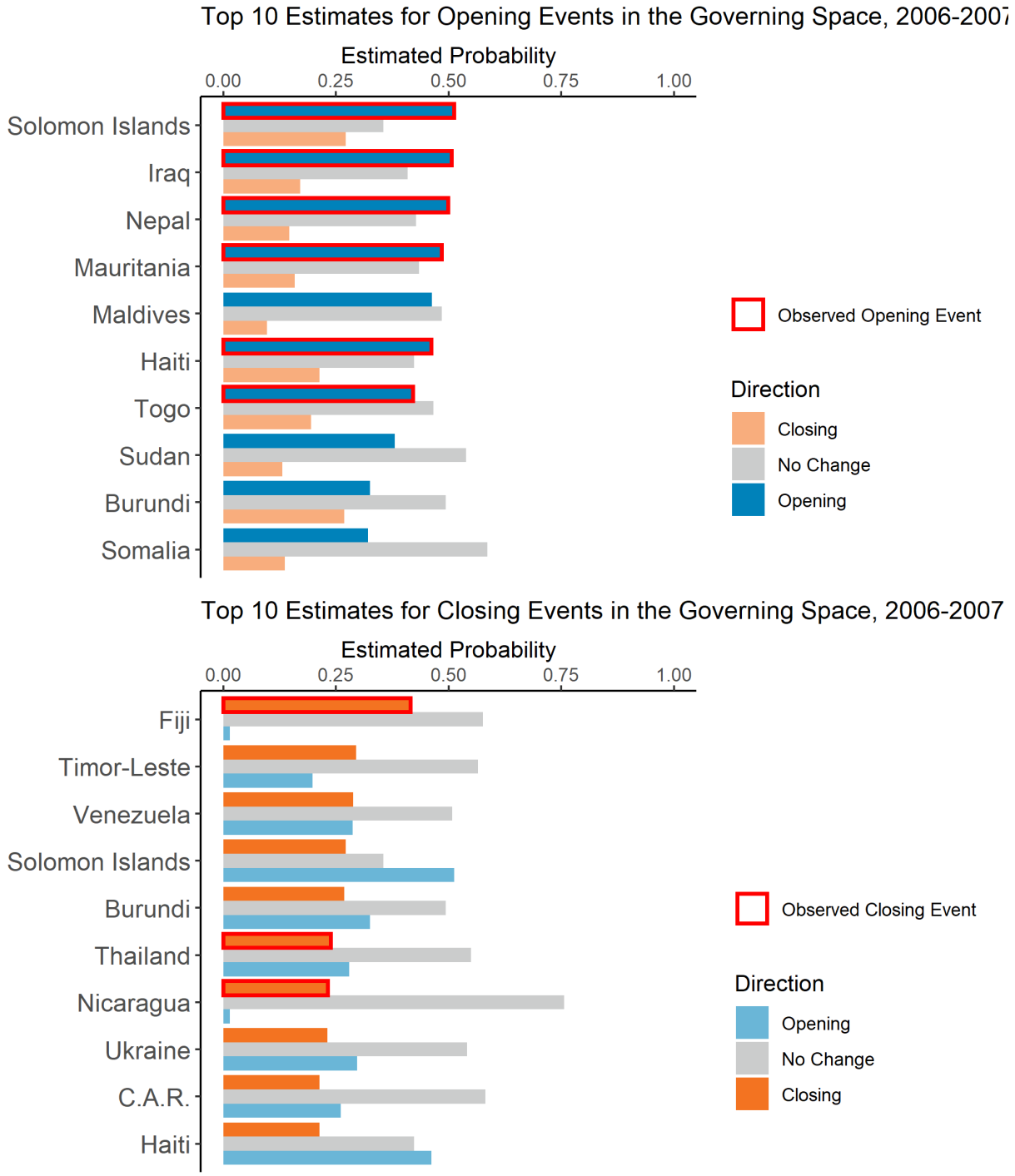


Figure 59: Test year estimates for the governing space, 2007–2008.

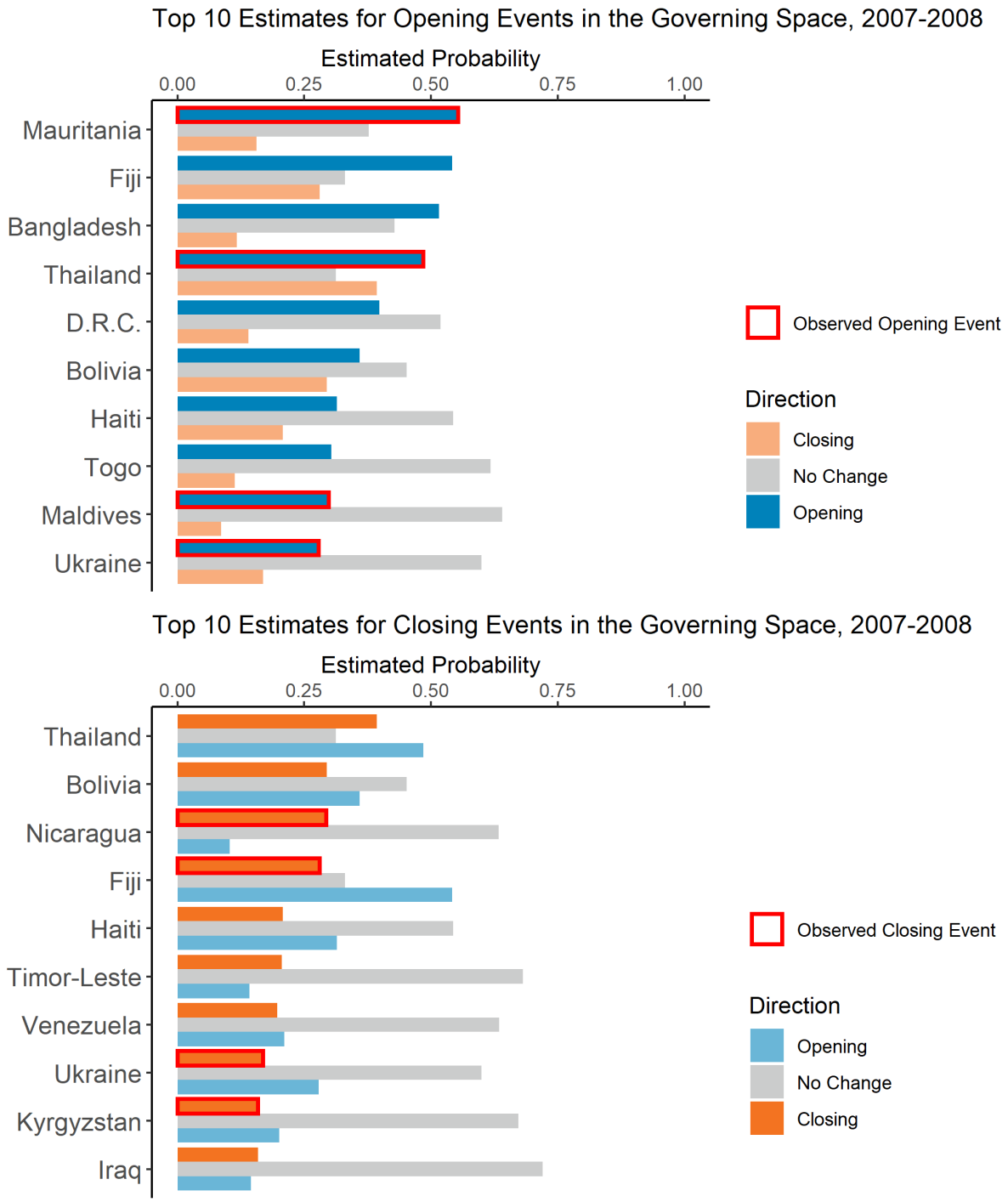


Figure 60: Test year estimates for the governing space, 2008–2009.

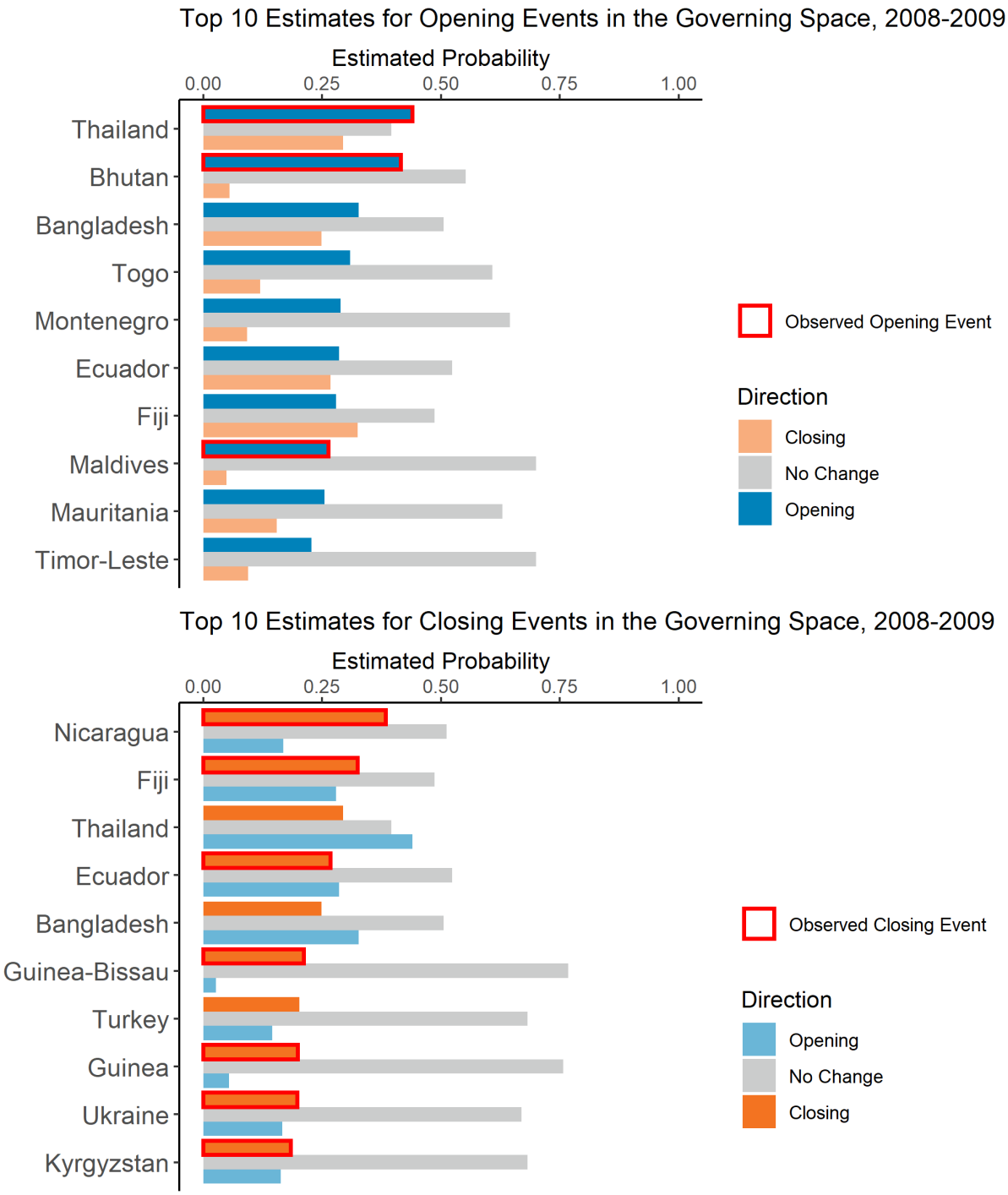


Figure 61: Test year estimates for the governing space, 2009–2010.

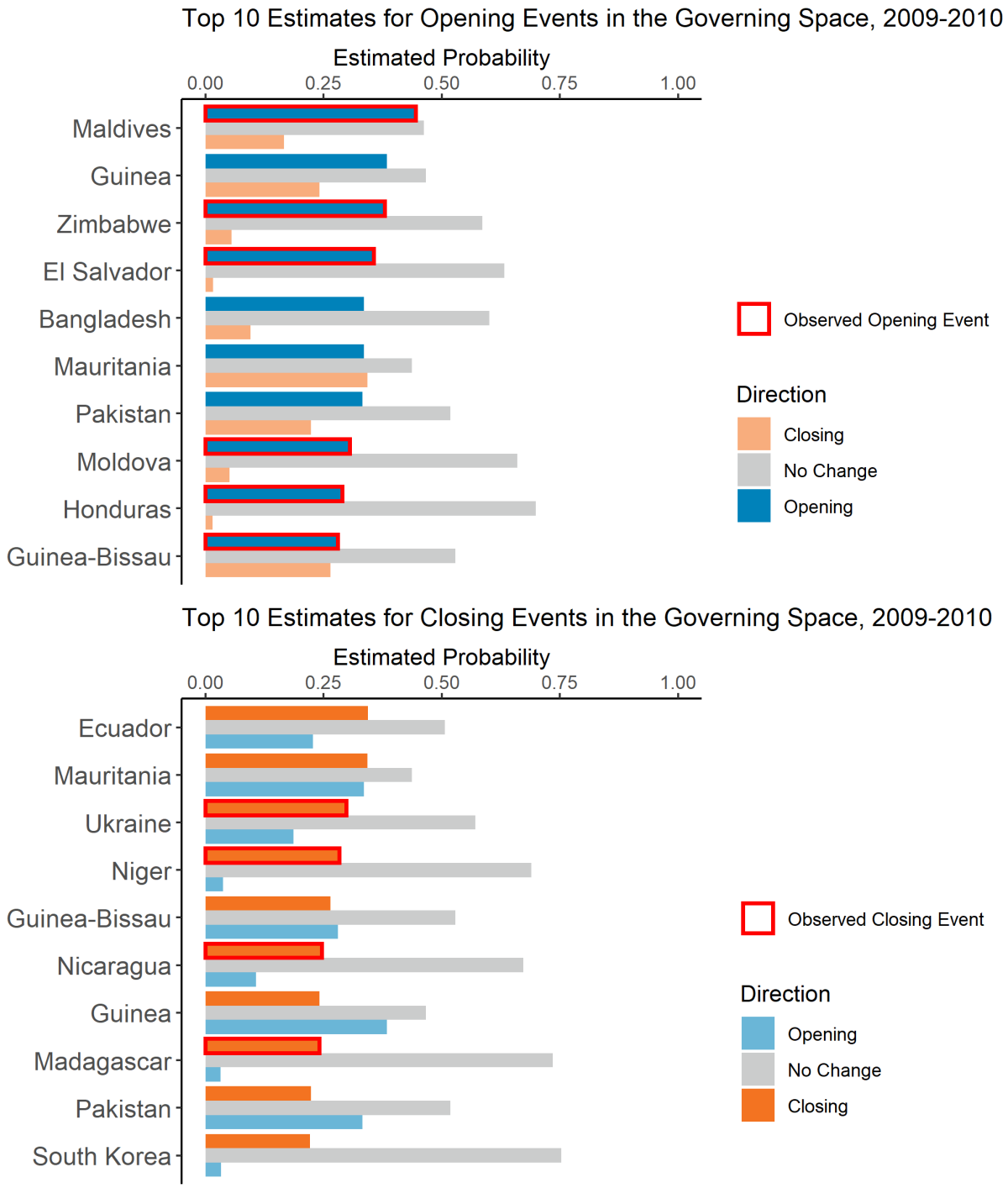


Figure 62: Test year estimates for the governing space, 2010–2011.

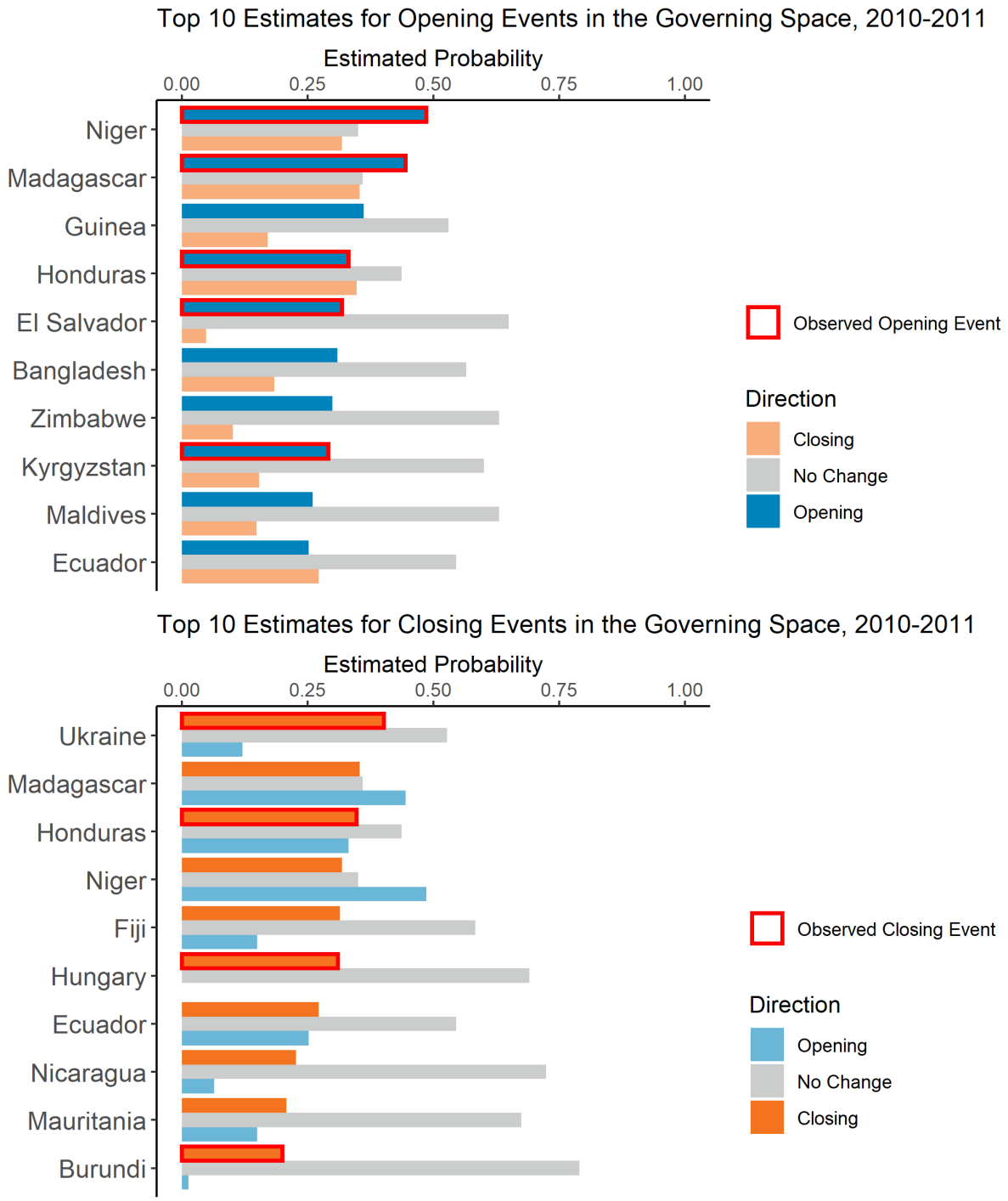


Figure 63: Test year estimates for the governing space, 2011–2012.

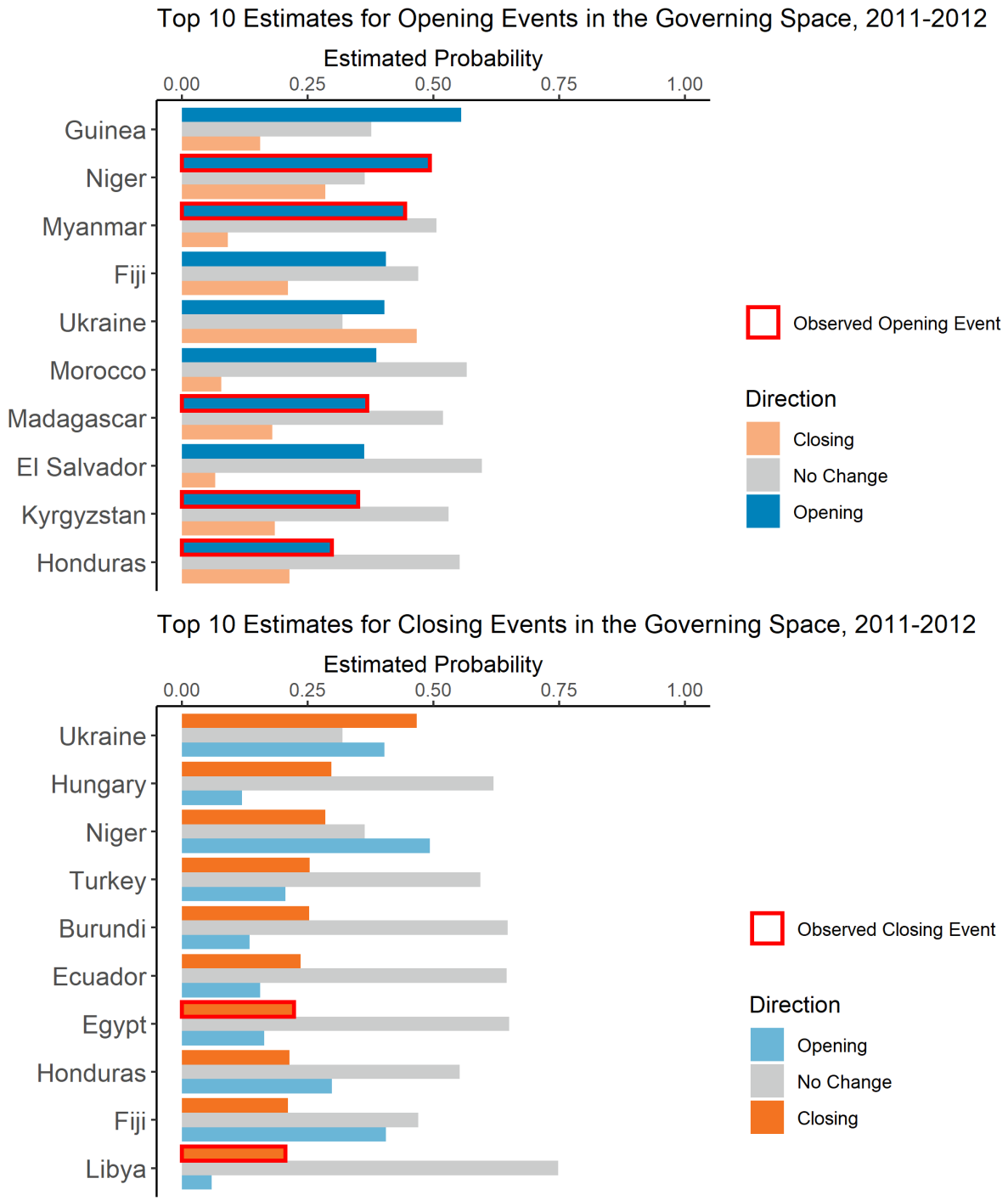


Figure 64: Test year estimates for the governing space, 2012–2013.

