Do Dictators Signal Strength with Elections?*

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What role do elections play in nondemocracies? In this paper, we offer an empirical test of a popular idea that authoritarian governments use elections to engineer overwhelming victories thus deterring potential opposition from challenging the regime. Using the data from the Russian Parliamentary elections in 2011 and a regionally representative public opinion survey, we find that the geographical allocation of electoral manipulation was the opposite of what the theory would imply: more manipulation happened in the areas where the regime was more popular. We also find that higher margins of victory for a pro-regime party failed to deter subsequent mass protests. We argue that these empirical patterns could be better explained not by the efforts of the regime to signal invincibility, but to gather information about public preferences on the support for the regime in the most ex-ante contested areas.

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1 Introduction

What role do elections play in nondemocracies? This question has emerged as a fundamental subject in studies of authoritarian regimes (Brancati, 2014; Gehlbach, Sonin and Svolik, 2016). One of the most frequent answers found in the literature is the following: the regime needs overwhelming victories, often manipulating the results to influence others' perception that it is, indeed, strong, thus deterring potential rivals from mounting a challenge to the incumbent (Magaloni, 2006; Simpser, 2013; Egorov and Sonin, 2014; Gehlbach and Simpser, 2015; Little, 2015; Geddes, Wright and Frantz, 2018).[1]

Despite the prominence of this family of ideas (hereafter, the Influence Theory), the empirical evidence in favor of them remains thin. It has been demonstrated that authoritarian survival is correlated with the existence of quasi-democratic institutions (Geddes, 2005) and with electoral fraud (Simpser, 2013). However, there is no empirical evidence that authoritarian regimes implement electoral manipulations because they want to signal their strength to their population. Most importantly, current literature is silent on two critical questions that have to be answered to test the empirical validity of this theory. First, do regimes try to engineer — through electoral manipulations — higher margins of victory when the perceived threat is higher. Second, do higher margins of victory deter subsequent political contestation?

Our paper answers these two questions in the context of Russian Parliamentary elections. The Russian institutional setting and unique combination of electoral and protest data allow us to reject the Influence Theory and provide evidence in favor of an alternative theory. First, we estimate the region-level amount of electoral manipulation in Russia in the 2011 Parliamentary election as a function of the pre-election protest sentiments (measured by a regionally representative survey and by actual incidences of public protests). We find that the relationship between electoral manipula-

[1] Specifically, Simpser (2013) writes: "Manipulating elections excessively and blatantly can make the manipulating party appear strong, while failing to manipulate in this manner can convey weakness. A party that is perceived to be powerful and resourceful will enjoy greater bargaining power, ampler scope for governing, a lesser need to share rents and to compromise in policy, and fewer challenges to its hold on office, than a party that is perceived to be weak and vulnerable."

tion and protest sentiments is the *opposite* of that which would be consistent with the Influence Theory. While the Influence Theory implies a positive relationship between the protest sentiments and the electoral manipulation, we find the relationship to be negative. This relationship holds regardless of the measurement of electoral manipulation, the inclusion of controls (urbanization, regional autonomy, various socioeconomic indicators, ethnic republics, etc.), and the measurements of protest sentiments (survey-based measures or actual pre-electoral protest behavior).

Second, we look at whether higher margins of victory for the winning party deter future protests (conditional on the support for the regime and the amount of electoral manipulation). If the Influence Theory is empirically relevant, we would expect fewer protests in places with higher margins of victory. However, we find no discernible relationship between higher margins of victory for the ruling party and post-election protests.

We use the case of Russia for several reasons. First, Russia's political regime is classified as competitive authoritarianism. It regularly conducts elections, but the de-facto rules in those elections are unfair to the opposition: it is outspent, harassed, faces various administrative obstacles, and lacks access to major state-controlled media outlets. Still, the opposition is often able to run political campaigns and mobilize its audiences. So, we would expect the Influence Theory to apply to Russia based on its regime type. More specifically, many of the formal models that spell out different versions of the Influence Theory (Simpser, 2013; Little, 2015; Egorov and Sonin, 2014; Gehlbach and Simpser, 2015) use Russia as an illustrative case or as a justification for some of the model assumptions. So, we believe that it is only fair to use a more detailed empirical analysis of Russia's case as a way to test the empirical relevance of the Influence Theory.[2]

[2]Another commonly invoked example is the case of Mexico under the Institutional Revolutionary Party (PRI) (Magaloni, 2006). We do not use this example in this paper because of the two reasons. First, we would like to test the Influence Theory using a currently existing regime. Second, as Geddes (2005) points out, the relevance of the influence considerations for the PRI might be a result of a specific institutional feature of that regime — strictly enforced executive term limits. In this sense, Russia's case is more relevant since it has many common features of modern "competitive autocracies" (Levitsky and Way, 2002).

We also answer the next logical question that comes out of our analysis: if the Influence Theory does not explain the pattern of electoral manipulation, then what does? We argue that the data are consistent with a different family of theories — the idea that elections are used by the regime to understand political preferences of the population (hereafter, the Information Theory). Armed with information, the regime can implement policies that target different groups of the population differently, based on the level of their support. For example, the regime can punish opposition strongholds.[3] Information about opposition constituencies is important regardless of whether the regime chooses carrots or sticks as the instruments for survival. For example, Treisman (2001) shows that the Russian government in 1993 and 1994 used transfers to pacify potential troublemakers among the regional governors, Magaloni (2006) shows that the PRI in Mexico rewarded its supporters and punished some of its opponents, and Blaydes (2011) demonstrates, among other things, that in Mubarak's Egypt, regions that supported the Muslim Brotherhood were less likely to get sewage services. Whether a government is punishing the opposition, rewarding supporters, or coopting the opposition, it needs accurate information about the level of support for the regime. The Information Theory implies that holding elections is a straightforward way to get this knowledge. This argument is consistent with Peter Lorentzen's "controlled burn" hypothesis (Lorentzen, 2013, 2014, 2015) which says that authoritarian governments might allow certain sincere expression of public preferences to collect data necessary for political survival.

If elections are used to get information, we argue, then it is more important for the regime to get precise information from the areas that are ex-ante perceived to be more contentious. Because the electoral manipulation can not be perfectly planned and involves some agency costs (Rundlett and Svolik, 2016), the reliance on electoral fraud will contaminate the much-needed information. Therefore, to the extent the electoral fraud is used in elections, it should be moved away from the most contentious areas. This is the exact pattern we see in the data: electoral manipulation being negatively

[3] A vast literature on machine politics and patronage dispensation evinces this in various developing countries (e.g., see Golden and Min (2013) for an excellent review).

correlated with the protest sentiments (and actual pre-electoral protests) in the region.

Because electoral manipulation is a covert activity, measuring it can be challenging. For our empirical evaluation, we rely on a set of statistical "fingerprints" of electoral manipulation calculated using precinct-level data. None of those indicators is conclusive by itself but, taken together, they elucidate the geographical distribution of electoral manipulation. We use indicators based on (i) the prevalence of integer proportions in turnout and vote proportions for the main pro-regime party (Rozenas, 2017); (ii) a model-based approach that distinguishes between incremental fraud and extreme fraud Klimek et al. (2012); Mebane (2016); (iii) deviations of the distributions of digits per Benford's Law (Kalinin and Mebane, 2011); (iv) share of precincts where voter turnout is larger than 90% for an additional suggestive measure of electoral manipulation. For our baseline specification, we use the first principal component from the PCA decomposition of the indicators, but we also demonstrate that our result — the substantive and statistically significant negative correlation between the protest potential and indicators electoral manipulation — does not depend on which of the methods we use.

Our main contention is that our results are inconsistent with the Influence theory but consistent with the Information Theory. The main challenge to our interpretation of the results is that they might capture not the regime's desire to manipulate elections, but the actual outcome of the manipulation that could be contaminated by other factors. For example, one might argue that the influence considerations would drive the allocation of the desired levels of the manipulations, but because it is harder to manipulate in the areas where many people are against the regime, the allocation of actual manipulation turns out to be the opposite of what the regime wants. We perform several additional tests to address this concern. First, we control for the actual popularity of the regime. We also control for the various proxies of the capacity of the society to organize a collective effort to prevent electoral manipulation: measurements of social capital and the presence of electoral observers.

We also consider the incentives of field agents who implement manipulations.[4] First, as Rundlett and Svolik (2016) have demonstrated, strategic complementarity among the field agents can generate more manipulation in the areas where the regime is more popular, even if the regime does not want it. We consider this explanation by controlling for the regime's popularity.

Second, because field agents come from the same population as people in a regionally representative survey, they might share the same grievances as the general population and thus be more reluctant to implement manipulation. Following Forrat (2018), we control for the wages of those agents (teachers and administrative personnel). Inclusion of these controls; however, does not substantially change the estimates of the effect of protest potential. We also show that our results are not driven by local political competition and pre-election-day electoral manipulations.

We see the main contribution of our paper in applying a theory-motivated empirical test that can probe one of the major theories of authoritarian institutions.[5] Our paper is also relevant to the literature on the determinants and motivations of electoral fraud. In particular, Rundlett and Svolik (2016) offer a model, based on a global game, where field agents, implementing electoral fraud are more likely to engage in electoral manipulation if they know that the regime is more popular and that they are less likely to be punished. We complement this approach by showing that electoral fraud, even in cases where the incumbent can win without manipulation, can follow from a strategic calculation by the regime. Our findings are also consistent with Rozenas (2016), who shows that insecure incumbents are more likely to manipulate elections.[6]

[4]In the Russian context, these agents are widely believed to be school teachers and administrative personnel (Forrat, 2018). While the federal-level elections are supervised by the Federal Election Commission, regional governors are often believed to play a major role in encouraging electoral fraud since they would want to demonstrate loyalty to the central government.

[5]It is important to note that we do not contend that the Influence and Information Theories are the only possible explanations for the role elections play in authoritarian countries. Several analysts have proposed other theories. According to Blaydes (2011), elections are used for managing conflict among members of the rent-seeking elite about who gets access to the spoils of government offices. Geddes (2009) suggests that autocrats create political parties to counterbalance a powerful military. Gandhi (2008) proposes a theory of authoritarian institutions as an arena for policy concessions. Malesky and Schuler (2010) contend that elections can be used to manage discontent. According to Boix and Svolik (2013), legislatures help reduce information asymmetry between an autocrat and his supporters. Truex (2017) suggests that legislatures serve to "collect preferences" of the subjects.

