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ABSTRACT

We study a dynamic model of protest and mobilization, in which the international community may intervene to sanction certain actions by the regime. We find that sanctioning public acts of repression, such as beating or arrests of protesters, can encourage the regime to prevent protest through less public means, such as obstruction or harassment of organizers. We show how to circumvent this problem by inferring the regime's efforts to prevent protest from the extent to which protest can be predicted in advance. We create a global, monthly index of protest prevention using a novel database of protest events that includes information on whether a protest was planned or anticipated in advance. We illustrate the value of the index by studying its evolution during the COVID-19 pandemic and other salient events. The international community can use the index to pressure regimes to permit protest.

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1 Introduction

The international community routinely sanctions acts of repression.[1] Some acts of repression, such as beating or arrest of protesters, are essentially public. Others, such as obstruction or harassment of organizers, are less public and therefore more deniable. It is practically and politically easier to sanction public acts.[2] But sanctioning public acts of repression may fail to deter less public ones, and might even encourage regimes to prevent protest in order to avoid public clashes.

We study the problem of monitoring repression when some forms of repression may not be public. We cast our analysis in a dynamic model of protest and repression. The model illustrates the pitfalls of basing sanctions only on public actions by the regime. It additionally shows how to infer efforts to prevent protest by using information on the extent to which protest can be predicted in advance. We apply the ideas from the model to a novel, global database of protest events that includes information on whether protest is planned or anticipated in advance. The result is a global, monthly index of protest prevention. We illustrate the value of the index by studying its evolution during the COVID-19 pandemic and other salient events, and we discuss how the international community can use the index to pressure regimes to permit more protest.

In the model, an opposition may seek to mobilize protest and a regime may seek to prevent it. If protest occurs, it may escalate, which leads to an absorbing state (say, revolution) that is appealing to the opposition but unappealing to the regime. The regime can reduce the risk of escalation by suppressing the protest, for example by beating or arresting protesters. We study the stationary equilibria in pure strategies of this dynamic game.

Issues of observability are central to our analysis. We assume that the international community can observe acts of suppression but not of prevention. We show that, under certain conditions, sanctioning suppression encourages prevention, because by preventing protest, the regime avoids the need to suppress it.

[1] In 2022, for example, the US announced sanctions against "Iranian Regime Officials Tied to Continued Violence Against Protesters" (U.S. Department of the Treasury 2022a). The US also announced sanctions against "Regime Officials and Military Affiliated Cronies in Burma," citing the regime's "targeting [of] political opposition leaders and peaceful demonstrators" (U.S. Department of the Treasury 2022b). See also Council of the European Union (2022a,b).

[2] Contrast two cases in Zimbabwe. In August 2018, international media published video and photo documentation of military firing on crowds of protesters, and beating individual protestors, in Harare (Burke 2018; Bearak 2018; see also Human Rights Watch 2018). In March 2011, international media reported that the Zimbabwean government had arrested organizers and mobilized riot police to prevent a planned protest in Harare (Mavhunga 2011; see also Human Rights Watch 2011). In the former case, the US issued new sanctions (U.S. Department of the Treasury 2020); in the latter case, the US expressed concern (Crowley 2011; CNN Wire Staff 2011).

We also assume the international community can observe the occurence of protest. We show that data on the occurrence of protest is not, in general, sufficient to infer the extent of prevention. If, however, the international community can also observe the probability of protest in each period (say, each day), we show that it is possible to infer the extent of prevention. In particular, under conditions we specify, the regime's equilibrium strategy takes the form of a cutoff in probability, such that the regime steps in to prevent protest if and only if protest is sufficiently probable. The cutoff can, under further conditions, be identified from the distribution of the probability of protest. We further show that observing the equilibrium probability of protest allows the international community to effectively sanction repression.

Identification of the regime's strategy rests on two key conditions. First, we assume that the technology for prevention features increasing returns, such that if the regime steps in at all to prevent protest, it exerts maximal effort—for example, by closing public squares, imposing curfews, and detaining potential organizers. This assumption, together with the structure of the model, implies that the regime's equilibrium strategy takes the form of a cutoff in probability. Second, we assume that grievances are such that, absent efforts to prevent it, protest would be arbitrarily probable at least some of the time. This assumption implies that the observed probability of protest will sometimes approach the cutoff for intervention by the regime, and therefore that the maximum probability of protest observed in equilibrium will coincide with the cutoff.

To apply these ideas, we assemble a new database of protest occurrence covering 150 countries from 2010 through 2021. The database comes from the text of security alerts produced by Crisis24, a global risk management firm. We use an automated process to parse the text of these alerts and identify protest events. We validate the automated parsing by comparison to human parsing on a random subset of cases, and we show that incidents of protest in our database are correlated with those in other academic databases of protest. Importantly, information in the security alerts allows us to tag certain protests as planned or anticipated in advance, something that other global databases do not permit. We supplement and validate these tags with data on a variety of other predictors of protest, including the frequency of internet searches about protest, the frequency of news mentions of protest, and the frequency of social media mentions of protest. In addition, we use the text of the alerts to tag protests involving violence or arrests, a proxy for the occurrence of suppression that we also validate by comparison with other data.

We develop two monthly indices of preventive repression. The first is (one minus) an indicator for whether a planned or anticipated protest occurs in the given month. The second is (one minus) the maximum probability of protest according to a forecasting model that is estimated on out-of-sample data using information on all of the predictors that we have collected. In practice these two indices are highly correlated, with the first being simpler to describe and implement, and the second more amenable to future extension as additional predictor variables become available. We show formally that, if the forecasting model is consistent for the true equilibrium probability of protest, the second index is consistent for an upper bound on one minus the regime's equilibrium cutoff, and we characterize the tightness of the bound. We also show the robustness of our results to a variety of alternative forecasting and estimation approaches, including finite-sample confidence bounds based on Lei (2023).

We validate our indices in several ways. For internal validation, we conduct a simulation exercise in which we simulate data from a known data-generating process, apply our estimation procedure, and compare the estimates to a (known) target value. We find that the estimator performs well in this exercise. For external validation, we compare our indices of prevention to a composite of expert ratings of freedom to protest in a cross-section of countries, and find that these are strongly correlated. We further show (in smaller samples) that our measure of preventiveness leads changes in expert-rated freedom, and is correlated with citizens' self-reported perceptions of the freedom to protest. We subject our key validation tests to a variety of falsification exercises to confirm that the good performance of our indices is not simply mechanical, and we show how to extend our analysis to account for the possibility that some forms of protest are more threatening to the regime than others.

We apply our indices to several topics of interest, first revisiting the topic of international sanctions. We show that sanctions are preceded, on average, by an increase in the frequency of suppression. In contrast, there is no evidence that sanctions are preceded by an increase in preventive repression. This evidence is consistent with our hypothesis that the international community tends to base sanctions on the most public forms of repression.

We next present what is to our knowledge the first high-frequency picture of preventive repression during the initial stages of the COVID-19 pandemic. Consistent with concerns raised at the time (Economist 2020), we find that preventive repression increased substantially during early lockdowns, as did the incidence of suppression. By the end of 2020, preventive repression had returned to its baseline levels, but the incidence of suppression had not.

Lastly, we study the dynamics of protest repression and incidence around elections. We find that protest prevention declines during election months, with a much greater decline in non-democracies than in democracies. The dynamics of protest suppression and incidence are, by contrast, more similar between democracies and non-democracies. We relate our findings to recent work on the role of elections in non-democracies.

Across these applications, we observe distinct dynamics of prevention, suppression, and incidence of protest at subannual frequencies. These applications therefore illustrate the value of measuring these concepts separately, and at high frequency, both for surveillance by the international community, and for research by social scientists.

The principal contribution of this paper is to develop and implement theoretically grounded tools for the real-time surveillance of preventive repression. To our knowledge no prior research has done this. The building blocks of our approach contribute to research on the theory and measurement of protest and repression.

Our main contribution to the theory of repression is a dynamic model that features both prevention and suppression of protest. We are not aware of prior work that shows conditions under which sanctioning suppression can encourage prevention of dissent. A large prior literature, reviewed for example in Gehlbach, Sonin, and Svolik (2016), studies the dynamics of protest, dissent, and repression, especially in autocracies (see also Davenport 2007; Earl 2011; Acemoglu, Egorov, and Sonin 2015; Davenport et al. 2019). Within this literature there are relatively few papers featuring a dynamic equilibrium model with protest prevention. Recent exceptions include De Jaegher and Hoyer's (2019) analysis of the backlash effects of preventing dissidents from participating in protest, and Gibilisco's (2021) analysis of center-periphery relations.[3]

Our main contribution to the measurement of protest is a new, global database that explicitly tags planned or anticipated protest. We are not aware of other global databases that tag planned or anticipated protests. The database we introduce also includes covariates that we use to fit a predictive model of protest, contributing to an active literature on the prediction of civil unrest.[4] Much of this literature focuses on the predictive task itself, whereas we use the prediction of protest as an input to measuring preventive repressiveness.[5]

Our main contribution to the measurement of repression is a global monthly index of preven-

[3]Aktan (2022a) studies a model featuring asymmetric information and both prevention and suppression of dissent in a stage game that is not repeated (see also Dragu and Przeworski 2019; Aktan 2022b).

[4]See, for example, Ramakrishnan et al. (2014), Hoegh et al. (2015), Hoegh, Ferreira, and Leman (2016), Qiao et al. (2017), Wu and Gerber (2018), Bagozzi, Chatterjee, and Mukherjee (2019), Deng, Rangwala, and Ning (2019), Hoegh (2019), and Ross et al. (2019). Mueller and Rauh (2018), among others, study prediction of related outcomes such as armed conflict. Zhao (2022) provides a survey.

[5]Langørgen (2016) argues that organized and spontaneous protests are likely to have different causal structures. Kuran (1991) studies the predictability of revolution; see also Sonin and Wright (2023).

tive repressiveness that is grounded in a theoretical model. We are not aware of existing global subannual indices of preventive repressiveness. Fariss (2014) measures trends over time in particular forms of repression such as killing by the state (see also Guriev and Treisman 2022).[6] Recent empirical studies of preventive repression include Truex's (2019) study of dissident arrests, Carter and Carter's (2022) study of propaganda-based threats in China, and Esberg's (2021) study of the treatment of politicians in Pinochet's Chile. These studies use data on specific, measurable forms of repression to study preventive repression in a particular context. By contrast, our indices are global, do not require enumeration of specific repressive acts, and are designed to capture the full extent to which a regime prevents protest, including by clandestine means.[7]

Several academic and nongovernmental projects publish annual indices of freedom based on expert ratings.[8] Our analysis shows the value of subannual measurement of repression, which could allow the international community to respond more quickly to changes in regime conduct. For example, both around COVID-19 lockdowns and around elections, our indices reveal changes in repressiveness at monthly frequency that are largely obscured by annual indices.[9] Our analysis also shows the possibility of using observational data, rather than expert ratings, to index preventive repressiveness.[10] Scholars have raised concerns about expert ratings' transparency and objectivity.[11] The automated indices we introduce entail a transparent mapping from inputs to outputs that is grounded in a formal model. The quality of the input data, and the assumptions on which

[6]A large literature studies the determinants of these and other repressive acts (e.g., Franklin 2008; Licht and Allen 2018; Scharpf et al. 2023).

[7]Danneman and Ritter (2014) and Carey et al. (2022) study, respectively, the effect of nearby civil war, and of oil discoveries, on preventive repression in a cross-national panel. Ritter and Conrad (2016) study the dynamics of dissent, prevention, and suppression in a panel of African provinces and a panel of US states. Gueorguiev (2017) and Esberg (2021), among others, consider the strategic distinction between private and public repression. For other work on the empirical dynamics of protest, dissent, and repression, see, for example, Moore (1998), Carey (2006, 2009), and Archibong, Moerenhout, and Osabuohien (2022).

[8]For indices related to repression of protest, see, for example, the *Freedom in the World* report's Freedom of Assembly index (Freedom House 2021b), the Varieties of Democracy Project's Freedom of Peaceful Assembly index (Pemstein et al. 2023), and the Cingranelli-Richards (CIRI) Human Rights Data Project's Freedom of Assembly and Association index (Cingranelli, Richards, and Clay 2014).

[9]On COVID-19 and dissent, see, e.g., Chenoweth (2022). On elections and political unrest see, e.g., Tucker (2007); Harish and Little (2017).

[10]Some indices use survey data to measure freedom at a point in time (e.g, Logan and Mattes 2012; Pickel, Breustedt, and Smolka 2016). We use related survey data to validate our indices in the cross-section of countries. Some indices incorporate information on *de jure* freedoms including those guaranteed by constitutions (e.g., Merkel et al. 2020). There is mixed evidence on whether such guarantees are associated with greater *de facto* freedoms (see, e.g., Keith and Poe 2004; Keith, Tate, and Poe 2009; Chilton and Versteeg 2015). See also the typology of human rights measurement in Landman (2004).

[11]On transparency see, e.g., Munck and Verkuilen (2002, p. 21) and Bradley (2015, p. 38); on objectivity and the possibility of political bias see, e.g., Mainwaring, Brinks, and Pérez-Liñán (2001), Steiner (2016), and Bush (2017). See also Little and Meng (Forthcoming).

the analysis rests, can be interrogated and improved. These advantages seem especially important because published indices of freedom already play a role in consequential public policy.[12]

The rest of the paper proceeds as follows. Section 2 presents the model, characterizes its equilibrium, and studies the effect of sanctions on repression. Section 3 formalizes our approach to identification and estimation of preventive repression. Section 4 describes our data and evidence on its validity. Section 5 describes our implementation of the indices of preventive repression, and provides evidence on their validity. Section 6 studies the dynamics of protest and repression around key events at monthly frequency. Section 7 concludes.

2 Model of Protest and Repression

There is a set of countries indexed by $i \in \{1,...,N\}$. In each country i there is a regime and an opposition. In each country i and in each period t, there is a prevailing environment $k_{it} \in \{0,1,...,K\}$, with $k_{it} = 0$ denoting that revolution has occurred. We can think of the environment $k_{it} \in \{1,...,K\}$ as incorporating time-varying payoff-relevant factors such as the resources of the regime, whether there is a public health crisis, etc. We can think of a period t as a calendar date.

In each country i and in each period t in which $k_{it} > 0$, a stage game is played, with decisions by nature independent across periods. The first segment of the stage game determines whether protest occurs. In this segment, nature first determines the extent of grievances $\omega_{it} \in [0,1]$ according to some distribution. Grievances may arise from economic hardship, natural disasters, and other shocks whose determinants we do not model explicitly, and their distribution may depend on the environment k_{it}. After observing grievances ω_{it}, the opposition then decides on a mobilization effort $m_{it} \in [0,1]$. After observing grievances ω_{it} and mobilization m_{it}, the regime then chooses a level of prevention $r_{it} \in [0,1]$. Protest may then occur with a probability $p(\omega_{it}, m_{it}, r_{it}; k_{it})$ increasing in grievances ω_{it} and mobilization m_{it} and decreasing in prevention r_{it}, where the function $p(\cdot;\cdot)$ may reflect a variety of processes.[13] If protest does not occur, the period ends. Note that,

[12] The US Millennium Challenge Corporation incorporates Freedom House's indices into its criteria for determining a country's eligibility for assistance (Millennium Challenge Corporation 2020). Canada's Country Indicators for Foreign Policy project integrates Freedom House indicators into data aimed at providing guidance to development-agency staff (Carment 2010). The Open Government Partnership Global Report cites Freedom House data in the context of identifying potential areas for future work and improvement (Open Government Partnership 2019, pp. 72, 78, 96).

[13] Consider, for example, a global game (Morris and Shin 1998) among a continuum of citizens who simultaneously decide whether to protest. A citizen's net payoff from protesting in country i and period t depends on grievances ω_{it}, mobilization m_{it}, prevention r_{it}, the environment k_{it}, and on whether the share of citizens protesting exceeds an uncertain threshold, about which each citizen receives a noisy private signal. Each citizen wants to protest only when

because $p(\cdot;\cdot)$ can depend on the environment k_{it}, it is without loss to suppose that the space of possible grievances, and the action spaces of the opposition and regime, do not depend on the environment.

If protest does occur, we move to the second segment of the stage game, which determines whether revolution occurs. Absent suppression, the probability of revolution is $q_{it} \in [0,1]$, chosen by nature according to a distribution that can depend on k_{it} but not on ω_{it}. After observing q_{it}, the regime decides whether to suppress, a decision we treat as binary to align with our data, and denote by $s_{it} \in \{0,1\}$. If the regime chooses to suppress, $s_{it} = 1$, the probability of revolution is $\underline{q}(k_{it}) \leq q_{it}$. After nature determines whether revolution occurs, the period ends.

If in a given period revolution occurs, the environment transitions permanently to $k_{it} = 0$ beginning with the next period. If in a given period revolution does not occur, the environment transitions according to a matrix $\mathbf{K}_i \in \mathbb{R}^{K \times K}$ such that the $(k,l)^{th}$ cell of $\mathbf{K}_i$ describes the probability of transitioning from environment k to environment l.[14] Note that, because the transition matrix $\mathbf{K}_i$ is country-specific, we can allow that some (or all) environments are specific to certain countries, and hence that objects that depend on the environment k_{it} implicitly depend on the country i.

When $k_{it} = 0$, the regime obtains per-period payoff $-\ell_i < 0$ and the opposition obtains per-period payoff $b_i \geq 0$, which we may alternatively think of as expected payoffs in a continuation game whose outcomes do not depend on those in the game we study. When $k_{it} > 0$, the regime obtains per-period payoff $d(k_{it}) - \rho(k_{it}) r_{it} - \sigma(k_{it}) s_{it}$ and the opposition obtains per-period payoff $-\mu(k_{it}) m_{it} - c(r_{it}, s_{it}, k_{it})$. Here, $\rho(k_{it})$, $\sigma(k_{it})$, and $\mu(k_{it})$ are positive scalar costs, $c(r_{it}, s_{it}, k_{it})$ is a nonnegative function weakly increasing in r_{it} and s_{it} with $c(0,0,k_{it}) = 0$, the scalar $d(k_{it}) > \rho(k_{it}) + \sigma(k_{it})$ is a benefit of control, and it is understood that $s_{it} = 0$ when protest does not occur. The regime and opposition discount their per-period payoffs according to discount factors $\delta \in [0,1)$ and $\beta \in [0,1)$, respectively.

We focus on subgame perfect equilibrium in stationary pure strategies, such that the regime's strategy can be written as $r^*(\omega_{it}, m_{it}; k_{it}), s^*(q_{it}; k_{it})$, the opposition's strategy can be written as $m^*(\omega_{it}; k_{it})$, and all strategies can depend on the prevailing environment k_{it}. To simplify ties, we

the share of protesting citizens exceeds the threshold. By standard results from the global games literature (Morris and Shin 2003, Proposition 2.2), in the limit as the noise in citizens' signals becomes vanishingly small, there is a unique equilibrium in which protest occurs with a probability $p(\cdot;\cdot)$ that depends on grievances ω_{it}, mobilization m_{it}, repression r_{it}, and the environment k_{it}.

[14] To close the model, we may imagine that in an initial period $t = 0$, an environment is chosen uniformly at random from among those environments that are reachable via $\mathbf{K}_i$.

suppose that when indifferent regarding whether or not to suppress, the regime does not suppress; when indifferent over multiple levels of prevention, the regime chooses the smallest of these; and that best responses are played even in environments and states that are never chosen by nature. As a shorthand, we will sometimes refer to a stationary equilibrium in pure strategies that obeys these tiebreaking rules as an *equilibrium*.

2.1 Characterization of Equilibrium

Fix a country i. In any equilibrium in stationary strategies, the regime's expected discounted payoff at the start of any period t in environment $k_{it} > 0$ can be written as a function $V^*(k_{it})$ of the environment, and likewise for the expected discounted payoff of the opposition $W^*(k_{it})$. For any $k_{it} > 0$, let $\overline{V}^*(k_{it}) = \sum_{l=1}^{K} \mathbf{K}_{i,k_{it},l} V^*(l)$ denote the expectation over $V^*(l)$ with respect to the transition probabilities starting from environment k_{it}, and define $\overline{W}^*(k_{it})$ analogously. In the case where revolution has occurred, i.e., where $k_{it} = 0$, the regime's and opposition's expected discounted payoffs, $V(0)$ and $W(0)$, do not depend on the equilibrium being played.[15]

To characterize equilibrium play, we work backwards through the stage game, beginning with the second segment. If a protest has occurred then, given our tiebreaking rule, the regime suppresses if and only if

$$\delta\left(q_{it}V(0) + (1-q_{it})\overline{V}^*(k_{it})\right) < \delta\left(\underline{q}(k_{it})V(0) + \left(1-\underline{q}(k_{it})\right)\overline{V}^*(k_{it})\right) - \sigma(k_{it}). \quad (1)$$

It is immediate that there is a cutoff $\overline{q}^*(k_{it}) \in \left[\underline{q}(k_{it}), 1\right]$ such that the regime suppresses if and only if $q_{it} > \overline{q}^*(k_{it})$.[16] Let $S^*(k_{it})$ denote the equilibrium probability of suppression and $Q^*(k_{it})$ the equilibrium probability of revolution in environment $k_{it} > 0$, conditional on the occurrence of protest.[17]

We next turn to the first segment of the stage game. We adopt the following restrictions on the function $p(\cdot;\cdot)$.