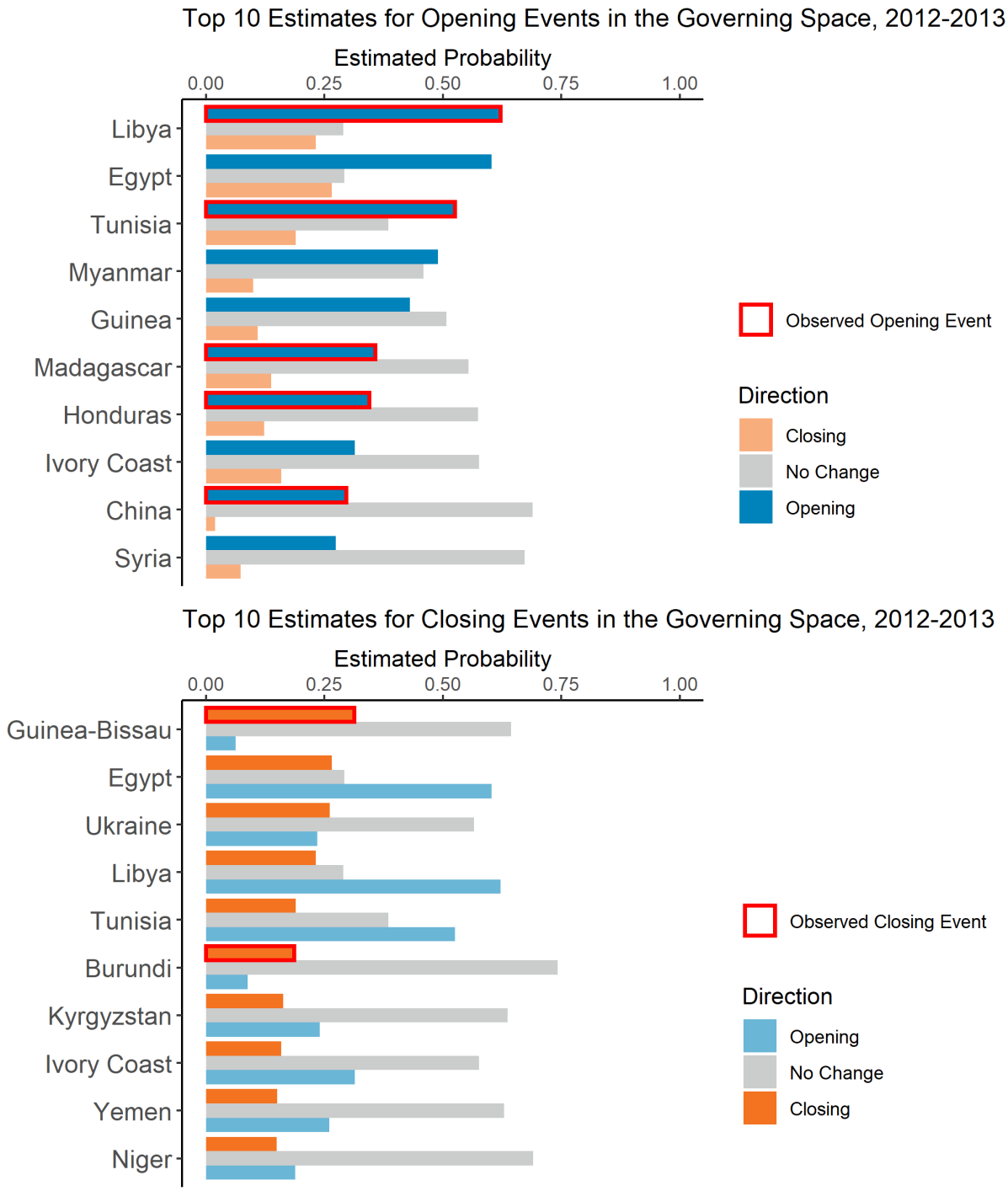


Figure 65: Test year estimates for the governing space, 2013–2014.

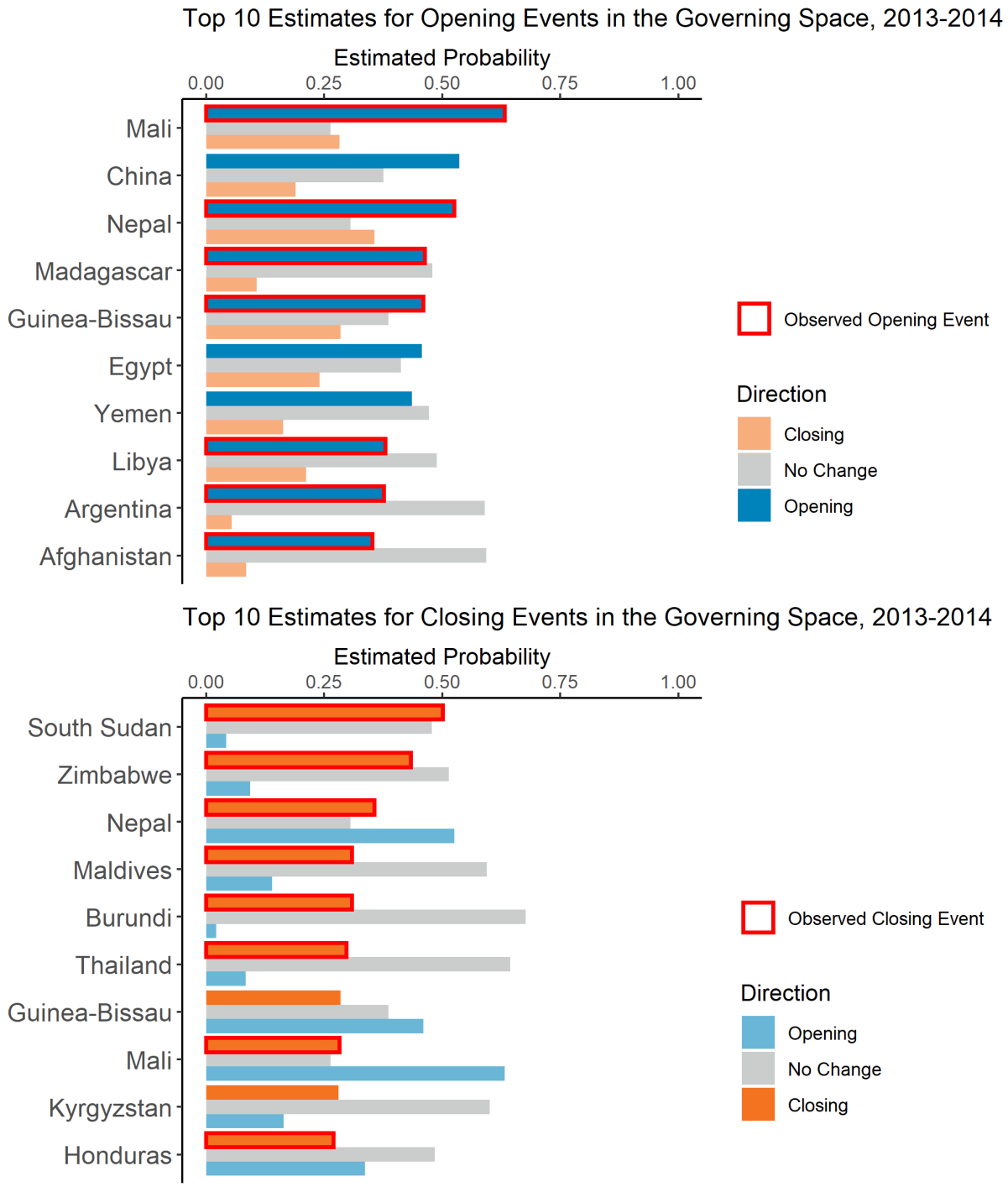


Figure 66: Test year estimates for the governing space, 2014–2015.

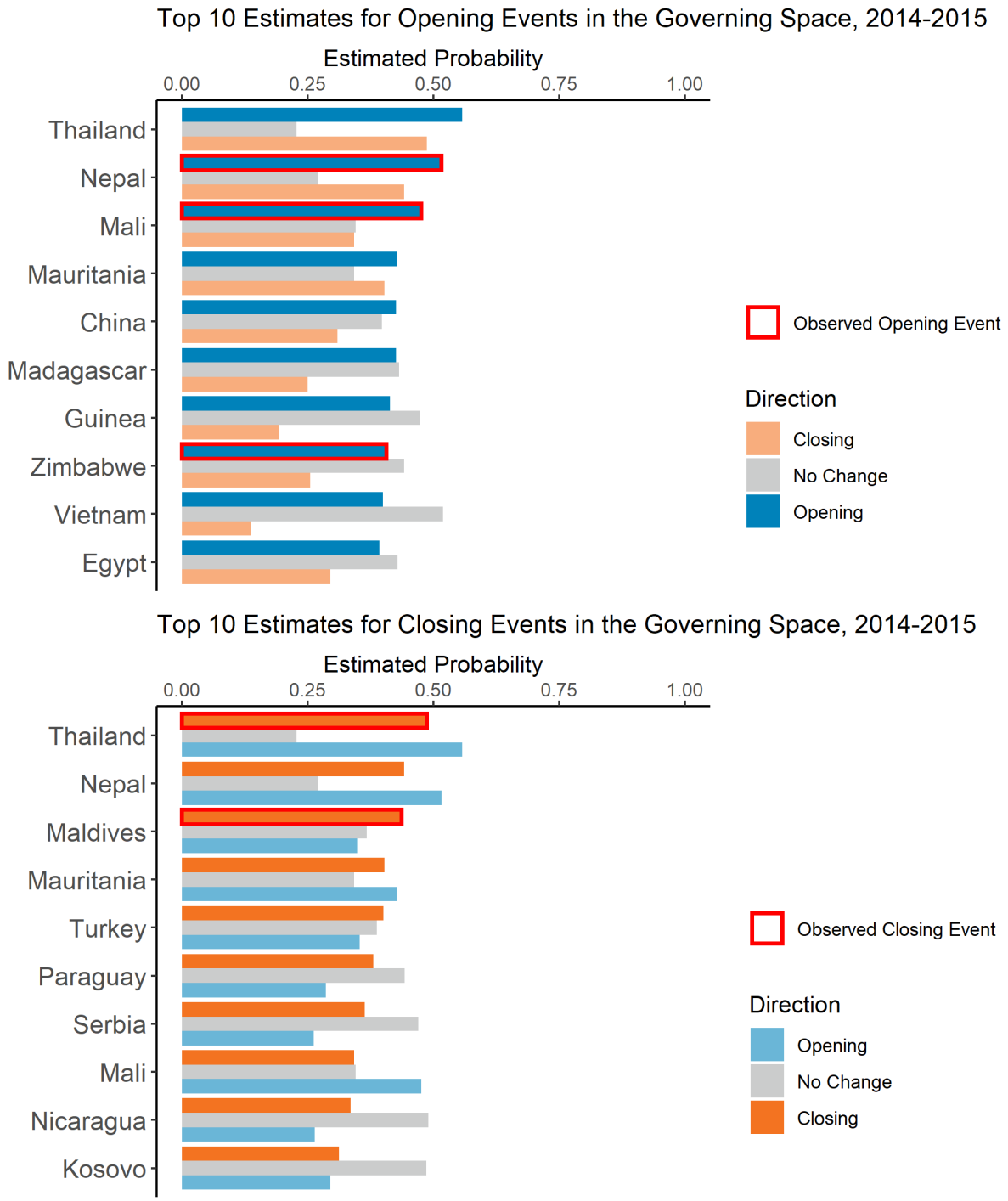


Figure 67: Test year estimates for the governing space, 2015–2016.

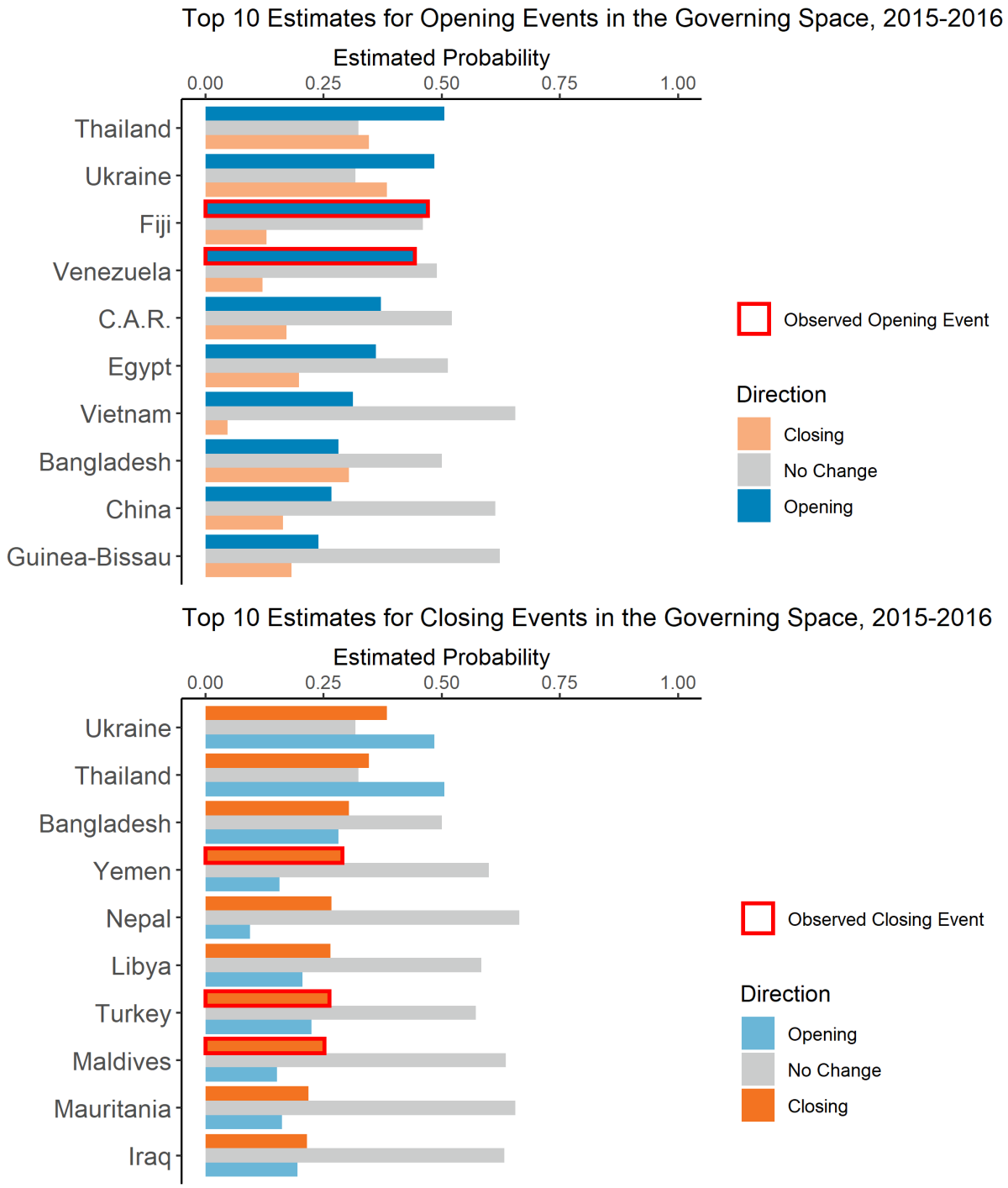


Figure 68: Test year estimates for the governing space, 2016–2017.

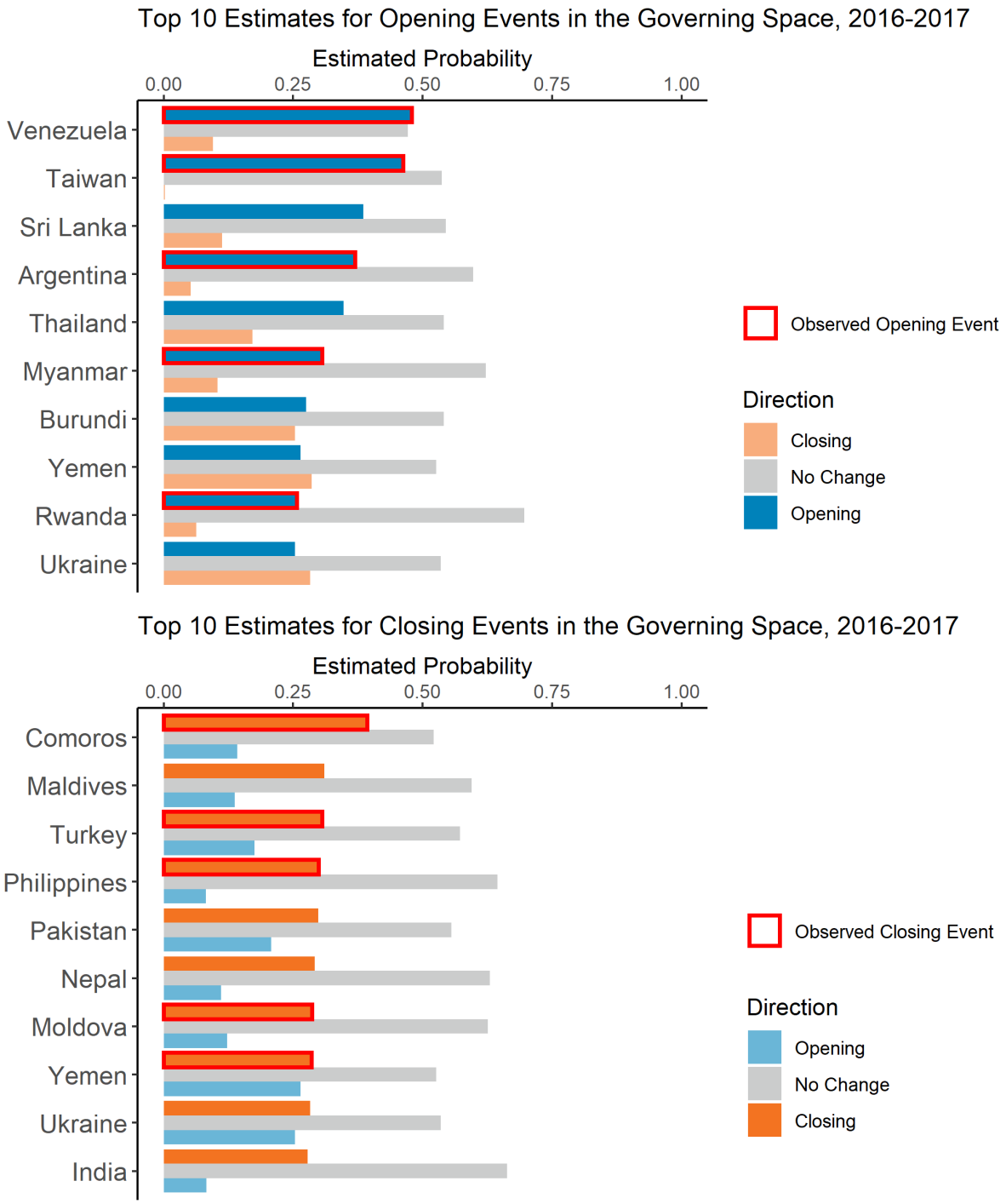
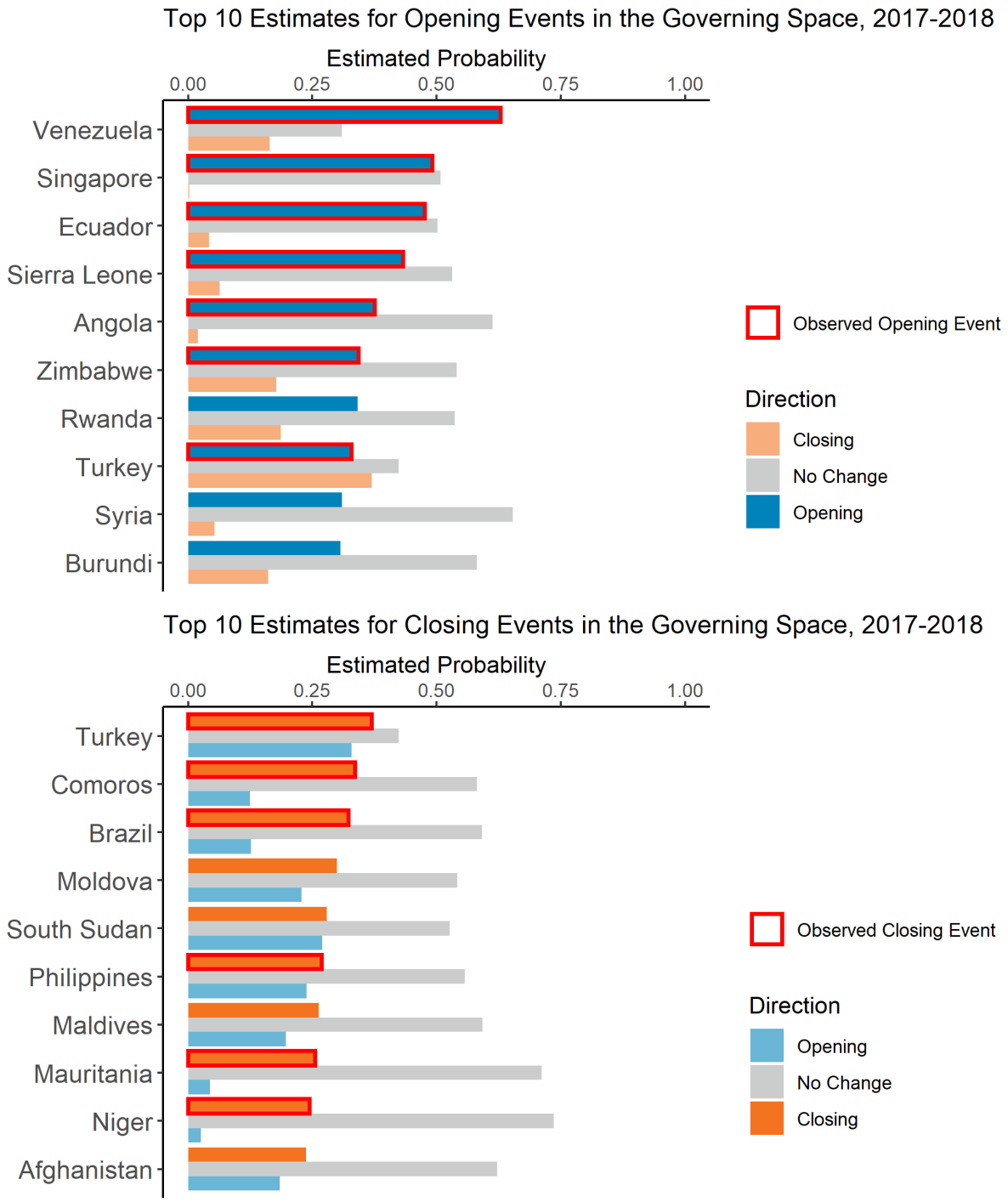


Figure 69: Test year estimates for the governing space, 2017–2018.