[6]Kalinin and Mebane (2011) look at electoral manipulation in the Russian context and argue that

Our results also pertain to the theory of "informational autocracy" (Guriev and Treisman, 2015, 2018), which postulates that modern authoritarian regimes survive not by mass repressions, but by controlling information flows and selective cooptation. Our results also contribute to the literature on the role of electoral fraud in autocracies. Gehlbach and Simpser (2015) offer a theory that incumbents manipulate elections to signal their strength to the bureaucracy, while Luo and Rozenas (2018) offer a theory of a trade-off between ex-ante and ex-post election rigging.[7] Literature on authoritarian backsliding (Nalepa, Vanberg and Chiopris, 2018; Svolik, 2018) emphasizes that political polarization allows incumbents to subvert democratic procedures. Consistently with these findings, our paper offers an evidence-based argument that heterogeneity of political preferences influences strategic allocation of electoral manipulation.

This paper is organized as follows: Section 2 provides an overview of the context of our study: the 2011 Russian parliamentary elections. Section 3 describes how we estimate the probability of electoral manipulation in different regions of Russia and describes the data. Section 4 presents the model specifications and empirical results. Section 5 details our tests for alternative explanations and provides robustness checks. Section 6 concludes.

2 Background: 2011 Russian Parliamentary Elections

The 2011 parliamentary election was widely criticized by international observers for being heavily manipulated.[8] Many cases of ballot stuffing were caught on video and posted on YouTube. In one such video, posted on-line by Yegor Duda (a volunteer observer), the chairman of a polling station was caught filling a stack of ballots.[9] In

regional authorities use electoral manipulation to signal loyalty to the central government.

[7] It is important to note that our argument is about how authoritarian regimes *use* elections but not why they choose to create or abolish political systems that involve elections. For example, Fearon (2011) argues that the regime that has already imposed elections cannot abolish them because the fact of not conducting elections at the pre-specified date can serve as a coordination device for the opponents of the regime to revolt.

[8] We provide additional background information on Russian Parliament in Appendix C.

[9] `www.youtube.com/watch?v=P_wWJnRclE8`. The story has been reported by The *New York Times*: `www.nytimes.com/2011/12/06/world/europe/russian-parliamentary-elections-criticized-by-west.html?_r=0`.

another video, a cameraman demonstrates that voters' pens in a polling station were filled with erasable ink.[10] Observers from the Organization for Security and Cooperation in Europe (OSCE) also found multiple "indications of possible fraud."

To quantify the extent of fraud in 2011, Enikolopov et al. (2013) use the random assignment of independent election observers to the polling stations in Moscow and found that the presence of observers reduced United Russia's (hereafter, UR) vote tally by 11 percentage points. Many more papers either demonstrate electoral fraud in Russian parliamentary elections or try to quantify it.[11]

In this paper, we use the presence of multiple instances of fraud in parliamentary elections to distinguish between the theories of electoral institutions. The Information Theory and the Influence Theory both imply heterogeneity of the allocation of manipulation across subnational units. The Influence Theory implies that regions where the regime is unpopular will be targeted with manipulation, whereas the Information theory implies that regions where the regime is ex-ante popular should stay relatively clean.

It is not our contention that the size of the manipulation in every region is determined inside the Kremlin. In fact, scholars have analyzed the role of local politics in electoral fraud (Kalinin and Mebane, 2011; Rundlett and Svolik, 2016). Nevertheless, the role of the central government is not absent. In particular, the central government is known to provide governors with informal expectations of how many votes it expects from their regions. According to the anonymous sources of the leading Russian business daily "*Vedomosti*," before the Parliamentary election of 2011, the operatives of Russian presidential administration have divided all the regions into three groups ("weak," "average," and "strong") and communicated to local bureaucrats the vote share they needed to achieve.[12] Of course, since the Kremlin had the access to the polling data, demanding those pre-specified vote shares is equivalent to demanding election rigging.

[10] www.youtube.com/watch?v=ezEFUGcdShE

[11] See Myagkov, Ordershook and Shakin (2005), Bailey (2008), Buzin and Lyubarev (2008), Myagkov and Ordeshook (2008); Kalinin and Mebane (2009, 2011), Shpilkin (2009), and Vorobyev (2011).

[12] www.vedomosti.ru/politics/articles/2011/10/13/skolko_nuzhno_edinoj_rossii

3 Data

This section briefly describes the data we use to test the empirical predictions of the competing theories. In the first test, the main dependent variable in our analysis is the region-level statistical forensic evidence for the electoral manipulations. The main explanatory variable is the region-level propensity to protest. In the second test, the main dependent variable is the actual number of post-2011 Parliamentary elections protests from Sobolev (2019) and the main explanatory variable is the officially announced vote shares of the the main pro-regime party, UR. We describe our sources and construction of other variables used as covariates in Appendix D.

3.1 *Measuring Protest Potential*

In Russia, the government takes the monitoring of protest potential seriously. The Russian presidential administration regularly commissions public-opinion surveys, with special attention given to presidential approval ratings toward, popularity of various policies pursued by the government, and the attitude to the leaders of the opposition movement. Major pollsters regularly brief Kremlin operatives on the latest changes in public opinion (Baker and Glasser, 2005; Ananyev and Rogov, 2018).

In this study, we rely on one of the large-scale surveys conducted by FOM (*Fond Obschestvennoe Mnenie*, literally "The Public Opinion Foundation"), one of the most reputable polling firms in Russia and a regular contractor for the Russian presidential administration. FOM conducts a type of regionally representative survey called a "georating": a representative sample of respondents in almost all of Russia's regions is asked a comprehensive array of questions designed to elicit attitudes toward the federal and regional governments, economic expectations, and so on.[13]

For this study, we are using a Georating survey conducted in February 2011 — the election took place that year on December 4. The question about protest potential

[13] The survey is conducted in 74 out of 83 regions in Russia. The missing regions are sparsely populated, so FOM decided that it would be prohibitively expensive to conduct a representative survey there. The non-missing regions cover more than 95% of Russian population.

was as follows: "Tell us please, do you notice people's discontent around you with the government authorities, the leadership of our region (the province, the republic), the protest sentiments? And if you notice, is this discontent growing or weakening lately?" There are five proposed answers: "Don't notice," "Increases," "Remains the same," "Decreases," and "Don't know." We compute the proxy for protest potential as the number of respondents who say that discontent and protest sentiments are increasing divided by the total number of respondents in a region (see Figure 1).[14]

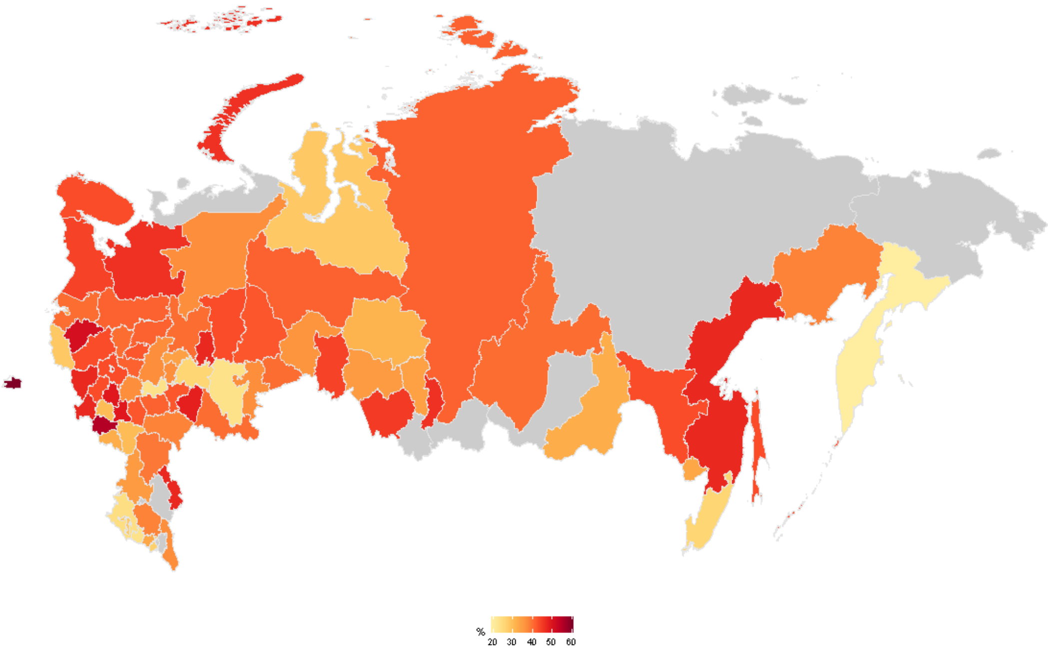


Figure 1: Map of Protest Potential in 2011

Note: This map depicts the level of protest potential by Russian regions in February 2011, according to FOM. The protest potential varies from about 20% to 60% of respondents who answered "Increases." The darker colors represent higher protest potential.

In Section F.1 we confirm our empirical results with the actual instances of pre-electoral protests as a measure of protest potential.

3.2 *Measuring Electoral Manipulation*

To measure electoral fraud, we use official polling-station-level voting data from the Central Election Commission (CEC) for the Russian parliamentary elections in

[14]In Section F.1 we show robustness of our results to alternative measures of protest potential from Robertson (2013).

2011.[15]

Electoral manipulation is a covert activity that in most cases cannot be measured directly, so one needs to rely on indirect measures. Statisticians and social scientists have proposed several methods of detecting fraud. Most of these methods rely on statistical artifacts that are unlikely to emerge under plausible models of voting. For example, one of the simplest possible statistics is the share of polling of stations where a particular party won nearly 100% of the votes. Even if one party is genuinely popular, such results might suggest electoral manipulation. While the measure on its own is certainly not sufficient to prove electoral manipulation beyond the shadow of a doubt, it may prove it if corroborated by other sorts of evidence.

Forensic methods that explore statistical irregularities to find evidence of covert activities are widely applied in different areas of social science. They are used to detect tax and accounting fraud (Heron and Lie, 2007), racial discrimination (Price and Wolfers, 2010), corruption in auctions (Porter and Zona, 1993; Andreyanov, Davidson and Korovkin, 2018), and electoral fraud (Kalinin and Mebane, 2011; Voigtländer and Voth, 2014).[16] In this paper, we use several forensic techniques to quantify the extent of electoral manipulation.

Spikes

Estimates of electoral fraud based on spikes are intuitive: field agents in the polling stations who add votes for the favored candidate often try to match certain arbitrary "round" numbers (e.g., 50%, 55%, or 60%). This results in a situation when in a distribution of the polling stations by the votes in favor of UR there are density spikes at round numbers.

We follow Rozenas (2017), who developed a statistical algorithm to compute electoral manipulations based on the difference between the abnormal share of votes on round numbers and predicted share of votes based on the distribution around them.

[15]Data are available at `www.cik.bg/`. To ensure that the data are not corrupted, we use the data collected by the nonprofit organization "Golos" ("Voice," `www.golosinfo.org/`), which scraped all the data after they were published online by the CEC.