Assumption 1. *The function $p(\cdot;k)$ satisfies the following for each $k > 0$:*

(a) $p(\omega, m, r; k)$ is concave in r for all $\omega, m \in [0,1]$.

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[15]Specifically, $V(0) = -\ell_i/(1-\delta)$ and $W(0) = b_i/(1-\beta)$, where we suppress the dependence on the country i for convenience.

[16]Specifically, $\overline{q}^*(k_{it}) = \min\left\{1, \underline{q}(k_{it}) + \frac{\sigma(k_{it})}{\delta\left(\overline{V}^*(k_{it}) - V(0)\right)}\right\}$ where $\overline{V}^*(k_{it}) - V(0) > 0$.

[17]That is, $S^*(k_{it}) = \Pr\left(q_{it} > \overline{q}^*(k_{it}) \mid k = k_{it}\right)$ and $Q^*(k_{it}) = S^*(k_{it})\underline{q}(k_{it}) + (1 - S^*(k_{it}))\mathrm{E}\left(q_{it} \mid q_{it} \le \overline{q}^*(k_{it}), k = k_{it}\right)$.

(b) $p(\omega, m, 1; k) = \underline{p}(k) \in [0,1)$ *for all* $\omega, m \in [0,1]$.

Assumption 1(a) states that the probability of protest is concave in the extent of prevention. Assumption 1(b) states that if the regime engages in maximal prevention then the probability of protest reaches some (possibly low) level $\underline{p}(k)$ regardless of the extent of grievances or mobilization.[18] We may think of these assumptions as reflecting a situation in which moderate levels of prevention are ineffective (as in, e.g., Zhukov 2023), and in which prevention reduces the efficacy of mobilization (as in, e.g., Tilly 1978, p. 100).

The regime's expected discounted payoff when choosing the level of prevention r_{it} is given by

$$\begin{aligned}\delta\left(p(\omega_{it}, m_{it}, r_{it}; k_{it})\, Q^*(k_{it})\, V(0) + (1 - p(\omega_{it}, m_{it}, r_{it}; k_{it})\, Q^*(k_{it}))\, \overline{V}^*(k_{it})\right)\\ +d(k_{it}) - \rho(k_{it})\, r_{it} - p(\omega_{it}, m_{it}, r_{it}; k_{it})\, \sigma(k_{it})\, S^*(k_{it})\,.\end{aligned} \tag{2}$$

Because of the form of (2), Assumption 1(a) implies that the regime's optimal level of prevention is either 0 or 1. Assumption 1(b) and our tiebreaking rule then imply that there is a cutoff $\overline{p}^*(k_{it}) \in \left[\underline{p}(k_{it}), 1\right]$ such that the regime engages in maximal prevention $r_{it} = 1$ if $p(\omega_{it}, m_{it}, 0; k_{it}) > \overline{p}^*(k_{it})$ and no prevention $r_{it} = 0$ otherwise.[19] Note that while our assumptions imply that $S^*(k_{it})$ and $Q^*(k_{it})$ do not depend on ω_{it}, it follows from (2) that a cutoff structure would still obtain if we instead allowed that these probabilities were increasing in ω_{it}, say because the distribution of q_{it} depends on ω_{it}.

To complete the characterization, note that by Assumption 1(b) the opposition does not benefit from mobilization when the regime engages in prevention. It follows that the opposition will choose $m^*(\omega_{it}; k_{it})$ such that, whenever possible, $p(\omega_{it}, m^*(\omega_{it}; k_{it}), 0; k_{it}) \leq \overline{p}^*(k_{it})$.

Collecting the preceding we have the following characterization.

Proposition 1. *Under Assumption 1, in any equilibrium and in any environment* $k_{it} > 0$*,*

(i) The regime suppresses if and only if $q_{it} > \overline{q}^*(k_{it})$ *for some particular* $\overline{q}^*(k_{it}) \in \left[\underline{q}(k_{it}), 1\right]$.

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[18] An example of a function satisfying Assumption 1 is

$$(1-r)\max\left\{\frac{\omega(m+\underline{m})}{(1-\omega)+\omega(m+\underline{m})}, \underline{p}(k)\right\} + r\underline{p}(k)$$

for $\underline{m}$, a positive constant.

[19] Specifically,

$$\overline{p}^*(k_{it}) = \min\left\{1, \underline{p}(k_{it}) + \frac{\rho(k_{it})}{\delta Q^*(k_{it})\left(\overline{V}^*(k_{it}) - V(0)\right) + \sigma(k_{it})\, S^*(k_{it})}\right\}.$$

(ii) The regime chooses $r_{it} = 1$ if $p(\omega_{it}, m_{it}, 0; k_{it}) > \overline{p}^*(k_{it})$, and $r_{it} = 0$ otherwise, for some particular $\overline{p}^*(k_{it}) \in [\underline{p}(k_{it}), 1]$.

(iii) The opposition chooses mobilization $m^*(\omega_{it}; k_{it})$ such that, whenever possible, $p(\omega_{it}, m^*(\omega_{it}; k_{it}), 0; k_{it}) \leq \overline{p}^*(k_{it})$.

We will refer to an equilibrium of the form in Proposition 1 as a *cutoff equilibrium*. Proposition 6 in Appendix A.1 gives example sufficient conditions for the existence of a cutoff equilibrium. Although we find the assumption that the opposition chooses mobilization before the regime chooses prevention to be descriptively realistic for many settings, if $r_{it} \in \{0, 1\}$ then a characterization analogous to Proposition 1 obtains if we instead suppose that the regime moves first.[20]

2.2 Sanctioning Suppression Can Encourage Prevention

Suppose that the international community can observe acts of suppression and sanction them. We can represent sanctions in the model as a change in the cost of suppression from $\sigma(k_{it})$ to $\sigma'(k_{it}) \geq \sigma(k_{it})$. Sanctions of this form can encourage prevention.

Proposition 2. *Suppose that $\underline{q}(k) = 0$ and that q_{it} has full support for all $k \in \{1, ..., K\}$ and consider the modified game formed by increasing $\sigma(k)$ to $\sigma'(k) \geq \sigma(k)$ in all environments $k \in \{1, ..., K\}$, leaving other primitives unchanged. Under Assumption 1 there is some $\overline{\sigma} > \underline{\sigma} > 0$ such that if $\sigma'(k) \geq \overline{\sigma} > \underline{\sigma} \geq \sigma(k) > 0$ for all $k \in \{1, ..., K\}$, then for any cutoff equilibrium $(\overline{p}^*(\cdot), \overline{q}^*(\cdot), m^*(\cdot))$ of the base game and any cutoff equilibrium $(\overline{p}^{**}(\cdot), \overline{q}^{**}(\cdot), m^{**}(\cdot))$ of the modified game, we have that $\overline{p}^{**}(k) \leq \overline{p}^*(k)$ for all $k \in \{1, ..., K\}$, with strict inequality if $\rho(k)$ is sufficiently small.*

Proposition 2 is proved in the appendix. Intuitively, large sanctions on suppression imply that, if protest occurs, the regime either pays a large cost to suppress it, or accepts a risk of revolution. These prospects encourage the regime to prevent protest.

Proposition 2 helps to motivate the importance of measuring prevention. We assume that the international community cannot directly observe acts of prevention, and so cannot directly influ-

[20] Specifically, suppose that the regime chooses the level of prevention $r_{it} \in \{0, 1\}$ before the opposition chooses the level of mobilization $m_{it} \in [0, 1]$. Then a characterization analogous to Proposition 1 obtains, writing the opposition's stationary pure strategy as $m^*(\omega_{it}, r_{it}; k_{it})$, modifying part (ii) of Proposition 1 to hold that $r^*_{it} = 1$ if and only if $p(\omega_{it}, m^*(\omega_{it}, 0; k_{it}), 0; k_{it}) > \overline{p}^*(k_{it})$, and modifying part (iii) of Proposition 1 to hold that the opposition chooses $m^*(\omega_{it}, 1; k_{it}) = 0$.

ence their cost $\rho(\cdot)$. Instead, we ask how the international community can infer the equilibrium *preventiveness* $1-\overline{p}^*(\cdot)$ of the regime.

3 Identification and Estimation of Preventiveness

3.1 Identification of Preventiveness from the Equilibrium Probability of Protest

Suppose the international community observes some data D^* arising from some cutoff equilibrium. We will here think of the data D^* as some functional of the joint equilibrium distribution of the variables in the game, and return to issues of estimation in the next subsection.

Definition 1. The preventiveness of the regime is **identified** from a given type of data if any two cutoff equilibria $(\overline{p}^*(\cdot), \overline{q}^*(\cdot), m^*(\cdot)), (\overline{p}^{**}(\cdot), \overline{q}^{**}(\cdot), m^{**}(\cdot))$ consistent with the same data D^* have the same preventiveness, $1-\overline{p}^*(\cdot) = 1-\overline{p}^{**}(\cdot)$.

Importantly, Definition 1 allows that the two equilibria $(\overline{p}^*(\cdot), \overline{q}^*(\cdot), m^*(\cdot))$, $(\overline{p}^{**}(\cdot), \overline{q}^{**}(\cdot), m^{**}(\cdot))$ may arise from different primitives.

Our main result is that preventiveness is identified from data on the equilibrium probability of protest if the distribution of grievances is sufficiently rich. For some equilibrium in stationary pure strategies, let $\Phi^*(\cdot)$ denote the distribution of the equilibrium probability of protest in each environment $k>0$.[21] We impose the following high-level condition on the distribution of grievances ω.

Assumption 2. *The random variable $p(\omega,0,0;k)$ has full support on $\left[\underline{p}(k), 1\right]$ in each environment $k>0$.*

Assumption 2 requires that, in any environment, arbitrarily high protest probabilities would sometimes be observed absent mobilization and prevention. We may think of this assumption as describing a situation in which grievances are pervasive (e.g., Jenkins and Perrow 1977, p. 251; Oberschall 1978, p. 298), and so may manifest as protest when the prevailing political structures do not prevent it (e.g., McAdam 1982, Chapter 3).

Proposition 3. *Under Assumption 2, the preventiveness of the regime is identified from data D^* that includes the distribution $\Phi^*(\cdot)$ of the equilibrium probability of protest.*

[21] That is, $\Phi^*(p';k) = \Pr(p(\omega, m^*(\omega;k), r^*(\omega, m^*(\omega;k);k);k) \le p'|k)$ for all $p' \in [0,1]$ and each environment $k>0$.

Proof. The proof is constructive, showing that if the data D^* arise from a cutoff equilibrium $(\overline{p}^*(\cdot), \overline{q}^*(\cdot), m^*(\cdot))$, then $\overline{p}^*(k) = \inf\{p \in [0,1] : \Phi^*(p;k) = 1\}$ in any environment $k > 0$. Fix some $k > 0$. First observe that $\Phi^*(\overline{p}^*(k);k) = 1$ so that $\overline{p}^*(k) \geq \inf\{p \in [0,1] : \Phi^*(p;k) = 1\}$. Next observe that, if $\overline{p}^*(k) > \underline{p}(k)$, then for any $p' < \overline{p}^*(k)$, by Assumption 2 we have that $\Pr(p(\omega,0,0;k) \in [p', \overline{p}^*(k)] \,|k) > 0$. But because by properties of a cutoff equilibrium we have that $p(\omega, m^*(\omega;k), 0;k) \leq \overline{p}^*(k)$ with probability one whenever $p(\omega,0,0;k) \leq \overline{p}^*(k)$, we also have that $\Phi^*(\overline{p}^*(k);k) - \Phi^*(p';k) > 0$ and therefore that $\Phi^*(p';k) < 1$. If instead $\overline{p}^*(k) = \underline{p}(k)$, then by Assumption 2 and the properties of a cutoff equilibrium, the equilibrium probability of protest has a point mass at $\overline{p}^*(k)$, so we again have that $\Phi^*(p';k) < 1$ for any $p' < \overline{p}^*(k)$. In either case, it follows that $\overline{p}^*(k) \leq \inf\{p \in [0,1] : \Phi^*(p;k) = 1\}$ and therefore that $\overline{p}^*(k) = \inf\{p \in [0,1] : \Phi^*(p;k) = 1\}$ as desired. □

The proof of Proposition 3 shows that in any environment $k > 0$, the threshold $\overline{p}^*(k)$ for prevention is given by the least upper bound on the equilibrium probability of protest. The construction in the proof makes clear that identification relies on the structure of a cutoff equilibrium only through the elements in parts (ii) and (iii) of Proposition 1. Although bunching of protest probabilities at the threshold $\overline{p}^*(k)$ can occur in our model, identification does not require observing such bunching.[22] Moreover, while our model allows for strategic behavior by the opposition, identification does not require it.[23]

The approach to identification in Proposition 3 relies on observing the distribution of the equilibrium probability of protest, and in particular the maximum of its support. Observing the frequency of protest alone is not sufficient for identification of prevention, even if the frequency of suppression is also observed. To formalize this, for any cutoff equilibrium $(\overline{p}^*(\cdot), \overline{q}^*(\cdot), m^*(\cdot))$ and any environment $k > 0$, let $P^*(k)$ denote the probability of protest.[24]

Proposition 4. *The preventiveness of the regime is not identified from data $D^* = (P^*(\cdot), S^*(\cdot))$ that includes only the probabilities of protest and suppression.*

Proposition 4 is proved in the appendix. An intuition is that the frequency of occurrence of protest $P^*(\cdot)$ reflects both the preventiveness of the regime $1 - \overline{p}^*(\cdot)$ and the extent of grievances ω.

[22]To see this, note that the conclusions of Proposition 3 hold in the case in which $\overline{p}^*(k) > \underline{p}(k)$ for all $k > 0$, so $\Phi^*(\cdot)$ need not have a point mass at $\overline{p}^*(k)$.

[23]Specifically, the conclusions of Propositions 1 and 3 continue to hold in the special case of our model in which $p(\omega,m,r;k) = p(\omega,m',r,k)$ for all $m, m', \omega, r \in [0,1]$ and for all $k > 0$, so the opposition is effectively passive.

[24]That is, $P^*(k) = R^*(k)\,\underline{p}(k) + (1 - R^*(k))\,\mathrm{E}(p(\omega, m^*(\omega;k), 0;k) \,|\, p(\omega, m^*(\omega;k), 0;k) \leq \overline{p}^*(k), k)$ where $R^*(k) = \Pr[p(\omega, m^*(\omega;k), 0;k) > \overline{p}^*(k) \,|k]$ is the probability of prevention.

Without knowledge of the extent of grievances ω, the form of $p(\cdot)$, and the other primitives of the model, it is not possible to infer $1-\overline{p}^*(\cdot)$ from P^*.

Data on the equilibrium probability of protest has economic as well as econometric value. Proposition 7 in Appendix A.2 shows a sense in which, if the international community is able to observe the equilibrium probability of protest, then the international community can design sanctions that are as effective as if the international community could directly influence the cost of prevention $\rho(\cdot)$, for example by directly observing (and sanctioning) prevention r.

3.2 Estimation of Preventiveness from Predictors of Protest

A cutoff equilibrium $(\overline{p}^*(\cdot), \overline{q}^*(\cdot), m^*(\cdot))$ is played. An econometrician observes data from a finite set of periods $\mathscr{T}(k)$ in each environment $k \in \{1,...,K\}$, where the periods are selected without knowledge of the outcome of the game. In each period $t \in \mathscr{T}(k)$, the econometrician observes an indicator $z_{it} \in \{0,1\}$ for whether protest occurs, an index of the environment $k_{it} = k$, and a potentially vector-valued predictor $\mathbf{x}_{it} \in \mathscr{X}$. The predictor may include direct indications of grievances ω_{it} or mobilization m_{it}, or even direct indications of upcoming protest. Formally, say that $\mathbf{x}_{it} = \chi(\omega_{it}, m_{it}, p^*_{it}, \varepsilon_{it}; k_{it})$ where $\chi(\cdot)$ is an unknown function,
$p^*_{it} = p(\omega_{it}, m^*(\omega_{it}; k_{it}), r^*(\omega_{it}, m^*(\omega_{it}; k_{it})); k_{it})$ is the equilibrium probability of protest, and ε_{it} is noise independent of all other random variables in the model.

Our approach to estimation has two parts. The first is to estimate the equilibrium probability of protest using the observed data. The second is to estimate preventiveness by taking the maximum estimated equilibrium probability of protest in each environment. For the first part, let $p^*(\mathbf{x}_{it}; k_{it}) = \Pr(z_{it} = 1|\mathbf{x}_{it}; k_{it})$ denote the equilibrium probability of protest given the observed predictors $\mathbf{x}_{it}$. Observe that if $\chi(\cdot)$ is one-to-one in ω_{it} or p^*_{it}, $p^*(\mathbf{x}_{it}; k_{it}) = p^*_{it}$; more generally, $p^*(\mathbf{x}_{it}; k_{it}) = \mathrm{E}(p^*_{it}|\mathbf{x}_{it}; k_{it})$. The econometrician uses the observed data to form an estimate $\hat{p}(\mathbf{x}_{it}; k_{it})$ of $p^*(\mathbf{x}_{it}; k_{it})$. We make the following high-level assumption on the econometrician's estimator.

Assumption 3. *For any* $\mathbf{x} \in \mathscr{X}$ *and environment* $k > 0$, $\hat{p}(\mathbf{x}; k) \xrightarrow{p} p^*(\mathbf{x}; k)$.

Assumption 3 states that the estimator $\hat{p}(\mathbf{x}; k)$ is consistent for the true probability $p^*(\mathbf{x}; k)$. Section 5.1 discusses conditions for Assumption 3 in the context of the particular estimators we use.

For the second part, given the estimates $\hat{p}_{it} = \hat{p}(\mathbf{x}_{it}; k_{it})$ for each $t \in \mathscr{T}(k)$, the econometrician estimates the preventiveness as $1 - \overline{p}(k)$ where $\overline{p}(k) = \max_{t \in \mathscr{T}(k)} \hat{p}_{it}$. By Assumption 3 and the continuous mapping theorem, $\overline{p}(k) \xrightarrow{p} \tilde{p}(k) = \max_{t \in \mathscr{T}(k)} p^*(\mathbf{x}_{it};k)$, and because $p^*(\mathbf{x}_{it};k_{it}) = \mathrm{E}(p^*_{it}|\mathbf{x}_{it};k_{it})$, we have that $\tilde{p}(k) \leq \overline{p}^*(k)$. Moreover, by standard facts about order statistics, if $\tilde{\Phi}^*(\cdot)$ is the distribution of $p^*(\mathbf{x}_{it};k)$, then $\Pr(\tilde{p}(k) > p') = 1 - \tilde{\Phi}^*(p')^{|\mathscr{T}(k)|}$ for any $p' \in [0, \overline{p}^*(k)]$. To summarize:

Proposition 5. *Under Assumption 3, for any $k > 0$,*

(a) *The estimator $1 - \overline{p}(k)$ converges in probability to an upper bound $1 - \tilde{p}(k) \geq 1 - \overline{p}^*(k)$ on preventiveness.*

(b) *For any value $p' \in [0, \overline{p}^*(k)]$, $1 - \tilde{p}(k)$ is contained in $[1 - \overline{p}^*(k), 1 - p')$ with probability $1 - \tilde{\Phi}^*(p')^{|\mathscr{T}(k)|}$ where $\tilde{\Phi}^*(\cdot)$ is the distribution of $p^*(\mathbf{x}_{it};k)$.*

Proposition 5(a) states that $1 - \overline{p}(k)$ is consistent for an upper bound on the preventiveness. Proposition 5(b) states how the tightness of the bound depends on the distribution $\tilde{\Phi}^*(\cdot)$ of $p^*(\mathbf{x}_{it};k)$, and the number of observations $|\mathscr{T}(k)|$. Notice that, if $\chi(\cdot)$ is one-to-one, then for any $p' < \overline{p}^*(k)$, we have that $\lim_{|\mathscr{T}(k)| \to \infty} \left(1 - \tilde{\Phi}^*(p')^{|\mathscr{T}(k)|}\right) = 1$.