Individual

Figure 70: Test year estimates for the individual space, 2006–2007.

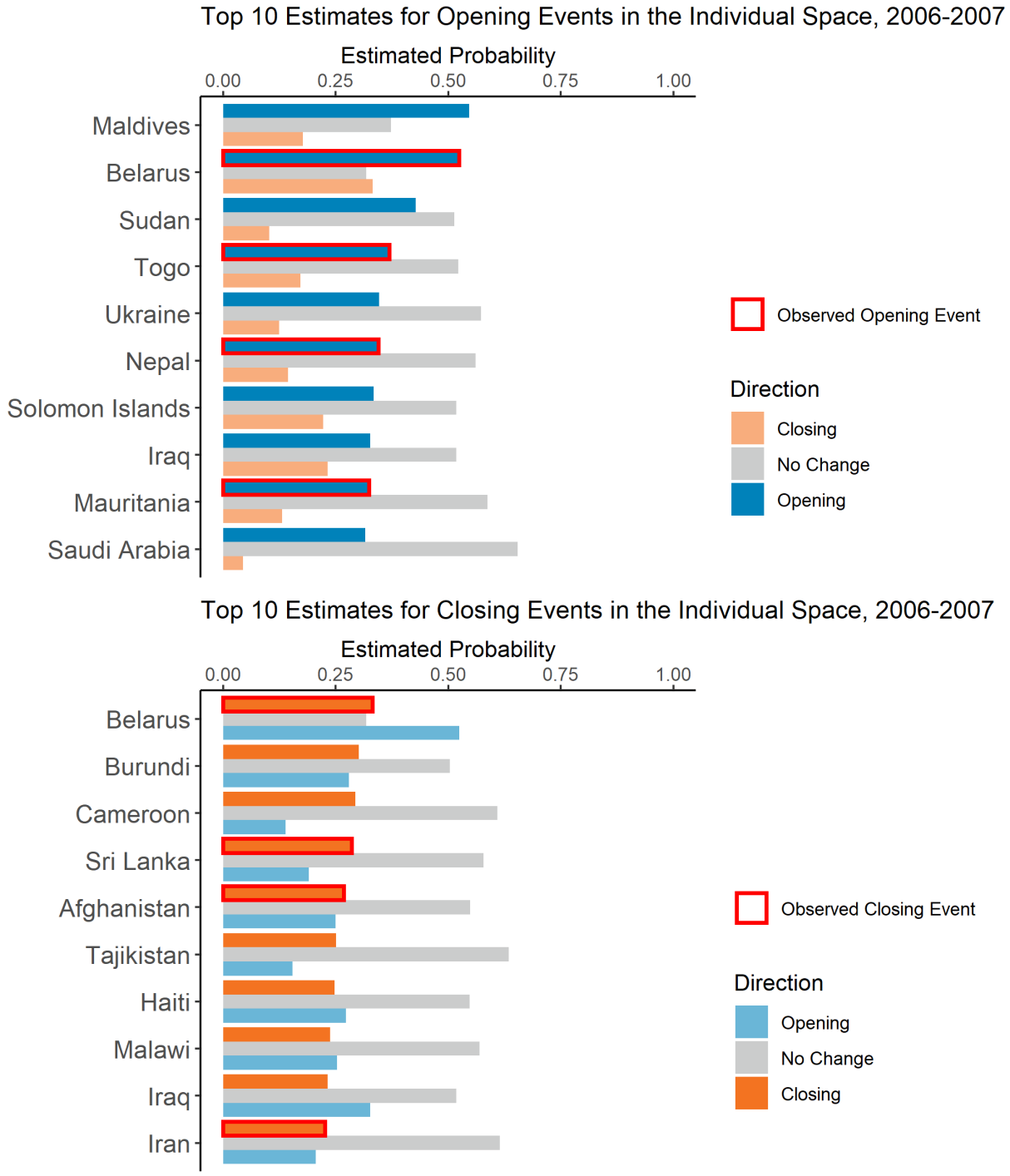


Figure 71: Test year estimates for the individual space, 2007–2008.

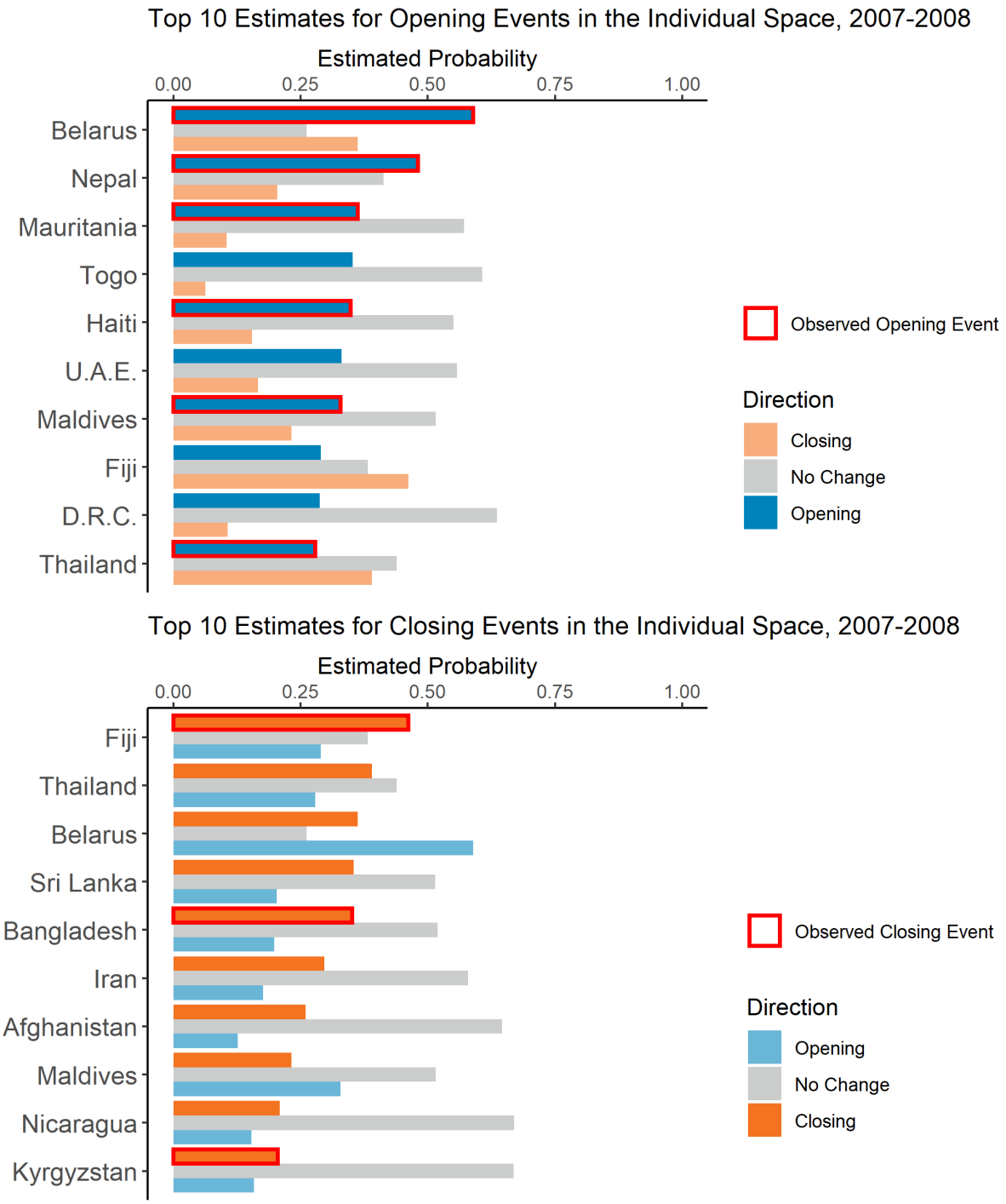


Figure 72: Test year estimates for the individual space, 2008–2009.

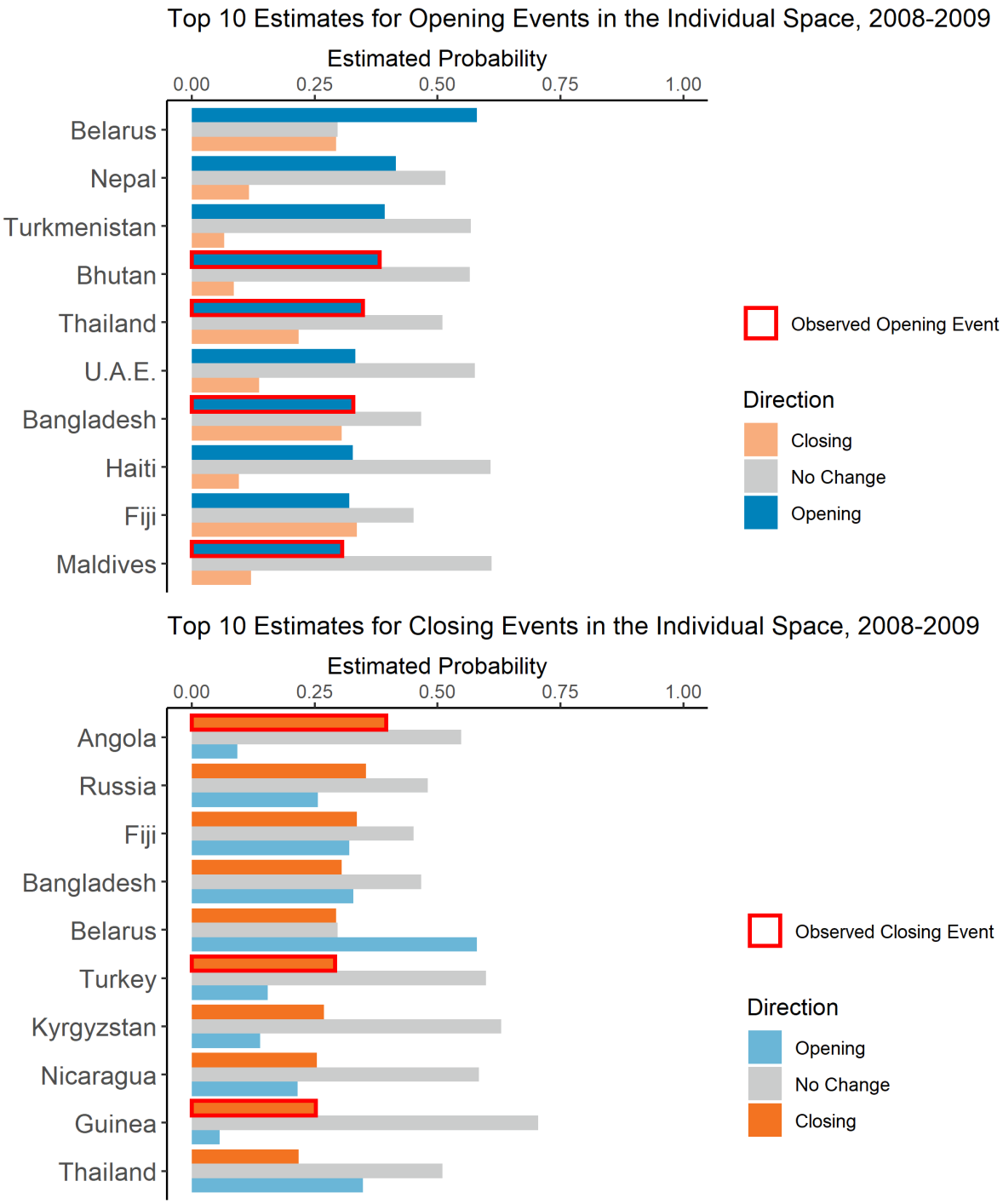


Figure 73: Test year estimates for the individual space, 2009–2010.

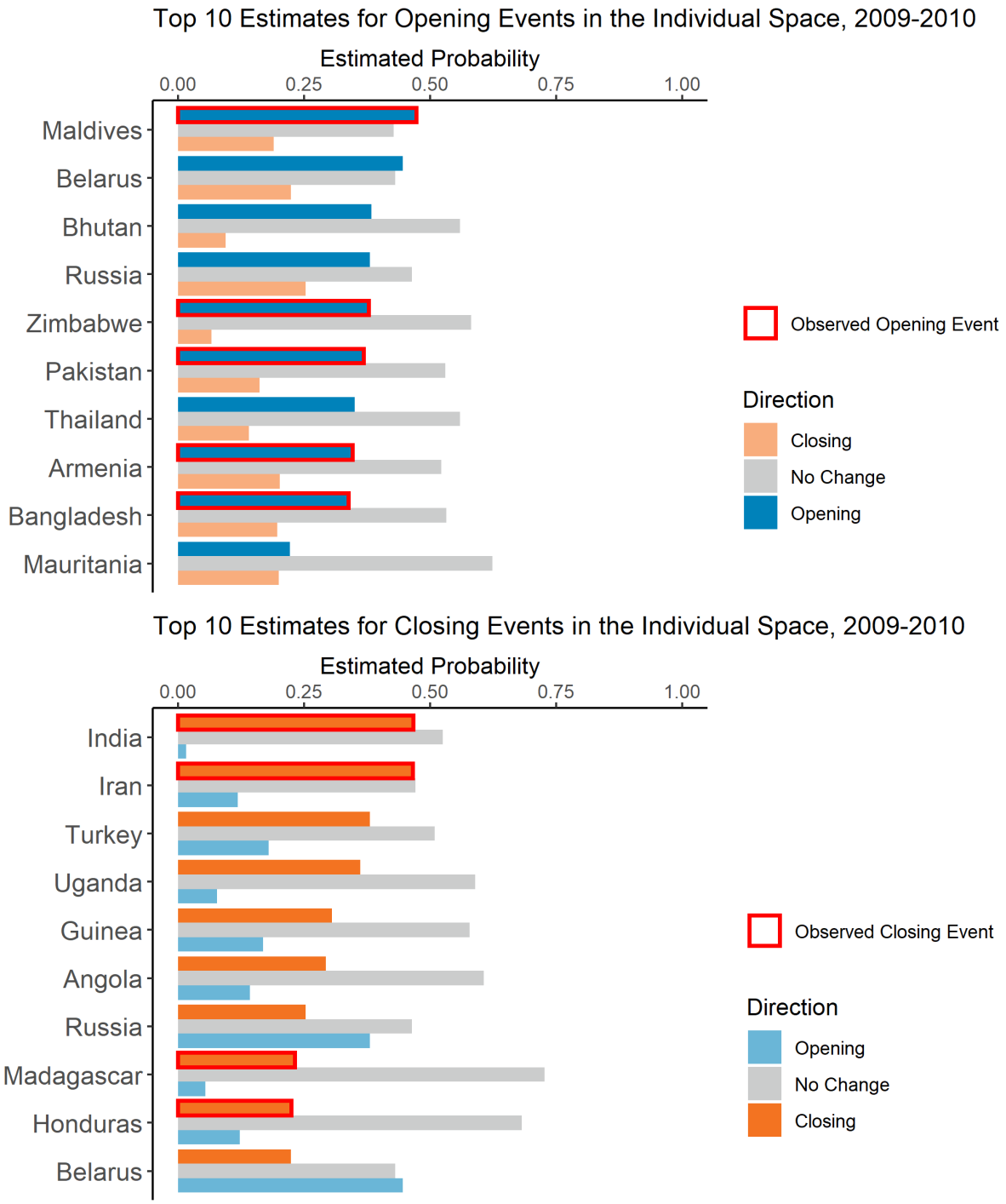


Figure 74: Test year estimates for the individual space, 2010–2011.

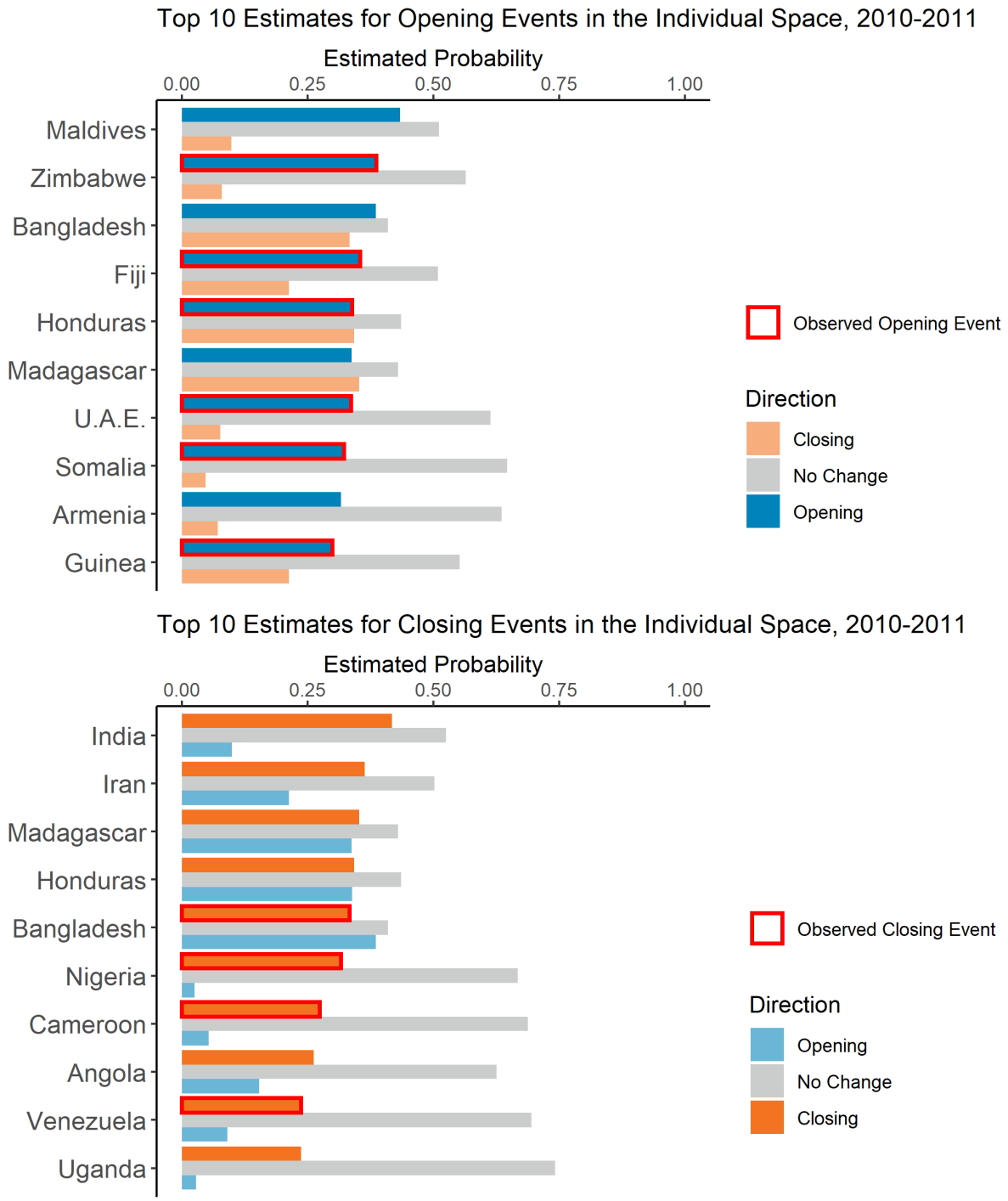


Figure 75: Test year estimates for the individual space, 2011–2012.