[16]For many other examples as well as a discussion of basic approaches, see Zitzewitz (2012).

We use Rozenas's *spikes* package to estimate region-level percentages of fraudulent precincts.[17]

Mixture Estimator

An estimate of fraud based on the mixture estimator is developed in Klimek et al. (2012). The method has three assumptions. First, votes come from a normal distribution. Second, there is incremental fraud, when all candidates receive additional votes through ballot stuffing (but maybe one more than other). And third, there is extreme fraud, when one candidate receives all the fraudulent votes. Overall, the empirical distribution of votes is a mixture of three normal distributions with three different humps: one for polling stations without fraud, one for polling stations with incremental fraud, and one for polling stations with extreme fraud.

Klimek et al. (2012) choose the parameters of these three distributions to compute the amount of incremental and extreme electoral manipulations. Mebane (2016) proposes an alternative, more robust method of estimating fraud based on the finite-mixture-likelihood method, in which the model's parameters are estimated before the fraud is estimated. Kalinin and Mebane (2017); Kalinin (2018) deployed these estimates to evaluate the integrity of Russian elections. Here, we use their estimates for the 2011 elections. For our estimates, we add up the proportions of polling stations with extreme and incremental fraud.

Benford's Law

One of our electoral-manipulation estimates is based on the generalized Benford's Law (hereafter, BL) which postulates a certain probability distribution that digits in a number follow (Benford, 1938). Kalinin and Mebane (2011) demonstrate, using simulations under a plausible data-generating process of voting, that the second digit in a vote count should follow a BL distribution.

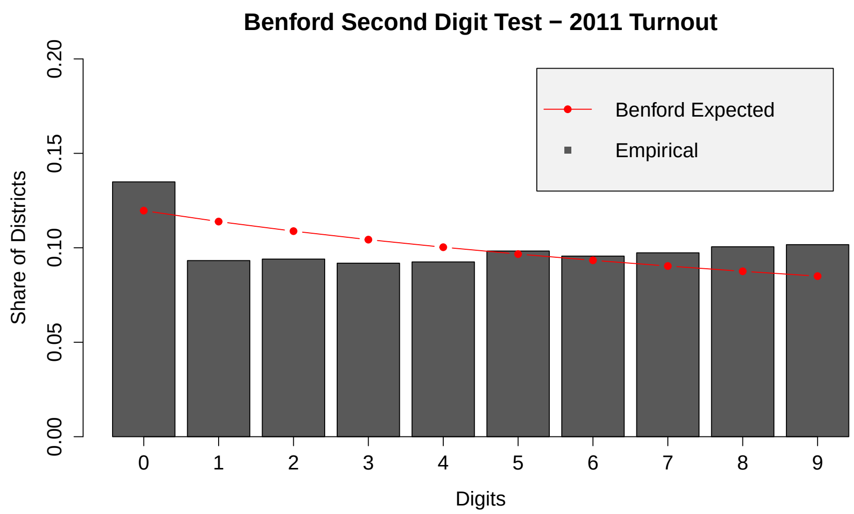
Its intuition is straightforward: if a number represents a naturally occurring phe-

[17] https://cran.r-project.org/web/packages/spikes/index.html.

nomenon, the distribution of its second digit should follow certain empirically established distribution. See Appendix E for details.

In this paper, for every Russian region, we calculate a mean absolute deviation (MAD) of actual digits' frequencies from the frequencies expected by BL. The higher the deviation is in a region; the more electoral manipulation should be plausibly expected there.

Figure 2 shows the difference between the actual frequencies of second digits and the frequencies that are predicted by the theory. According to BL, the frequencies of digits should gradually go down as numbers represented by the digits increase from 0 to 9. The empirical distribution is different: there is a bump at digit "0," while all other digits have very similar frequencies.



Note: On the horizontal axis: every digit that can appear in a turnout number. On the vertical axis: share of polling stations with a particular digit in a second place in a turnout number. *Source*: Central Election Commission of the Russian Federation.

Using BL for election forensics has been criticized in other literature. In some contexts, tests based on BL have been shown to "detect electoral manipulation where it most likely did not happen and miss electoral manipulation where it most likely did happen.[18] We take these concerns seriously: we computed eight types of electoral fraud estimates based on BL and compute the first principal component of all mea-

[18]For example, Deckert, Myagkov and Ordeshook (2011) document departures from BL distribution in the elections in developed democracies where no other evidence of electoral manipulation exists.

sures. In particular, we use four "Second Digit" and four "Last Digit" tests based on UR's count, UR's share, turnout count, and turnout share.[19]

Extreme Turnout

Extreme turnout is plausibly the simplest and most intuitive proxy for electoral manipulations. Many observers of Russia's elections agree that the precincts where more than 90% of voting population showed up to vote are likely to be manipulated (Shen, 2012). We construct a variable that represents the share of polling stations where turnout was over 90% of the total registered voters.[20]

Comparison of Electoral Fraud Measures

All measures described above are efficient in detecting electoral manipulations. Moreover, spikes and mixture estimator measures are currently considered the state-of-the-art ways of measuring electoral fraud (Hicken and Mebane, 2015). Nevertheless, each measure can be criticized for its assumptions.

As Rozenas (2017) points out, spikes can be vulnerable to a confounding "feedback loop"; if the regime learns of this method fraud of detection, it can direct polling-stations field agents not to create round numbers for the UR's turnout or vote count.

The mixture estimator does not work if the regime's goal is not to make one candidate win but to increase turnout by adding votes to all candidates. Alternatively, the mixture estimator will fail if assumptions of the model do not hold. For example, if a country's voting behavior is bimodal, as among anglophone vs. francophone parts of Canada (Klimek et al., 2012). However, in our case, we use regional measures of electoral manipulations, and the regional population is likely to be relatively homogeneous in their political preferences even within the ethnic republics.

As we noted above, BL test is not free from Type I and Type II errors. At the same

[19] We use the simplest possible measure: sum of absolute deviations of observed digit frequencies from the frequencies implied by the Benford distribution. Medzihorsky (2015) offers a different approach which is based on latent class framework.

[20] All results hold if we construct this measure as the share of polling stations where UR won over 90% of the votes.

time, extreme turnout is a crude measure of electoral manipulation in that it does not detect relatively small manipulations.

Thought all these measures can be criticized for some drawbacks, they do complement each other. In Table 1, we demonstrate that all of them exhibit very strong correlation, suggesting that if all of them yield consistent results in our empirical specification, the result is not likely caused by a statistical artifact in the data. We also construct a first principal component of the four measures (that draws equally from all four variables) and use it as our baseline estimate for electoral fraud.

	Spikes	Mixture Est.	Digit Est.	Extr. Turnout	PCA
Spikes	1				
Mixture Est.	0.71	1			
Digit Est.	0.41	0.49	1		
Extr. Turnout	0.66	0.87	0.61	1	
PCA	0.82	0.92	0.71	0.94	1

Table 1: Correlations of the Measures of Electoral Manipulations

4 Empirical Specifications and Results

In this section, we offer two tests of the Influence Theory. First, we regress our region-level estimates of electoral manipulation on the survey-based estimates protest potential (we later confirm the results with the actual pre-election protests data). Second, we regress post-election instances of protest on the officially announced vote shares of the main pro-regime party, UR, controlling for the popularity of the regime and the estimates of electoral manipulation.

4.1 *Voter Fraud and Protest Potential*

In this section, we build a set of statistical linear models that control for a set of potential confounders: variables that might influence electoral manipulation as well as regional propensity to protest. Here, we still try to keep our parsimonious, controlling only for the most relevant covariates.[21]

We estimate the following specification:

$$Manip_i = \alpha + \beta ProtestP_i + \mathbb{X}_i'\Gamma + \epsilon_i, \tag{1}$$

where $Manip_i$ is a measure of electoral fraud in region i. To make sure that our results are not driven by a specific choice of measure, we use all four measures mentioned previously: Kalinin and Mebane's mixture model estimates, Rozenas's spikes, proportion of precincts with extreme turnout, and an index based on digit tests. Because these measures produce results on different scales, we demean them and divide by the standard deviation.

The main explanatory variable $ProtestP_i$ is a measure of protest potential of region i: the share of the Georating's respondents who say that protest inclinations are increasing.[22] As we discussed, if electoral fraud is used to deter protests and prevent opposition mobilization, then it should be more prevalent in the regions where such mobilization is ex-ante most likely. Thus, the Influence Theory would imply a positive effect of protest propensity on electoral fraud. Alternatively, negative β implies that our results support the Information Theory.

The vector $\mathbb{X}_i$ represents a series of region-level control variables described below. First, we control for the level of gross regional product (GRP) per capita — the most basic way to capture the level of economic development. Scholars have shown that the level of economic development is a powerful determinant of many social, economic, and political characteristics of a polity.

Second, we control for characteristics that might facilitate collective action and information dissemination: level of education, access to the Internet, and population density. Previous studies have demonstrated these variables can impact both the level

[21] We use only cross-sectional data in our analysis. While polling-level data also exist for the 2003 and 2007 parliamentary elections, reliable survey-based data on the regional variation of protest sentiment for the majority of Russian regions are available only for 2011.

[22] In Section F.1 we confirm that the results remain the same if we use the instances of actual pre-electoral protests as a measure of protest potential.

of electoral fraud and the level of protest potential (Enikolopov, Makarin and Petrova, 2016; Enikolopov et al., 2017; Skovoroda and Lankina, 2017).[23] Third, we control for distance from Moscow to capture parsimoniously the geographical heterogeneity of Russia. (We consider other ways to capture this heterogeneity in Section 5.)

Finally, to capture some of the political and geographical heterogeneity among the regions, we include an indicator variable for the existence of a "subnational autonomy" treaty between the central government and the region. Such treaties were signed in the 1990s, when Russia's first president, Boris Yeltsin, tried to win the acquiescence of regional power brokers. The first treaty was signed in 1994 by Boris Yeltsin and Mentimer Shaimiev, Tatarstan's leader. Soon this example was followed by treaties with Bashkorstostan, Buryatia, some of other "ethnic republics," and regions with strong subnational patron-client networks. As a result, those regions have been able to enjoy some autonomy for many years and build strong subnational authoritarian regimes.

Those are the controls that we include in the main specification. However, some other variables might also be relevant: e.g., characteristics of the economy, poverty, social spending, and reliance on resource extraction. We consider an extended set of controls and other robustness checks in Section F.4.