Proposition 5 concerns a scenario where the estimated probability of protest $\hat{p}(\mathbf{x};k)$ approaches the true probability of protest $p^*(\mathbf{x};k)$. Plug-in estimators of extremal probabilities can exhibit poor finite-sample behavior (e.g., Lei et al. 2021). Online Appendix Table 1 therefore presents results using both (i) an alternative estimator that is unbiased for an upper bound of preventiveness and (ii) an indicator for whether a finite-sample confidence bound constructed following Lei (2023) contains nearly full preventiveness, $1 - \overline{p}^*(k) \approx 1$. While the nature of the covariates in our setting means that these alternative approaches produce estimates similar to our baseline, the alternatives may be of interest to future researchers who may encounter different data structures.

4 Data on Protest and Predictors

To estimate preventiveness, we require data on an indicator z_{it} for the occurrence of protest in country i on date t, and on a vector $\mathbf{x}_{it}$ of predictors of protest. This section describes our main sources and definitions for these variables. Online Appendix Section B includes further details, and information on additional data sources used in sensitivity analysis. Throughout, we define a country i to correspond to the definition in the ISO 3166 (International Organization for Standardization 2021).

4.1 Protest Occurrence, Suppression, and Anticipation

Our main source of information on protest is a database of security alerts obtained from Crisis24 (2022), a global risk management firm.[25] Crisis24 staff produce these alerts to keep clients appraised of current and anticipated events, including those that may impact travel. Each alert corresponds to an event or set of events that has happened, is happening, or is expected to happen. For each alert, the database includes the country, a short title and longer description, and fields indicating the date and time of the alert.

We parse the text fields using a set of rules described in more detail in Online Appendix Section B.1. From the text fields we identify whether the alert relates to a protest, and, when possible, the dates of the protest. We include in our main analysis protests for which we are able to identify a specific date, and show in Online Appendix Table 1 the sensitivity of our main results to including a further set of protests for which we infer a date based on grammatical and other cues. From the text fields of the alerts, we also construct an indicator for evidence of use of force (violence or arrests).

For each country i and date t, we define an indicator $z_{it} \in \{0,1\}$ equal to one if an alert indicates the occurrence of a protest on the given date, and zero otherwise. We define an indicator $s_{it} \in \{0,1\}$ equal to one if an alert published on the given date indicates the occurrence of protest and use of force, and zero otherwise. These variables proxy for their theoretical counterparts.

For each country i and date t, we also define an indicator $a_{it} \in \{0,1\}$ equal to one if an alert posted at least one day earlier indicates the occurrence of a protest on the given date, and zero otherwise. This variable forms an important part of the predictor vector $\mathbf{x}_{it}$. We are not aware of another database that makes it possible to define such a variable on a large scale.

4.2 Additional Predictors of Protest

As additional elements of the predictor vector $\mathbf{x}_{it}$ we obtain the variables described below. For each variable, we standardize its daily value by subtracting its mean and dividing by its standard deviation, both calculated over the preceding 90 days, excluding protest days. If the rolling-window standard deviation is zero, or if data are missing for the given variable, country, and date, we set the standardized value to zero.

[25] The alerts concern events in 235 countries between March 2009 and November 2022.

4.2.1 Search Query Volume: Google Trends

From Google Health Trends (Google 2021, 2023), we obtain daily data on searches about political demonstrations in each country.[26] The search data are reported as a (known) multiple of the probability that a given user session includes a search for the given topic, with a value of zero when the query does not meet reporting standards (Google 2019; see also Zepecki et al. 2020).[27]

4.2.2 News Mentions: The GDELT Event Databases

From the GDELT Event Database (GDELT Project 2020, 2023) we obtain daily data on the number of mentions of protest, as a share of all mentions of a given country, for each country.[28] These data are in turn sourced from various international news sources and wire services (Leetaru and Schrodt 2013).

4.2.3 Social Media Mentions: Twitter Data

Using Twitter's advanced search functionality (Twitter 2020, 2023), for each country we obtain daily data on the number of non-withheld English-language tweets containing both the name of the country and either the keyword "protest" or the keyword "demonstration."[29]

4.3 Estimation Sample

Our sample period $t \in \{1,...,T\}$ is the set of dates from 2010-2021.[30] Our sample countries $i \in \{1,...,N\}$ are the 150 countries with a population of at least 1,000,000 in 2010 and for which

[26]The searches use entity code `/m/0gnwz4` and cover 249 countries from 2009 through 2022. For use in sensitivity analysis, for each country we also obtain daily data on searches conducted in the US and UK about the country.

[27]These probabilities are calculated on a random sample of searches. The random sample is redrawn daily. We compute an average of valid returned values across runs executed on at least 15 different days, and therefore corresponding to at least 15 different random samples.

[28]The event code for protest is 14 and the data cover 274 countries from 2009 through 2022. We use data GDELT 1.0 (GDELT Project 2020) for years 1979 through 2020 and GDELT 2.0 (GDELT Project 2023) for years 2021 through 2022.

[29]The data cover 195 countries from 2009 through 2022. We obtain analogous data on tweets in the country's official language for use in sensitivity analysis. Our list of countries and official languages is based on UNGEGN's list of country names (United Nations Group of Experts on Geographical Names 2019). In some cases we use short versions of country names rather than official ones (e.g., "Venezuela" rather than "Bolivarian Republic of Venezuela").

[30]Because we have access to data on predictors of protest beginning in 2009, beginning the sample period in 2010 allows us to use lagged values of predictors in our analysis. Because we have access to data for only part of 2022 for some of our main variables, ending the sample period in 2021 avoids including a partial year in the analysis, and allows us to use leading values of predictors in sensitivity analysis.

there is at least one year in the sample period with at least 10 alerts in the Crisis24 database.[31]

4.4 Data Validation

We take several steps to validate our data. First consider the protest occurrence indicator z_{it}. Online Appendix Section B.1 discusses the results of an audit study comparing the accuracy of the parser to the accuracy of human data entry operators. Protests flagged by the parser are correct 80 percent of the time, versus 68 percent of the time for the human operator. The human operator flags more protests, leading to more true positives and more false positives.

Online Appendix Figure 3 compares the protest occurrence indicator z_{it} to one constructed based on the Mass Mobilization Data Project (MMDP; Clark and Regan 2021) and the Integrated Crisis Early Warning System (ICEWS; Boschee et al. 2015), two databases with substantial (though not complete) coverage of our sample countries and period. The alternative indicator is strongly related to the indicator z_{it}. Online Appendix Table 1 shows the sensitivity of our findings to including or excluding protests flagged in these external databases.

Next, consider the suppression indicator $s_{it} \in \{0,1\}$. Online Appendix Figure 4 compares the suppression indicator s_{it} to one constructed based on data from the Armed Conflict Location & Event Data Project (ACLED; Raleigh et al. 2010), a database with a specific focus on conflict, though less overlap with our sample than the other two. The alternative indicator is strongly related to the indicator s_{it}.

Lastly, consider the predictors $\mathbf{x}_{it}$. Although we are not aware of another global database of protest predictors against which we can compare the predictors we have collected, we can check whether the predictors we have collected are related to one another. Online Appendix Figure 5 shows event-study plots of the standardized value of search query volume, news mentions, and Twitter mentions in the days surrounding the anticipated occurrence of a protest as indicated by the variable a_{it}. As we would expect, all of the predictors we plot are higher on the date of an anticipated protest than on surrounding dates, and are higher on average in the seven days prior to an anticipated protest than in the days preceding.

[31] We obtain data on 2010 population from the World Bank (2021). For Taiwan, we obtain population data from National Statistics, Republic of China (2010). Online Appendix Table 1 shows results where we increase the population threshold to 2,000,000 as well as results where we increase the alerts threshold to 20.

5 Implementation and Validation of Indices of Preventiveness

5.1 Implementation

To implement the estimator of preventiveness $1-\overline{p}(k)$ defined in Section 3.2, we need to define the environments k_{it}, the predictors $\mathbf{x}_{it}$, and the estimator $\hat{p}(\mathbf{x}_{it};k_{it})$ of the probability of protest.

We take an environment k_{it} to be a country-month. Intuitively, including more dates in a given environment gives us more information with which to estimate preventiveness, but also risks conflating settings with different primitives, and makes our indices less useful for real-time surveillance. Online Appendix Table 1 presents results where we instead take an environment to be a two-month rather than one-month period.

We take the predictors $\mathbf{x}_{it}$ to consist of the indicator a_{it} of anticipated protest described in Section 4.1, indicators for days of the week, and seven lags each of the standardized values of demonstration search query volume, protest news mentions, and protest Twitter mentions in English described in Section 4.2. Online Appendix Table 1 shows results where we add a number of additional predictor variables.

We take two approaches to defining the estimator $\hat{p}(\mathbf{x}_{it};k_{it})$ of the probability of protest. For the first, univariate approach, we assume that $p^{*}(\mathbf{x};k)\approx a$, i.e., that protest is nearly certain when anticipated and nearly impossible otherwise. We take as our estimator $\hat{p}(\mathbf{x}_{it};k_{it})=a_{it}$ so that Assumption 3 holds trivially. Online Appendix Table 1 shows results from a modification of this approach in which we assume that $p^{*}(\mathbf{x};k)=p_{i}(a)$ for all k.

For the second, multivariate approach, we assume that $p^{*}(\mathbf{x};k)=p^{*}(\mathbf{x};\theta)$ for $p^{*}(\mathbf{x};\theta)$ a known function and θ a parameter whose dimension is fixed with respect to the number of time periods t in the sample. In our baseline implementation, we assume that $p^{*}(\mathbf{x};\theta)$ takes a logistic form and estimate θ via maximum likelihood, pooling data across countries.[32] To avoid overfitting, we estimate θ separately using data from even years and data from odd years, and use the estimate from the opposite-parity years to form the prediction $\hat{p}\left(\mathbf{x}_{it};\hat{\theta}\right)$ for each country i and date t. Assumption 3 then holds under standard conditions as the number of time periods t grows large. Online Appendix Table 1 shows results from a range of alternative estimators and specifications for $p^{*}(\mathbf{x};k)$, including estimation by penalized maximum likelihood (lasso), changing the functional

[32] That is, we assume that

$$\ln\left(\frac{p^{*}(\mathbf{x};\theta)}{1-p^{*}(\mathbf{x};\theta)}\right)=\mathbf{x}\theta.$$

form of $p^*(\mathbf{x};\theta)$, allowing the parameters θ to differ by country, and using a random sample split rather than one based on year parity.

The two approaches we take to estimation have different strengths and weakenesses. The univariate approach is simple to describe and implement and requires only data on a single variable, a_{it}. This approach might be attractive to a policymaker wanting a coarse early warning of changes in preventiveness. The multivariate approach uses more of the available information, making it amenable to improvement as additional predictors become available. Figure 1 shows that, in practice, the two approaches produce nearly identical estimates in our sample, with estimates highly correlated both across countries and within countries over time. For compactness of presentation, we proceed using the multivariate approach as our baseline, and report our main findings using the univariate approach in Online Appendix Table 1.

5.2 Internal Validation from a Simulation

The first column of Table 1 shows simulation evidence on the performance of our baseline multivariate estimator. In each of a set of simulation replications, we randomly generate an indicator of protest occurrence as a sequence of independent Bernoulli draws, with success probabilities given by the estimated equilibrium protest probabilities $\hat{p}(\mathbf{x}_{it};k_{it})$. We then re-implement the estimator, taking the observed values of $\mathbf{x}_{it}$ as given and using the simulated protest occurrence indicator in place of the observed indicator.[33]

We compare estimated preventiveness in each country-month to the value $1-\tilde{p}(k_{it})$, which is known from the simulated data-generating process.[34] The first column of Table 1 shows that the estimated preventiveness is very correlated with, and very close numerically to, this target value.

The second column of Table 1 shows evidence from a falsification exercise, in which we use the same simulated data, but reverse time in estimating the predictive model, predicting protest based on future rather than past values of the predictor variables. If the variation in the estimator were driven by variation in ancillary factors such as the quality of the measurement of the predictors $\mathbf{x}_{it}$, instead of by variation in the *ex ante* predictability of protest, the performance of the estimator might be similar in both columns of Table 1. In fact the table shows that the performance of the estimator is much worse in the falsification exercise than in the baseline exercise.

[33] Appendix B.1 discusses findings from an additional simulation exercise in which we intentionally introduce misclassification in our assignment of protest dates.

[34] Specifically, in the simulated data-generating process, $1-\tilde{p}(k) = 1-\max_{t\in\mathcal{T}(k)}\hat{p}(\mathbf{x}_{it};k)$ for each country-month k.

5.3 External Validation Across Countries

We are not aware of existing global subannual indices of preventive repressiveness against which to validate our measure. However, it is possible to compare our measure of preventiveness to measures of repressiveness at the country level.

We attempted to identify all global, annual indices of freedom to protest that cover a significant portion of our sample period and are not themselves constructed as aggregates of other indices. For each available country and sample year, we obtained data on the Freedom in the World measure of freedom of assembly (FITW; Freedom House 2021a; category E1), the Varieties of Democracy measure of freedom of assembly (VDem; Coppedge et al. 2023; variable `v2caassemb`), and the Civil Liberties Dataset measure of freedom of assembly and association (CLD; Skaaning 2022; variable `freass`). These indices are based on expert assessment and do not distinguish between prevention and suppression; we may therefore think of them as reflecting some combination of both of preventiveness and suppressiveness, i.e., of $1-\overline{p}^{*}(k)$ and $1-\overline{q}^{*}(k)$.

To form a country-level summary of the expert indices, we take the negative of the average of each expert index over the sample period and calculate the first principal component of these averages across countries. The first principal component of the expert indices has an absolute correlation of at least 0.954 with each of the individual average indices.

The top row of Figure 2 plots the relationship of the average preventiveness (y-axis, left plot) and the share of months with an incident of suppression (y-axis, right plot) to the first principal component of the expert indices (x-axis). Each measure is highly statistically significantly related to the expert indices.

We do not expect a perfect correlation for a variety of reasons, including that each measure is intended to capture only a single dimension of repression, whereas the expert indices combine both. Consistent with this, the lower left plot of Figure 2 shows that a weighted average of our measures of preventiveness and suppressiveness has a visually tighter relationship with the expert indices than either on its own.

The lower right plot of Figure 2 shows the results of a falsification exercise in which we construct an analogue of our preventiveness measure using alerts related to weather events instead of protests. If the relationship between preventiveness and the expert indices depicted in the upper left plot were due to variation in data coverage or other mechanical factors, we might observe a similar relationship in the lower right plot. In fact, we find that the placebo measure is not strongly related to the expert indices, and we can reject the hypothesis that the slope of the relationship to the first principal component of the expert indices is identical between mean preventiveness and the counterpart constructed based on weather alerts ($p = 0.0111$).

We can also compare our measure of preventiveness to related concepts measured in survey data. Online Appendix Figure 6 shows that preventiveness is related to citizens' perceptions of restrictions on freedom to protest as reported in the Arab Barometer (2022), the most direct multicountry survey of freedom to protest during the relevant period of which we are aware, with the caveat that even these data cover only a small number of countries.

5.4 External Validation Over Time

Global, annual indices of freedom change infrequently.[35] However, it is possible to use the (relatively rare) instances of large changes in expert-rated freedom to study the corresponding dynamics of our indices.

Figure 3 shows the dynamics of preventiveness, suppression, and protest around periods when one or more of the expert indices indicates a large change in freedom to protest. Panel A considers cases where the change indicates worsening freedom. Panel B considers cases where the change indicates improving freedom. In each case, we compare the evolution of the given measure to that of the first principal component of the (negative) expert indices.

The first column of plots in Figure 3 shows that preventiveness tends to increase in advance of a worsening in rated freedom (Panel A) and decrease in advance of an improvement in rated freedom (Panel B). Importantly, in both cases the change in preventiveness precedes the change in the expert indices, suggesting the value of real-time measurement. Moreover, neither suppression (second column) nor incidence of protest (third column) consistently leads the change in rated freedom. Preventiveness therefore appears to be the most consistent leading indicator of changes in rated freedom among the statistics depicted in Figure 3, though we caveat that the analysis is based on a small number of cases, and so comes with considerable statistical noise (see Online Appendix Figure 7).

5.5 Alternative Definitions of Protest

Some events that would be called protests in common parlance are not a threat to the regime and are therefore unlikely to be prevented. We can accommodate such events in our model by supposing

[35] For example, across the 1200 country-years in our sample for which its change is measured, FITW's index of freedom of assembly changes only 131 times. In 19 of these cases, the change fully reverses within one year.

that there are protests that will not lead to revolution. We can accommodate such events in our empirical analysis by excluding from the definition of protest those events that may not pose a threat to the regime.

Online Appendix Table 1 illustrates this possibility by showing how our results vary as we exclude, respectively, protests that appear to support the regime, protests that involve small numbers of participants, and protests that begin as labor actions (strikes), all of which may be relatively less threatening to the regime. Although our data source does not include a detailed classification of protest types, future researchers with access to such a classification might be able to adapt our approach to compare preventiveness between protest types, for example between protests calling for regime change and protests calling for policy reform.

6 Dynamics of Protest and Repression

Here we use the index of preventiveness to study the subannual dynamics of protest and repression. We focus on questions that are of substantive interest, and that allow us to illustrate the value of subannual measurement.

6.1 Sanctions

Our first application is to the dynamics of protest and repression preceding the announcement of international sanctions. We obtain information on sanctions during our sample period from the Global Sanctions Data Base (GSDB 2023; see also Felbermayr et al. 2020; Kirilakha et al. 2021). We supplement these data with dates of sanction announcements based on our own searches of news archives. We focus on cases where the sanctioning entity includes the UN, EU, US, or at least one other member of the OECD. We group sanctions by whether they are related to human rights and democracy, versus some other category (e.g., territorial conflict).

We hypothesize that the international community is more likely to sanction regimes in response to public acts of suppression than in response to less visible acts of prevention. Panel A of Figure 4 shows the evolution of preventiveness, incidence of suppression, and incidence of protest around the occurrence of sanctions related to human rights and democracy. We control for the incidence of protest when studying the evolution of preventiveness and suppression. Consistent with our hypothesis, we find no evidence of an increase in preventiveness in advance of sanctions, but we find evidence of an increase in the incidence of suppression: sanctions tend to follow suppression.

The linear trends in preventiveness and incidence of suppression are substantively and statistically different ($p < 0.0001$).

We further hypothesize that acts of suppression will be less important in triggering sanctions not related to human rights or democracy. Panel B of Figure 4 repeats the analysis in Panel A, but for sanctions not related to human rights or democracy. Consistent with our expectation, the linear trend of incidence of suppression in advance of sanctions in this category is statistically insignificant, and smaller than the corresponding trend for sanctions related to human rights or democracy ($p = 0.016$).

The findings in Figure 4 do not establish a causal link from repression to sanctions, but they are consistent with a dynamic whereby more visible acts of repression are more likely to trigger sanctions. Proposition 2 shows that such a dynamic can encourage regimes to engage in prevention. Proposition 7 in Appendix A.2 shows that the international community can use the information underlying our index of preventiveness to discourage prevention.

6.2 COVID

Our second application is to the evolution of repression following the onset of the COVID-19 pandemic. Near the start of the pandemic, there was widespread concern that public health measures would be used as a pretext for repression (Economist 2020). At the time of these events there was no real-time index of preventive repression. We can use our data to see whether our indices could have been useful as a real-time indicator of repression.

Figure 5 shows the evolution of preventiveness, incidence of suppression, and incidence of protests during the first year of the pandemic. We control for the incidence of protest when studying the evolution of preventiveness and suppression. In the first six months following the onset of lockdowns, preventiveness increased sharply and incidence of protests declined. The increase in preventiveness was smaller than the decrease in incidence, suggesting the value of measuring preventive repression directly, though we note the difference in parameters is not statistically significant ($p = 0.1134$). Both preventiveness and incidence returned to pre-lockdown levels by the end of 2020. In contrast, the incidence of suppression increased steadily over the months following the onset of lockdowns, and did not return to its baseline level during 2020. Online Appendix Figure 8 repeats this analysis with controls for the severity of public health conditions.

Importantly, annual indices of freedom cannot capture the dynamics in Figure 5 even retrospectively. For example, FITW was updated in March 2020 and February 2021 (Freedom House

2020, 2021b), VDem in March 2020 and March 2021 (Coppedge et al. 2020, 2021), and CLD in March 2020 and April 2021 (Skaaning 2022).

6.3 Elections

Our final application is to the dynamics of protest and repression around elections. We obtain data on the dates of national elections from ElectionGuide (International Foundation for Electoral Systems 2021). Because we expect the role of elections to differ between democracies and non-democracies, we obtain from the Polity Project (Center for Systemic Peace 2021) an annual classification of countries into democracies and non-democracies (with non-democracies defined as autocracies and anocracies).