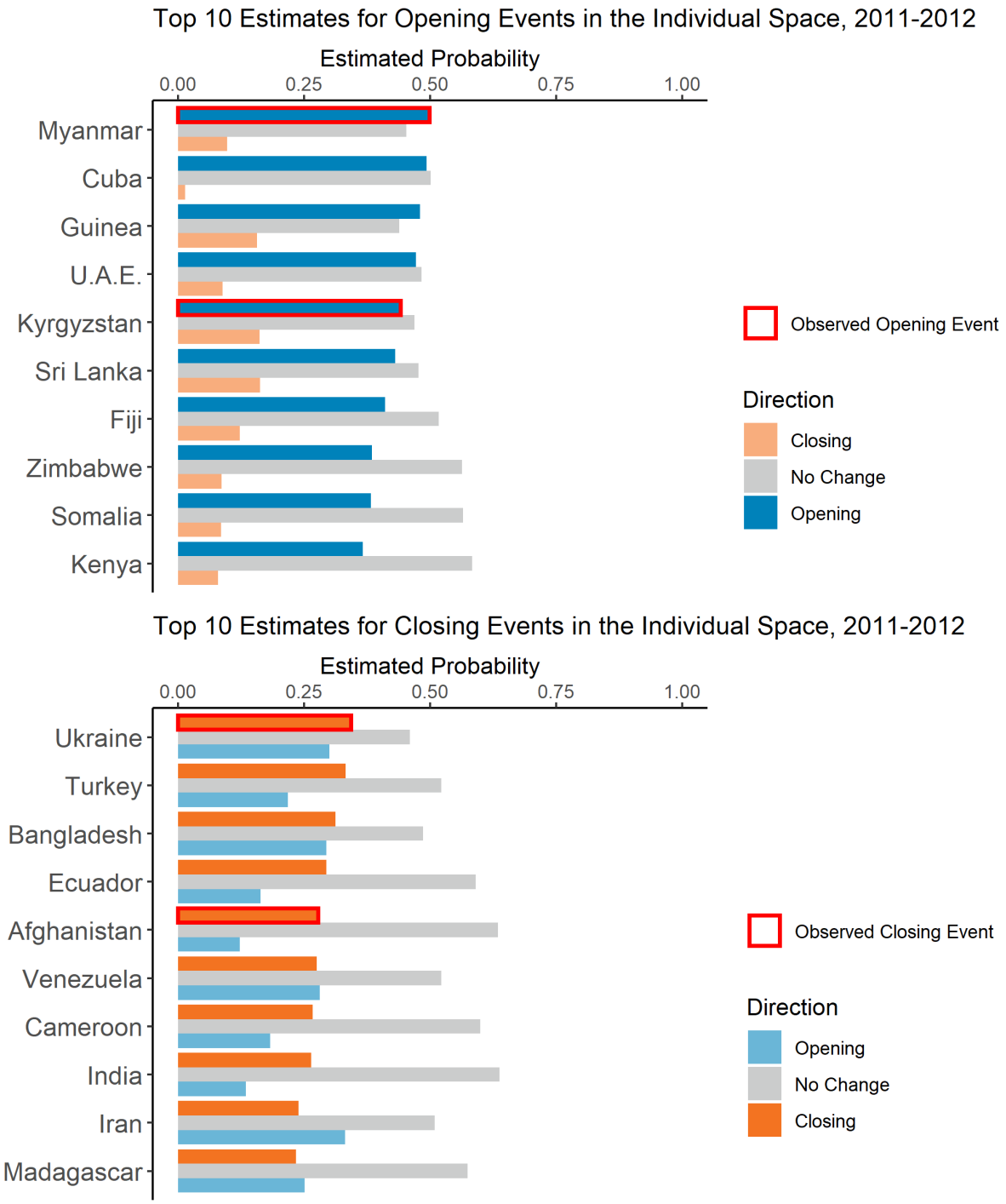


Figure 76: Test year estimates for the individual space, 2012–2013.

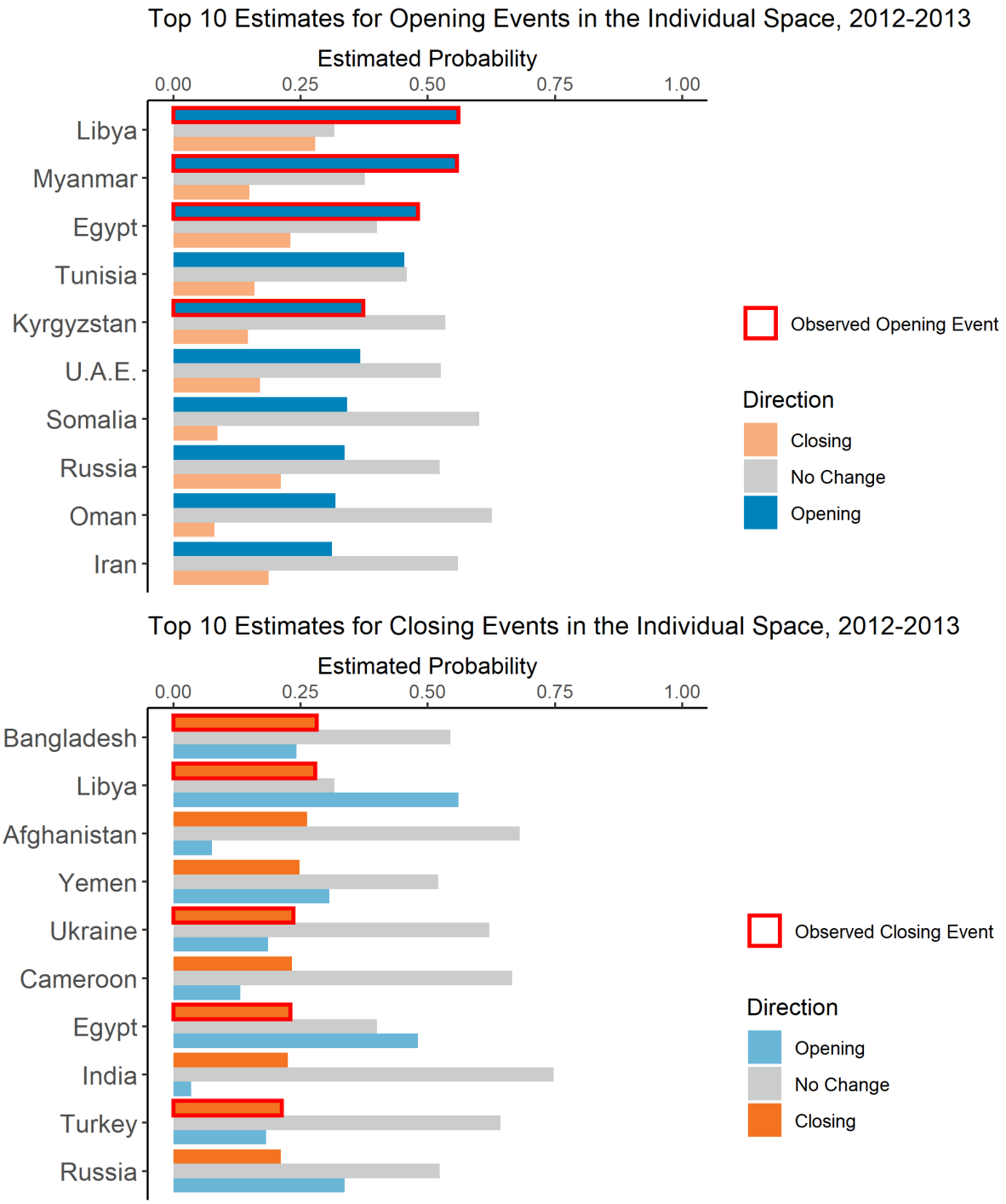


Figure 77: Test year estimates for the individual space, 2013–2014.

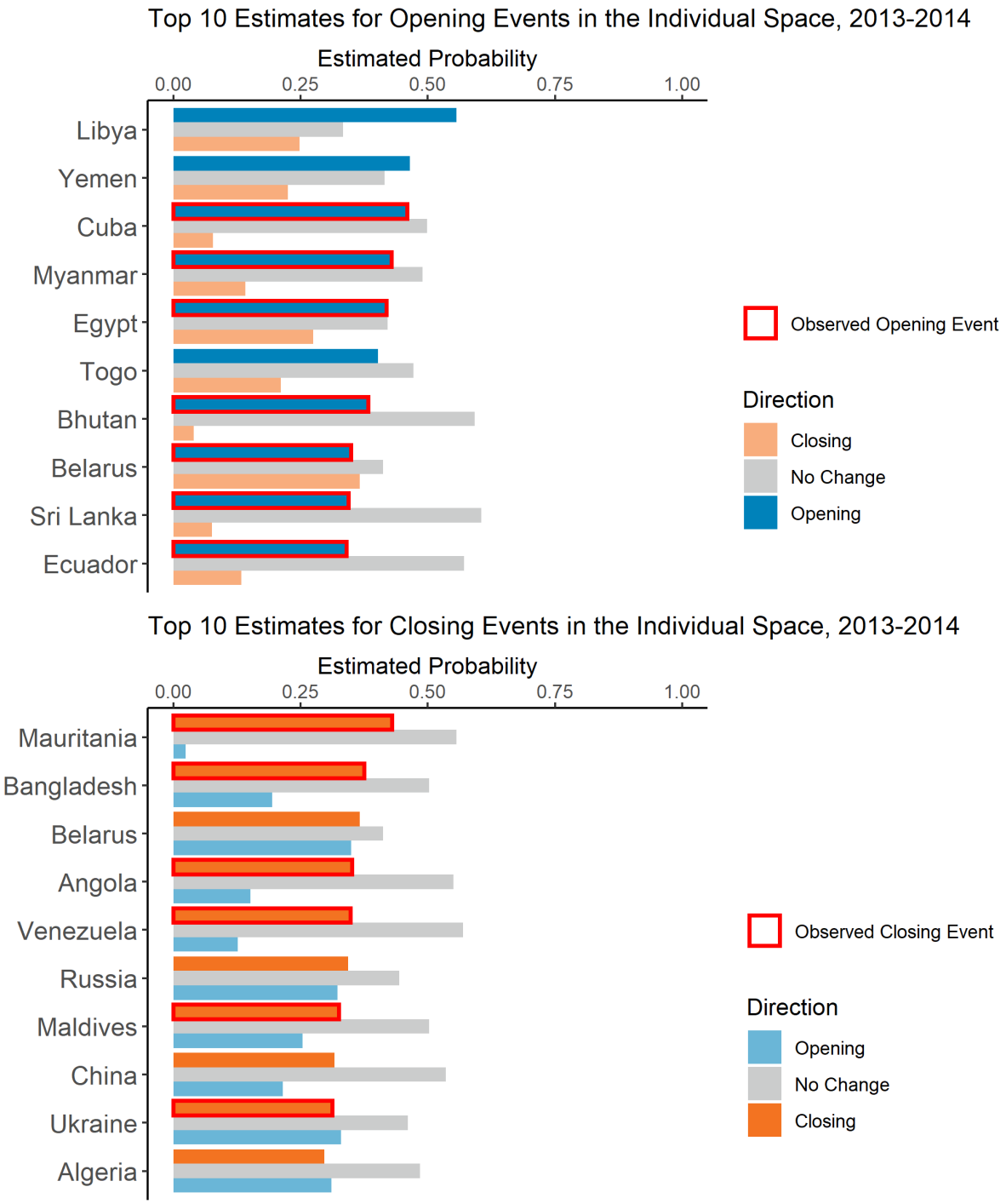


Figure 78: Test year estimates for the individual space, 2014–2015.

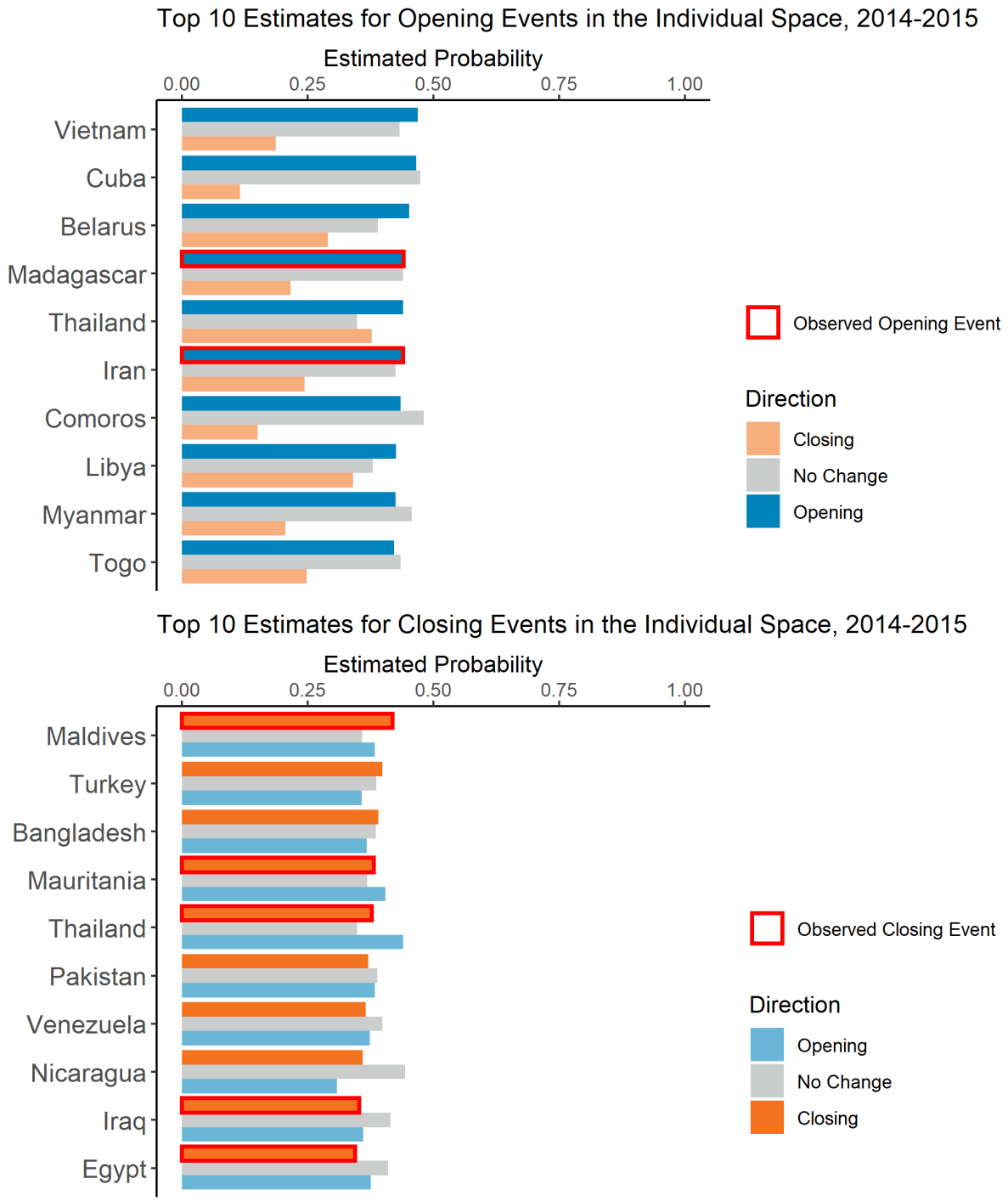


Figure 79: Test year estimates for the individual space, 2015–2016.

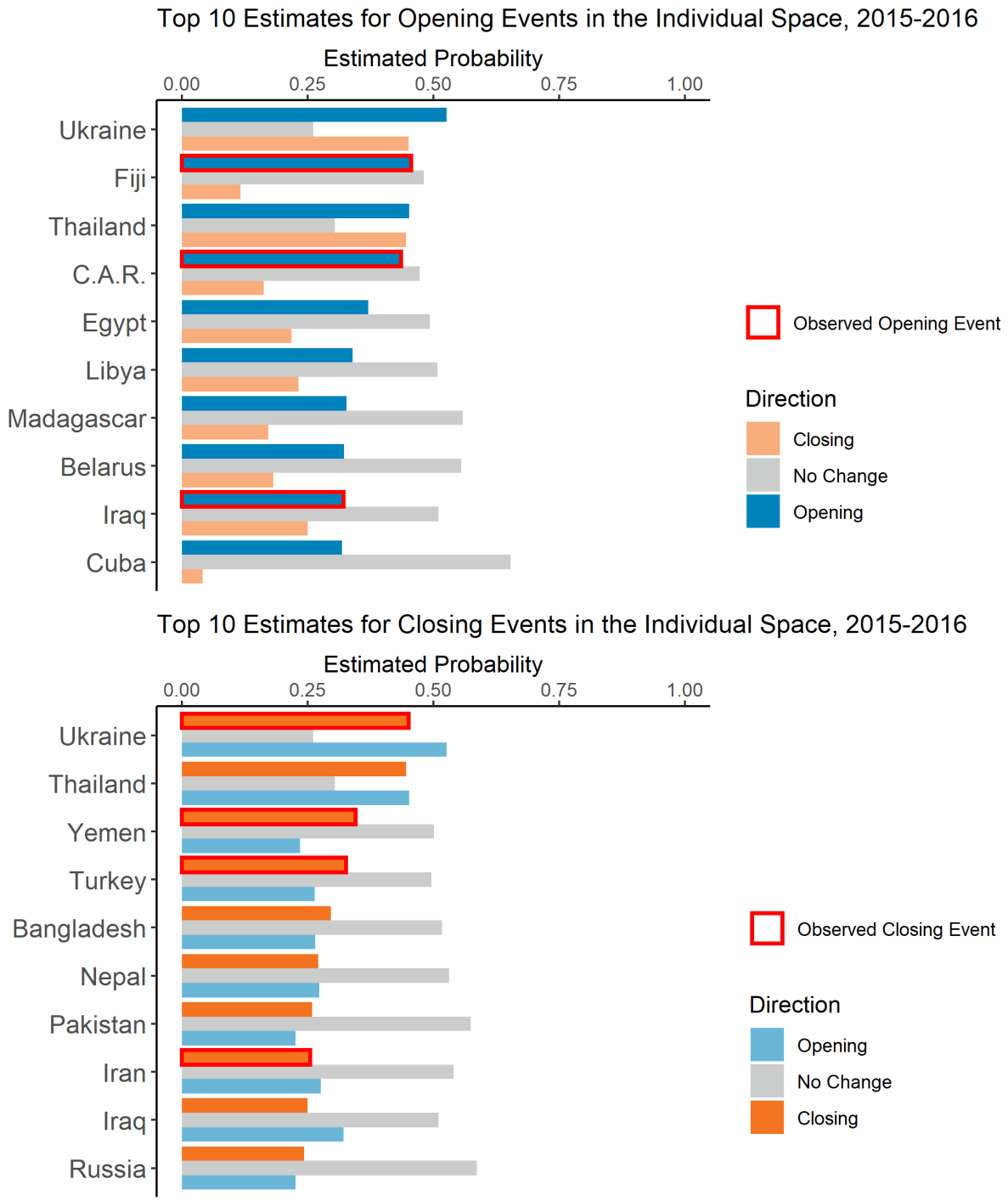


Figure 80: Test year estimates for the individual space, 2016–2017.