Table 2 presents the regression results. Each column corresponds to a different measure of electoral manipulation. We use Rozenas's spikes as the dependent variable in column 1, Kalinin and Mebane's mixture model estimates in column 2, digit-test index in column 3, and the proportion of precincts with extreme turnout in column 4. We see that the effect of protest potential is statistically significant and substantively large for all measures of electoral fraud.[24]

The magnitude differs across specifications. We see the largest magnitude for the

[23]Ideally, we would include the polling station treatment indicators from Enikolopov et al.'s 2013 Moscow 2011 field experiment. However, we can't do it as our electoral fraud data is measured on the regional level.

[24]Our results also hold for the specification without any covariates: we present scatter plots in Figure A.2. Table A11 presents the results for dependent variables where the measure has substantive interpretation in terms of the shares of fraudulent polling stations (spikes, mixture models, and extreme turnout) without studentizing the dependent variable. Also, Table A13 presents all the results for the digit tests separately.

	Dependent variable: Electoral fraud				
	Spikes	Mixture Est.	Digit Est.	Extr. Turnout	PCA
	(1)	(2)	(3)	(4)	(5)
Protest Potential	-2.748^{**}	-5.173^{***}	-2.747^{**}	-4.837^{***}	-4.651^{***}
	(1.238)	(1.531)	(1.349)	(1.508)	(1.387)
GRP	-0.340^{**}	-0.097	-0.141	-0.021	-0.168
	(0.150)	(0.186)	(0.164)	(0.183)	(0.168)
Education	0.051^{**}	0.039	0.054^{**}	0.033	0.051^{**}
	(0.021)	(0.026)	(0.023)	(0.026)	(0.024)
Internet	0.003	1.961	-2.342	2.295	0.783
	(1.617)	(1.999)	(1.761)	(1.970)	(1.811)
Pop. Density	-0.119	-0.143	-0.140	-0.132	-0.156
	(0.092)	(0.114)	(0.101)	(0.113)	(0.104)
Distance to Moscow, km	-0.052	-0.187	0.164	-0.001	-0.034
	(0.093)	(0.115)	(0.101)	(0.113)	(0.104)
Treaty	0.129	0.062	-0.238	0.091	0.027
	(0.152)	(0.188)	(0.166)	(0.186)	(0.171)
Constant	-0.972	-0.803	1.083	-0.908	-0.555
	(1.411)	(1.744)	(1.537)	(1.718)	(1.580)
Observations	74	74	74	74	74
R^2	0.281	0.376	0.256	0.352	0.358

Note: (*a*) We don't use weights; however, our results hold if we use population weights. The results are available on request. (*b*) The following variables are used as controls: log of GRP, education, Internet penetration, population density, distance to Moscow (km), an indicator variable for the autonomy treaty, and a constant. (*c*) Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 2: Measures of Electoral Manipulation and Protest Potential

Kalinin and Mebane's mixture model estimates (column 2), and the smallest magnitude for Rozenas's spikes estimates (column 1). Even the smallest estimates are quantitatively large: a 10 percentage points increase in protest potential is associated with a 0.27 standard deviation of spikes.[25] Coefficients for the protest variable in columns 1

[25]The difference between two regions, one on 25th and one on 75th percentile, of protest sentiment is 0.095. For simplicity, hereafter we will use 10 percent as the interquartile range.

and 3 are not statistically different from each other. The same is true for coefficients in columns 2 and 4.

Because protest potential varies from around 20 percent to around 60 percent, our model implies that the largest possible in-sample change in protest potential reduces electoral fraud by a magnitude from 1.2 standard deviation (for Rozenas's spikes and digit-test estimates) to 2.8 standard deviations (for Kalinin and Mebane's mixture model estimates and proportion of precincts with extreme turnout).

In column 5, we use the first principal component of the four measures of electoral fraud as a dependent variable. Similarly to previous columns, the results are significant: a 10 percentage point increase in protest potential is associated with a 0.46 standard deviation lower instance of electoral fraud.

We see that, across specifications, GRP per capita is negatively associated with the observable fingerprints of electoral fraud (though the estimate is statistically significant only for spikes). Somewhat surprisingly, in three of the specifications, the level of education (share of people with college degrees among the employed) is positively correlated with the measures of fraud.[26] Other control variables appear to be insignificant.

Figure 3 presents a set of the added-variable plots with the linear fit for all four fraud measures. The plots demonstrate that the results in Table 2 are likely to be driven by broad patterns in the data, not by the set of specific distinct observations.

Overall, we have demonstrated that there is a negative correlation between the level of electoral manipulation and the protest potential of a region. The correlation remains negative and substantively nontrivial when we adjust for a set of potential confounders. This set of results is arguably inconsistent with the Influence Theory, since the electoral manipulations were seemingly distributed away from the regions with high protest potential. In the next section, we consider another prediction of the Influence Theory: that high voting margins deter potential protests.

[26]The goal of these specifications is to control for potential confounders of the relationship between protest potential and electoral manipulation, not the variables that confound a relationship between protest potential and education. Thus, this particular estimate must not be interpreted causally.

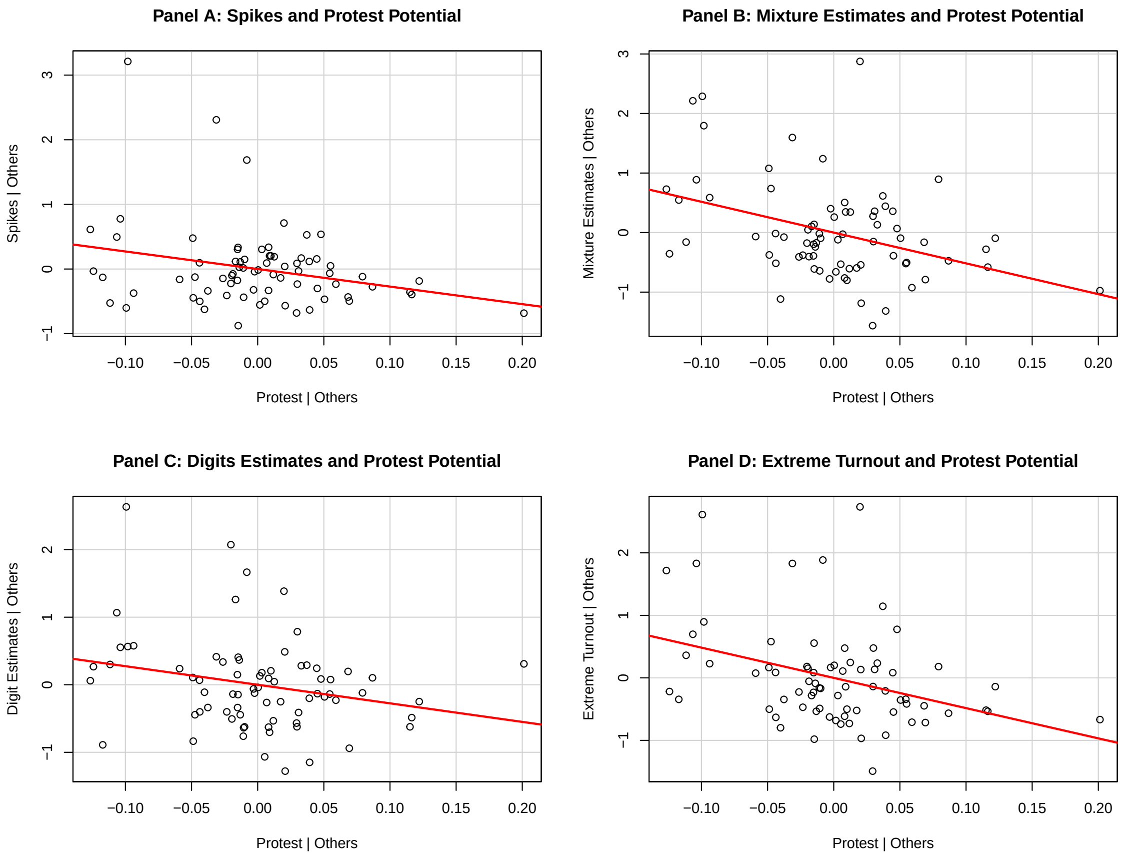


Figure 3: Electoral Fraud and Protest Potential: Added Variable Plots

Note: (*a*) Panels A through D above correspond to columns (1) through (4) of Table 2. (*b*) The plots were created using *AvPlot* command from *car* package in R.

4.2 *Ruling Party Results and Subsequent Protests*

One of the key ideas of the Influence Theory is that the potential dissidents, once they observe the results of the elections, feel deterred if the ruling party wins. In this section, we test if this mechanism is consistent with the observed data. We use the data from the post-election protest in Russia on December 10th, 2011, right after the Parliamentary Elections. The largest protest happened in Moscow, where between 25,000 and 60,000 people showed up on Bolotnaya Square (with some activists claiming that attendance was as high as 100,000) (Sobolev, 2019). We use the data from Sobolev (2019), collected from Russian media sources, on instances and sizes of protests in Russian regions.

The main advantage of these data is that, for every region, it has the number of protesters reported by the law enforcement authorities, and the number reported by the activist organizers of the protests. We use all these numbers as outcomes, and the official share of the votes for UR, the main pro-regime party, as an independent variable. Our specification is the following:

$$PROTEST_i = \alpha + \beta_1 UR_i + \beta_2 Manip_i + \beta_3 PutinApproval_i + \mathbb{X}_i'\Gamma + \epsilon_i. \qquad (2)$$

Here $PROTEST_i$ is a measure of protests on December 10, 2011 in region i. We use two measures of protests (extensive and intensive margin). The first is a dummy equal to one if region i had a protest and zero otherwise. Second is a log number of protests in regions where protest had happened. If the Influence Theory is correct we would expect UR_i — a reported share of votes received by United Russia, the main pro-regime party — to be negatively correlated with the post-election protests. We control for the most important variables that can correlate with both, post-election protests and UR vote share. First, we control for the PCA estimates of fraud (since the alleged fraud was the main rallying cry for the protesters and could also influence the official numbers). We also add a proxy for pre-treatment UR vote share — $PutinApproval_i$ — a survey-based popularity of the regime before the election (region-level approval of Vladimir Putin). Finally, X_i contains a vector of controls from the previous specification 1.

Table 3 presents the results. Column 1 shows the results if the dependent variable is binary: an incidence of protest. Column 2 presents the results with log number of protesters (in the regions where protests happened) estimated by the organizers. Column 3 presents the results of the estimation with log number of protesters reported by the law enforcement. Neither pre-election popularity of Putin, nor electoral manipulations are significant across any specification.[27]

The share of UR is not significant predictor in any of the specifications. It seems to be negatively correlated with protest incidence, but positively correlated with protest

[27] We use simple OLS specifications here since those are the most interpretable. However, we have also estimated other over-dispersed and hurdle models with the same data. We also have estimated the regressions without log transformations and without removing observations without protests. In none of those models, UR share emerged as an important predictor of the protest incidence/size.