Figure 6 shows the dynamics of preventiveness, incidence of suppression, and incidence of protest around election months. Panel A considers democracies. Panel B considers non-democracies. We control for the incidence of protest when studying the evolution of preventiveness and suppression.

Figure 6 shows that preventiveness falls during election months relative to surrounding months. In democracies, the decline is 6.2 percentage points (SE = 2.3), whereas in non-democracies, it is 20.6 percentage points (SE = 3.6). The difference between these two estimates is substantively and statistically significant ($p = 0.0008$). The fact that protest prevention decreases around elections, especially in non-democracies, is in line with a literature that sees elections as an opportunity to signal regime strength (Little 2017; Egorov and Sonin 2021; see also Little, Tucker, and LaGatta 2015), maintain accountability for officials (Gehlbach and Simpser 2015), or create an outlet for elite dissent (Woo and Conrad 2019). All of these motivations would justify relaxing constraints on dissent.[36]

Preventiveness evolves differently than the other variables that we study. Figure 6 shows that protest incidence increases during election months relative to surrounding months. In democracies, the increase in incidence is slightly greater than the decrease in preventiveness ($p = 0.4876$); in non-democracies, the increase in incidence is substantively (and marginally statistically significantly) smaller than the decrease in preventiveness ($p = 0.0621$). In contrast to preventiveness, the difference in the change in incidence between democracies and non-democracies is not statistically

[36]Elections may also bring international scrutiny that makes prevention more difficult (Hyde 2007; Scharpf et al. 2023). Online Appendix Figure 9 shows that there is a small but statistically insignificant decrease in preventiveness during the months of international meetings and sporting events.

significant ($p = 0.4508$). Figure 6 also shows evidence of an increase in the incidence of suppression during election months, though the increase is statistically marginal and not substantively or statistically different between democracies and non-democracies ($p = 0.7013$).[37]

7 Conclusions

We introduce a global, monthly index of preventive repression. The index is grounded in a dynamic model of protest and repression, and is calculated from a novel database of protest and protest predictors. We validate the data and index using a variety of external sources. We use the index to exhibit the dynamics of protest and repression around the announcement of international sanctions, the COVID-19 pandemic, and the occurrence of elections.

Our empirical analysis shows evidence consistent with international sanctions reacting more strongly to acts of suppression than to acts of prevention. Our theoretical analysis implies that sanctioning public acts of suppression may encourage more clandestine or deniable acts of prevention. The index we introduce provides a tool for the international community to pressure regimes to permit protest, thus potentially ensuring more balanced incentives to limit repression.

Although we focus on political protest, we believe the ideas we develop here could be extended to other forms of dissent, such as public criticism of the regime by journalists. Such applications seem a promising direction for future work.

Appendix: Proofs

Proof of Proposition 2

In any equilibrium, $\overline{V}^*(k) \leq \overline{V} = \max_{k \in \{1,\ldots,K\}} d(k)/(1-\delta)$ and $\overline{V}^*(k) - V(0) \geq \ell_i$ where $\overline{V} > 0$ and $\ell_i > 0$ do not depend on the equilibrium or on $\sigma(\cdot)$.

Now by the arguments supporting Proposition 1 we have that in any cutoff equilibrium $(\overline{p}^*(\cdot), \overline{q}^*(\cdot), m^*(\cdot))$ and in any environment $k > 0$,

$$\overline{q}^*(k) = \min\left\{1, \frac{\sigma(k)}{\delta\left(\overline{V}^*(k) - V(0)\right)}\right\}$$

[37] The fact that protest incidence (and, possibly, suppression) increases around elections is in line with a literature that sees elections as focal points for the expression of dissent (Tucker 2007; Little, Tucker, and LaGatta 2015) and as occasions for conflict (Wilkinson 2004; Harish and Little 2017).

and

$$\overline{p}^*(k) = \min\left\{1, \underline{p}(k) + \frac{\rho(k)}{\delta Q^*(k)\left(\overline{V}^*(k) - V(0)\right) + \sigma(k) S^*(k)}\right\}.$$

Suppose that $\underline{\sigma} \geq \sigma(k) > 0$ for all $k \in \{1, ..., K\}$ for some $\underline{\sigma} < \delta\ell_i$, from which it follows that $\overline{q}^*(k)$ is interior in any environment $k > 0$. Because $Q^*(k_{it}) \leq \overline{q}^*(k)$ and $S^*(k) \leq 1$, we then have that

$$\overline{p}^*(k) \geq \min\left\{1, \underline{p}(k) + \frac{\rho(k)}{2\underline{\sigma}}\right\}$$

in any environment $k > 0$.

Next suppose that $\sigma'(k) \geq \overline{\sigma} > 0$ for all $k \in \{1, ..., K\}$ for some $\overline{\sigma}$. In any cutoff equilibrium and in any environment $k > 0$ we must have that

$$\overline{q}^{**}(k) \geq \min\left\{1, \frac{\overline{\sigma}}{\delta\left(\overline{V} - V(0)\right)}\right\}$$

and therefore that

$$Q^{**}(k) \geq \overline{Q}(k, \overline{\sigma}) \equiv \Pr_k\left(q_{it} < \min\left\{1, \frac{\overline{\sigma}}{\delta\left(\overline{V} - V(0)\right)}\right\}\right) \mathrm{E}_k\left(q_{it} | q_{it} < \min\left\{1, \frac{\overline{\sigma}}{\delta\left(\overline{V} - V(0)\right)}\right\}\right)$$

where $\overline{Q}(k, \overline{\sigma}) > 0$ for all k because the distribution of q_{it} has full support, and where $\Pr_k(\cdot)$ and $\mathrm{E}_k(\cdot)$ denote, respectively, the probability and expectation with respect to the distribution of random variables in environment k. Letting $\overline{Q}(\overline{\sigma}) = \min_{k \in \{1, ..., K\}} \overline{Q}(k, \overline{\sigma}) > 0$, it follows that

$$\overline{p}^{**}(k) \leq \min\left\{1, \underline{p}(k) + \frac{\rho(k)}{\overline{Q}(\overline{\sigma})\,\delta\ell_i}\right\}.$$

The desired result follows taking any $0 < \overline{\sigma} < \min_{k \in \{1, ..., K\}} d(k) - \rho(k)$ and then taking $0 < \underline{\sigma} < \frac{1}{2}\overline{Q}(\overline{\sigma})\,\delta\ell_i < \delta\ell_i$ such that $\underline{\sigma} < \overline{\sigma}$. $\square$

Proof of Proposition 4

It suffices to construct a counterexample to Definition 1. Suppose there is a single environment, $K = 1$, and drop the index k for convenience. Suppose further that $\underline{p} = 0$, that $q_{it} = \underline{q} \in (0, 1)$ with probability one, that ω is continuously distributed with full support on $[0, 1]$, and that $p(\omega, m, 0; 1) = \omega$ for all $\omega, m \in [0, 1]$. It is immediate that in any cutoff equilibrium $m^*(\omega) = 0$

for all $\omega \in [0,1]$, that $\overline{q}^* \geq \underline{q}$, and therefore that $S^* = 0$. We further have that

$$\overline{p}^* = \min\left\{1, \frac{\rho}{\delta \underline{q}\left(\overline{V}^* - V(0)\right)}\right\}.$$

Let G denote the distribution of ω and fix primitives ρ, $V(0)$, $\underline{q}$, G such that an equilibrium exists with $\overline{p}^* = \frac{\rho}{\delta \underline{q}\left(\overline{V}^* - V(0)\right)} \in (0,1)$. Write $P^* = G(\overline{p}^*)\,\mathrm{E}_G(\omega|\omega \leq \overline{p}^*)$. Consider a change in the distribution of ω from G to G' such that there is some $0 < \overline{p}^{**} < \overline{p}^*$ with $P^* = G'(\overline{p}^{**})\,\mathrm{E}_{G'}(\omega|\omega \leq \overline{p}^{**})$. Define $\overline{V}^{**}(\rho)$ as the analogue of $\overline{V}^*$ in a game with grievances distributed according to G', cutoff $\overline{p}^{**}$, and cost of prevention ρ. Because $\overline{V}^{**}(\rho)$ is continuous in ρ and $0 < \ell_i \leq \overline{V}^{**}(\rho) - V(0) \leq (d + \ell_i)/(1-\delta)$ for any ρ, we can find some ρ' such that

$$\overline{p}^{**} = \min\left\{1, \frac{\rho'}{\delta \underline{q}\left(\overline{V}^{**}(\rho') - V(0)\right)}\right\}.$$

Thus $\overline{p}^{**}$ is supported as an equilibrium of the game with grievances distributed according to G' and cost of prevention ρ'. We have therefore constructed two cutoff equilibria consistent with the data $D^* = (P^*, 0)$ but with different preventiveness $1 - \overline{p}^* \neq 1 - \overline{p}^{**}$. $\square$

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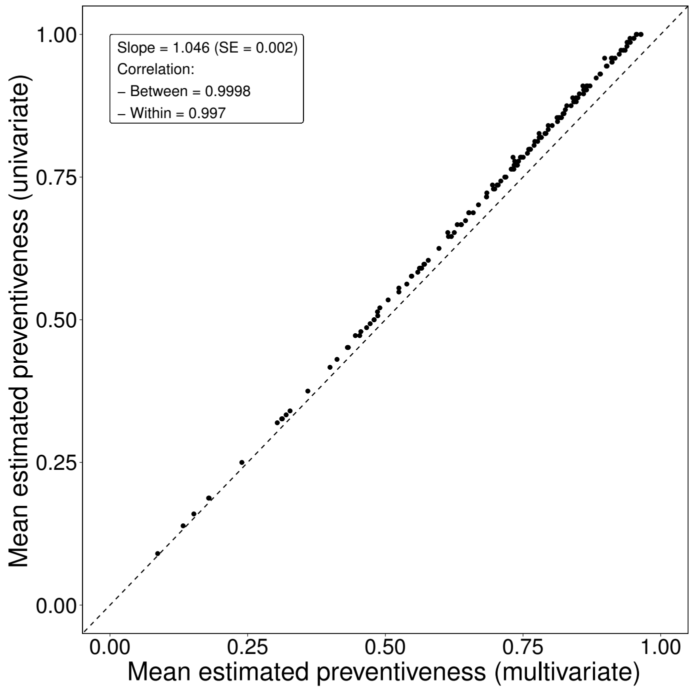
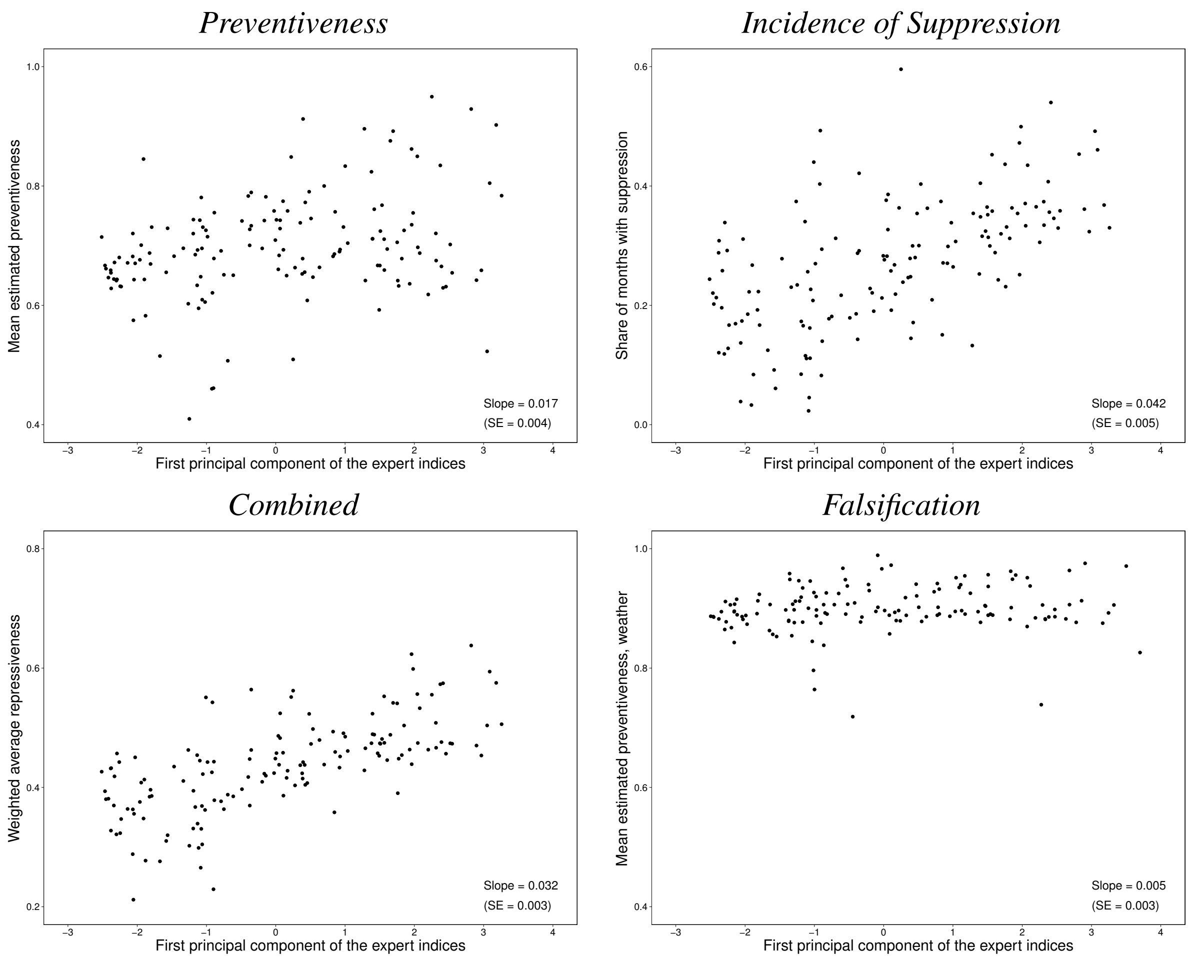
Figure 1: Comparison of Estimation Approaches



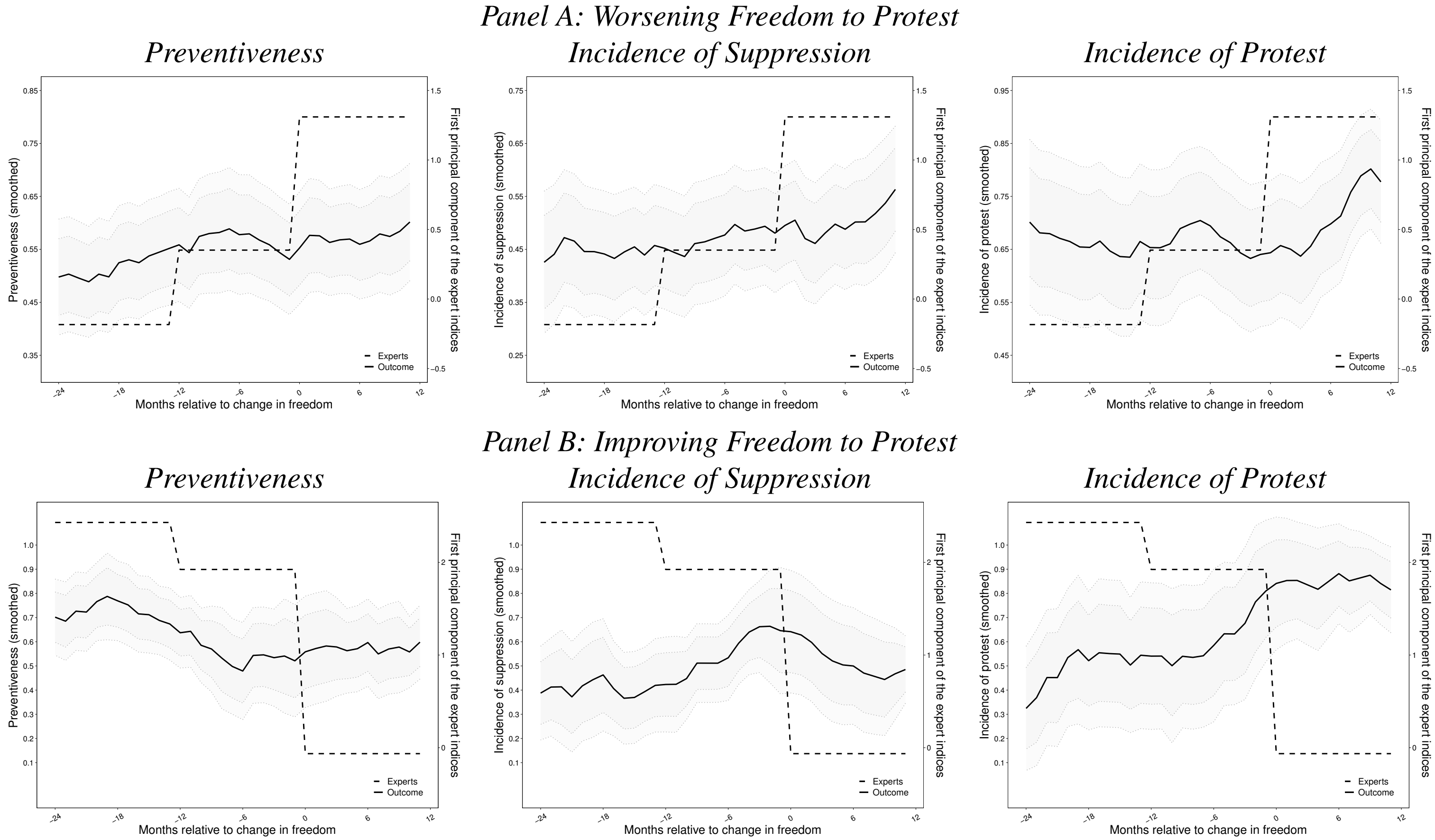
Notes: The plot compares estimated preventiveness between the univariate and multivariate approaches defined in Section 5.1. The plot is a scatterplot, across countries, of the mean value of estimated preventiveness using the univariate approach (y-axis) against the mean value of estimated preventiveness using the multivariate approach (x-axis). The dashed line is a 45-degree line. The text box reports the slope of a regression of the y-axis variable on the x-axis variable along with its standard error. The text box also reports the between-country and within-country correlations in estimated preventiveness between the two approaches. The between-country correlation is the Pearson correlation of the y-axis and x-axis variables depicted on the plot. The within-country correlation is the Pearson correlation of the pooled monthly first differences of estimated preventiveness between the univariate and multivariate approaches.