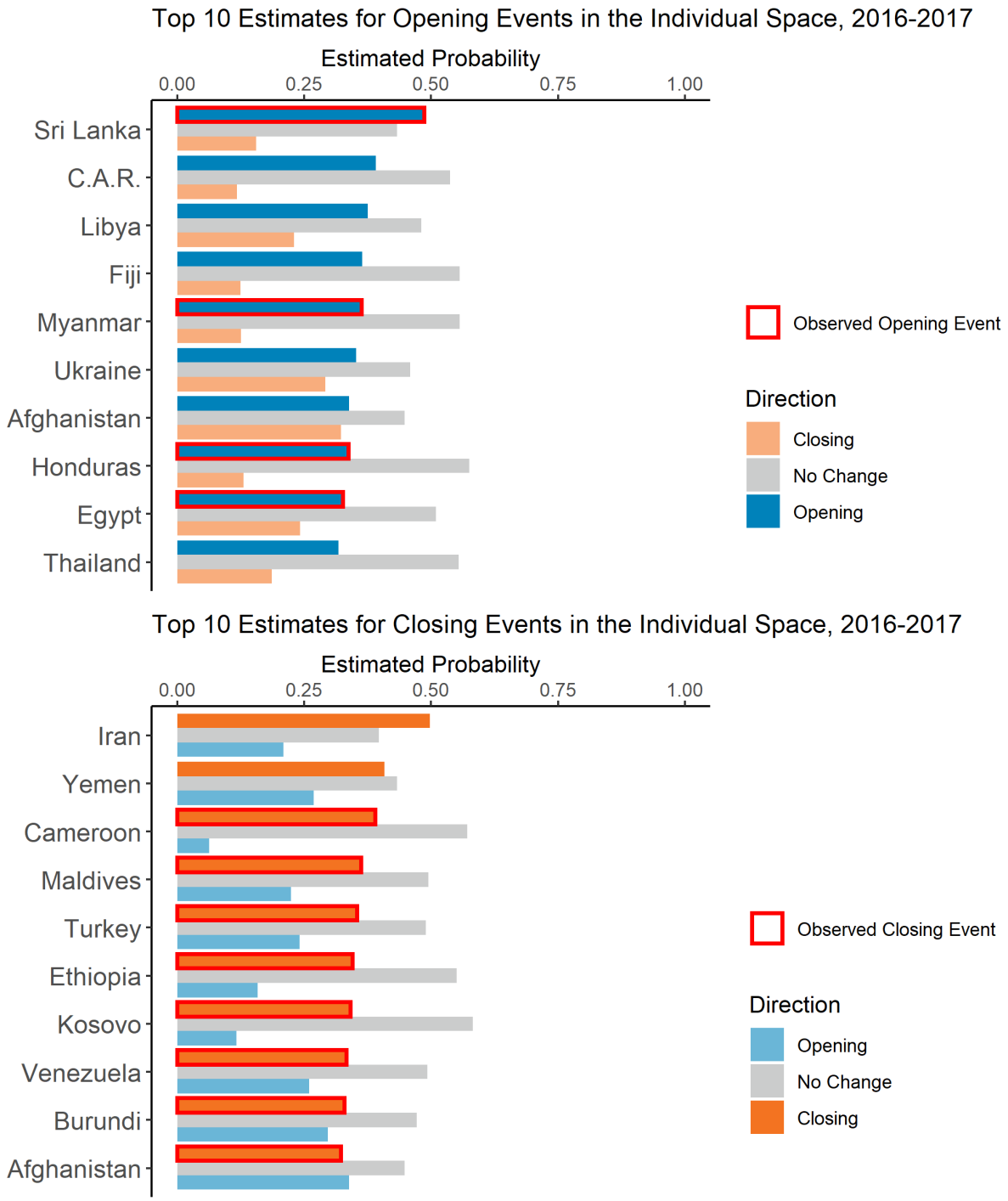
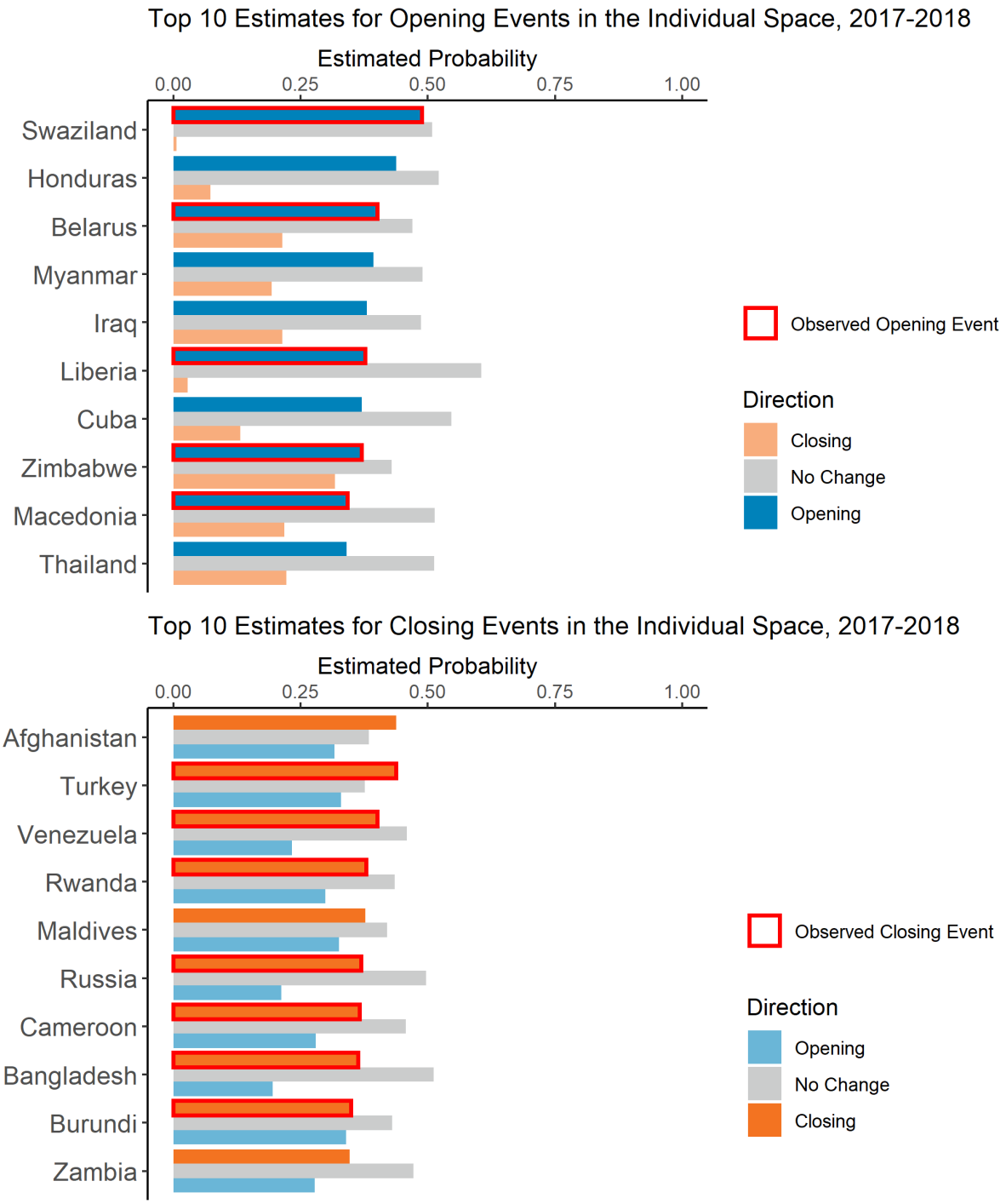


Figure 81: Test year estimates for the individual space, 2017–2018.



Informational

Figure 82: Test year estimates for the informational space, 2006–2007.

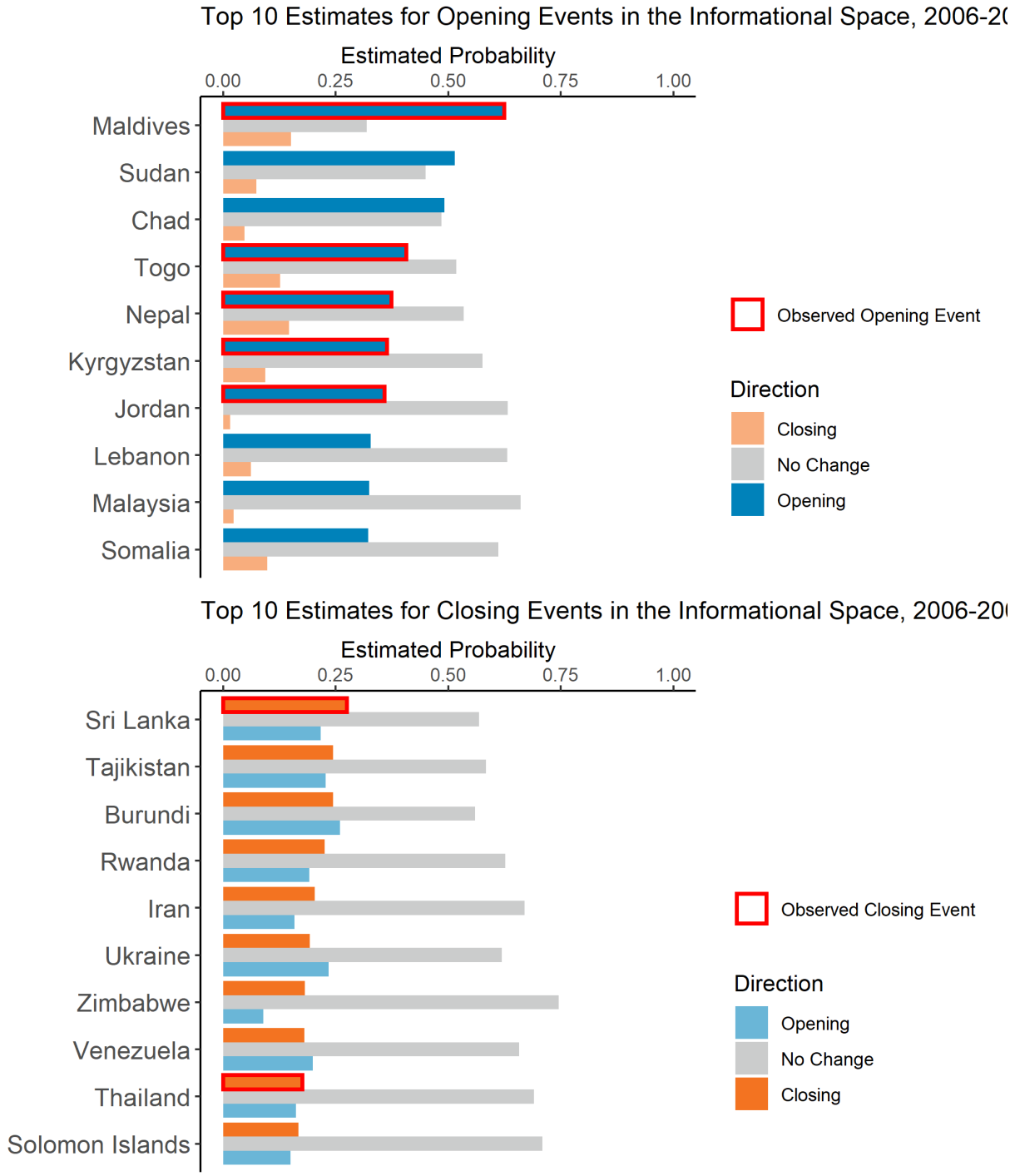


Figure 83: Test year estimates for the informational space, 2007–2008.

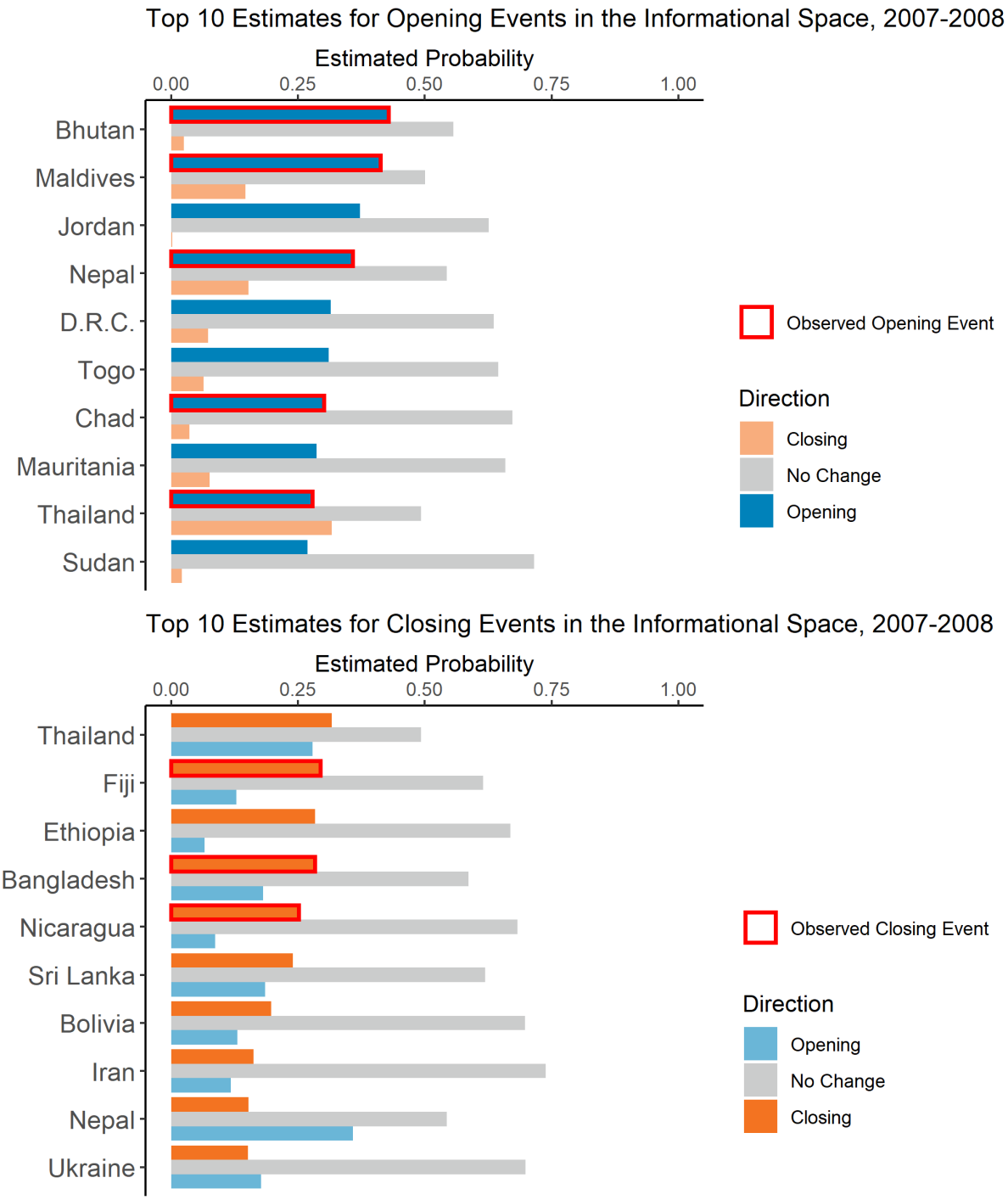


Figure 84: Test year estimates for the informational space, 2008–2009.

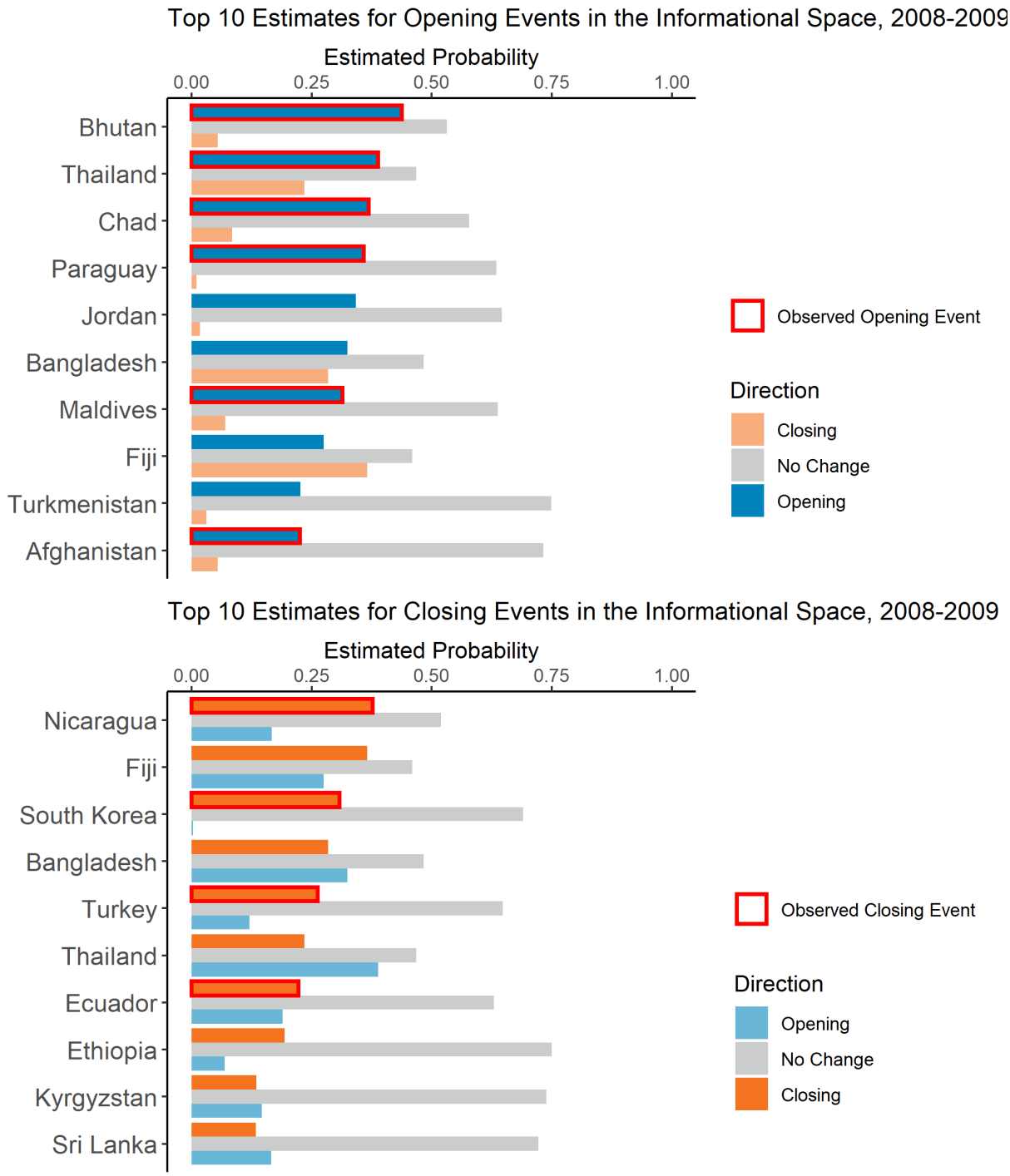


Figure 85: Test year estimates for the informational space, 2009–2010.

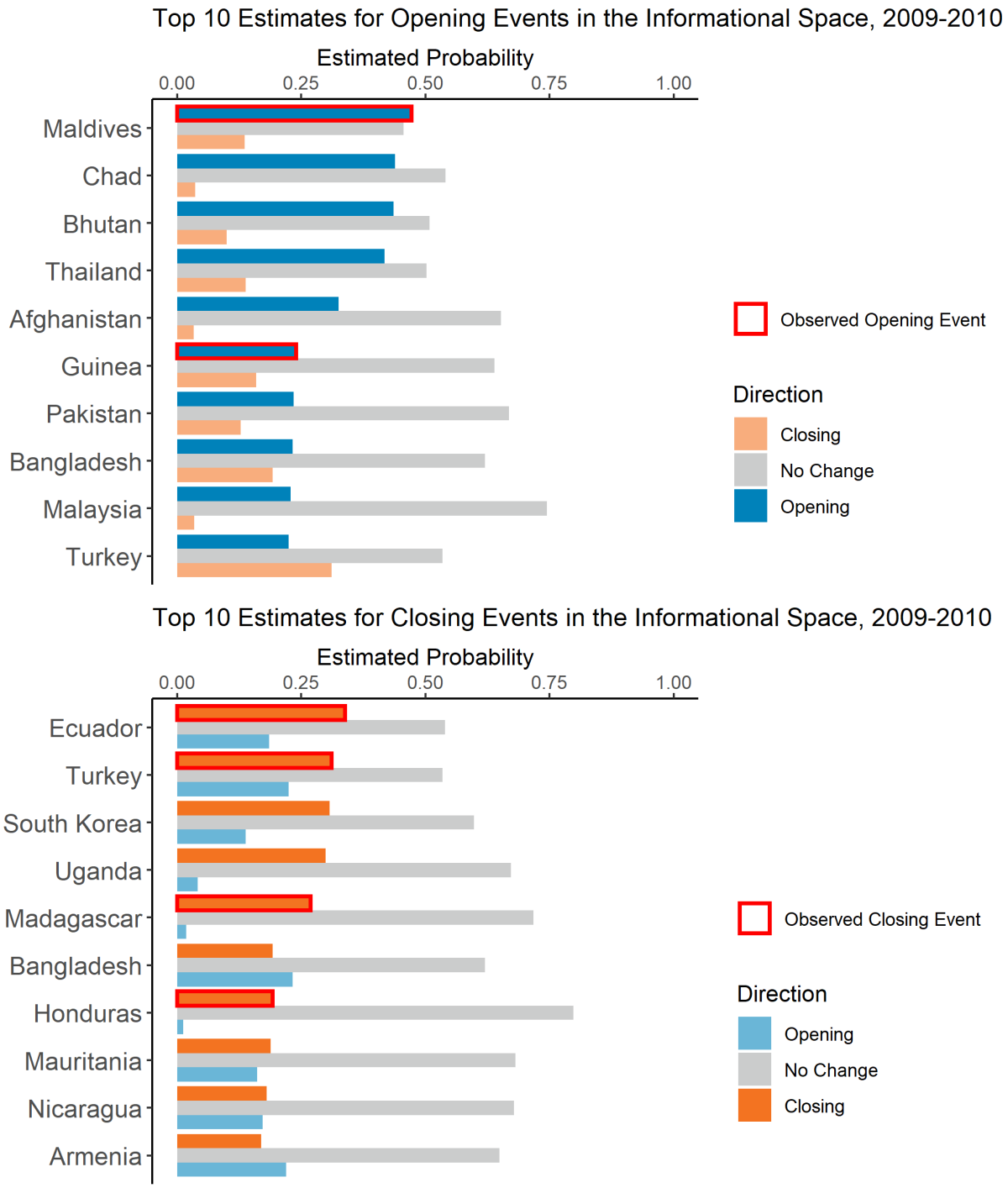


Figure 86: Test year estimates for the informational space, 2010–2011.