	Dependent variable:		
	1(Protest)	Log Org. Est.	Log Authority Est.
	(1)	(2)	(3)
UR vote share	−0.704	0.132	0.002
	(0.661)	(2.068)	(1.917)
El. manipulation	−0.081	0.270	0.306
	(0.118)	(0.423)	(0.389)
Putin's Approval	0.194	−0.106	0.485
	(0.671)	(1.904)	(1.850)
GRP	−0.056	0.171	−0.053
	(0.100)	(0.308)	(0.291)
Education	−0.024	0.017	0.034
	(0.015)	(0.043)	(0.040)
Internet	−0.180	1.957	2.261
	(0.945)	(2.225)	(2.089)
Pop. Density	0.086	0.330**	0.291**
	(0.063)	(0.143)	(0.131)
Distance to Moscow	0.039	−0.135	−0.074
	(0.058)	(0.136)	(0.132)
Treaty	−0.042	0.155	−0.265
	(0.100)	(0.244)	(0.230)
Constant	1.653*	5.403**	4.121*
	(0.912)	(2.205)	(2.144)
Observations	74	53	50
R^2	0.250	0.375	0.415

Note: (*a*) Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 3: Results of United Russia and Subsequent Protests

size (conditional on the incidence of protest) as reported by the activists, and seems to be very close to zero for the size of the protests reported by the authorities. The only significant predictor in our model is population density. In general, we fail to reject the hypothesis that incidence/size of the protest is unrelated to the reported result of the incumbent conditional on pre-electoral popularity of the incumbent. This conclusion is, again, inconsistent with the Influence Theory.

5 Alternative Explanations and Robustness

In the previous sections, we find evidence against the Influence Theory. We argue that the allocation of electoral manipulation is consistent with a different theory — the Information Theory. If the regime uses the election results to gather information, then the regions with higher ex-ante probability of protests should stay relatively clean.

Section B presents a simple simulation-based argument that quantifies this logic. The main assumption here is that the regime cannot perfectly dictate the amount of manipulated votes: there always be noise because of all kinds of agency costs (Rundlett and Svolik, 2016) or electoral monitoring (Enikolopov et al., 2013). Thus, the actual amount of manipulated votes could be either larger or smaller than desired by the regime. Because of that, when the regime conducts electoral manipulation in the high-protest areas, it adds noise to the information it needs for survival. So, in the Information Theory, the regime should allocate electoral manipulation into the areas where it is ex-ante popular.

Here, we rule out a set of alternative explanations that are unrelated to the information-gathering goals of the regime, but might also potentially explain the negative correlation of protest potential and electoral manipulation.

5.1 Alternative Explanation I: Election Monitoring

One of the specific mechanisms through which protest potential might be linked to electoral manipulation is election monitoring. In 2011, the opposition parties campaigned to recruit more activists to volunteer to monitor the elections. The campaign to "crowdsource" election monitoring had some success (Bader, 2013). E.g., Enikolopov et al. (2013) show that polling stations monitored by independent activists had fewer episodes of electoral vote manipulations.

We address concerns regarding electoral monitoring and social capital in Table A1. First, in column 1 we replicate the baseline specification from column 5 of Table 2. We add a control for political activism in column 2. The data come from the non-for-profit organization Voice ("*Golos*"), which created a system, SMS-TSIK, where observes could text the results of the elections in their polling stations. The variable that Voice measures is the share of polling stations in each region where observers were present during the March 2012 presidential election.[28] Though it was a different election, it took place only three months after the parliamentary elections of 2011, and the same networks of activists were used. Thus, we assume it is a reasonable proxy for political activism during the 2011 elections. The resulting coefficient of interest remained significant and even increased in magnitude. At the same time, Voice's estimate is negative and significant and is consistent with the predictions by Enikolopov et al. (2013), suggesting that the presence of observers decreases electoral manipulation.

In column 3, we use alternative measure of electoral monitoring from Buzin, Brondum and Robertson (2016). In particular, we use a dummy if the region had independent observers during the 2011 parliamentary elections. The results are similar to those in column 2: the proxy for observers is negative and significant (regions with observers had 0.55 standard deviation less fraud); point-estimate for the effect of protest becomes larger in magnitude.[29]

In columns 4–6, we test whether social capital is an important source of omitted variable bias. We use various measures such as the number of blood donors, trust, and the number of people who say in the survey that they would turn to their community in time of need. In column 4, we add a region-level control for the number of blood donors. The magnitude of the resulting coefficient becomes smaller but remains highly significant, thus supporting our main finding. Similarly, we add controls for level of trust and participation in community services in columns 5 and 6, respectively. The

[28]For more information about the construction of variables introduced in this section, see the Appendix D.

[29]The results also hold if we use share of polling stations that had observers.

estimate for protests remains significant and does not differ from the one in column 4.

5.2 *Alternative Explanation II: Past Electoral Fraud and Manipulation Skills of Field Agents*

Another important possible alternative explanation concerns the possibility that electoral manipulation in the past influences the protest potential today.[30]

Thus if field agents that conducted more electoral fraud in previous Parliamentary elections of 2007 became more skillful and can make more (or costs of making fraud are lower) electoral manipulations in 2011. At the same time protests may correlate with the electoral fraud in 2007, thus biasing our estimate of interest.

However, the literature suggests that electoral fraud has a strong positive effect on protests, as people become unsatisfied with electoral manipulations (Tucker, 2007; Way, 2008; Beissinger, 2011; Wellman, Hyde and Hall, 2017). However, in this case the bias will be against us finding negative effect of protest on electoral fraud. And as our coefficient is negative and significant, without bias it should be even larger in magnitude and even strengthening our results.

5.3 *Alternative Explanation III: Strategic Complementarities among Field Agents*

In a recent article, Rundlett and Svolik (2016) presented a model based on a global games framework, where they demonstrate that if agents expect to be rewarded if the incumbent wins, and they know that other field agents have the same expectation, then they will be more likely to collectively overshoot the targeted level of manipulation. Thus, in areas where the regime is more popular, we expect to see more manipulation.

We address this concern in Table A2. The first column contains the baseline regression for the comparison. In column 2, we first control for the regime's popularity

[30]Electoral manipulation in 2011 should not affect protest potential in 2011, as the election took place *after* the survey.

measured as the share of respondents supporting Putin. Putin's support is positive and significant: a 10 percentage point increase in the regime's popularity increases electoral fraud by 0.26 of its standard deviation. This result is consistent with the argument made by Rundlett and Svolik (2016). The point estimates for protests decrease in magnitude (from 4.7 to 3.7) while remaining significant and nontrivial in size.

We also include as controls alternative measures of regime popularity. In column 3, we use Dmitry Medvedev's support instead. The results remain significant. We also use approval for UR and for a regional governor in columns 4 and 5 respectively. While the coefficient for UR's approval remains significant, the one for the governor does not. Nevertheless, the estimate for protests remains stably negative and significant.

5.4 *Alternative Explanation IV: Unreliable Field Agents*

In Russia, field agents implementing electoral fraud do not come from the elite; they come from the masses. So, if the masses are disgruntled and want to protest, then the field agents might share the same sentiment and be reluctant to manipulate. Thus, if protests are positively correlated with dissatisfaction of the field agents, our estimates would be biased. To deal with this source of omitted-variable bias, we add controls for average wage of school teachers in that region. As most of the polling stations in Russia are located in schools, teachers are allegedly the main source of electoral manipulation. By coincidence, school teachers have dismally low salaries even compared to public-sector employees. Thus, controlling their salary we gauge their dissatisfaction and effort of committing electoral fraud.

The results are presented in Table A3. Similarly, the first column contains the baseline regression for the comparison. We add controls for price levels and average monthly wages in the region. These variables may be confounding and correlate with electoral fraud and protest level. To address the threat of unreliable field agents, we add a control for wages of public employees (working in regional administration) in column 2. They are the primary field agents, so their low wages may positively correlate with protest level, and negatively correlate with electoral fraud, thus confounding the results. The point-estimate for protests remains negative and significant, while decreasing slightly in magnitude. In column 3, we use expenditures for public goods provision as a control; however, the results hold. Following Forrat (2017) and Forrat (2018), we control for expenditures directly related to school teachers — the agents responsible for supervising polling stations. We add share of regional expenditures on education in column 4, and wages of school teachers in column 5. Wages of school teachers are positively correlated with electoral fraud, supporting the findings of Forrat (2017). In column 5, we also add control for the size of public sector; however, it does not affect our results. Nevertheless, while unreliable field agents indeed may affect efficiency of electoral manipulation, this factor does not contradict our main findings.

5.5 *Alternative Explanation V: Institutional Explanations*

In this section we address additional institutional concerns regarding institutional factors that may distort our results. Results of this section are presented in Table A4 where the first column contains the baseline results.

Bader and van Ham (2015) and Reisinger and Moraski (2017) argue that electoral manipulation is more likely to happen in regions that have both a larger non-Russian population and also some autonomy from so-called "ethnic republics."[31] To address possible bias caused by ethnic republics with traditionally low levels of protests and high levels of electoral fraud, we add an indicator variable for ethnic republics in the baseline specification in column 2. This anomaly is consistent with our measure of electoral manipulation: deviations from the baseline measure of electoral fraud are 107% of standard deviation larger in the ethnic republics. The coefficient for protests remains significant, though its magnitudes decreases by 39%.

In case protest potential and electoral fraud are correlated with political culture (e.g., Hale, 2007) in column 3, we introduce control for "political competition." This variable is measure in an expert survey by the Carnegie Center (Petrov and Titkov,

[31] Table A12 shows that national republics are much more likely to have polling stations with near 100% turnout.

2013) and is, probably, the best available proxy for the political culture. It is negatively (but insignificant) correlated with electoral fraud suggesting, that regions with higher political competition may indeed experience less manipulations; however, the coefficient of interest does not change. In case Carnegie Center's measure do not fully grasps regional democratic proclivities we control for the urbanization in column 4. The coefficient for urbanization is negative and significant; however, our results hold.

In column 5, we employ these three institutional controls together. The coefficient for protests remains significant, while decreasing slightly in magnitude: a 10 percentage point increase in protest sentiments decreases electoral manipulations by 0.26 of its standard deviation.

Another potential explanation would be that regime cares only about overall federal results and does not care about the regional results. Several observations are not consistent with this. First, we know from a major business daily *Vedomosti* reporting that Presidential Administration gives different goals to different regions in terms of electoral manipulation.[32] Second, if we assume that by pushing the regional governors towards electoral manipulation, the regime maximizes total aggregate results for the pro-regime party, then we might expect more manipulation in more populous regions (where maximizing the share of fraudulent polling station would deliver the highest amount of additional votes). Table A14 shows that this is not the case: the association between population and electoral fraud estimate is negative, and the effect of protest potential remains the same if we control for the population.