Figure 2: External Validation Across Countries



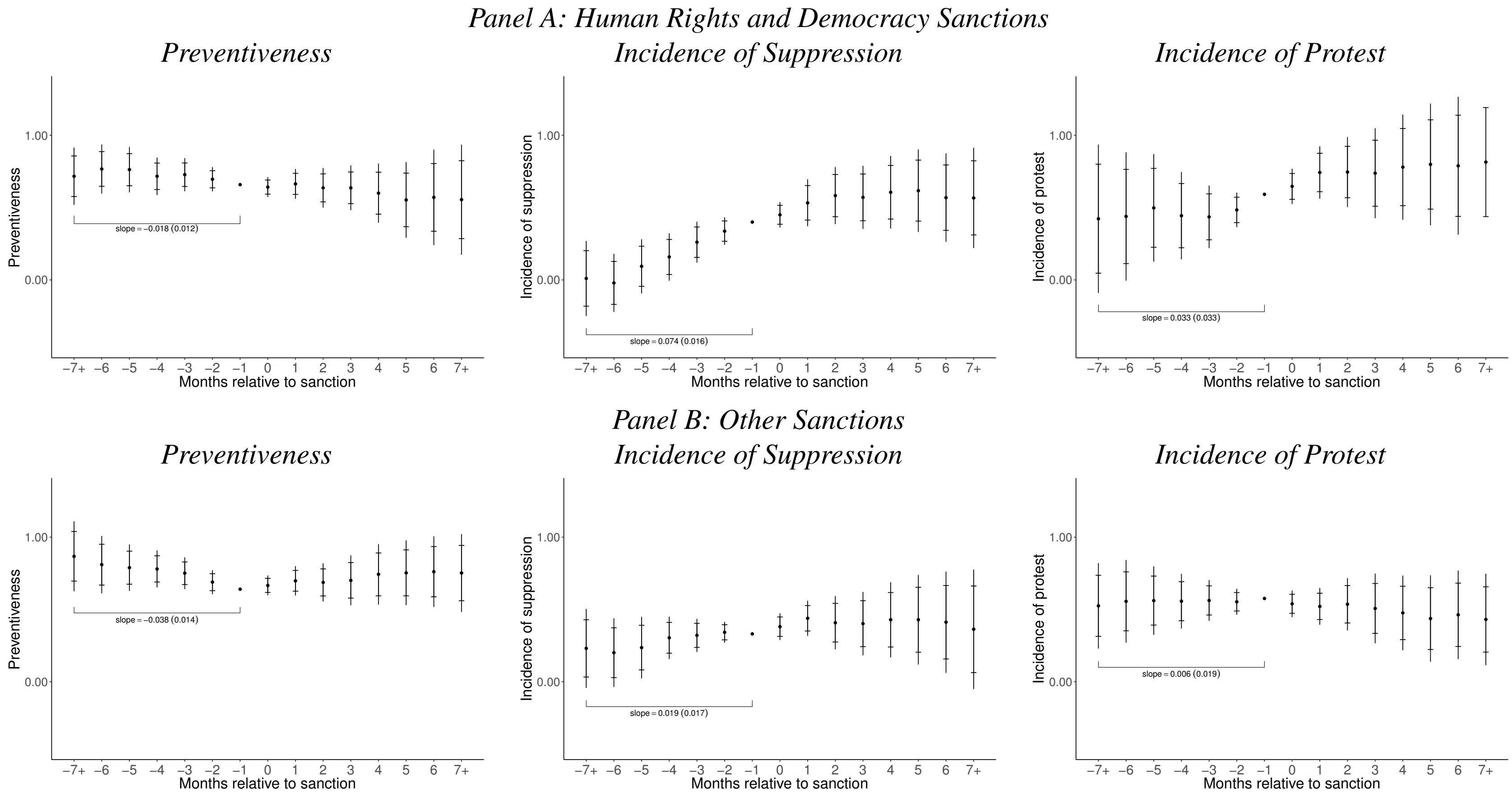
Notes: Each plot compares a different measure (y-axis) to the first principal component of (negative) expert indices of freedom to protest (x-axis). In the upper left plot, the y-axis variable is the mean preventiveness across months for the given country. In the upper right plot, the y-axis variable is the share of months in which an incident of suppression occurs in the given country. In the lower left plot, the y-axis variable is a weighted average of mean preventiveness and share of months with an incident of suppression, with the weights proportional to the coefficients from a regression of the first principal component on each of these two variables, controlling for the share of months with a protest in the given country. In the lower right plot, the y-axis variable is an analogue of preventiveness for weather, calculated as one minus the share of months with an anticipated weather event. Each variable is residualized with respect to the share of months with an event (protest or weather), and is then recentered by adding a constant equal to the sample mean. Each plot excludes countries with a recentered y-axis value outside of $[0, 1]$ (0 countries in the upper left plot, 1 in the upper right, 0 in the lower left, and 7 in the lower right.). Each plot displays the slope of a regression of the y-axis value on the x-axis value, along with its standard error.

Figure 3: External Validation Over Time



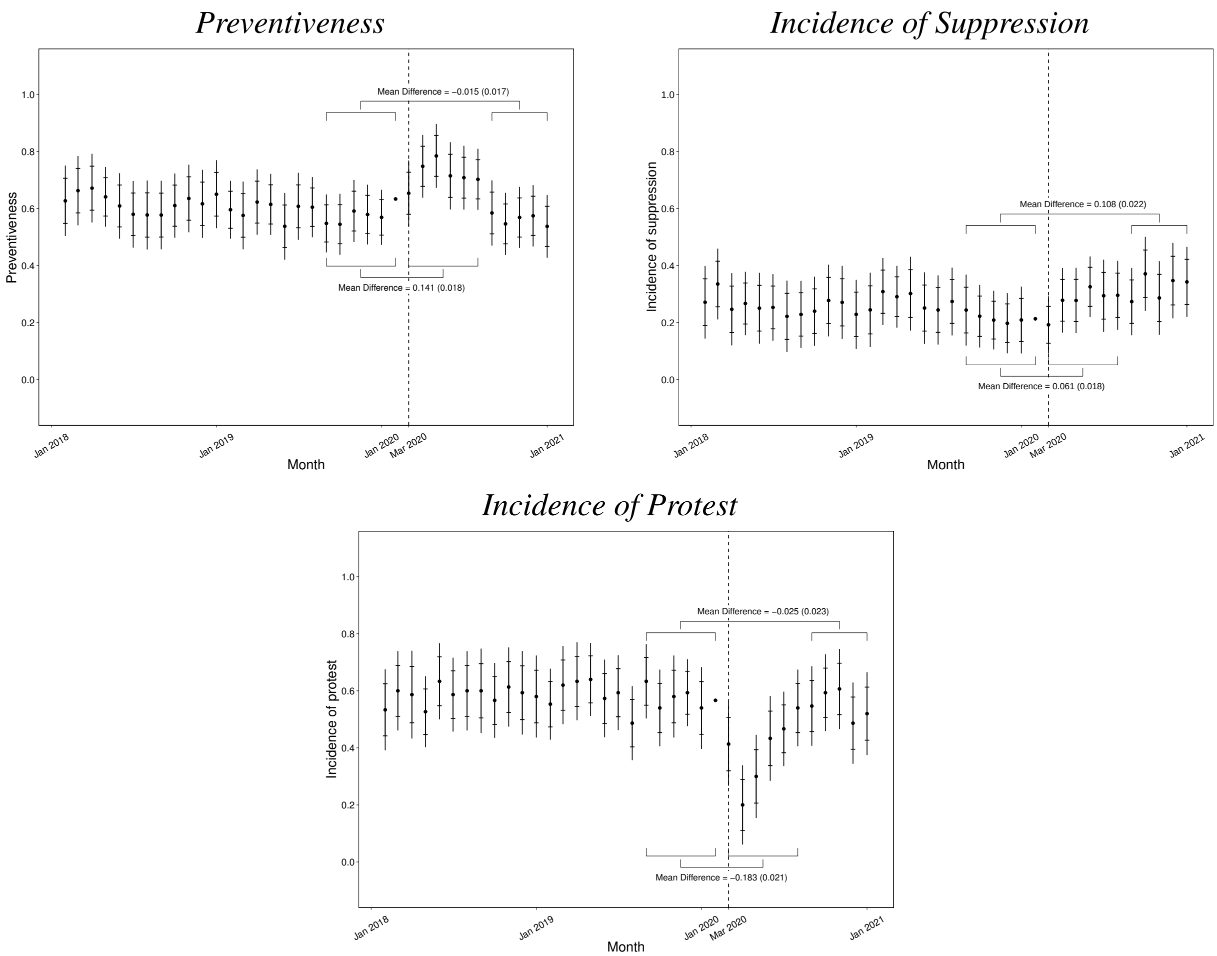
Notes: The figure shows smoothed monthly event-study plots of preventiveness (left), incidence of suppression (center), and incidence of protest (right) around large changes in expert indices of freedom to protest. We define a large change as a case in which one or more expert indices of the country's freedom to protest worsens (Panel A) or improves (Panel B) by at least two units (out of four or five) on net in a span of two years. The right-side y-axis shows the mean of the first principal component of the (negative) expert indices, with loadings determined as in Figure 2. To construct each plot, we estimate a regression with the left-side y-axis variable as the dependent variable. In each regression, the unit of analysis is the country-month, the sample includes all country-months where all three expert indices are available, the model includes fixed effects for calendar months, and the independent variables of interest are individual indicators for each of the 36 months before and 24 months after the change in freedom, with a separate indicator for country-months more than 36 months before the change. For the plots of preventiveness and incidence of suppression, the regression additionally controls for an indicator for the incidence of protest in the given country and month. We smooth the coefficients using a 12-month backward-looking moving average, and recenter their values by adding a constant so that the mean of the displayed values is equal to the sample mean of the corresponding dependent variable in the plotting window. The inner shaded region depicts 95% pointwise confidence intervals and the outer shaded region depicts 95% uniform sup-t bands. The countries experiencing large changes in freedom are Belarus, Benin, Burundi, Chile, India, Iraq, Libya, Mali, Nicaragua, and Thailand in Panel A and Cote d'Ivoire, Gambia, Libya, Sudan, Thailand, and Tunisia in Panel B.

Figure 4: Dynamics of Repression and Protest Around International Sanctions



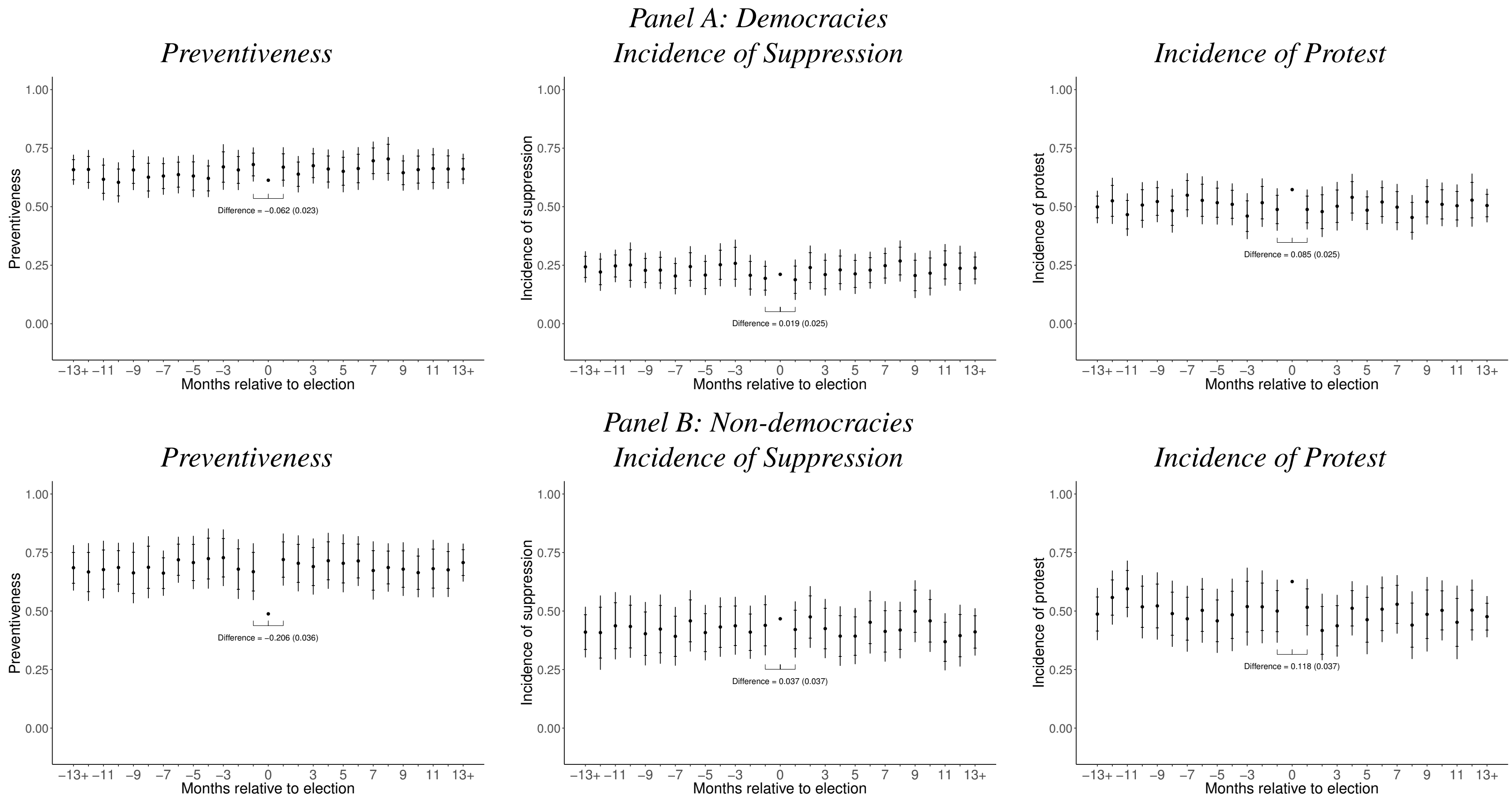
Notes: The figure shows monthly event-study plots of preventiveness (left), incidence of suppression (center), and incidence of protest (right) around the announcement of sanctions by the UN, EU, US, or at least one other OECD member country. Panel A considers sanctions related to human rights or democratic order; Panel B considers all remaining sanctions. Each column of plots is constructed from a single regression in which the unit of analysis is the country-month and the model includes country and month fixed effects; for the regressions with preventiveness or incidence of suppression as the dependent variable, we additionally control for an indicator for incidence of protest. All regressions include, for each sanction type, a contemporaneous indicator for the announcement of sanctions, five leads (relative months -6 through -2) and six lags (relative months 1 through 6) of this indicator, and two variables reflecting the cumulative number of announcements more than six months in the future and more than six months in the past. The first lead (relative month -1) is excluded as a normalization. We recenter the y-axis in each plot by adding a constant equal to the sample mean of the dependent variable in months one prior to those with the given type of announcement. The inner bars depict 95% pointwise confidence intervals and the outer lines depict 95% uniform sup-t bands, both based on inference clustered by country. Labeled on each plot is the least-squares estimate of the slope of the coefficients from $-7+$ through -1 along with the corresponding standard error.

Figure 5: Dynamics of Repression and Protest Around COVID Lockdowns



Notes: The figures show monthly event-study plots of preventiveness (upper left), incidence of suppression (upper right), and incidence of protest (bottom) around the onset of COVID-19 lockdowns. Each plot is constructed from a separate regression in which the unit of analysis is the country-month, the sample includes months February 2018 through January 2021, and the model includes fixed effects for country. For the plots of preventiveness and incidence of suppression, the regression additionally controls for an indicator for the incidence of protest in the given country and month. The independent variables of interest are indicators for the calendar months from February 2018 through January 2021, excluding February 2020 as a normalization. In each plot, we recenter the y-axis by adding a constant equal to the sample mean of the dependent variable in February 2020. The inner bars depict 95% pointwise confidence intervals and the outer lines depict 95% uniform sup-t bands, both based on inference clustered by country. Labeled on each plot is the difference in the average coefficient between the six months beginning in March 2020 and the six months ending in February 2020, as well as the difference in the average coefficient between the five months beginning in September 2020 and the six months ending in February 2020, along with the corresponding standard errors.

Figure 6: Dynamics of Repression and Protest Around Elections, Democracies vs. Non-democracies



Notes: The figure shows monthly event-study plots of preventiveness (left), incidence of suppression (center), and incidence of protest (right) around elections. Each plot is constructed from a separate regression in which the unit of analysis is the country-month and the model includes fixed effects for country and for calendar month. The independent variables of interest are 12 leads and lags of an indicator for the occurrence of an election, and two variables reflecting the cumulative number of elections 13 or more months in the future and the cumulative number of elections 13 or more months in the past. For the plots of preventiveness and incidence of suppression, the regression additionally controls for an indicator for the incidence of protest in the given country and month. The contemporaneous election indicator is excluded as a normalization. In each plot, we recenter the y-axis by adding a constant equal to the sample mean of the dependent variable in election months. The inner bars depict 95% pointwise confidence intervals and the outer lines depict 95% uniform sup-t bands, both based on inference clustered by country. In Panel A the sample includes country-years classified as democracies by the Polity Project. In Panel B the sample includes country-years classified as non-democracies (autocracies or anocracies) by the Polity Project. Labeled on each plot is the difference between the coefficient for the election month and the average of the coefficients for the preceding and following months, along with the corresponding standard error.

Table 1: Simulation Evidence on the Performance of the Estimator

	Baseline	Falsification (Reverse time)
Within-country correlation	0.9991	0.0765
	(0.0002)	(0.0005)
Share with abs. err. ≤ 0.01	0.9549	0.3784
	(0.0047)	(0.0059)

Notes: The table shows average statistics across 50 replicates of a simulation exercise described in Section 5.2, with standard deviations in parentheses. In the "Baseline" column we apply our baseline multivariate estimator. In the "Falsification (Reverse time)" column we reverse time in estimating the predictive model, predicting protest based on future rather than past values of the predictor variables. The "Within-country correlation" is the Pearson correlation in pooled monthly first differences between the estimated preventiveness and one minus the largest probability of protest in the simulated data-generating process. The "Share with abs. err. ≤ 0.01" is the share of country-months in which the difference between the estimated preventiveness and one minus the largest probability of protest is no more than 0.01 in absolute value.

Online Appendix for

Measuring the Tolerance of the State: Theory and Application to Protest

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A Additional Theoretical Results

A.1 Existence of a Cutoff Equilibrium

Proposition 6. *Suppose that, for all environments $k_{it} > 0$, the distributions of ω_{it} and q_{it} are continuous, and $p(\omega_{it}, m_{it}, 0; k_{it})$ is continuous in ω_{it} and m_{it} and strictly concave in m_{it}. Then under Assumption 1 a cutoff equilibrium exists.*

Proof. For $\mathscr{K} = (1,...,K)$, let $\xi(\cdot,\cdot) = (m(\cdot,\cdot), \overline{p}(\cdot), \overline{q}(\cdot)) \in [0,1]^{[0,1]\times K} \times [0,1]^K \times [0,1]^K$ be a strategy profile for a cutoff equilibrium. For any strategy profile ξ define the opposition's best response correspondence

$$\Xi_M(\xi) = \underset{m\in[0,\overline{m}(\cdot;\cdot)]}{\arg\max} -\mu(\cdot)m + p(\cdot,m,0;\cdot)Q^*(\xi,\cdot)\beta\left(W(0) - \overline{W}^*(\xi;\cdot)\right) - p(\cdot,m,0;\cdot)S^*(\xi,\cdot)c(0,1,\cdot)$$

where $Q^*(\xi,k)$ is the equilibrium probability of revolution given protest in environment k under strategy profile ξ, $\overline{W}^*(\xi;k)$ is the opposition's expected discounted payoff under strategy profile ξ starting from environment k, $S^*(\xi,k)$ is the equilibrium probability of suppression given protest in environment k under strategy profile ξ, $\overline{m}(\omega;k) = \max\{m \in [0,1] : p(\omega,m,0;k) \leq \overline{p}(k)\}$ is the largest mobilization the opposition will consider given grievances $\omega \in [0,1]$ and environment $k > 0$, and we have used the necessary condition in Proposition 1(iii). Because $p(\omega,m,0;\cdot)$ is continuous in ω and m, it follows that $\overline{m}(\omega;\cdot)$ is continuous in ω. Thus, $\Xi_M(\xi)$ is nonempty and upper hemi-continuous in ω. The coefficient of $p(\cdot,m,0;\cdot)$ is $\left[Q^*(\xi,\cdot)\beta\left(W(0) - \overline{W}^*(\xi;\cdot)\right) - S^*(\xi,\cdot)c(0,1,\cdot)\right]$, which does not depend on ω, or on the opposition's choice variable m in the optimization problem above. If the coefficient is strictly positive, becaue $p(\cdot,m,0;\cdot)$ is strictly concave in m, the opposition's optimization problem has a unique solution and hence $\Xi_M(\xi)$ is single-valued. If the coefficient is nonpositive, then the opposition will choose $m = 0$ and again $\Xi_M(\xi)$ is single-valued. Thus, for each environment k, $\Xi_M(\xi)$ maps ξ into the space of bounded continuous functions $m(\cdot,k)$ on $[0,\overline{m}(\cdot;k)]$.

Define the regime's best response function in cutoff strategies as

$$\Xi_p(\xi) = \min\left\{1, \underline{p}(\cdot) + \frac{\rho(\cdot)}{\delta Q^*(\xi,\cdot)\left(\overline{V}^*(\xi,\cdot) - V(0)\right) + \sigma(\cdot)S^*(\xi,\cdot)}\right\}$$

$$\Xi_q(\xi) = \min\left\{1, \underline{q}(\cdot) + \frac{\sigma(\cdot)}{\delta\left(\overline{V}^*(\xi,\cdot) - V(0)\right)}\right\}$$

where $\overline{V}^*(\xi,\cdot)$ is defined analogously to $\overline{W}^*(\xi;\cdot)$.