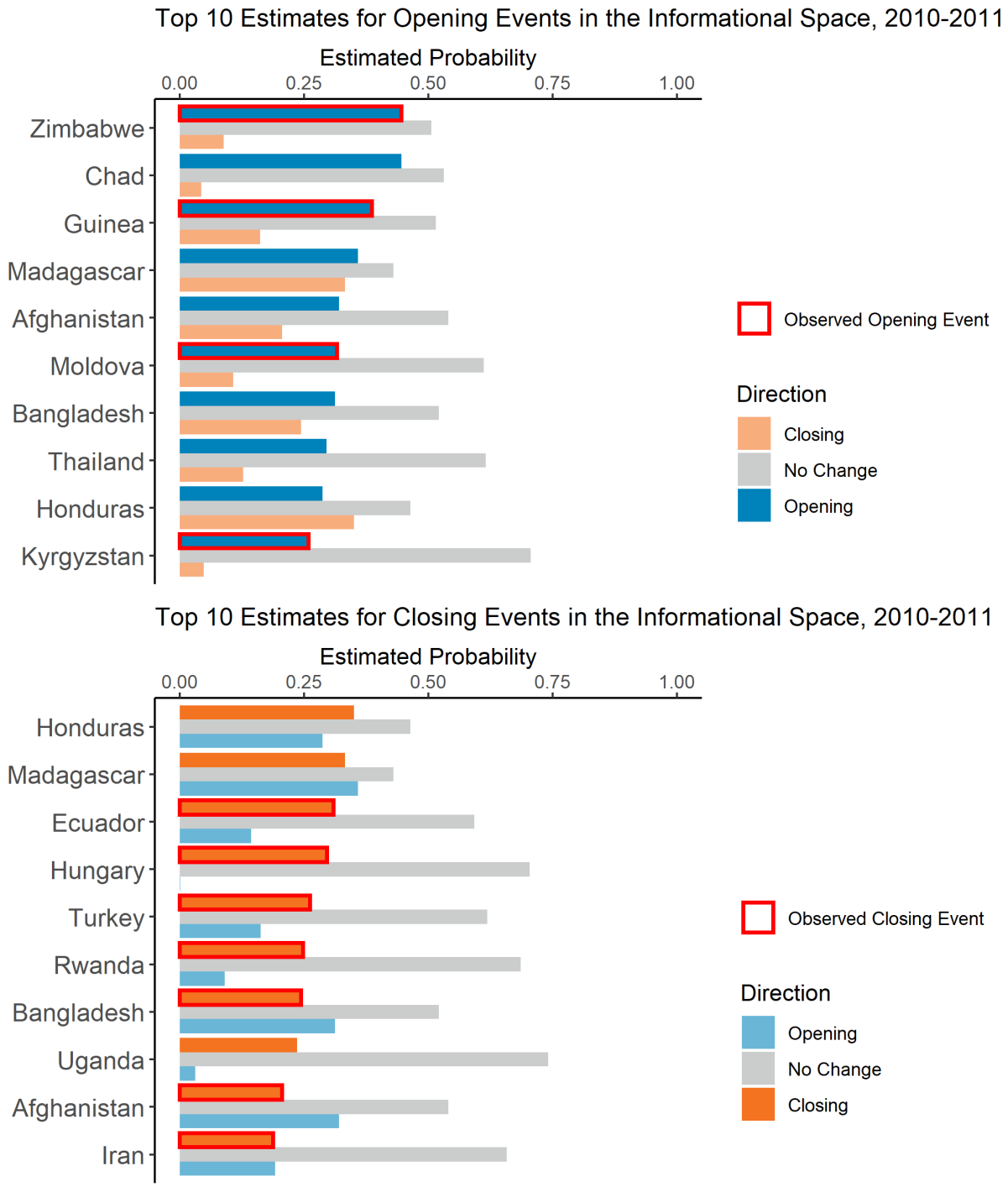


Figure 87: Test year estimates for the informational space, 2011–2012.

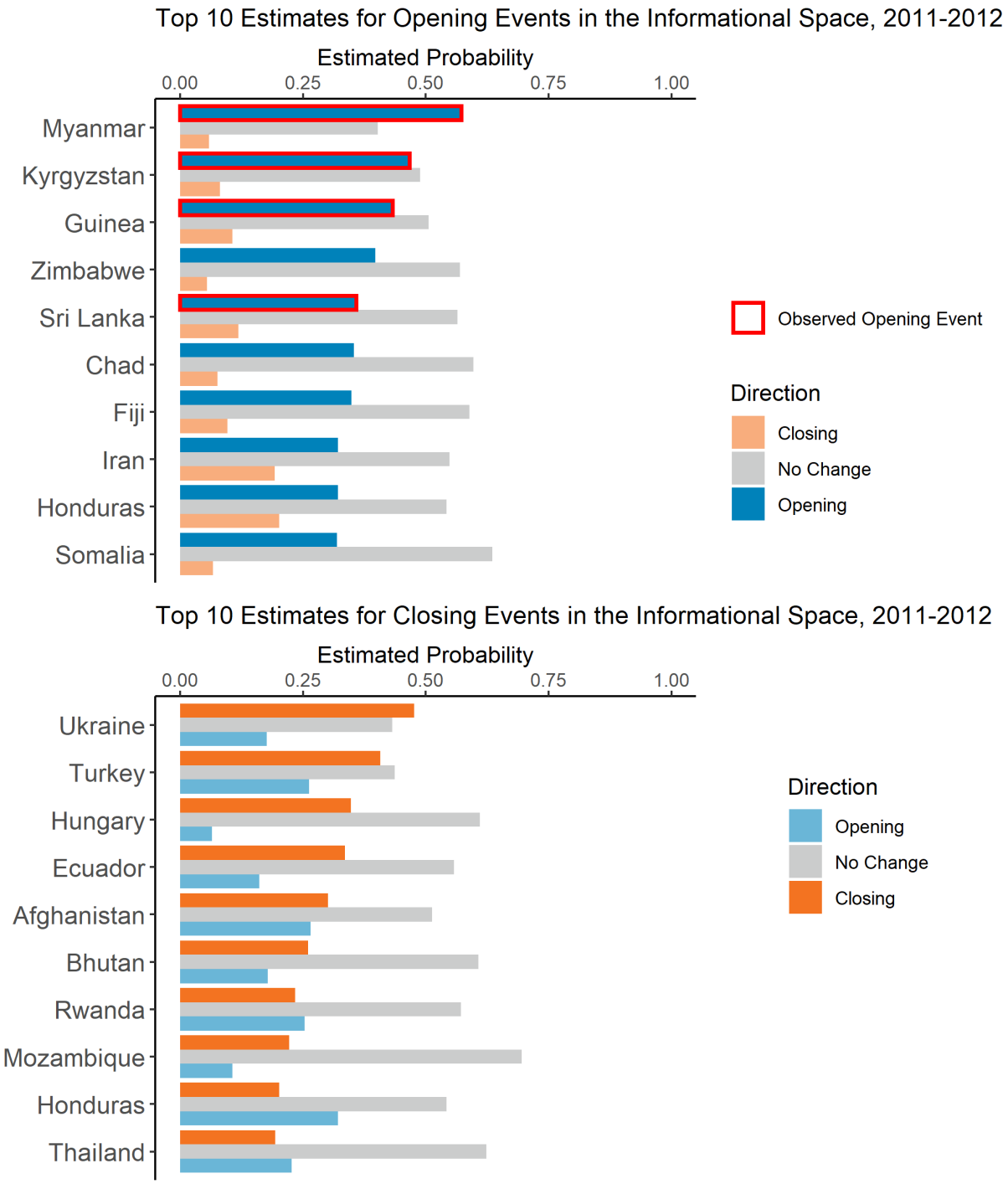


Figure 88: Test year estimates for the informational space, 2012–2013.

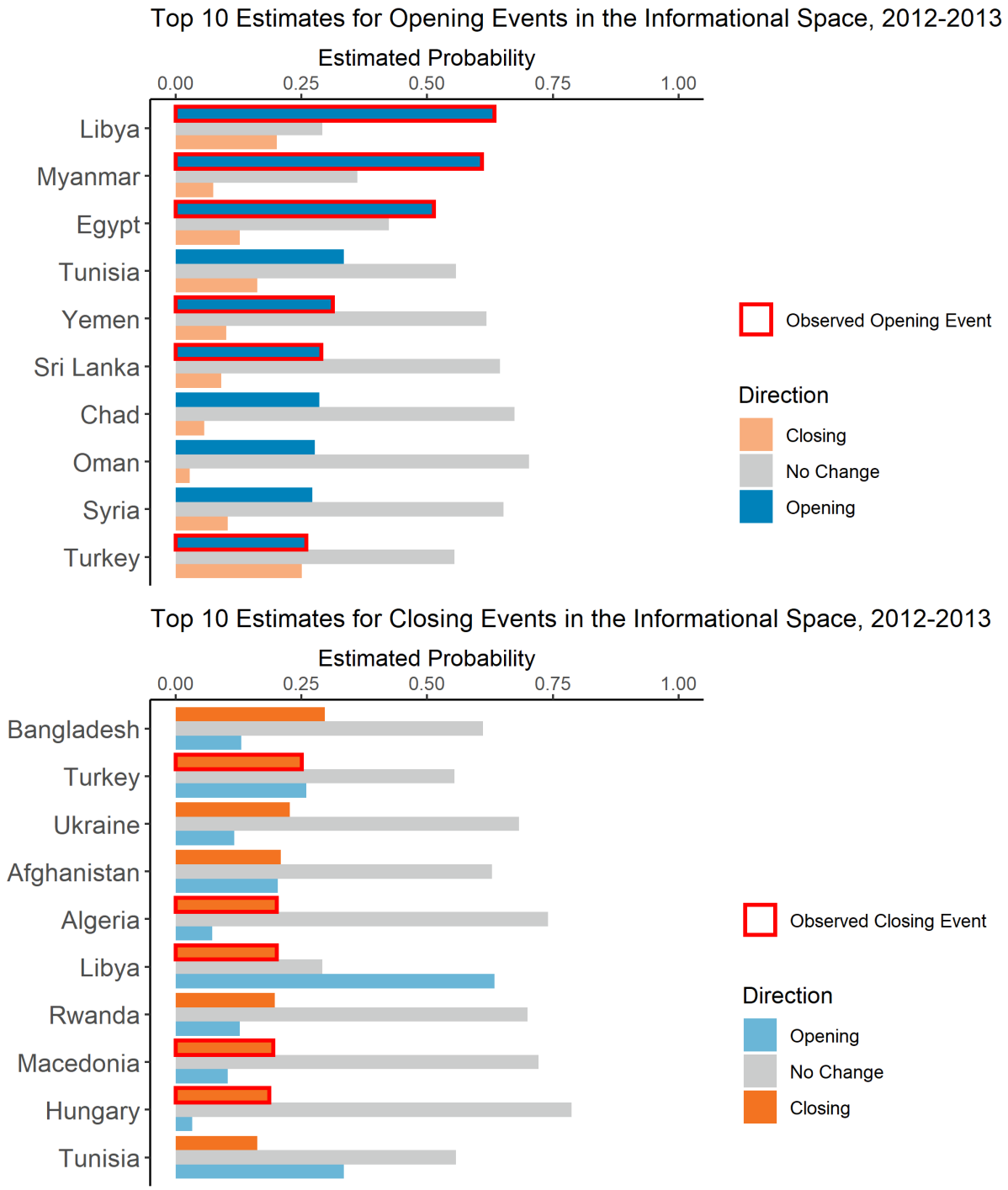


Figure 89: Test year estimates for the informational space, 2013–2014.

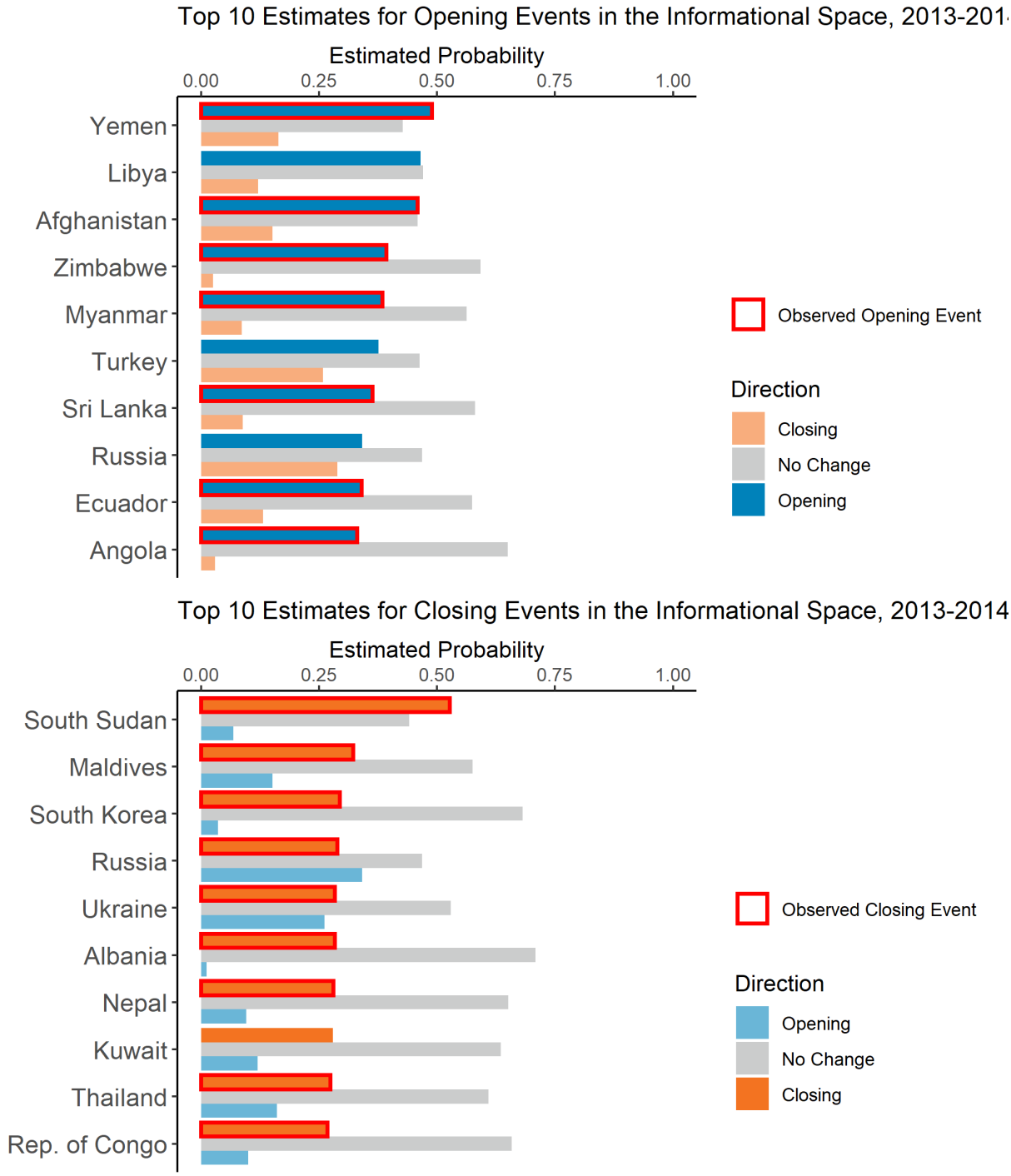
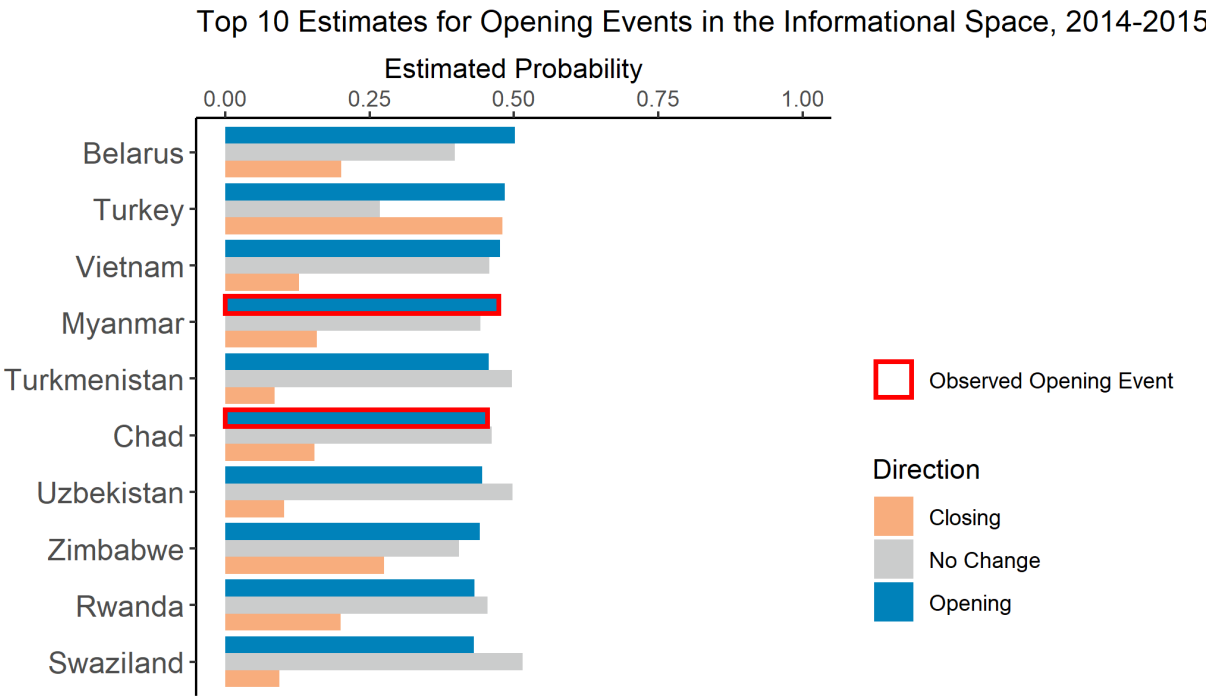


Figure 90: Test year estimates for the informational space, 2014–2015.



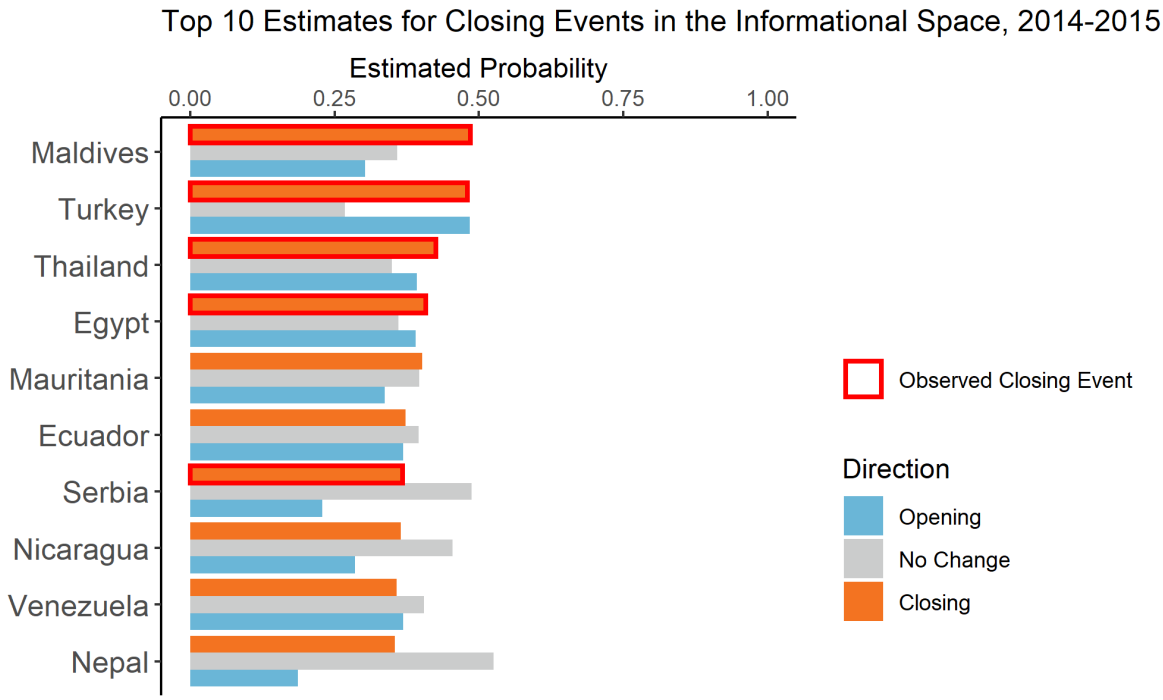


Figure 91: Test year estimates for the informational space, 2015–2016.

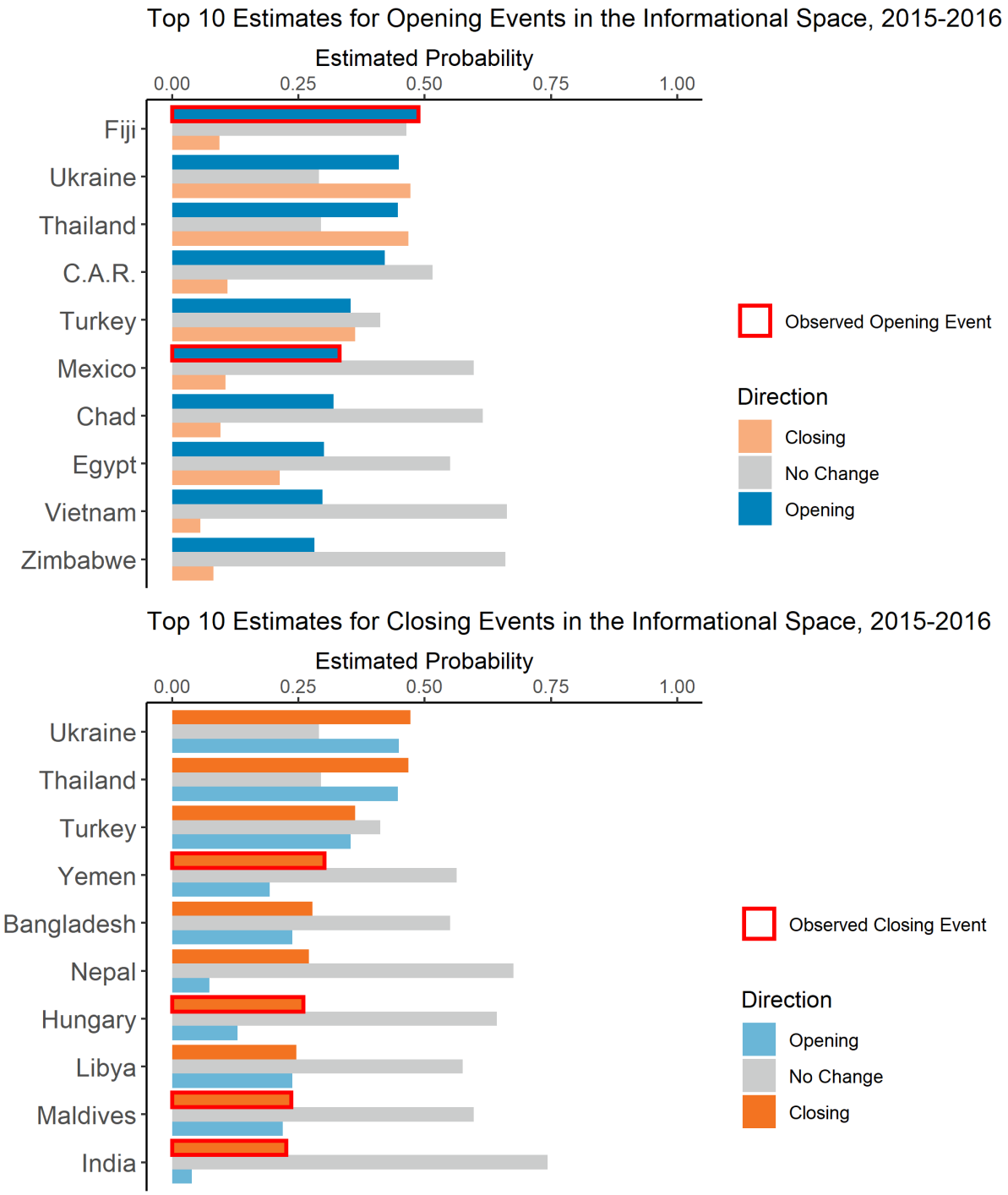


Figure 92: Test year estimates for the informational space, 2016–2017.