To conclude, in this Section we addressed main alternative explanations. In Appendix F.1, we show that our results are robust to usage of alternative measure of protest potential. In Appendix F.2 we address the possibility of the pre-election day fraud. In case the government is afraid of the protests that can be caused by the electoral manipulations during the election day, they may substitute it with pre-election day manipulations. We find to correlation between protest potential and pre-election fraud, and demonstrate that its inclusion as a control variable does not affect our re-

[32] www.vedomosti.ru/politics/articles/2011/10/13/skolko_nuzhno_edinoj_rossii

sults. In Appendix F.4, we also address some additional concerns regarding possible omitted-variable bias. Table A8 shows that our results are robust to inclusion of controls on geographical coordinates, number of regional newspapers, share of oil and gas sector of regional economies, and share of unemployment. In Appendix F.5, following Oster (2017), we also explore the sensitivity of our results to the potential omitted variables and show that the effect of unobservables should be very large to nullify our findings. Finally, Appendix F.6 shows that our results are robust to outliers.

6 Discussion of External Validity and Conclusion

Questions about the role of institutions in non democracies are important for understanding politics around the world. In this paper, we offer an empirical evidence to probe one of the major theories of authoritarian institutions: the Influence Theory.

The Influence Theory implies that the government uses elections to project strength and deter potential opposition. It implies that electoral manipulation is used in places where the regime is less popular, as a way to deter potential opposition. At the same time the Information Theory implies that government uses elections to identify the true level of support for the regime. It implies that electoral manipulation will be used in places where protest potential is low, so this activity does not interfere much with the goal of getting accurate information. Therefore, a negative association between electoral manipulation and protest sentiment is consistent with the Information Theory and not consistent with the Influence Theory.

We tested the association between regime popularity and protest potential using data from the 2011 parliamentary elections in Russia and a regionally representative public-opinion poll. We found that the association between the digital fingerprints of electoral fraud and region-level protest sentiment is negative and substantial, thus corroborating the Information Theory. We also did not find that incidence and size of actual protests is unrelated to the reported results of the incumbent, that is, again, inconsistent with the Influence Theory.

To reiterate an earlier point, this empirical exercise does not suggest that these two theories exhaust the list of possible roles for authoritarian institutions. We focus on these theories because they produce different empirical predictions about the spatial distribution of electoral manipulation. Other theories, while being plausible, might not have empirical predictions related to electoral manipulation. We leave differentiating the effects suggested by those theories for further research.

Our results hold for a political regime with strong surveillance capacities (Soldatov and Borogan, 2015). Even though the current Russian regime does rely on pollsters and security agencies to deliver information about potential protest activity, it also seems to rely on electoral results to improve its understanding of public preferences.

There are many different political regimes whose institutions vary in the degrees of repressiveness. Our findings may not fit every political regime. However, a set of regimes exists, defined by Levitsky and Way (2002), as competitive autocracies e.g., Iran, Egypt (under Mubarak), Mexico (under PRI), Russia, Turkey, Ukraine (under Yanukovich). In such regimes, an incumbent has an unfair advantage over the opposition in elections. But the opposition exists, and often it can participate in the elections in some form and run campaigns. It is reasonable to expect that our results will hold in such political regimes, but further research is needed to make predictions regarding other authoritarian regimes.

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Online Appendix

to

"Do Dictators Signal Strength with Elections?"

A Tables

	Dependent variable: Electoral fraud (PCA)					
	Baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Protest	-4.65^{***}	-4.82^{***}	-5.03^{***}	-3.21^{***}	-3.29^{***}	-3.28^{***}
	(1.39)	(1.37)	(1.32)	(0.94)	(0.95)	(0.95)
Voice		-7.43^{*}				
		(4.35)				
Observers			-0.55^{***}			
			(0.19)			
Donors				0.03^{**}		
				(0.01)		
Trust					-0.78	
					(1.11)	
Community						-2.95
						(6.49)
Controls	✓	✓	✓	✓	✓	✓
Observations	74	74	74	66	68	68
R^2	0.358	0.386	0.435	0.350	0.285	0.281

Note: (*a*) In all columns, we take specification from the baseline results, i.e., Table 2, and extend it by adding further controls. (*b*) The main dependent variable is a first principal component of the four measures of electoral fraud: spikes, mixture estimator, BL, and extreme turnout. (*c*) Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A1: Alternative Explanation I: Observers and Social Capital

	Dependent variable: Electoral fraud (PCA)				
	Baseline	Putin	Medvedev	UR	Governor
	(1)	(2)	(3)	(4)	(5)
Protest	−4.651***	−3.725***	−3.991***	−3.859***	−4.403***
	(1.387)	(1.387)	(1.407)	(1.393)	(1.415)
Approval of Putin		2.611**			
		(1.052)			
Approval of Medvedev			2.163*		
			(1.160)		
Approval of UR				2.813**	
				(1.263)	
Approval of Governor					0.706
					(0.773)
Controls	✓	✓	✓	✓	✓
Observations	74	74	74	74	74
R^2	0.358	0.414	0.391	0.404	0.366

Note: (*a*) In all columns, we take specification from the baseline results, i.e., Table 2, and extend it by adding further controls. (*b*) The main dependent variable is a first principal component of the four measures of electoral fraud: spikes, mixture estimator, BL, and extreme turnout. (*c*) Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A2: Alternative Explanation III: Strategic Complemetarities among Field Agents

	Dependent variable: Electoral fraud (PCA)					
	Baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Protest	-4.651^{***}	-3.510^{**}	-3.920^{**}	-4.213^{***}	-4.594^{***}	-4.295^{***}
	(1.387)	(1.323)	(1.541)	(1.442)	(1.401)	(1.350)
Prices		-0.034	-0.013	-0.059	-0.088	-0.089
		(0.092)	(0.108)	(0.102)	(0.100)	(0.926)
Avg. Wages		-0.175^{***}	-0.008	0.009	-0.175^{*}	0.001
		(0.059)	(0.048)	(0.034)	(0.101)	(0.030)
Admin. Wages		0.153^{***}				
		(0.041)				
Expenditure			0.091			
			(0.233)			
Educ. GRP				0.156		
				(0.163)		
Educ. Wages					0.153^{**}	
					(0.075)	
Share Pub. Sect.						1.476
						(1.550)
Controls	✓	✓	✓	✓	✓	✓
Observations	74	74	72	74	74	74
R^2	0.358	0.483	0.357	0.376	0.406	0.375

Note: (*a*) In all columns, we take specification from the baseline results, i.e., Table 2, and extend it by adding further controls. (*b*) The main dependent variable is a first principal component of the four measures of electoral fraud: spikes, mixture estimator, BL, and extreme turnout. (*c*) Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A3: Alternative Explanation IV: Unreliable Field Agents

	Dependent variable: Electoral fraud (PCA)				
	(1)	(2)	(3)	(4)	(5)
Protest	-4.651***	-2.836**	-4.403***	-3.873***	-2.559**
	(1.311)	(1.105)	(1.259)	(1.287)	(1.087)
Ethnic Republic		1.069***			0.949***
		(0.287)			(0.265)
Political Competition			-0.209		-0.115
			(0.143)		(0.124)
Urbanization				-0.0281**	-0.0125
				(0.0118)	(0.0100)
Controls	✓	✓	✓	✓	✓
Observations	74	74	74	74	74
R^2	0.358	0.555	0.388	0.428	0.580

Note: (*a*) In all columns, we take specification from the baseline results, i.e., Table 2, and extend it by adding further controls. (*b*) The main dependent variable is a first principal component of the four measures of electoral fraud: spikes, mixture estimator, BL, and extreme turnout. (*c*) Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A4: Alternative Explanation V: Additional Institutional Explanations

B Theoretical Expectations for Influence Theory and Information Theory

This section derives the predictions about the amount of electoral manipulation under different theories of authoritarian elections. We argue that under the Influence Theory, a regime's ex-ante expectations of protest potential are positively related to the probability of electoral manipulation. Under the Information Theory, the opposite is true: a regime's ex-ante expectations of protest potential are inversely related to the probability of electoral manipulation.

The intuition behind these predictions is straightforward: if the Influence Theory is accurate and the regime tries to deter potential opposition candidates from organizing a successful protest, electoral manipulation is more meaningful when public support for the regime is low, and the probability of a rebellion is high.[33] If the Information Theory is accurate, it is critical that the regime learns where its support is low. In this case, a regime's manipulation of elections (which adds more noise to the electoral results, since it is impossible to control the exact number of manufactured votes) in areas where the regime suspects it has little support might contaminate the much-needed signal about the regime's true level of support.[34]

One might wonder what the point of election fraud is in Information Theory, given both that the regime's goal is to gather information and that electoral fraud just adds noise to the signal. As we noted previously, first and foremost, the ruling elite (a party or an individual leader) needs to win an election to remain in power.[35] This goal is the same in both theories, and electoral fraud is one of the tools a regime may use to achieve this goal.[36]

Table A5 summarizes the expectations under both theories. Influence Theory posits

[33]Our argument is related to the predictions from several formal models of electoral autocracies. Gehlbach and Simpser (2015) argue that the relationship between the manipulation and the ruler's popularity is positive if the goal of the ruler is to induce bureaucratic effort and the ruler can choose the effectiveness of manipulation. The key difference with our setup and the setup of Gehlbach and Simpser (2015) is that the manipulation is observable by the bureaucrats in Gehlbach and Simpser (2015). In our computational setup, we assume that the audience understand the capacities of the regime and the incentives of the regime, but the number of manipulated votes in unobserved. Another model related to ours is Egorov and Sonin (2014) that shows that the relationship between manipulation and the popularity of the regime is non-monotonic if the act of holding elections itself is endogenous. In our setup, the ruler is not given an option to abolish the elections at will but is allowed to implement manipulations, which is consistent with the stylized facts about competitive autocracies. Another important argument that derives a non-monotonic relationship between the regime's popularity and election rigging is Rozenas (2012). Our difference from Rozenas's setup is that we assume that the rigging influences post-election stability through calculation of the dissidents (in the Influence theory) or through the regime's information accumulation (in the Information theory).

[34]Alternative argument would be that clean elections help the regime to acquire information not about the preference of the underlying population but capacity of local power-brokers to control their population. However, model implications would be similar.

[35]It is also impossible to get rid of the electoral fraud even if the regime wishes so (Rundlett and Svolik, 2016). The central government also uses the percentage for the ruling party as a tool to evaluate sub-national power-brokers (Zhuravskaya, 2010). This creates additional incentives to conduct electoral manipulations.