Now define the mapping $\Xi(\cdot)$ such that $\Xi(\xi) = \left(\Xi_M(\xi), \Xi_p(\xi), \Xi_q(\xi)\right)$. Because by the arguments underlying Proposition 1 any best response is in the range of $\Xi(\cdot)$, it suffices to show that the mapping $\Xi(\cdot)$ has a fixed point. Observe that $\Xi(\cdot)$ maps a Banach space into itself and is convex-valued for all ξ. Because the distributions of ω_{it} and q_{it} are continuous, the real-valued functions $\overline{W}^{*}(\xi;\cdot)$ and $\overline{V}^{*}(\xi,\cdot)$ are continuous in ξ under the sup norm, and so the mapping $\Xi(\cdot)$ is upper hemicontinuous in ξ. Hence $\Xi(\cdot)$ has a fixed point by the Kakutani-Fan-Glicksberg Theorem. □

A.2 Basing Sanctions on the Equilibrium Probability of Protest

Proposition 7. *Consider the modified game formed by increasing $\rho(k)$ to $\rho'(k) \geq \rho(k)$ in all environments $k \in \{1,...,K\}$, leaving other primitives unchanged. If $(\overline{p}^{**}(\cdot), \overline{q}^{**}(\cdot), m^{**}(\cdot))$ is a cutoff equilibrium of the modified game then it is also an equilibrium of an alternative game in which $\rho''(k) = \rho(k)$ and the regime pays a (possibly negative) cost $\gamma(p(\omega_{it}, m_{it}, r_{it}; k_{it}); k)$ after each period t.*

Proof. Under the cutoff equilibrium $(\overline{p}^{**}(\cdot), \overline{q}^{**}(\cdot), m^{**}(\cdot))$, in any environment $k > 0$

$$\overline{p}^{**}(k) = \min\left\{1, \underline{p}(k) + \frac{\rho'(k)}{\delta Q^{**}(k)\left(\overline{V}^{**}(k) - V(0)\right) + \sigma(k) S^{**}(k)}\right\}$$

and

$$\overline{q}^{**}(k) = \min\left\{1, \underline{q}(k) + \frac{\sigma(k)}{\delta\left(\overline{V}^{**}(k) - V(0)\right)}\right\}.$$

For each $k > 0$, take

$$\gamma(p;k) = \gamma_0(k) - \gamma_1(k)(1-p)$$

where

$$\delta\gamma_1(k) = \frac{\rho'(k) - \rho(k)}{\rho'(k)}\left(\delta Q^{**}(k)\left(\overline{V}^{**}(k) - V(0)\right) + \sigma(k) S^{**}(k)\right)$$

and

$$\gamma_0(k) = \gamma_1(k)(1 - P^{**}(k)) - \left(\rho'(k) - \rho(k)\right) R^{**}(k).$$

Conjecture a cutoff equilibrium $(\overline{p}^{**}(\cdot), \overline{q}^{**}(\cdot), m^{**}(\cdot))$ of the alternative game. The opposition has no incentive to deviate by construction of the regime's strategy. The regime has no incentive to deviate from the proposed suppression strategy because the choice of $\gamma_0(k)$ ensures no change in the regime's expected per-period payoff in any environment $k > 0$, and hence no change in continuation payoffs.

What remains is to establish that the regime does not have an incentive to deviate from the proposed prevention strategy. The regime's expected discounted payoff when choosing the level of prevention r_{it} is given by

$$\delta\left(\begin{array}{c} p\left(\omega_{it},m_{it},r_{it};k_{it}\right)Q^{**}\left(k_{it}\right)V\left(0\right)+\left(1-p\left(\omega_{it},m_{it},r_{it};k_{it}\right)Q^{**}\left(k_{it}\right)\right)\overline{V}^{**}\left(k_{it}\right) \\ +\gamma_{0}\left(k\right)-\gamma_{1}\left(k\right)\left(1-p\left(\omega_{it},m_{it},r_{it};k_{it}\right)\right) \end{array}\right).$$
$$+d\left(k_{it}\right)-\rho\left(k_{it}\right)r_{it}-p\left(\omega_{it},m_{it},r_{it};k_{it}\right)\sigma\left(k_{it}\right)S^{**}\left(k_{it}\right)$$

By arguments analogous to those underlying Proposition 1, the regime will choose $r_{it}=1$ if $p\left(\omega_{it},m_{it},0;k_{it}\right)>\overline{p}''\left(k\right)$ and $r_{it}=0$ otherwise, where

$$\overline{p}''\left(k\right)=\min\left\{1,\underline{p}\left(k\right)+\frac{\rho\left(k\right)}{\delta Q^{**}\left(k\right)\left(\overline{V}^{**}\left(k\right)-V\left(0\right)\right)+\sigma\left(k\right)S^{**}\left(k\right)-\delta\gamma_{1}\left(k\right)}\right\}.$$

That $\overline{p}''\left(k\right)=\overline{p}^{**}\left(k\right)$ then follows from the construction of $\gamma_{1}\left(k\right)$ and $\gamma_{0}\left(k\right)$. □

B Additional Details on Data Sources and Variable Construction

B.1 Parsing of Crisis24 Security Alerts

Elements Used in Main Analysis

We identify protest-related alerts using information provided in alert descriptions. We classify an alert as protest-related if its description includes the words "protest," "demonstration," or "demonstrator," or words with those keywords at the root.[1] We exclude from our search of the description text some generic warnings such as "We advise our clients to stay away from protests." We classify an alert as including evidence of use of force if it contains indicative phrases such as "protestors clash with the police" or "hundreds arrested during protests."

We extract, for each alert, any dates mentioned in the alert's title provided that the title contains a protest-related structure such as "protest" or "demonstration." We consider all such dates to be protest dates.[2] We also extract, for each alert, any dates mentioned in the alert's description in the same sentence as a protest-related structure. If we do not extract any protest dates from a protest-related alert's title, then we consider the latest date extracted from the alert's description to be a protest date.

[1] Because some protests originate or manifest as labor strikes, we also classify as protest-related alerts whose descriptions contain one of the words "worker," "union," "labor," or "labour" and the root "strike" in the same sentence, except when "strike" is part of the word "airstrike." Online Appendix Table 1 reports results excluding strikes from the sample.

[2] Date information typically includes the month and day of month, e.g., "May 20." We treat these dates as referring to the year in which the alert is published, unless the alert is published in December (January) and the date is in January (December), in which case we treat the date as referring to the year following (preceding) the alert's publication.

Online Appendix Figure 1 illustrates the main elements of our approach using example alerts drawn from our data.

Elements Used in Sensitivity and Falsification Analysis

We classify alerts into temporal categories based on syntactic and semantic information in alert titles. We classify an alert as pertaining to a future protest if its title contains a future-related word such as "announce" along with a protest-related keyword, or if its title contains a protest-related verb preceded by "to," as in "to protest." We classify an alert as pertaining to a present protest if its title contains present-related words such as "continued," "ongoing," or "underway" appearing in the same sentence with a protest-related keyword. We classify a protest alert as pertaining to a past protest if its title contains protest-related verbs in the past tense, such as "protested" or "demonstrated," or if its title does not contain word structures indicative of being about the present or future.[3] We use these classifications to include additional protests described in alerts from whose text fields we were not otherwise able to infer protest dates.[4]

We extract, for each alert, information about the number of participants in the protests mentioned in the text fields. This information is often in the form of a broad quantitative statement (e.g., "hundreds of protesters gathered" or "around 500 protestors gathered"). We classify an alert as pertaining to small protests if the alert contains information about the number of participants for at least one protest, and if there is no information indicating a protest with one thousand or more participants.

We also extract, for each alert, information about whether the protests mentioned in the text fields are in support of or against the regime. The text fields can include statements such as "government supporters took to the streets" or "thousands protested against the government." Using this information, we classify a protest alert as pertaining to pro-regime protests if it includes statements indicating protests in support of the regime but does not include statements indicating protests against the regime.

We also identify alerts pertaining to weather events. We classify an alert as weather-related if it is not identified as protest-related, and contains a weather-related keyword such as "rain" or "storm" in its title. We consider a date to have a weather event if a weather-related alert was published on that date. We classify a weather-related alert as related to an anticipated weather event if its title includes structures indicative of being about the future, such as "forecast" or "anticipated." We consider a date to have an anticipated weather event if an alert related to an anticipated weather

[3] We also search for specific clauses such as "hundreds of people gather" that, according to our reading of alerts, typically indicate that the event was in the past even though they are written in the present tense.

[4] Specifically, we consider a country-date to have a protest if there was a future protest-related alert published on the preceding day, if there was a continued protest-related alert published on the same day, or if there was a past protest-related alert published the day after.

event was published on that date.

Audit of Parser Quality

To assess the quality of the rules we use to parse text fields, we compare the performance of our parser to the performance of human data entry operators on a random sample of alerts. The data entry operators were trained to enter data on protest occurrence based on the text fields, using a web form that we helped to develop. Each alert was keyed by two independent data entry operators, with a reconciliation process for discrepancies. The firm providing data entry services was given a financial incentive for accurate entry.

We used our own judgment to manually date all protests described in 100 randomly chosen alerts, excluding 4 alerts due to ambiguities. Across the 96 remaining alerts, our parsing rules identified 71 dates with protest, of which we classify 57 as correct and 14 as incorrect. Across these same 96 alerts, the human data entry operators identified 119 dates with protest, of which we classify 81 as correct and 38 as incorrect.

When we modify the simulation in Table 1 to incorporate a fraction of falsely classified protest dates that matches the fraction we measure in the audit, the correlation between the true and estimated target parameters remains large at 0.9991.

B.2 Financial Indices Used in Sensitivity Analysis

We obtain daily data on a range of financial indices. Online Appendix Figure 2 gives the dates of coverage of each index for each sample country.[5] We now discuss each index in more detail.

B.2.1 Exchange Rates

We obtain daily data on exchange rates with respect to the US Dollar for a set of currencies from Bloomberg L.P. (2021a). We match currencies to countries using the ISO 4217 (International Organization for Standardization 2018). For countries that adopted the Euro during our sample period, we use the exchange rate of the official currency prior to the transition.

B.2.2 Sovereign Bond Indices

We obtain from Bloomberg L.P. (2018) and J.P. Morgan (2021) daily data on the yield index from J.P. Morgan's Emerging Market Bond Index Global (EMBIG). We use data quoted to maturity whenever available (usually until 2018) and data quoted to worst otherwise. For 59 countries, we

[5] To accommodate weekends and holidays, we impute the value of each indicator to its last recorded value when there is a gap of one or two days between consecutive recorded values.

observe data for both forms of quotes for at least 158 dates. Using these periods of overlap we calculate the correlation between the daily change in the index quoted to maturity and the daily change in the index quoted to worst, separately by country. We find that the correlation is above 0.9 for all 59 countries, and above 0.99 for all except 5 of these countries.

B.2.3 Stock Market Indices

We obtain from Bloomberg L.P. (2021b) data on the MSCI Inc. (formerly Morgan Stanley Capital International) indices. For each country, we observe a daily sub-index for the MSCI price, measured in USD whenever possible and the local currency otherwise, and a daily sub-index for the MSCI trading volume.

Online Appendix Figure 1: Illustrations of Security Alert Parsing

protest-related term
date
generic text

Sample Alert A

Country: Nigeria

Published at: 2017-03-22

Title: Nationwide NULGE Protests Begin

Content: According to local media sources on Wednesday, *22 Mar*ch, the Nigerian Union of Local Government Employees (NULGE) has commenced a nationwide protest calling for a constitutional amendment granting Local Government Areas autonomy. Protests began in Nasarawa state and are predicted to continue across the country until President Muhammadu Buhari intervenes. Travellers are advised to avoid political protests and exercise caution in the vicinity of gathering crowds in order to minimise the risk of exposure to potential crowd disturbances. Monitor local media sources for more information about how the protests will affect specific regions and the effect these may have on overland travel.

Sample Alert B

Country: Peru

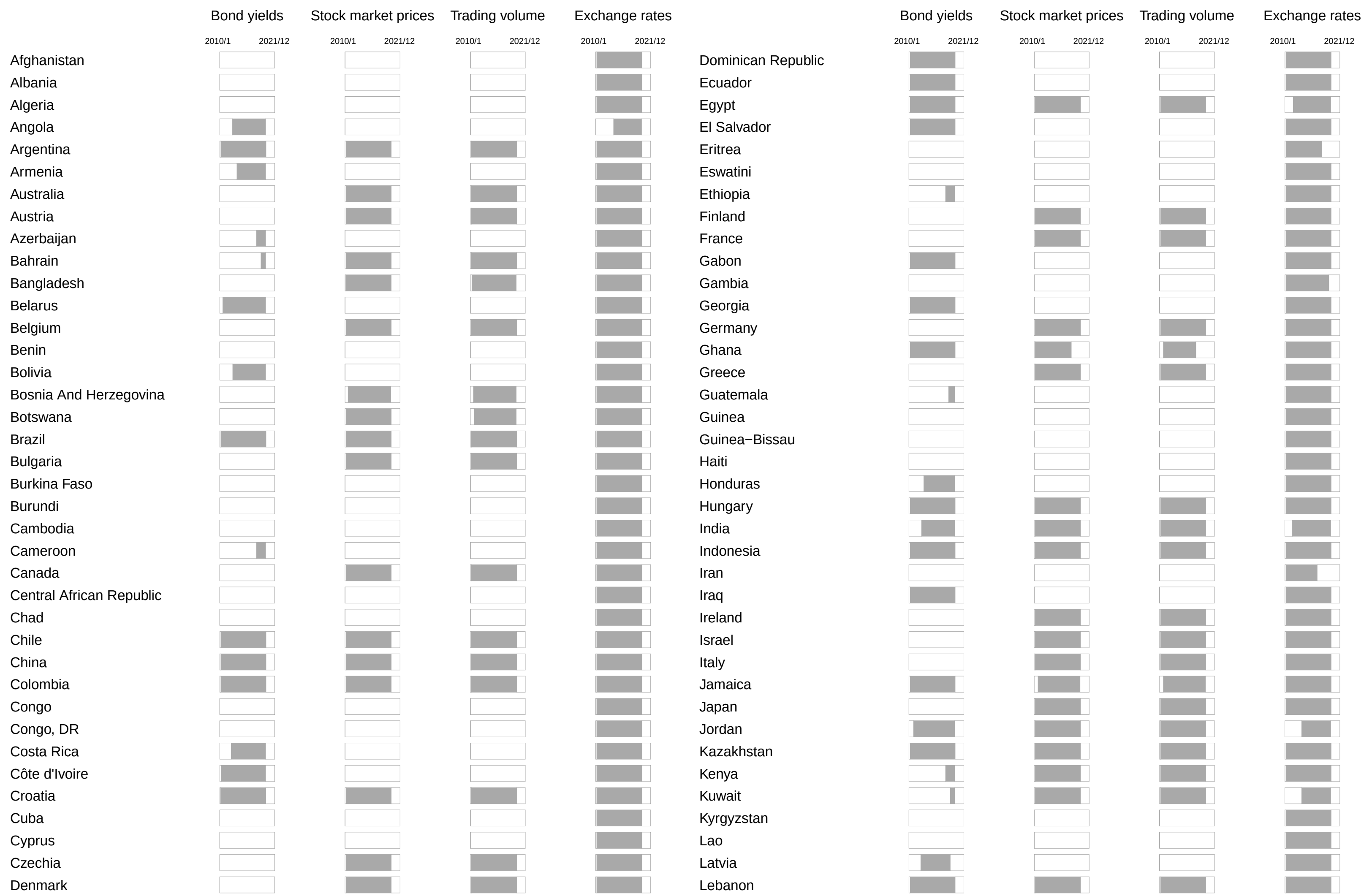
Published at: 2018-07-06

Title: Protest to be Held in Arequipa on *10 Jul*y over Cost of Public Transport

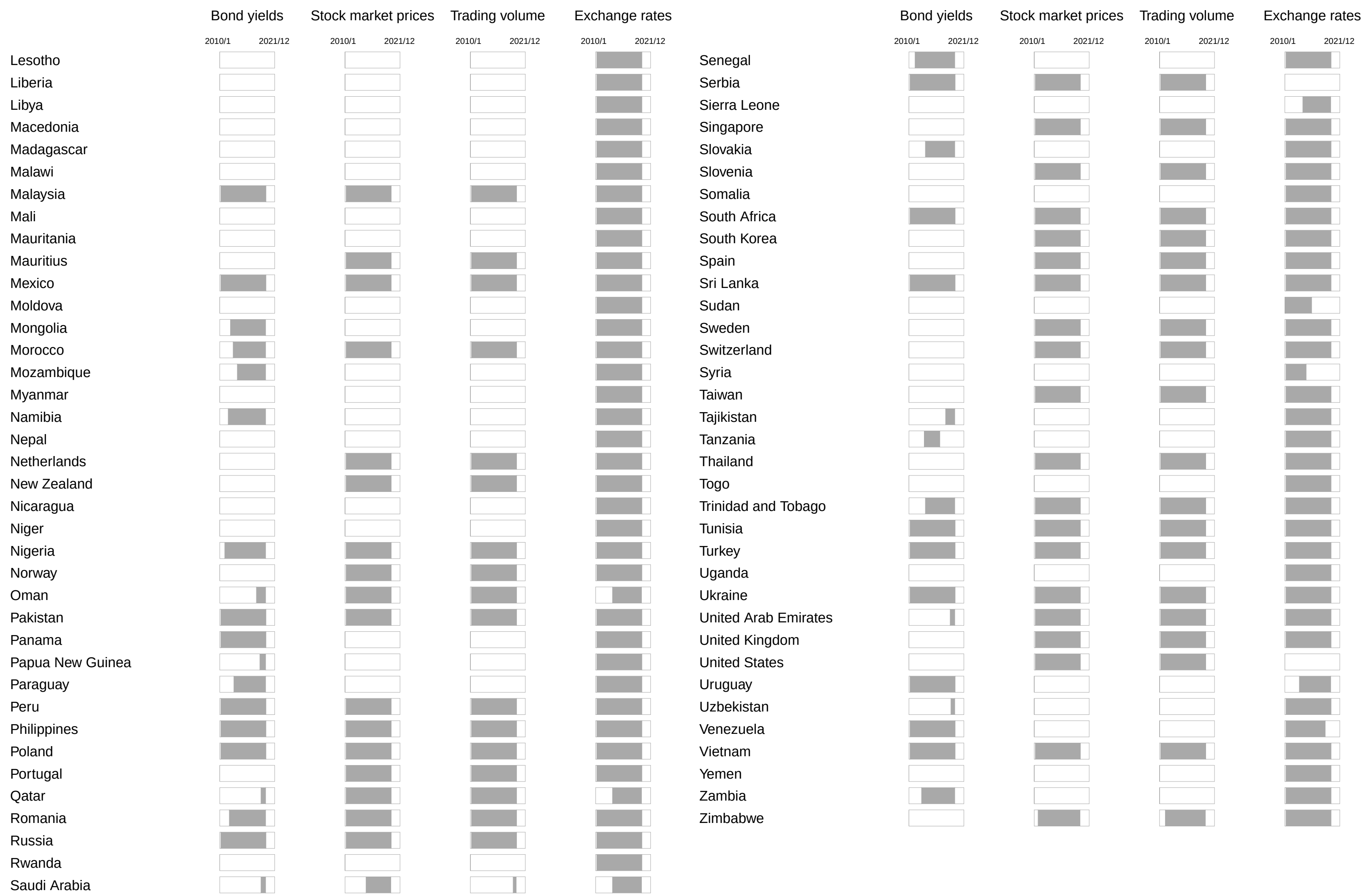
Content: According to local media reports, a protest march is set to be held in Arequipa city over the high cost of public transportation. The action is being organised by a number of civil society organisations and is set to occur on Tuesday, 10 July. Protesters are also angry about poor service and regular accidents. Members in Arequipa are advised to avoid the demonstrations due to the associated risks of exposure to opportunistic crime, unruly crowd behaviour, and police crowd control measures. Monitor local media sources to remain aware of current tensions and for any updates related to planned or ongoing unrest in your area of operation.

Notes: For each sample alert we illustrate (i) terms used to identify protest-related alerts (highlighted in gray), (ii) dates used to identify the date of the protest (italicized), and (iii) generic text that our parser ignores (grayed out).

Online Appendix Figure 2: Coverage of Financial Indices



Online Appendix Figure 2: Coverage of Financial Indices (Continued)



Notes: For each sample country (in rows) and each financial indicator (in columns), the filled region of the timeline depicts the dates during the sample period for which data are available.