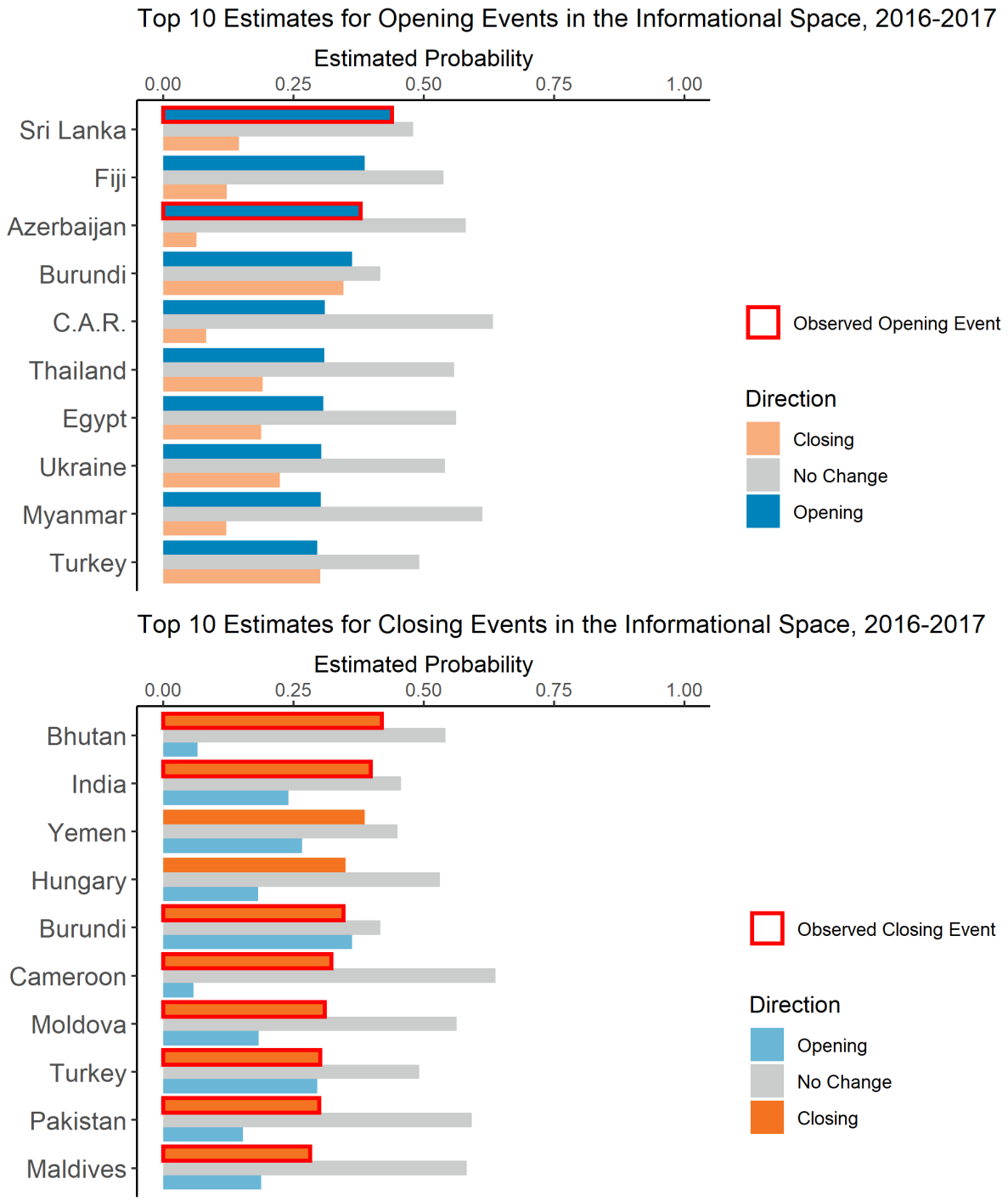
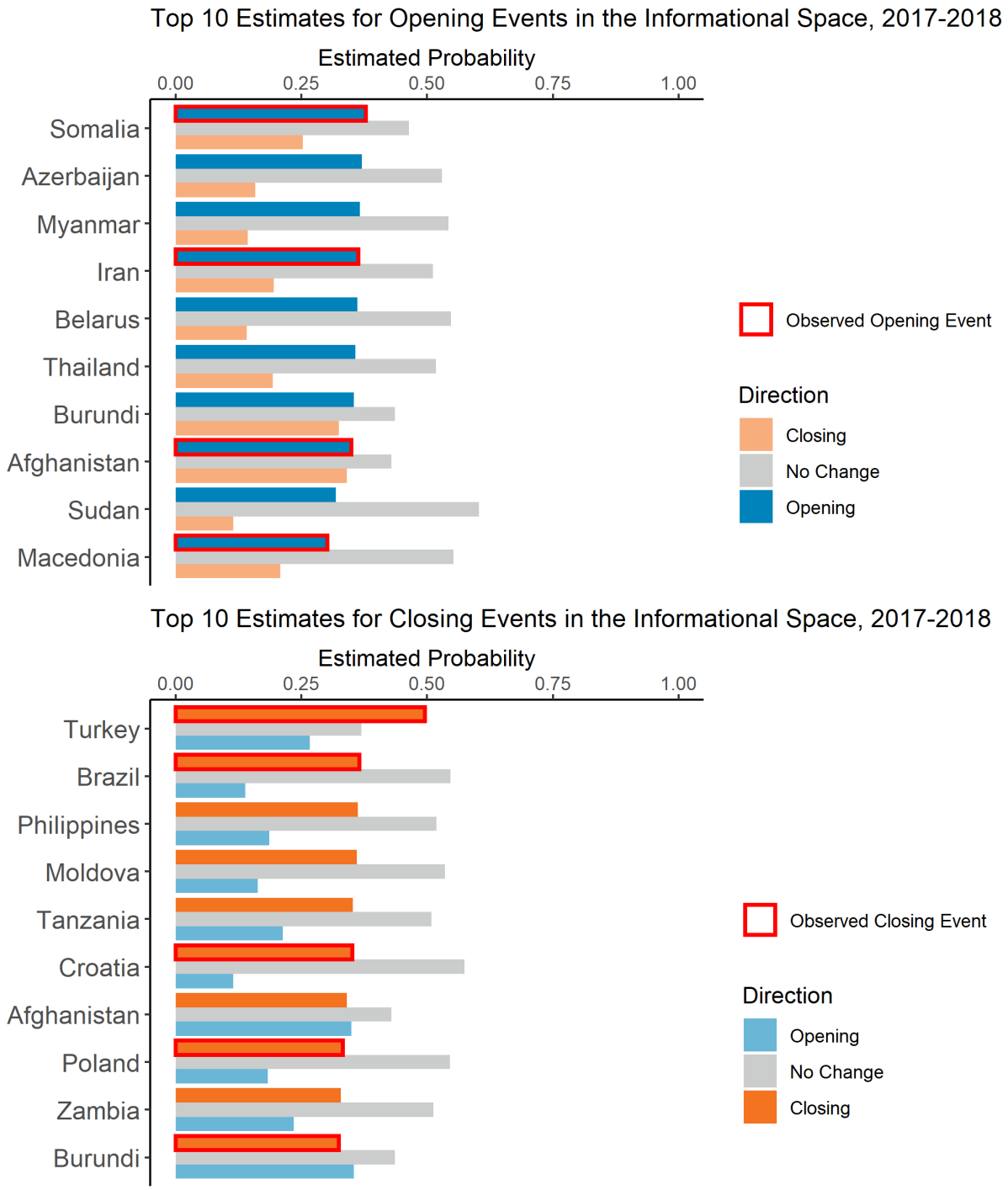


Figure 93: Test year estimates for the informational space, 2017–2018.



D Data Appendix

This appendix provides basic summary statistics for each of the explanatory variables in our dataset.

Table 18: Variables and Descriptive Statistics

Variable	Min	Max	Mean	Median	SD
v2x_polyarchy	0.01	0.95	0.45	0.45	0.29
v2x_liberal	0.00	0.98	0.54	0.54	0.29
v2xdl_delib	0.01	0.99	0.56	0.56	0.30
v2x_jucon	0.00	0.99	0.53	0.53	0.31
v2x_frassoc_thick	0.02	0.96	0.55	0.55	0.34
v2xel_frefair	0.00	0.99	0.47	0.47	0.35
v2x_elecoff	0.00	1.00	0.77	0.77	0.41
v2xlg_legcon	0.00	0.98	0.47	0.47	0.34
v2x_partip	0.02	0.89	0.41	0.41	0.21
v2x_cspart	0.02	0.99	0.58	0.58	0.28
v2x_egal	0.06	0.98	0.59	0.59	0.23
v2xeg_eqprotec	0.02	0.99	0.61	0.61	0.26
v2xeg_eqaccess	0.02	0.99	0.58	0.58	0.24
v2xeg_eqdr	0.01	0.98	0.58	0.58	0.28
v2x_diagacc	-2.15	2.18	0.37	0.37	1.04
v2xex_elecleg	0.00	1.00	0.84	0.84	0.33
v2x_civlib	0.01	0.98	0.60	0.60	0.29
v2x_clphy	0.01	0.99	0.58	0.58	0.31
v2x_clpol	0.01	0.99	0.58	0.58	0.33
v2x_clpriv	0.00	0.97	0.63	0.63	0.29
v2x_corr	0.01	0.98	0.51	0.51	0.30
v2x_EDcomp_thick	0.00	0.96	0.51	0.51	0.29
v2x_elecreg	0.00	1.00	0.86	0.86	0.35
v2x_freexp	0.01	0.99	0.57	0.57	0.32
v2x_gencl	0.00	0.98	0.61	0.61	0.27
v2x_gencs	0.01	0.98	0.61	0.61	0.25
v2x_hosabort	0.00	1.00	0.00	0.00	0.04
v2x_hosinter	0.00	1.00	0.01	0.01	0.09
v2x_rule	0.00	1.00	0.52	0.52	0.31
v2xcl_acjst	0.00	1.00	0.58	0.58	0.29
v2xcl_disc	0.01	0.99	0.59	0.59	0.31
v2xcl_dmove	0.00	0.97	0.64	0.64	0.26
v2xcl_prpty	0.00	0.95	0.60	0.60	0.27
v2xcl_slave	0.00	0.97	0.64	0.64	0.24
v2xel_elecparl	0.00	1.00	0.22	0.22	0.41
v2xel_elecpres	0.00	1.00	0.10	0.10	0.30
v2xex_elecreg	0.00	1.00	0.49	0.49	0.50
v2xlg_elecreg	0.00	1.00	0.86	0.86	0.35
v2ex_legconhog	0.00	1.00	0.43	0.43	0.49
v2ex_legconhos	0.00	1.00	0.26	0.26	0.44
v2x_ex_confidence	0.00	1.00	0.33	0.33	0.38
v2x_ex_direlect	0.00	1.00	0.37	0.37	0.47

Table 18: Variables and Descriptive Statistics *(continued)*

Variable	Min	Max	Mean	Median	SD
v2x_ex_hereditary	0.00	1.00	0.04	0.04	0.16
v2x_ex_military	0.00	1.00	0.18	0.18	0.23
v2x_ex_party	0.00	1.00	0.15	0.15	0.21
v2x_execorr	0.01	0.98	0.49	0.49	0.30
v2x_legabort	0.00	1.00	0.00	0.00	0.04
v2xlg_leginter	0.00	1.00	0.02	0.02	0.14
v2x_neopat	0.01	0.99	0.51	0.51	0.31
v2xnp_client	0.01	0.99	0.48	0.48	0.26
v2xnp_pres	0.01	0.99	0.47	0.47	0.32
v2xnp_regcorr	0.01	0.98	0.50	0.50	0.30
v2elvotbuy	-2.99	3.40	0.05	0.05	1.34
v2elfrcamp	-2.24	2.95	0.40	0.40	1.33
v2elpdcamp	-2.73	3.38	0.10	0.10	1.37
v2elpaidig	-2.58	3.16	0.08	0.08	1.30
v2elmonref	0.00	1.00	0.03	0.03	0.16
v2elmonden	0.00	1.00	0.02	0.02	0.15
v2elrgstry	-3.97	2.87	0.33	0.33	1.28
v2elirreg	-3.08	3.11	0.08	0.08	1.35
v2elintim	-4.04	3.44	0.01	0.01	1.42
v2elpeace	-4.58	2.55	0.17	0.17	1.26
v2elfrfair	-3.41	2.88	0.01	0.01	1.51
v2elmulpar	-3.53	2.54	0.13	0.13	1.45
v2elboycot	-4.41	1.93	0.13	0.13	1.19
v2elaccept	-3.81	2.69	-0.01	-0.01	1.34
v2elasmoff	-6.67	0.88	-0.03	-0.03	1.02
v2eldonate	-2.56	3.90	-0.20	-0.20	1.34
v2elpubfin	-2.59	3.77	-0.01	-0.01	1.46
v2ellocumul	0.00	60.00	14.83	14.83	10.52
v2elprescons	0.00	31.00	2.73	2.73	4.41
v2elprescumul	0.00	36.00	4.84	4.84	6.72
v2elembaut	-2.64	3.82	0.32	0.32	1.70
v2elembcap	-3.00	3.65	0.42	0.42	1.48
v2elreggov	0.00	1.00	0.78	0.78	0.42
v2ellocgov	0.00	1.00	0.96	0.96	0.20
v2ellocons	0.00	60.00	8.21	8.21	9.03
v2elrsthos	0.00	1.00	0.88	0.88	0.33
v2elrstrct	0.00	1.00	0.91	0.91	0.29
v2psparban	-3.70	2.89	0.28	0.28	1.78
v2psbars	-3.73	3.09	0.49	0.49	1.70
v2psoppaut	-3.54	3.53	0.40	0.40	1.91
v2psorgs	-3.10	3.21	0.68	0.68	1.40
v2psprbrch	-3.19	3.54	0.66	0.66	1.37
v2psprlnks	-3.21	3.51	0.12	0.12	1.38
v2psplats	-3.16	3.35	0.39	0.39	1.63
v2pscnslnl	-2.68	4.61	0.15	0.15	1.36
v2pscohesv	-3.69	2.56	0.70	0.70	1.22

Table 18: Variables and Descriptive Statistics *(continued)*

Variable	Min	Max	Mean	Median	SD
v2pscomprg	-3.43	2.58	0.46	0.46	1.20
v2psnatpar	-2.77	3.02	0.11	0.11	1.41
v2pssunpar	-2.75	2.80	0.00	0.00	1.59
v2exremhsp	-2.50	4.16	-0.30	-0.30	1.20
v2exdfdshs	-3.49	3.03	-0.17	-0.17	1.50
v2exdfcbhs	-3.38	2.46	0.17	0.17	1.50
v2exdfvths	-3.40	2.52	-0.10	-0.10	1.50
v2exdfdmhs	-3.28	2.40	0.15	0.15	1.64
v2exdfpphs	-2.55	3.33	0.34	0.34	1.48
v2exhoshog	0.00	1.00	0.39	0.39	0.49
v2exrescon	-3.22	3.48	0.30	0.30	1.42
v2exbribe	-3.14	3.61	0.01	0.01	1.54
v2exembez	-3.23	3.57	0.05	0.05	1.55
v2excrptps	-3.07	4.00	-0.16	-0.16	1.51
v2exthftps	-3.14	3.71	0.04	0.04	1.52
v2ex_elechos	0.00	1.00	0.46	0.46	0.50
v2ex_hogw	0.00	1.00	0.38	0.38	0.47
v2expathhs	0.00	8.00	5.23	5.23	2.37
v2lgbicam	0.00	2.00	1.26	1.26	0.60
v2lgqstexp	-2.34	2.32	0.26	0.26	1.33
v2lginvstp	-2.94	3.84	0.23	0.23	1.48
v2lgotovst	-2.97	3.12	0.19	0.19	1.40
v2lgcrrpt	-3.28	3.32	-0.09	-0.09	1.33
v2lgoppart	-2.53	3.51	0.29	0.29	1.58
v2lgfunds	-2.43	2.42	0.22	0.22	1.29
v2lgdsadlobin	-9.37	0.60	-0.06	-0.06	0.97
v2lglegplo	-3.78	1.96	0.35	0.35	1.19
v2lgcomslo	-3.50	3.74	0.65	0.65	1.09
v2lgsrvlo	-2.21	2.15	-0.04	-0.04	1.36
v2ex_hosw	0.00	1.00	0.62	0.62	0.47
v2lgamend	0.00	1.00	0.43	0.43	0.50
v2dlreason	-2.91	3.72	0.45	0.45	1.34
v2dlcommon	-3.57	2.90	0.42	0.42	1.18
v2dlcountr	-3.36	3.58	0.21	0.21	1.43
v2dlconslt	-3.05	4.46	0.57	0.57	1.41
v2dlengage	-3.12	3.46	0.47	0.47	1.42
v2dlencmps	-3.45	3.44	0.55	0.55	1.23
v2dlunivl	-3.29	3.41	0.67	0.67	1.13
v2jureform	-3.61	3.40	0.02	0.02	1.16
v2jupurge	-3.83	2.85	0.43	0.43	1.26
v2jupoatck	-4.45	3.05	0.33	0.33	1.24
v2jupack	-4.45	1.71	-0.05	-0.05	1.24
v2juaccnt	-3.09	3.64	0.50	0.50	1.28
v2jucorrdc	-3.40	3.45	0.04	0.04	1.52
v2juhcind	-3.21	3.47	0.11	0.11	1.47
v2juncind	-3.38	3.36	0.26	0.26	1.47

Table 18: Variables and Descriptive Statistics *(continued)*

Variable	Min	Max	Mean	Median	SD
v2juhccomp	-3.91	2.88	0.27	0.27	1.46
v2jucomp	-3.46	3.26	0.20	0.20	1.47
v2jureview	-2.72	1.84	0.20	0.20	1.24
v2clacfree	-3.51	3.80	0.63	0.63	1.66
v2clrelig	-3.93	2.80	0.64	0.64	1.47
v2cltort	-3.07	3.66	0.40	0.40	1.63
v2clkill	-3.51	3.51	0.65	0.65	1.66
v2cltrnslw	-3.73	4.17	0.48	0.48	1.53
v2clrspct	-3.68	4.46	0.20	0.20	1.51
v2clfmove	-4.21	2.95	0.66	0.66	1.47
v2cldmovem	-5.02	2.69	0.75	0.75	1.28
v2cldmovew	-4.76	3.24	0.70	0.70	1.40
v2cldiscm	-3.78	3.88	0.52	0.52	1.67
v2cldiscw	-3.53	3.50	0.50	0.50	1.57
v2clslavem	-4.10	3.03	0.89	0.89	1.12
v2clslavef	-4.28	2.97	0.68	0.68	1.11
v2clstown	-4.20	3.29	0.13	0.13	1.36
v2clprptym	-4.40	2.42	0.65	0.65	1.26
v2clprptyw	-3.75	2.82	0.62	0.62	1.33
v2clacjstm	-4.06	3.90	0.55	0.55	1.47
v2clacjstw	-3.97	3.72	0.50	0.50	1.47
v2clacjust	-2.66	3.59	0.84	0.84	1.20
v2clsocgrp	-3.00	3.10	0.54	0.54	1.30
v2clrgunev	-2.94	2.79	0.35	0.35	1.30
v2svdomaut	-3.18	2.17	1.04	1.04	0.72
v2svinlaut	-3.15	2.73	1.11	1.11	0.75
v2svstterr	33.75	100.00	91.23	91.23	10.59
v2cseeorgs	-3.23	3.55	0.51	0.51	1.59
v2csreprss	-3.73	3.38	0.52	0.52	1.63
v2cscnsult	-2.45	3.85	0.41	0.41	1.47
v2csprtcpt	-3.53	3.26	0.35	0.35	1.46
v2csgender	-3.50	3.24	0.80	0.80	1.08
v2csantimv	-2.97	4.01	-0.52	-0.52	1.26
v2csrlgrep	-4.12	2.88	0.58	0.58	1.45
v2csrlgcon	-2.85	3.05	0.16	0.16	1.32
v2mecenefm	-3.09	3.57	0.23	0.23	1.67
v2mecrit	-3.31	3.60	0.36	0.36	1.69
v2merange	-3.11	3.17	0.30	0.30	1.63
v2meharjrn	-3.09	3.98	0.29	0.29	1.62
v2meslfcen	-3.24	3.27	0.22	0.22	1.55
v2mebias	-3.58	3.73	0.28	0.28	1.69
v2mecorrpt	-3.18	3.46	0.17	0.17	1.64
v2pepwrses	-2.95	2.99	0.48	0.48	1.14
v2pepwrsoc	-2.64	3.40	0.54	0.54	1.26
v2pepwrgen	-2.88	3.88	0.57	0.57	1.20
v2pepwrort	-2.20	3.48	-0.15	-0.15	1.25