[36]Scholars of authoritarian regimes list some other instruments ruling parties use for winning the authoritarian elections: unfair access to media, police intimidation of the opposition, and use of the state budget to finance an electoral campaign of an incumbent. See, for example, Levitsky and Way (2002).

Theory	Danger for the Regime	Goal of the Regime
Information	Regime decides that protest potential is low, but it is high	Minimize false positives
Influence	Dissidents decide that protest potential is high and they are right	Minimize true negatives

Note: Comparison of the theories and their predictions. We call *positive* a situation when the protest potential is low (it is a positive piece of news for the regime). *False positive* happens when the region is classified (by the regime) as having a low protest potential (classified as *positive*) after observing all signals, but, in fact, has high protest potential. Analogously, we call *negative* a situation when the protest potential is high (it is a negative piece of news for the regime). *True negative* happens when a region is classified (by the dissidents) as having high protest potential (classified as *negative*), and this classification is correct.

Online Appendix Table A5: Comparison of Theories

that the goal of the regime is to deter the dissidents from staging a protest. Because protests are ex-ante more likely to happen when the prior knowledge is that the protest potential is high, then the most effective spatial allocation of the electoral manipulation is to the places with high ex-ante protest potential. If the election correctly reveals that the regime is not popular, and the dissidents decide to revolt, it is the worst outcome for the regime. We call this outcome *true negative*: dissidents decide that the regime is not popular, and they are correct. So, under the Influence Theory, the goal of the regime would be to minimize true negatives.[37]

Information Theory posits that the goal of the region is to learn where the protest potential is high and to dispense patronage or repression in those areas. Because we assume that the uncertainty about the protest is the highest where ex-ante protest potential is high, the improvement of the precision of the regime's knowledge would be achieved when those areas stay relatively clean of manipulation. The worst outcome of the regime is that the protest potential is high, but the regime decides that the protest potential is low and thus does not perform any policies (patronage or repression) that would insulate him from the potential revolt. We call this outcome *false positive*. Under the Information Theory, the goal of the regime is to minimize false positives.[38] It is important to note that the agents are "rational" in both theories: they correctly infer the bias introduced by electoral fraud, but because the electoral fraud introduces noise, it influences the variance of the subjective estimates.

We offer a simple Monte Carlo simulation to help illustrate the expectations that

[37]Another way to think about the Influence Theory is that government only need to win, and show high support of the regime overall. However we assume that dissidents can see the local support for Putin, and the government doesn't want them to know it. It is reasonable to assume this as most of protests and protest movements in Russia (and other countries) are grounded on the local agenda (e.g., Saint Isaac's Cathedral in Saint Petersburg, dump in Volokolamsk, or fire in the mall in Kemerovo. See more in Greene (2014).

[38]We also assume that if protest potential is low, there will be no protests. However, in the places where protest potential is high, protests will happen only if the capacity to organize collective action is high enough. Thus, automatically, the Information Theory suggests that information would be most useful where there is not only the highest protest potential but also the most uncertainty about discontent.

come from different theories, a stylized scenario of an authoritarian election with a possibility of fraud most relevant for our Russian case: the regime observes an initial signal about the distribution of preferences, then decides where to implement fraud, and then observes the results of the elections.

Here is a more detailed description:

- Step 0: Each of the N regions (i) has a true level of protest sentiment s_i. It is unobserved by either the regime of the local dissidents, and their prior is uninformative.

- Step 1: A noisy signal is received by the regime about the regime popularity in each region: $A_i^r \sim \mathcal{N}(s_i, \sigma_1^r)$. One can think of this signal as a regionally representative public opinion poll, of which σ_1^r is a total survey error. Dissidents in every region observe a potentially different signal from the same underlying distribution of preferences: $A_i^d \sim \mathcal{N}(s_i, \sigma_1^d)$.

- Step 2: As elections are coming, the regime decides how intensely it will manipulate the election in each region. Following the literature on formal models of autocracy (Gehlbach, Sonin and Svolik, 2016), we assume that the public understands the incentives of the regime and discounts manipulated results. But as field agents implement electoral fraud in a noisy way, it follows that the higher the level of fraud, the noisier the signal resulting from the elections — both for the public and for the regime.[39] In our simulation, we offer two scenarios: positive correlation between protest potential and fraud, and negative correlation.

- Step 3: The electoral results are observed. For computational convenience, we assume that the results are: $R_i \sim \mathcal{N}(s_i, \sigma_2^i)$. In other words, the election provides another signal of the underlying popularity of the regime, but the precision is different for every region and depends on the decisions the regime made in the previous step. The regime doesn't know the mean (the true level of protest potential which is unobserved), but it knows the variance, because it is an increasing or decreasing function of the signal the regime got on the previous step.

- Step 4: After observing the electoral results, the regime and the dissidents update their expectations about the popularity of the regime according to Bayes Rule. The regime combines A_i^r and R_i, while the dissidents combine A_i^d and R_i.

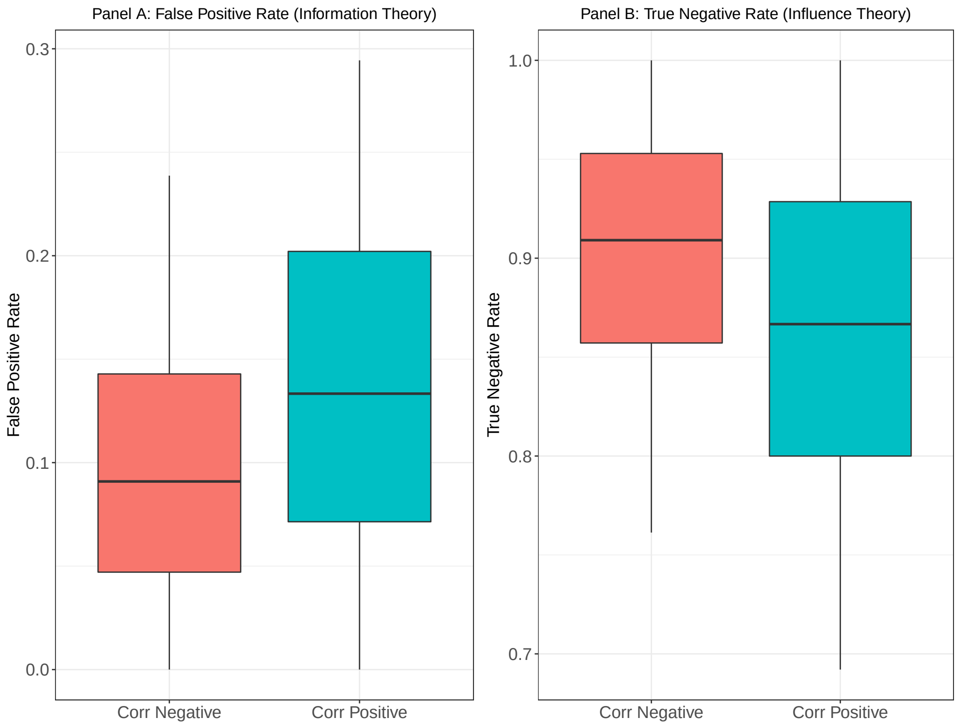
- Step 5: After the election, the Information Theory implies that the regime identifies the opposition stronghold and tries to either punish or pacify them. The Influence Theory implies that dissidents in every region solve the same problem: they rebel if they decide that they live in an opposition stronghold, and if they are right about it, their rebellion becomes problematic for the regime. In the simulations, we assume that a region i is an opposition stronghold if $s_i > 1$ (that is, if the level of true opposition sentiment is among approximately the top 15% of all the regions). All the regions are classified as either safe for the regime ("positives") if they are in the bottom 85% of the posterior expectation of protest potential (posterior estimate of $s_i < 1$) or unsafe for the regime ("negatives") if they are in the top 15% of the posterior expectation of protest potential (posterior estimate of $s_i > 1$).

[39]Informally, this mechanism is described in Magaloni (2006), while Egorov and Sonin (2014) offer a rigorous formal theory of how a rational public reacts to potentially fraudulent elections.

As a result of this simulation, we get conflicting predictions from the different theories. Under the Information Theory, the regime's goal is **to minimize the false positive rate** of the classification of the regions, because the worst that can happen (from the regime's point of view) is that a region it considers safe and thus overlooks when doling out punishment/patronage in reality turns out to be unsafe.

Under the Influence Theory, the regime's goal should be different: **to minimize the true negative rate.** If the goal is to dissuade dissidents from rebelling in a region where the regime is truly unpopular, then the worst that can happen (again, from the regime's point of view) is that the dissidents, after observing the election results, correctly identify unsafe regions and rebel there.

Figure A.1 shows the estimated false positive rates and true negative rates under different regimes of electoral fraud: when the correlation between the first signal of protest potential and fraud is positive and when the correlation is negative. By comparing the bars within the panels, we demonstrate that the two theories have mutually exclusive implications.



Online Appendix Figure A.1: Simulated Classifications of Regions

Note: Winsorized distributions of false positive and true negative rates under different regimes of electoral fraud: a negative correlation between the regime's ex-ante expectations about protest potential and electoral fraud (labeled *Corr Negative*) and a positive correlation between the regime's ex-ante expectations about protest potential and electoral fraud (labeled *Corr Negative*).

We see that if a correlation between the initial knowledge about protest potential and electoral fraud is negative, the false positive rate is lower (the red bar is lower than blue bar in Panel A) – this is what the regime wants under the Information Theory. But the true negative rate is higher (the red bar is higher than the blue bar in Panel B) — the opposite of what regime wants under the Influence Theory). If the correlation is positive, then the opposite is true: the false positive rate is higher (the blue bar is higher than the red bar in Panel A) — an undesirable outcome under Information

Theory — but the true negative rate is lower (blue bar is lower than red bar in Panel A) — a desirable outcome under Influence Theory. Thus, under this logic, by observing an empirical correlation between electoral manipulation and protest potential in a different regime, we might discern the goals of the regime: a negative correlation would be consistent with the Information Theory, while a positive correlation would be consistent with the Influence Theory.

C Background: Russian Parliament

The lower house of the Russian Parliament ("Russian State Duma," or "*Gosudarstvennaya Duma*") is the major legislative body in Russia. According to the Constitution, it is responsible for lawmaking, major foreign policy decisions, no-confidence votes, and impeaching the president.

During the period that we focus on, the Duma was elected every four years through a closed-list proportional representation system. Every ballot had a list of parties, and a voter was allowed to vote for any one party. The 450 seats in the Duma are distributed among the parties that pass the 7% threshold proportional to their election results. Parties that win less than 7% of the votes receive no seats. Those seats that they could have received are redistributed among the winning parties thus increasing their presence in the Duma, in proportion to the votes they received.