C Additional Empirical Results

Online Appendix Table 1: Sensitivity Analysis (Panel A, univariate approach)

	Experts	Sanctions	COVID		Elections	
	Slope		Initial	Later	Dem.	Non-dem.
Baseline	0.018	-0.017	0.151	-0.016	-0.066	-0.220
	(0.005)	(0.013)	(0.019)	(0.018)	(0.024)	(0.037)
Modifying predictive model						
Country-specific sample frequencies	0.016	-0.015	0.144	-0.014	-0.064	-0.213
	(0.004)	(0.012)	(0.018)	(0.017)	(0.023)	(0.036)
Modifying implementation						
Environments as two-months	0.025	—	—	—	—	—
	(0.004)					
Modifying protest definition						
Exclude pro-regime protests	0.018	-0.019	0.149	-0.017	-0.063	-0.221
	(0.005)	(0.013)	(0.019)	(0.018)	(0.024)	(0.037)
Exclude small protests	0.017	-0.012	0.136	-0.006	-0.057	-0.209
	(0.005)	(0.012)	(0.018)	(0.017)	(0.025)	(0.037)
Exclude strikes	0.013	-0.018	0.150	-0.017	-0.073	-0.220
	(0.004)	(0.012)	(0.018)	(0.018)	(0.024)	(0.036)
Include protests with uncertain dates	0.016	-0.019	0.150	-0.021	-0.076	-0.218
	(0.004)	(0.014)	(0.018)	(0.018)	(0.026)	(0.037)
Modifying sample						
Increase population threshold	0.021	-0.011	0.157	-0.020	-0.067	-0.220
	(0.005)	(0.013)	(0.020)	(0.019)	(0.025)	(0.041)
Increase alerts threshold	0.022	-0.010	0.165	-0.019	-0.067	-0.233
	(0.005)	(0.013)	(0.020)	(0.020)	(0.026)	(0.040)
Modifying data sources						
Include protests in MMDP/ICEWS	0.018	-0.020	—	—	-0.083	-0.257
	(0.005)	(0.017)			(0.027)	(0.042)
Exclude protests not in MMDP/ICEWS	0.018	-0.018	—	—	-0.074	-0.225
	(0.005)	(0.014)			(0.026)	(0.038)

Online Appendix Table 1: Sensitivity Analysis (Panel B, multivariate approach)

	Experts	Sanctions	COVID		Elections	
	Slope		Initial	Later	Dem.	Non-dem.
Baseline	0.017	-0.018	0.141	-0.015	-0.062	-0.206
	(0.004)	(0.012)	(0.018)	(0.017)	(0.023)	(0.036)
Modifying predictive model						
Include additional predictors	0.017	-0.018	0.173	0.001	-0.065	-0.212
	(0.004)	(0.012)	(0.018)	(0.017)	(0.024)	(0.036)
Use penalization	0.017	-0.018	0.141	-0.015	-0.062	-0.206
	(0.004)	(0.012)	(0.018)	(0.017)	(0.023)	(0.036)
Use probit	0.017	-0.018	0.142	-0.015	-0.062	-0.206
	(0.004)	(0.012)	(0.018)	(0.017)	(0.023)	(0.036)
Predict separately by country	0.016	-0.012	0.124	-0.031	-0.046	-0.190
	(0.005)	(0.012)	(0.017)	(0.017)	(0.021)	(0.034)
Modifying estimator						
Unbiased estimate of upper bound	0.015	-0.015	0.146	-0.008	-0.079	-0.214
	(0.004)	(0.012)	(0.017)	(0.018)	(0.025)	(0.039)
Confidence bound for preventiveness	0.015	-0.013	0.148	-0.008	-0.083	-0.209
	(0.004)	(0.012)	(0.017)	(0.018)	(0.024)	(0.039)
Modifying implementation						
Environments as two-months	0.023	—	—	—	—	—
	(0.004)					
Split sample randomly	0.017	-0.017	0.142	-0.015	-0.062	-0.207
	(0.004)	(0.012)	(0.018)	(0.017)	(0.023)	(0.036)
Modifying protest definition						
Exclude pro-regime protests	0.017	-0.020	0.139	-0.017	-0.059	-0.208
	(0.004)	(0.012)	(0.018)	(0.017)	(0.023)	(0.036)
Exclude small protests	0.016	-0.013	0.126	-0.007	-0.053	-0.199
	(0.004)	(0.012)	(0.017)	(0.016)	(0.024)	(0.037)
Exclude strikes	0.012	-0.019	0.140	-0.017	-0.069	-0.208
	(0.004)	(0.012)	(0.017)	(0.017)	(0.023)	(0.036)
Include protests with uncertain dates	0.015	-0.021	0.139	-0.020	-0.072	-0.207
	(0.004)	(0.013)	(0.018)	(0.017)	(0.025)	(0.036)
Modifying sample						
Increase population threshold	0.019	-0.012	0.146	-0.020	-0.063	-0.206
	(0.004)	(0.012)	(0.019)	(0.018)	(0.024)	(0.040)
Increase alerts threshold	0.021	-0.012	0.154	-0.018	-0.062	-0.218
	(0.005)	(0.012)	(0.019)	(0.019)	(0.025)	(0.039)
Modifying data sources						
Include protests in MMDP/ICEWS	0.016	-0.020	—	—	-0.074	-0.234
	(0.004)	(0.016)			(0.025)	(0.039)
Exclude protests not in MMDP/ICEWS	0.012	-0.019	—	—	-0.046	-0.144
	(0.003)	(0.011)			(0.017)	(0.024)

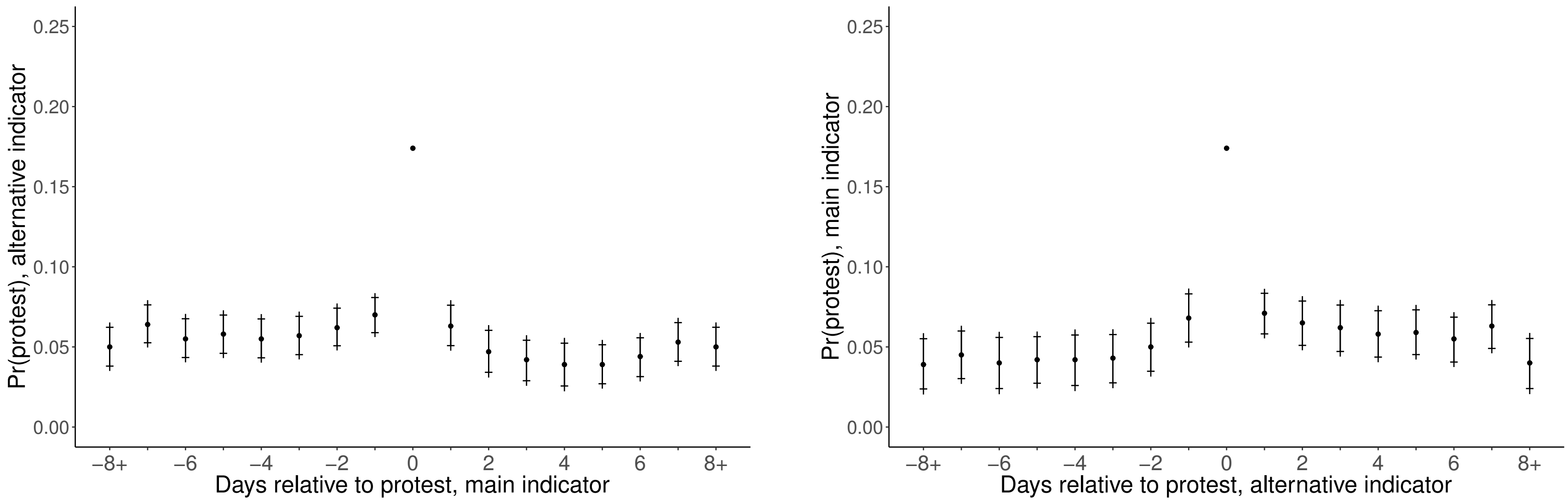
Online Appendix Table 1: Sensitivity Analysis (notes)

- In **Panel A**, each row corresponds to a set of estimates of preventiveness, using the univariate approach to the estimation of protest probabilities described in Section 5.1.
- In **Panel B**, each row corresponds to a set of estimates of preventiveness, using the multivariate approach to the estimation of protest probabilities described in Section 5.1.
- The **columns** are as follows, with standard errors in parentheses.
  - The "Experts: Slope" column reports the coefficient corresponding to that labeled in the upper left plot of Figure 2.
  - The "Sanctions" column reports the slope corresponding to that in the event study of preventiveness around U.S.-imposed sanctions in Panel A of Figure 4.
  - The "Covid: Initial" and "Covid: Later" columns report differences in average coefficients corresponding to those in the event studies of preventiveness around the onset of COVID-19 lockdowns in Figure 5.
  - The "Elections: Democracies" and "Elections: Non-democracies" columns report differences in coefficients between an election month and the average of the months immediately prior to and after an election month in democracies and non-democracies corresponding to those in Figure 6.
- **Baseline** corresponds to our baseline implementation.
- **Modifying predictive model** corresponds to modifying our model and esimator for $p^*(\mathbf{x};k)$.
  - "Include additional predictors" corresponds to including in covariates $\mathbf{x}_{it}$ seven lags of standardized values of search query volume about the country in the US and UK (Section 4.2); protest Twitter mentions in the country's official languages (Section 4.2); a set of financial indices (Online Appendix B.2); an indicator for whether an election occurred in the given country within seven days of the given date (Section 6.3); and an indicator for whether a protest occurred in the given country on the same date in the previous year.
  - "Country-specific sample frequencies" corresponds to a specification of the binary approach where we take $p^*(\mathbf{x};k) = p_i(a)$. We estimate $p_i(a)$ with the corresponding conditional sample frequencies for the given country i, excluding the data for the given month to avoid overfitting.
  - "Use penalization" corresponds to estimation by L1-penalized maximum likelihood, with the penalty parameter chosen via 10-fold cross-validation where the folds are equal-sized groups of country-years.
  - "Use probit" corresponds to assuming that $p^*(\mathbf{x};\theta)$ takes a probit form.
  - "Predict separately by country" corresponds to estimating the predictive model underlying $p^*(\mathbf{x};k)$ separately by country using L1-penalized maximum likelihood, excluding countries for which this is infeasible, with the penalty parameter chosen via 10-fold cross-validation where the folds are approximately equal-sized groups of consecutive months.

Online Appendix Table 1: Sensitivity Analysis (notes. continued)

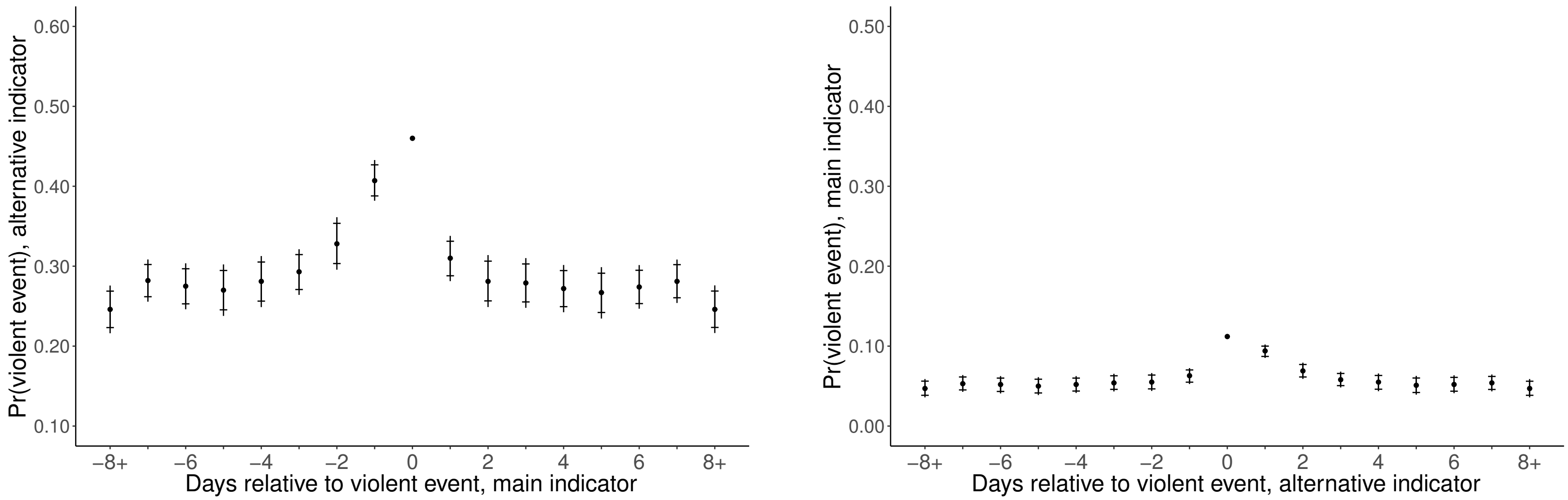
- **Modifying estimator** corresponds to modifying our estimator of preventiveness.
  - "Unbiased estimator of upper bound" corresponds to estimating preventiveness with an indicator for whether no protest occurs on the date t with the largest value of $\hat{p}(\mathbf{x}_{it}; k_{it})$ in the given country-month k_{it}.
  - "Confidence bound for preventiveness" corresponds to estimating preventiveness with an indicator for whether an 80 percent confidence bound, constructed following Lei (2023), equation (6), contains nearly full preventiveness, $1 - \overline{p}^*(k) \geq 0.9$.
- **Modifying implementation** corresponds to modifying our implementation of the approach and estimator.
  - "Environments as two-months" corresponds to letting each environment k_{it} consist of two-month groups instead of a single calendar month.
    * We exclude results for columns that report estimates from regression models with independent variables defined at the level of the calendar month.
  - "Split sample randomly" corresponds to randomly splitting calendar years to avoid overfitting, instead of the even-odd split we use in our baseline implementation.
- **Modifying protest definition** corresponds to modifying our definition and parsing of protests from security alerts.
  - "Exclude pro-regime protests" corresponds to excluding alerts that explicitly mention protests in favor of the regime but do not explicitly mention protests against the regime.
  - "Exclude small protests" corresponds to excluding alerts that only mention protests attended by fewer than a thousand people.
  - "Exclude strikes" corresponds to excluding alerts whose only protest-related keywords are strike-related.
  - "Include protests with uncertain dates" corresponds to including protests whose dates we were not able to infer from text fields.
- **Modifying sample** corresponds to changing the sample of countries.
  - "Increase population threshold" corresponds to restricting the sample to countries with a population of at least 2,000,000 in 2010, keeping the alerts threshold as in baseline.
  - "Increase alerts threshold" corresponds to restricting the sample to countries in which there is at least one year in the sample period with at least 20 alerts in the Crisis24 database, keeping the population threshold as in baseline.
- **Modifying data sources** corresponds to changing the source of data for measuring protest.
  - "Include protests in MMDP/ICEWS" corresponds to including in z_{it} country-dates classified as a protest day according to at least one of the MMDP or ICEWS protest indicators described in Section 4.1 and Online Appendix Figure 3.
  - "Exclude protests not in MMDP/ICEWS" corresponds to excluding from z_{it} protests for which MMDP does not indicate a beginning or ongoing protest in the same calendar week, and ICEWS does not indicate any protest-related stories in the same calendar week, provided that the country-week is covered by at least one of these sources.
  - Because the coverage of MMDP/ICEWS varies over the sample period, we exclude results for columns that report time trends from regression models without calendar time fixed effects.

Online Appendix Figure 3: Relationship Among Alternative Indicators of Protest Activity



Notes: The plots show the relationship between our main indicator of protest occurrence (z_{it}) and an alternative indicator constructed from the Mass Mobilization Data Project (MMDP; Clark and Regan 2021) and the Integrated Crisis Early Warning System (ICEWS; Boschee et al. 2015). We perform the analysis on the subset of our sample countries and period covered by these two alternative data sources, where we define the coverage of a country by a data source as the period from the beginning of the first year in which the source records a protest in the given country through the last full year included in the data source. This results in a sample of 144 countries over the period from 2009 through 2019. From MMDP, we obtain information on the start and end date of citizen demonstrations against the government (which we manually correct in a subset of cases), and we create an indicator equal to one on any country-date on which a protest begins. From ICEWS, we obtain information on the number of protest-related stories appearing in the news about a given country, and we create an indicator equal to one on any date on which there is a protest-related story but no protest-related story in the preceding five days. We then construct an alternate indicator equal to one on any date in which either our MMDP or ICEWS indicator is equal to one. Each plot is constructed from a regression in which the unit of analysis is the country-date and the model includes country and date fixed effects. The independent variables of interest are seven leads (relative days -7 through -1) and seven lags (relative days 1 through 7) of our main protest indicator z_{it} in the left plot and seven leads and lags of the alternative indicator in the right plot. Two variables reflecting the cumulative number of protests more than seven days in the future and more than seven days in the past are included in both columns as well. The contemporaneous protest indicator is excluded as a normalization. The dependent variable is the alternative indicator in the left plot and our main protest indicator z_{it} in the right plot. We recenter the y-axis in each plot by adding a constant equal to the sample mean of the dependent variable on dates on which there is a protest according to the indicator used in the x-axis. The inner bars depict 95% pointwise confidence intervals and the outer lines depict 95% uniform sup-t bands, both based on inference clustered by country.

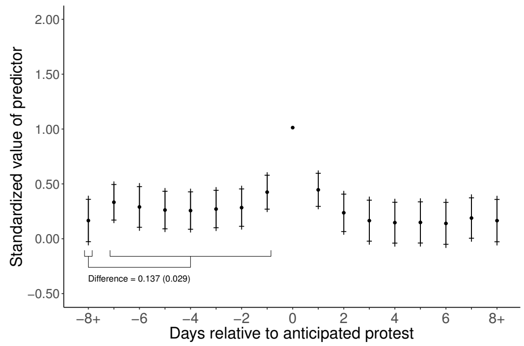
Online Appendix Figure 4: Relationship Among Alternative Indicators of Suppression



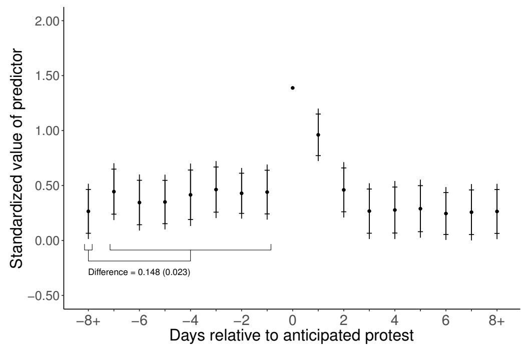
Notes: The plots show the relationship between our main indicator of suppression (s_{it}), and an alternative indicator constructed from the Armed Conflict Location & Event Data Project (ACLED 2022). We perform the analysis on the subset of our sample countries and period that is covered by ACLED. This results in an unbalanced panel of 150 countries over the period from 2010 through 2021. To construct the alternative indicator of suppression, we create an indicator for whether ACLED includes any events categorized as “Protest” or “Riot” with “military versus rioters” or “military versus protesters” interactions on the given country-date. Each plot is constructed from a regression in which the unit of analysis is the country-date and the model includes country and date fixed effects. The independent variables of interest are seven leads (relative days -7 through -1) and seven lags (relative days 1 through 7) of our main indicator in the left plots and seven leads and lags of the alternative indicator in the right plots. Two variables reflecting the cumulative number of events more than seven days in the future and more than seven days in the past are included in both columns as well. The contemporaneous event indicator is excluded as a normalization. The dependent variable is the alternative indicator in the left plots and our main indicator in the right plots. We recenter the y-axis in each plot by adding a constant equal to the sample mean of the dependent variable on dates on which there is an event according to the indicator used in the x-axis. The inner bars depict 95% pointwise confidence intervals and the outer lines depict 95% uniform sup-t bands, both based on inference clustered by country.