Table 18: Variables and Descriptive Statistics *(continued)*

Variable	Min	Max	Mean	Median	SD
v2peedueq	-3.10	3.63	0.40	0.40	1.48
v2pehealth	-3.27	3.69	0.43	0.43	1.50
is_leg	0.00	1.00	0.91	0.91	0.28
is_elec	0.00	1.00	0.86	0.86	0.35
is_election_year	0.00	1.00	0.26	0.26	0.44
diff_year_prior_v2x_frassoc_thick	-0.48	0.70	0.00	0.00	0.05
diff_year_prior_v2xel_frefair	-0.47	0.65	0.00	0.00	0.05
diff_year_prior_v2x_elecoff	-0.67	0.82	0.00	0.00	0.06
diff_year_prior_v2xlg_legcon	-0.50	0.80	0.00	0.00	0.05
diff_year_prior_v2x_partip	-0.67	0.83	0.01	0.01	0.06
diff_year_prior_v2x_cspart	-0.86	0.92	0.01	0.01	0.08
diff_year_prior_v2x_egal	-1.00	1.00	0.01	0.01	0.17
diff_year_prior_v2xeg_eqprotec	-0.87	0.94	0.01	0.01	0.09
diff_year_prior_v2xeg_eqaccess	-0.36	0.52	0.00	0.00	0.03
diff_year_prior_v2xeg_eqdr	-0.51	0.71	0.01	0.01	0.05
diff_year_prior_v2x_diagacc	-0.24	0.44	0.00	0.00	0.03
diff_year_prior_v2xex_elecleg	-0.54	0.66	0.00	0.00	0.04
diff_year_prior_v2x_civlib	-0.34	0.55	0.00	0.00	0.04
diff_year_prior_v2x_clphy	-0.35	0.52	0.00	0.00	0.03
diff_year_prior_v2x_clpol	-1.81	2.64	0.02	0.02	0.16
diff_year_prior_v2x_clpriv	-1.00	1.00	0.00	0.00	0.15
diff_year_prior_v2x_corr	-0.59	0.68	0.00	0.00	0.05
diff_year_prior_v2x_EDcomp_thick	-0.70	0.74	0.00	0.00	0.06
diff_year_prior_v2x_elecreg	-0.72	0.83	0.01	0.01	0.06
diff_year_prior_v2x_freexp	-0.46	0.78	0.00	0.00	0.04
diff_year_prior_v2x_gencl	-0.64	0.49	0.00	0.00	0.04
diff_year_prior_v2x_gencs	-0.54	0.70	0.01	0.01	0.06
diff_year_prior_v2x_hosabort	-1.00	1.00	0.00	0.00	0.18
diff_year_prior_v2x_hosinter	-0.55	0.79	0.00	0.00	0.06
diff_year_prior_v2x_rule	-0.47	0.63	0.00	0.00	0.04
diff_year_prior_v2xcl_acjst	-0.26	0.59	0.01	0.01	0.04
diff_year_prior_v2xcl_disc	-1.00	1.00	0.00	0.00	0.05
diff_year_prior_v2xcl_dmove	-1.00	1.00	0.00	0.00	0.13
diff_year_prior_v2xcl_prpty	-0.49	0.64	0.00	0.00	0.04
diff_year_prior_v2xcl_slave	-0.59	0.69	0.00	0.00	0.05
diff_year_prior_v2xel_elecparl	-0.69	0.75	0.00	0.00	0.06
diff_year_prior_v2xel_elecpres	-0.45	0.83	0.00	0.00	0.05
diff_year_prior_v2xex_elecreg	-0.47	0.64	0.00	0.00	0.04
diff_year_prior_v2xlg_elecreg	-0.51	0.71	0.00	0.00	0.04
diff_year_prior_v2ex_legconhog	-1.00	1.00	0.00	0.00	0.64
diff_year_prior_v2ex_legconhos	-1.00	1.00	0.00	0.00	0.44
diff_year_prior_v2x_ex_confidence	-1.00	1.00	0.01	0.01	0.15
diff_year_prior_v2x_ex_direlect	-1.00	1.00	0.00	0.00	0.17
diff_year_prior_v2x_ex_hereditary	-1.00	1.00	0.00	0.00	0.14
diff_year_prior_v2x_ex_military	-1.00	1.00	0.00	0.00	0.16
diff_year_prior_v2x_ex_party	-1.00	1.00	0.00	0.00	0.09

Table 18: Variables and Descriptive Statistics *(continued)*

Variable	Min	Max	Mean	Median	SD
diff_year_prior_v2x_execorr	-1.00	1.00	0.00	0.00	0.16
diff_year_prior_v2x_legabort	-0.60	0.50	0.00	0.00	0.02
diff_year_prior_v2xlg_leginter	-0.73	1.00	0.00	0.00	0.08
diff_year_prior_v2x_neopat	-0.80	0.80	0.00	0.00	0.05
diff_year_prior_v2xnp_client	-0.66	0.58	0.00	0.00	0.05
diff_year_prior_v2xnp_pres	-1.00	1.00	0.00	0.00	0.06
diff_year_prior_v2xnp_regcorr	-1.00	1.00	0.00	0.00	0.20
diff_year_prior_v2elvotbuy	-0.71	0.46	0.00	0.00	0.04
diff_year_prior_v2elfrcamp	-0.50	0.30	0.00	0.00	0.04
diff_year_prior_v2elpdcamp	-0.84	0.56	0.00	0.00	0.05
diff_year_prior_v2elpaidig	-0.65	0.46	0.00	0.00	0.04
diff_year_prior_v2elmonref	-2.88	2.77	0.00	0.00	0.24
diff_year_prior_v2elmonden	-4.00	4.51	0.02	0.02	0.29
diff_year_prior_v2elrgstry	-2.97	3.69	0.02	0.02	0.27
diff_year_prior_v2elirreg	-2.29	4.14	0.02	0.02	0.26
diff_year_prior_v2elintim	-1.00	1.00	0.00	0.00	0.11
diff_year_prior_v2elpeace	-1.00	1.00	0.00	0.00	0.09
diff_year_prior_v2elfrfair	-2.73	3.55	0.01	0.01	0.24
diff_year_prior_v2elmulpar	-3.19	3.11	0.00	0.00	0.27
diff_year_prior_v2elboycot	-3.35	4.57	0.01	0.01	0.29
diff_year_prior_v2elaccept	-3.62	3.78	0.00	0.00	0.30
diff_year_prior_v2elasmoff	-3.02	4.70	0.01	0.01	0.34
diff_year_prior_v2eldonate	-4.26	4.61	0.02	0.02	0.34
diff_year_prior_v2elpubfin	-4.78	4.76	0.00	0.00	0.37
diff_year_prior_v2ellocumul	-4.22	4.25	0.01	0.01	0.34
diff_year_prior_v2elprescons	-7.22	6.93	0.00	0.00	0.39
diff_year_prior_v2elprescumul	-2.11	3.17	0.04	0.04	0.22
diff_year_prior_v2elembaut	-1.54	3.92	0.02	0.02	0.22
diff_year_prior_v2elembcap	0.00	3.00	0.23	0.23	0.46
diff_year_prior_v2elreggov	-19.00	3.00	0.10	0.10	0.58
diff_year_prior_v2ellocgov	0.00	3.00	0.13	0.13	0.40
diff_year_prior_v2ellocons	-3.09	3.92	0.02	0.02	0.27
diff_year_prior_v2elrsthos	-2.26	3.90	0.02	0.02	0.22
diff_year_prior_v2elrstrct	-1.00	1.00	0.00	0.00	0.05
diff_year_prior_v2psparban	-1.00	1.00	0.00	0.00	0.04
diff_year_prior_v2psbars	-25.00	3.00	0.15	0.15	0.93
diff_year_prior_v2psoppaut	-1.00	1.00	0.00	0.00	0.08
diff_year_prior_v2psorgs	-1.00	1.00	0.00	0.00	0.06
diff_year_prior_v2psprbrch	-3.44	4.75	0.03	0.03	0.35
diff_year_prior_v2psprlnks	-2.68	4.39	0.03	0.03	0.31
diff_year_prior_v2psplats	-3.63	4.48	0.03	0.03	0.33
diff_year_prior_v2pscnslnl	-3.13	3.65	0.01	0.01	0.23
diff_year_prior_v2pscohesv	-3.08	3.16	0.01	0.01	0.22
diff_year_prior_v2pscomprg	-2.67	2.90	0.01	0.01	0.21
diff_year_prior_v2psnatpar	-2.52	3.90	0.01	0.01	0.22
diff_year_prior_v2pssunpar	-3.35	3.02	0.02	0.02	0.22

Table 18: Variables and Descriptive Statistics *(continued)*

Variable	Min	Max	Mean	Median	SD
diff_year_prior_v2exremhsp	-1.99	2.38	0.00	0.00	0.20
diff_year_prior_v2exdfdshs	-3.27	3.63	0.00	0.00	0.22
diff_year_prior_v2exdfcbhs	-3.75	2.98	0.00	0.00	0.36
diff_year_prior_v2exdfvths	-3.92	4.11	0.02	0.02	0.27
diff_year_prior_v2exdfdmhs	-3.74	3.06	0.01	0.01	0.28
diff_year_prior_v2exdfpphs	-4.13	2.84	-0.01	-0.01	0.27
diff_year_prior_v2exhoshog	-3.23	3.32	0.00	0.00	0.23
diff_year_prior_v2exrescon	-3.03	3.28	-0.01	-0.01	0.24
diff_year_prior_v2exbribe	-3.28	3.04	-0.01	-0.01	0.24
diff_year_prior_v2exembez	-2.65	2.99	0.01	0.01	0.21
diff_year_prior_v2excrptps	-1.00	1.00	0.00	0.00	0.14
diff_year_prior_v2exthftps	-3.96	5.17	0.01	0.01	0.29
diff_year_prior_v2ex_elechos	-3.81	3.29	0.00	0.00	0.24
diff_year_prior_v2ex_hogw	-2.85	3.12	0.00	0.00	0.24
diff_year_prior_v2expathhs	-2.52	2.92	-0.01	-0.01	0.19
diff_year_prior_v2lgbicam	-2.65	2.80	0.00	0.00	0.21
diff_year_prior_v2lgqstexp	-1.00	1.00	0.01	0.01	0.16
diff_year_prior_v2lginvstp	-1.00	1.00	0.00	0.00	0.10
diff_year_prior_v2lgotovst	-8.00	8.00	0.04	0.04	0.98
diff_year_prior_v2lgcrrpt	-2.00	2.00	0.01	0.01	0.27
diff_year_prior_v2lgoppart	-2.15	4.15	0.02	0.02	0.33
diff_year_prior_v2lgfunds	-2.66	3.77	0.02	0.02	0.33
diff_year_prior_v2lgdsadlobin	-2.89	3.43	0.02	0.02	0.33
diff_year_prior_v2lglegplo	-3.97	3.94	-0.01	-0.01	0.30
diff_year_prior_v2lgcomslo	-2.73	4.51	0.02	0.02	0.36
diff_year_prior_v2lgsrvlo	-3.58	2.81	0.01	0.01	0.29
diff_year_prior_v2ex_hosw	-9.37	9.85	0.00	0.00	0.33
diff_year_prior_v2lgamend	-3.21	4.46	0.01	0.01	0.30
diff_year_prior_v2dlreason	-3.33	4.80	0.02	0.02	0.28
diff_year_prior_v2dlcommon	-3.17	2.31	0.00	0.00	0.27
diff_year_prior_v2dlcountr	-1.00	1.00	0.00	0.00	0.10
diff_year_prior_v2dlconslt	-1.00	1.00	0.00	0.00	0.13
diff_year_prior_v2dlengage	-3.35	3.55	0.02	0.02	0.29
diff_year_prior_v2dlencmps	-2.24	3.03	0.01	0.01	0.25
diff_year_prior_v2dlunivl	-3.13	5.17	0.02	0.02	0.32
diff_year_prior_v2jureform	-3.32	4.82	0.02	0.02	0.32
diff_year_prior_v2jupurge	-3.45	3.81	0.02	0.02	0.31
diff_year_prior_v2jupoatck	-2.99	2.43	0.01	0.01	0.24
diff_year_prior_v2jupack	-3.38	4.00	0.01	0.01	0.22
diff_year_prior_v2juaccnt	-4.81	4.62	0.00	0.00	0.52
diff_year_prior_v2jucorrdc	-3.85	2.96	0.01	0.01	0.34
diff_year_prior_v2juhcind	-4.56	3.45	0.00	0.00	0.33
diff_year_prior_v2juncind	-3.52	3.72	0.01	0.01	0.32
diff_year_prior_v2juhccomp	-3.49	2.67	0.01	0.01	0.22
diff_year_prior_v2jucomp	-2.80	2.92	0.00	0.00	0.19
diff_year_prior_v2jureview	-2.79	4.52	0.01	0.01	0.27

Table 18: Variables and Descriptive Statistics *(continued)*

Variable	Min	Max	Mean	Median	SD
diff_year_prior_v2clacfree	-2.59	4.37	0.01	0.01	0.24
diff_year_prior_v2clrelig	-2.63	3.68	0.01	0.01	0.23
diff_year_prior_v2cltort	-3.51	3.54	0.01	0.01	0.23
diff_year_prior_v2clkill	-2.61	3.39	0.02	0.02	0.24
diff_year_prior_v2cltrnslw	-4.32	4.15	0.02	0.02	0.31
diff_year_prior_v2clrspct	-3.59	3.77	0.01	0.01	0.24
diff_year_prior_v2clfmove	-3.66	3.75	0.02	0.02	0.30
diff_year_prior_v2cldmovem	-3.67	4.05	0.02	0.02	0.31
diff_year_prior_v2cldmovew	-3.80	3.26	0.01	0.01	0.27
diff_year_prior_v2cldiscm	-3.73	4.21	0.01	0.01	0.26
diff_year_prior_v2cldiscw	-3.43	4.75	0.02	0.02	0.26
diff_year_prior_v2clslavem	-4.81	5.44	0.01	0.01	0.25
diff_year_prior_v2clslavef	-4.65	4.50	0.02	0.02	0.22
diff_year_prior_v2clstown	-3.70	4.53	0.02	0.02	0.33
diff_year_prior_v2clprptym	-3.27	4.01	0.02	0.02	0.30
diff_year_prior_v2clprptyw	-4.91	2.74	0.01	0.01	0.19
diff_year_prior_v2clacjstm	-4.02	3.73	0.01	0.01	0.18
diff_year_prior_v2clacjstw	-3.47	4.14	0.02	0.02	0.24
diff_year_prior_v2clacjust	-3.35	4.41	0.02	0.02	0.19
diff_year_prior_v2clsocgrp	-3.91	3.83	0.02	0.02	0.19
diff_year_prior_v2clrgunev	-4.66	2.96	0.01	0.01	0.23
diff_year_prior_v2svdomaut	-4.21	2.79	0.02	0.02	0.22
diff_year_prior_v2svinlaut	-3.10	3.39	0.01	0.01	0.19
diff_year_prior_v2svstterr	-2.11	2.77	0.01	0.01	0.19
diff_year_prior_v2cseeorgs	-3.06	2.88	0.00	0.00	0.21
diff_year_prior_v2csreprss	-1.85	4.57	0.01	0.01	0.22
diff_year_prior_v2cscnsult	-1.80	4.64	0.01	0.01	0.22
diff_year_prior_v2csprtcpt	-49.20	38.70	0.01	0.01	2.35
diff_year_prior_v2csgender	-2.80	4.33	0.03	0.03	0.29
diff_year_prior_v2csantimv	-3.98	4.54	0.02	0.02	0.32
diff_year_prior_v2csrlgrep	-3.01	3.13	0.02	0.02	0.31
diff_year_prior_v2csrlgcon	-3.48	4.31	0.03	0.03	0.28
diff_year_prior_v2mecenefm	-2.46	2.91	0.02	0.02	0.18
diff_year_prior_v2mecrit	-3.80	3.99	-0.01	-0.01	0.36
diff_year_prior_v2merange	-2.72	4.36	0.01	0.01	0.26
diff_year_prior_v2meharjrn	-2.86	3.47	0.01	0.01	0.25
diff_year_prior_v2meslfcen	-2.48	4.78	0.02	0.02	0.33
diff_year_prior_v2mebias	-2.57	4.96	0.03	0.03	0.30
diff_year_prior_v2mecorrpt	-4.10	4.76	0.03	0.03	0.30
diff_year_prior_v2pepwrses	-2.44	4.01	0.02	0.02	0.29
diff_year_prior_v2pepwrsoc	-3.38	4.66	0.02	0.02	0.32
diff_year_prior_v2pepwrgen	-3.29	4.59	0.03	0.03	0.33
diff_year_prior_v2pepwrort	-2.80	5.01	0.02	0.02	0.27
diff_year_prior_v2peedueq	-2.94	3.44	0.00	0.00	0.23
diff_year_prior_v2pehealth	-2.02	3.08	0.01	0.01	0.19
diff_year_prior_is_jud	-2.05	2.76	0.03	0.03	0.19

Table 18: Variables and Descriptive Statistics *(continued)*

Variable	Min	Max	Mean	Median	SD
diff_year_prior_is_leg	-1.05	2.21	0.02	0.02	0.14
diff_year_prior_is_elec	-2.27	2.60	0.01	0.01	0.17
diff_year_prior_is_election_year	-2.11	2.24	0.01	0.01	0.17
state_age	1.00	203.00	74.71	74.71	61.09
log_state_age	0.00	5.31	3.90	3.90	1.01
pop	115.77	1415045.93	35898.91	35898.91	126355.79
log_pop	4.75	14.16	9.04	9.04	1.62
infmort	1.60	208.69	50.35	50.35	44.00
gdp_growth	-83.37	453.82	3.61	3.61	10.17
gdp_pc_growth	-83.81	444.67	1.81	1.81	10.12
log_gdp	18.46	30.48	24.04	24.04	2.20
log_gdp_pc	4.41	11.68	8.10	8.10	1.56
epr_groups	1.00	58.00	4.68	4.68	5.56
epr_elf	0.01	1.00	0.58	0.58	0.30
epr_excluded_groups_count	0.00	55.00	2.43	2.43	4.90
epr_excluded_group_pop	0.00	0.98	0.15	0.15	0.21
epr_inpower_groups_count	1.00	15.00	2.25	2.25	2.15
epr_inpower_groups_pop	0.02	1.04	0.77	0.77	0.26
epr_regaut_groups_count	0.00	42.00	0.82	0.82	3.44
epr_regaut_group_pop	0.00	1.00	0.06	0.06	0.20
pt_coup_attempt	0.00	1.00	0.03	0.03	0.18
pt_coup_attempt_num	0.00	4.00	0.04	0.04	0.21
pt_coup_num	0.00	2.00	0.02	0.02	0.13
pt_coup	0.00	1.00	0.02	0.02	0.13
pt_failed_coup_attempt_num	0.00	4.00	0.02	0.02	0.16
pt_failed_coup_attempt	0.00	1.00	0.02	0.02	0.13
pt_coup_total	0.00	23.00	2.00	2.00	3.37
pt_failed_coup_attempt_total	0.00	1.00	0.00	0.00	0.01
pt_coup_attempt_total	0.00	28.00	3.13	3.13	4.80
pt_coup_num5yrs	0.00	5.00	0.10	0.10	0.36
pt_failed_coup_attempt_num5yrs	0.00	1.00	0.00	0.00	0.01
pt_coup_attempt_num5yrs	0.00	9.00	0.20	0.20	0.61
pt_coup_num10yrs	0.00	6.00	0.21	0.21	0.60
pt_failed_coup_attempt_num10yrs	0.00	1.00	0.00	0.00	0.01
pt_coup_attempt_num10yrs	0.00	10.00	0.43	0.43	1.03
years_since_last_pt_coup	0.00	203.00	42.91	42.91	45.20
years_since_last_pt_failed_coup_attempt	0.00	203.00	49.50	49.50	54.26
years_since_last_pt_coup_attempt	0.00	203.00	38.32	38.32	45.50
internal_confl	0.00	1.00	0.17	0.17	0.38
internal_confl_major	0.00	1.00	0.05	0.05	0.22
internal_confl_minor	0.00	1.00	0.13	0.13	0.34
internal_confl_part	0.00	1.00	0.29	0.29	0.45
internal_confl_part_major	0.00	1.00	0.15	0.15	0.35
internal_confl_part_minor	0.00	1.00	0.18	0.18	0.39
war	0.00	1.00	0.03	0.03	0.17
war_major	0.00	1.00	0.02	0.02	0.13

Table 18: Variables and Descriptive Statistics *(continued)*

Variable	Min	Max	Mean	Median	SD
war_minor	0.00	1.00	0.01	0.01	0.12
any_conflict	0.00	1.00	0.30	0.30	0.46
any_conflict_major	0.00	1.00	0.16	0.16	0.36
any_conflict_minor	0.00	1.00	0.19	0.19	0.39
ext_conf	0.00	1.00	0.16	0.16	0.37
ext_conf_major	0.00	1.00	0.11	0.11	0.31
ext_conf_minor	0.00	1.00	0.08	0.08	0.26