Online Appendix Figure 5: Profile of Predictor Variables Around Anticipated Protest

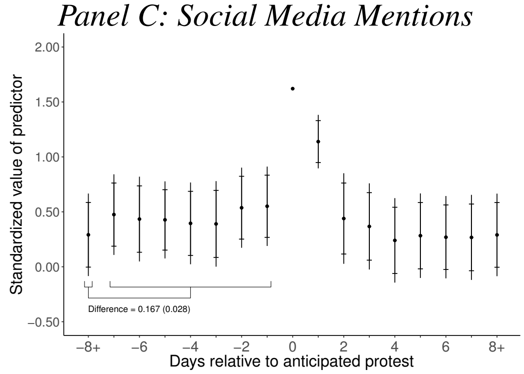
Panel A: Search Query Volume



Panel B: News Mentions

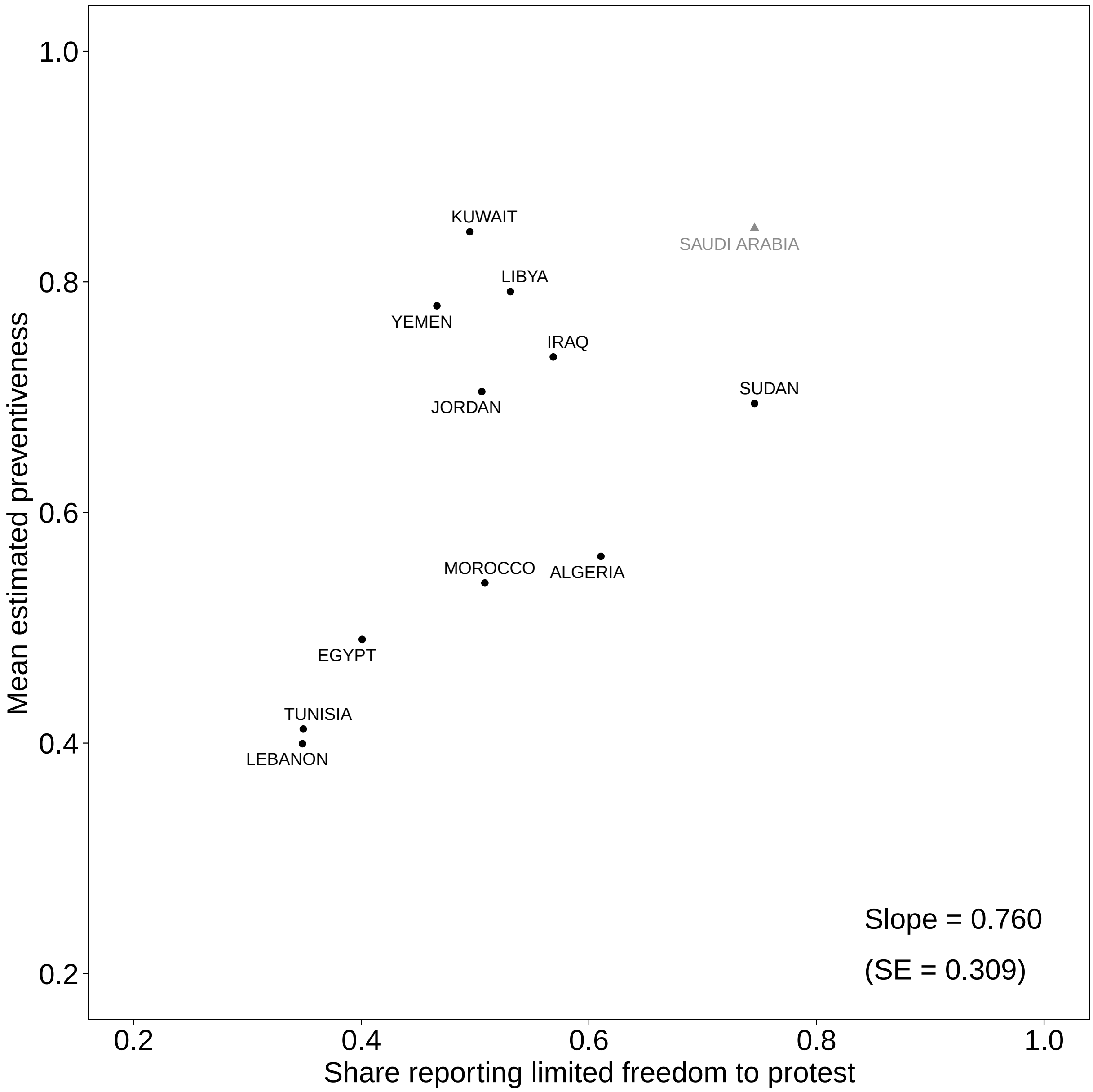


Panel C: Social Media Mentions



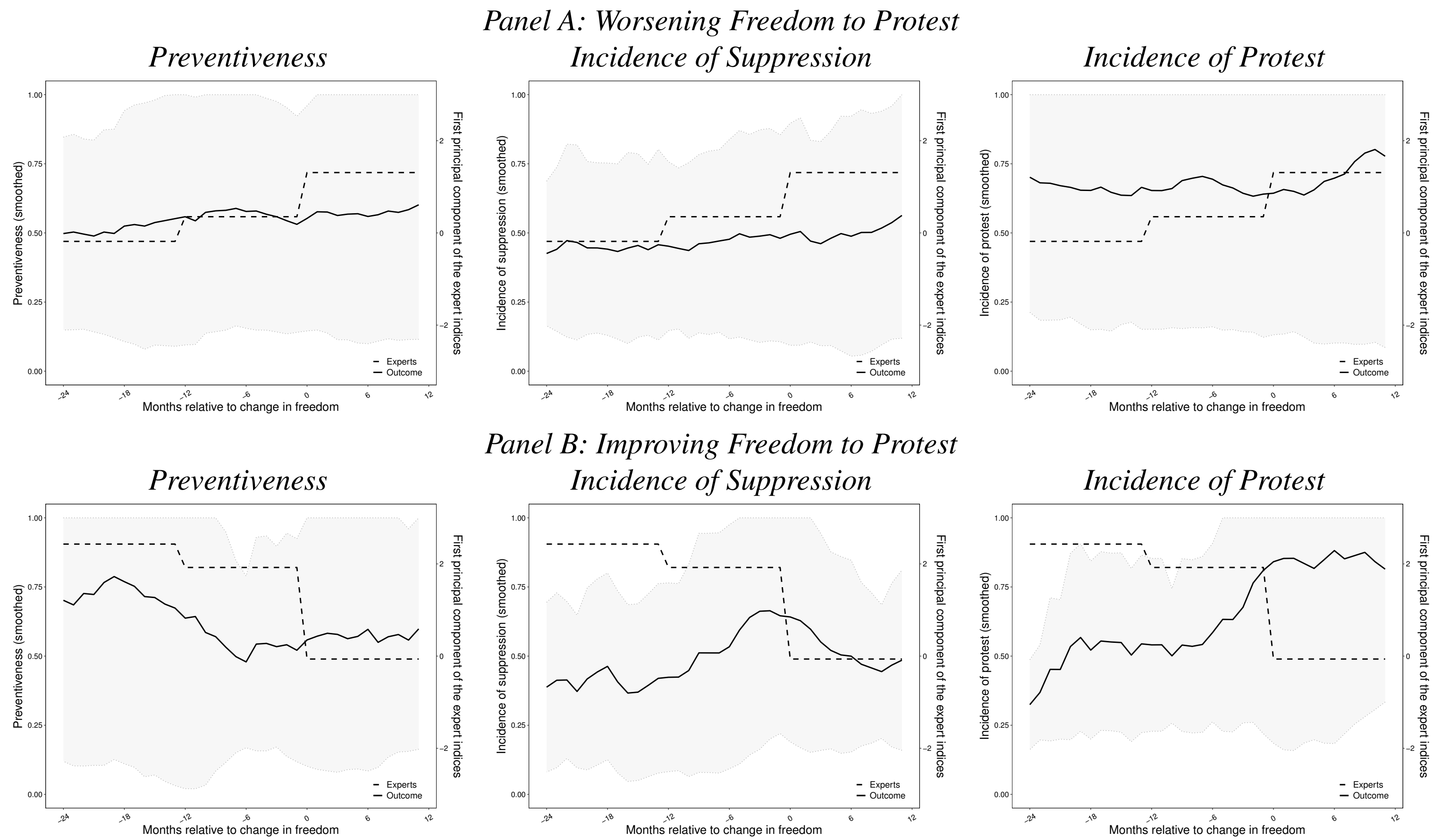
Notes: The figure shows daily event-study plots of standardized values of predictor variables around dates with an anticipated protest. Each plot is constructed from a regression in which the unit of analysis is the country-date and the model includes country and date fixed effects. The independent variables of interest are seven leads (relative days -7 through -1) and seven lags (relative days 1 through 7) of an indicator a_{it} for the anticipated occurrence of a protest, as well as two variables reflecting the cumulative number of anticipated protests more than seven days in the future (relative day -8+) and more than seven days in the past (relative day 8+). The contemporaneous anticipated protest indicator is excluded as a normalization. We recenter the y-axis in each plot by adding a constant equal to the sample mean of the dependent variable on dates with an anticipated protest. The inner bars depict 95% pointwise confidence intervals and the outer lines depict 95% uniform sup-t bands, both based on inference clustered by country. Labeled on each plot is the difference between the coefficient on relative day -8+ and the average coefficient on relative days -7 through -1, along with the corresponding standard error.

Online Appendix Figure 6: Relationship of Preventiveness to Perceived Limits on Freedom to Protest, Arab Barometer



Notes: The figure shows a scatterplot of the mean estimated preventiveness (y-axis) against the share of survey respondents reporting limited freedom to protest (x-axis) in countries included in the Arab Barometer (2022). Survey respondents were asked, "To what extent do you think that freedom to participate in peaceful protests and demonstrations is guaranteed in your country?" The x-axis variable gives the mean share of respondents answering "guaranteed to limited extent" or "not guaranteed," among those giving a valid response, across survey waves II (2010-11), III (2012-14), IV (2016-17), and V (2018-19). The question was not asked in Saudi Arabia, and we impute the x-axis value for Saudi Arabia to be the maximum among the surveyed countries. The plot displays the slope of a regression of mean estimated preventiveness on share reporting limited freedom, along with its standard error.

Online Appendix Figure 7: External Validation Over Time

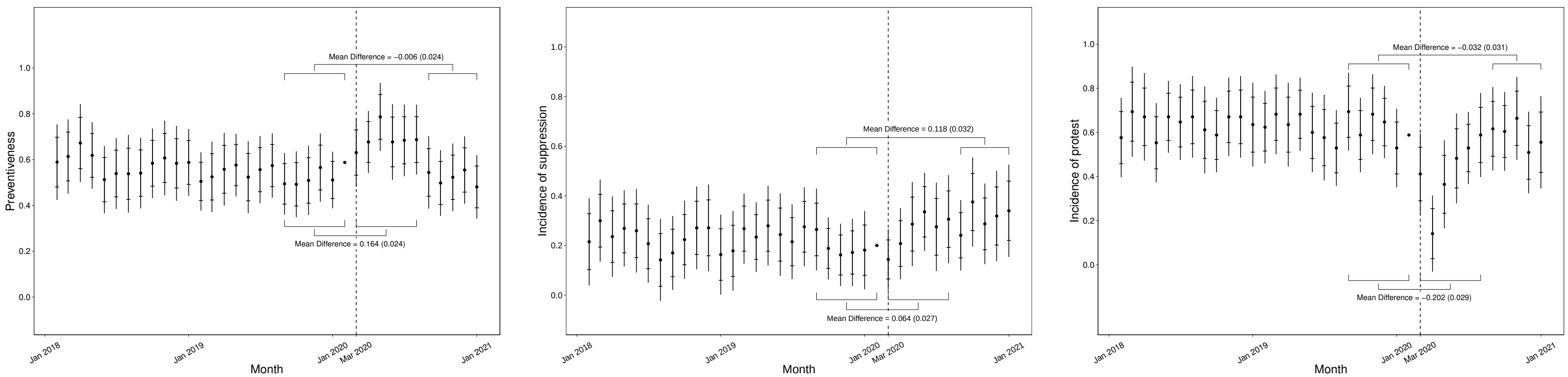


Notes: The figure shows smoothed monthly event-study plots of preventiveness (left), incidence of suppression (center), and incidence of protest (right) around large changes in expert indices of freedom to protest. We define a large change as a case in which one or more expert indices of the country's freedom to protest worsens (Panel A) or improves (Panel B) by at least two units (out of four or five) on net in a span of two years. The right-side y-axis shows the mean of the first principal component of the (negative) expert indices, with loadings determined as in Figure 2. To construct each plot, we estimate a regression with the left-side y-axis variable as the dependent variable. In each regression, the unit of analysis is the country-month, the sample includes all country-months where all three expert indices are available, the model includes fixed effects for calendar months, and the independent variables of interest are individual indicators for each of the 36 months before and 24 months after the change in freedom, with a separate indicator for country-months more than 36 months before the change. For the plots of preventiveness and incidence of suppression, the regression additionally controls for an indicator for the incidence of protest in the given country and month. We smooth the coefficients using a 12-month backward-looking moving average, and recenter their values by adding a constant so that the mean of the displayed values is equal to the sample mean of the corresponding dependent variable in the plotting window. The shaded region depicts 95% pointwise credible intervals based on a Bayesian bootstrap with 80 replicates, with the shaded region restricted to the y-axis range.

Online Appendix Figure 8: Dynamics of Repression and Protest Around COVID Lockdowns, Controlling for Mortality

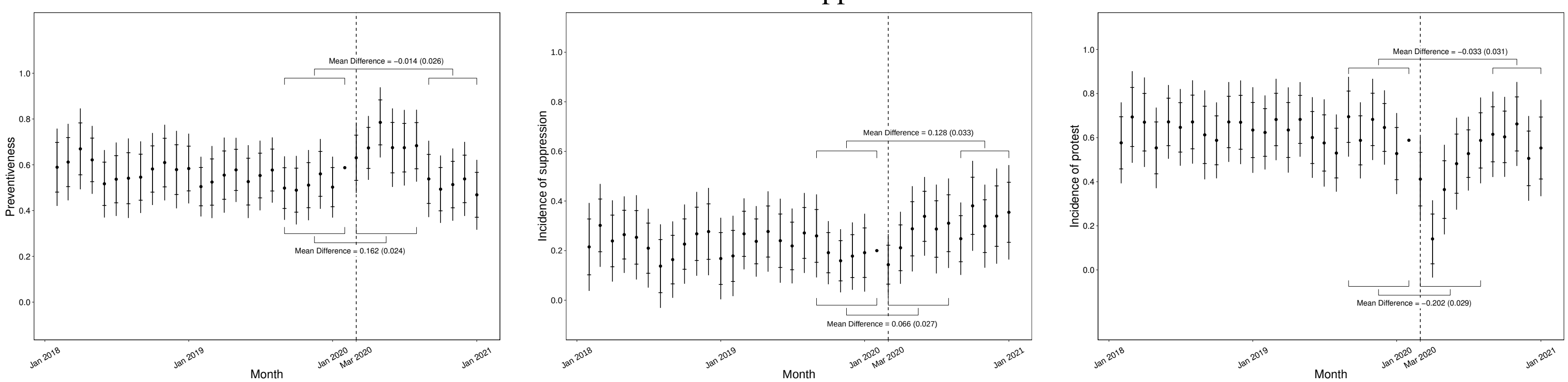
Panel A: Not controlling for mortality

Preventiveness | Incidence of Suppression | Incidence of Protest



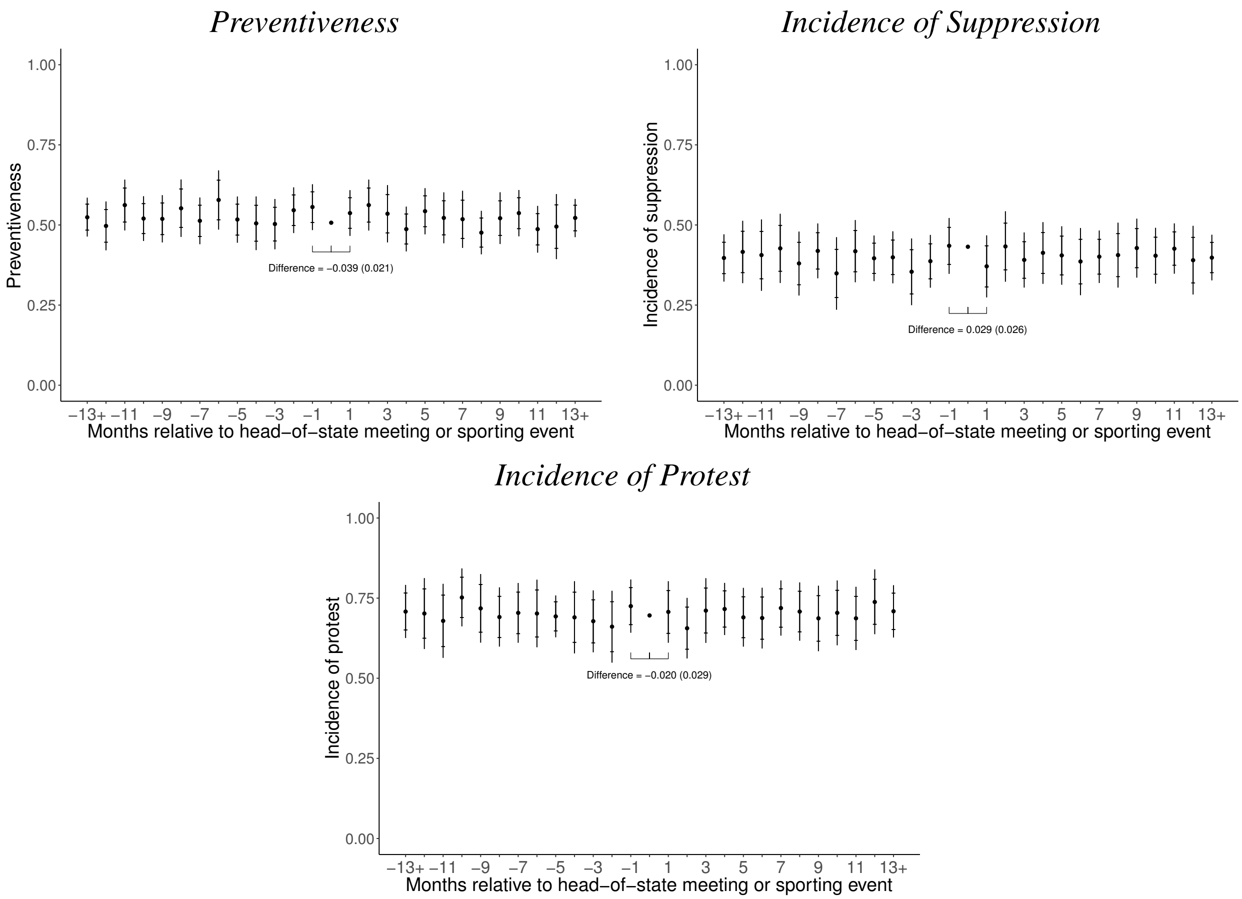
Panel B: Controlling for mortality

Preventiveness | Incidence of Suppression | Incidence of Protest



Notes: The figures show monthly event-study plots of preventiveness (left), incidence of suppression (center), and incidence of protest (bottom) around the onset of COVID-19 lockdowns. Each plot is constructed from a separate regression in which the unit of analysis is the country-month, the sample includes months February 2018 through January 2021 for the 85 countries for which Karlinsky and Kobak (2021, 2023) include data on monthly mortality rates, and the model includes fixed effects for country. For the plots in Panel A, we do not control for mortality. For the plots in Panel B, we add a control for the log of the per capita mortality rate. For the plots of preventiveness and incidence of suppression, the regression additionally controls for an indicator for the incidence of protest in the given country and month. The independent variables of interest are indicators for the calendar months from February 2018 through January 2021, excluding February 2020 as a normalization. In each plot, we recenter the y-axis by adding a constant equal to the sample mean of the dependent variable in February 2020. The inner bars depict 95% pointwise confidence intervals and the outer lines depict 95% uniform sup-t bands, both based on inference clustered by country. Labeled on each plot is the difference in the average coefficient between the six months beginning in March 2020 and the six months ending in February 2020, as well as the difference in the average coefficient between the five months beginning in September 2020 and the six months ending in February 2020, along with the corresponding standard errors.

Online Appendix Figure 9: Dynamics of Repression and Protest Around International Meetings and Sporting Events



Notes: The figure shows monthly event-study plots of preventiveness (upper left), incidence of suppression (upper right), and incidence of protest (bottom) around international governmental meetings and sporting events. Each plot is constructed from a separate regression in which the unit of analysis is the country-month and the model includes fixed effects for country and for calendar month. The independent variables of interest are 12 leads and lags of an indicator for the occurrence of an international event, and two variables reflecting the cumulative number of international events 13 or more months in the future and the cumulative number of international events 13 or more months in the past. For the plots of preventiveness and incidence of suppression, the regression additionally controls for an indicator for the incidence of protest in the given country and month. The contemporaneous international event indicator is excluded as a normalization. In each plot, we recenter the y-axis by adding a constant equal to the sample mean of the dependent variable in event months. The inner bars depict 95% pointwise confidence intervals and the outer lines depict 95% uniform sup-t bands, both based on inference clustered by country. Labeled on each plot is the difference between the coefficient for the event month and the average of the coefficients for the preceding and following months, along with the corresponding standard error. The international governmental meetings we consider are organized by ACS, APEC, ASEAN, AU, BRICS, CARICOM, CHOGM, COMESA, ECOWAS, European Council, G7, G15, G20, IGAD, LAS, NATO, NC, OIC, OSCE, PIF, SAARC, and the UN. The sporting events we consider are AFC Asian Cup, AFC Champions League Finals, Asian Games, CAF Africa Cup of Nations, UEFA Champions League Finals, Commonwealth Games, CONCACAF Gold Cup, Confederations Cup, COMEBOL CONMEBOL Copa America, CONMEBOL Libertadores Finals, Cricket World Cup, Gulf Cup, OFC Nations Cup, Tour de France, UEFA European Championship, Wimbledon, Olympics, and the FIFA World Cups.

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