Here we offer a brief description of the major parties in Russia. The biggest party in terms of parliamentary representation is United Russia ("*Edinaya Rossiya*"). It won 49% in 2011 and is closely aligned with Vladimir Putin.[40] UR is expected to be a major beneficiary of electoral manipulation (see Reuter (2017) on the origins of UR as a dominant party). Next, with 19% of the 2011 vote, is the CPRF ("Communist Party of the Russian Federation"). The main legal opposition party, CPRF considers itself the successor of the Communist Party of the Soviet Union. Two other parties passed the threshold in 2011: the nationalist Liberal Democratic Party of Russia (LDPR), 11.6%, and a socialist party, Just Russia (JR), 13.2%.

D Data Appendix

In this section, we discuss sources and data construction for the control variables used in baseline regressions and robustness checks. Most of the data come from two sources: the International Center for the Study of Institutions and Development (ICSID) databases collected by the National Research University Higher School of Economics; "georating" survey by FOM ("The Public Opinion Foundation"). All variables are from the 2011 calendar year, unless stated otherwise.

- GRP: Gross regional product (a subnational equivalent of GDP), log of millions of rubles, basic prices.[41] Source: ICSID.

[40] He was number one on the party list in 2007, and his hand-picked successor, Dmitry Medvedev, led the party into the 2011 elections.

[41] In Russia, GRP is measured in basic prices, i.e., net of taxes, including subsidies on products. GRP is determined by using the production approach, i.e., as the difference between the region's gross output and intermediate consumption, or as the sum total of all the values added by all the economic activities in the region.

- Education: Share of people with higher education: BA/BS or above, (*"vysshee obrazovanie"*). Source: ICSID.

- Internet: Internet penetration. Source: ICSID.

- Pop. Density: population density. Source: ICSID.

- Distance to Moscow: Distance from a regional capital to Moscow, in kilometers. Source: ICSID.

- Treaty: Indicator variable for the existence of a treaty between the central government and the region. Source: `www.politika.su/reg/dogovory.html`.

- Ethnic Republic: Indicator variable for the region to be an ethnic republic.

- Educ. Wage: Average monthly wage of a school teacher in a province in 2013, in rubles. Source: Rosstat — Central Statistical Database, Incomes and Standard of Living.

- Educ. GRP: Educational expenditures as a share of GRP. Source: ICSID.

- Expenditure: Indicator of efficiency of public spending. Source: ICSID.

- Admin. Wage: Average monthly wage of public service employee in a province, in rubles. Source: ICSID.

- Avg. Wage: Average monthly wage in a province, in rubles. Source: ICSID.

- Prices: Consumer price index, December-to-December, expressed as a percentage. Source: ICSID.

- Approval of the Putin: Share of respondents who strongly or somewhat strongly approve of the actions of Prime Minister Putin. Source: FOM georating.

- Approval of Medvedev: Share of respondents who strongly or somewhat strongly approve of the actions of President Medvedev. Source: FOM georating.

- Approval of UR: Share of respondents who strongly or somewhat strongly approve of the actions of the Parliament party "United Russia." Source: FOM georating.

- Approval of Governor: Share of respondents who strongly or somewhat strongly approve of the actions of the local governor in each region. Source: FOM georating.

- Voice: Share of total number polling stations in each region that had observers during the presidential elections of 2012. Source: `www.sms-cik.org/`.

- Observers: Indicator variable for regions with observers during the parliamentary elections of 2011. Source: Buzin, Brondum and Robertson (2016).

- Donors: Number of blood donors per capita in each region. Source: Collected from `www.yadonor.ru` by the "Blood Service" program.

- Trust: Share of people that responded that generally people should be trusted out of the total number of respondents in each region. Source: FOM georating.

- Community: Share of respondents in each region who participate in community services. Source: FOM georating.
- Share of votes for UR: official share of votes that UR received during the 2011 Parliamentary elections. Source: www.cik.bg/.
- Number of actual protest: Dummy or a number of protests that happened after 2011 Parliamentary elections in each region. Source: Sobolev (2019).

E Methods of Electoral Manipulation Estimation: Benford's Law

One of the measures of fraudulent elections employs Benford's Law. Traditionally, Benford's Law postulates nonuniform distribution of leading digits in large data sets. Here we apply Benford's Law to the second digit of two sets of data: turnout percentages and percentage of the total vote won by UR. We cannot use first digit, because turnout is capped by construction with digit three: there is no polling station in Russia with at least 4,000 people. Thus, following the existing literature we use second digit.

Benford's Law has been demonstrated to describe the distribution of the heights of buildings around the world (regardless of the unit of measurement), the length of rivers, voting results, economic performance, the urban population, the size of the human genome, and many other phenomena.[42] As most distributions appear to be smooth and symmetric due to the Central Limit Theorem (according to Hill (1995)), data tend to follow Benford's Law; if they do not, then most probably certain types of errors have to be introduced to the data.

The method based on Benford's Law has been borrowed from fraud detection in statistics (e.g., Leemis, Schmeiser and Evans (2000); Diekmann (2007); Corazza, Ellero and Zorzi (2018)), forensic financial accounting (e.g., Drake and Nigrini (2000); Durtschi, Hillison and Pacini (2004); Nigrini (2012); Amiram, Bozanic and Rouen (2015)), and finance (e.g., De Ceuster, Dhaene and Schatteman (1998); Tam Cho and Gaines (2007); Pimbley (2014)). For electoral fraud detection, it was first used in Pericchi and Torres (2004). This method operates under the following assumption: if a person writes fictional figures in a report, they instinctively try to distribute them evenly; that is, all figures will meet in the first place with the same probability.

Benford's Law distribution is widely used in papers employing forensic methods to study electoral fraud (Mebane, 2006*a*,*b*, 2007*a*,*b*, 2008*b*; Kalinin, 2008; Kalinin and Mebane, 2009, 2011). For example, Mebane (2007*a*) studies parliamentary elections in Mexico in 2006, by comparing differences between the means of the second digits with the means expected according to the 2BL distribution. In addition, Kalinin (2008) and Mebane (2008*b*) used the same data as we do, counting second-digit conditional means to compare them with other fraud-detection methods.

Benford's Law (Raimi, 1976; Hill, 1995) stipulates that the probability of a number that begins with a set of digits is $\log_{10}\left(1+\frac{1}{n}\right)$. Therefore, we can sum over the probabilities that $11, 21, ..., 91$ each existing to get the probability of the second digit being

[42] The site http://testingbenfordslaw.com/ can find a large number of such examples. An overview of the 2011 Russian parliamentary elections by Mellnik, Mellnik and Zhelev (2015) can be found here:
http://testingbenfordslaw.com/2011-russian-parlimentary-elections-united-russia.

a 1. If we do this for all digits, we reach the following table of probabilities for second digits:

2nd Digit	0	1	2	3	4	5	6	7	8	9
Prob. , %	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50

In general, the joint distribution of any combination of digits is as follows (Hill, 1995):

$$Pr\left(D_1 = d_1, ..., D_n = d_n\right) = \log_{10}\left(1 + \frac{1}{\sum d_i \cdot 10^{k-i}}\right). \tag{3}$$

And in our case, we define the marginal distribution for the second digit $d_2 = 0, 1, ..., 9$ as follows:

$$Pr\left(d_2\right) = \sum_{k=1}^{9} \log_{10}\left(1 + \frac{1}{10k + d_2}\right). \tag{4}$$

Mebane (2006*a*) proves that Benford's Law can be applicable to the second digits of votes. He provides Pearson chi-squared statistics for two kinds of tests. The first is whether the distributions of the second digits of vote counts for various US elections match the distribution specified by Benford's Law. Second is whether the second digits occur equally often (uniform distribution). He computes two statistics,

$$X^2_{B_2} = \sum_{i=0}^{9} \frac{(d_{2i} - d_2 q_{B_2 i})^2}{d_2 q_{B_2 i}} \text{ and } X^2_{U_2} = \sum_{i=0}^{9} \frac{(d_{2i} - d_2/10)^2}{d_2/10},$$

where $q_{B_2 i}$ denotes the expected relative frequency with which the second significant digit is i (shown above), d_{i2} the number of times the second digit is i among the J precincts being considered, and set $d_2 = \sum_{i=1}^{9} d_{2i}$. By comparing these two statistics with $\chi^2(9)$ - distribution, which has a critical value of 16.9 at the 5% confidence level, and conducting a similar test with the first digit Mebane (2006*a*) concludes that usage of the second-digit test is more appropriate.

The measures constructed for this paper are the mean absolute deviations (MAD) from this distribution.[43] We take this Benford's Law distribution and compare it to the distribution of second digits in the data. Then we use shares to describe both distributions (e.g., 0.1135). Then,we calculate the absolute difference between the expected Benford's Law distribution and the empirical distribution at each digit. Finally, we sum all of these deviations, then we take the mean of the deviations, producing the mean absolute deviation.

The MAD is constructed as follows:

$$MAD = \frac{\sum_{i=1}^{10} |AD - ED|}{10}, \tag{5}$$

where AD is an actual distribution — the empirical frequency of the number and ED is an expected distribution — the theoretical frequency expected by Benfords distribution. The scale invariance of the MAD statistic makes it useful when examining

[43]We do not use the Kolmogorov-Smirnov statistic; it becomes less useful as total number of digits used increases (Nigrini, 2012). As a result, the Kolmogorov-Smirnov statistic tends toward over-rejection as the pool of digits increases. On the other hand, MAD does not take the total number of digits into account.

large pools of digits, since the number of polling stations in each region and (sometimes) year is different.

Implementing this in R Development Core Team (2008) is simple thanks to the 'benford.analysis' package. This package creates the Benford's Law distribution for the first two digits and the empirical distribution. We followed the procedure above (summing over $11, 21, ..., 91$) to get the second-digit distribution for both Benford's Law and empirical distribution. We then constructed the MAD from these two distributions.

Our results also hold if we use the "Digit Deviation" (Turnout) test from Mebane (2008*a*) and Kalinin and Mebane (2011). It represents the sum of absolute deviations from a uniform distribution of the trailing digit in turnout percentages.

To calculate this, we first constructed the expected distribution of trailing digits $0, 1, ..., 9$ as if all were equally probable (each occur with probability 0.1). Then, we rounded all of the turnout data to the nearest 1 and observed in the data the frequency of trailing digits in turnout data. For example, if the turnout is 69.3%, we round to 69 and the trailing digit is 9. We then calculate the share of data that ends in each digit. Therefore, if fraud exists, we should expect anomalies in this data (especially deviations at 0 and 5, given tendencies of past Russian elections). We then summed the deviations from the expected distribution across all digits 0 to 9.

F Additional Robustness and Sensitivity Checks

F.1 Robustness to Alternative Measures of Protest Potential

In this Section, we check sensibility of our results to alternative measures of the explanatory variable.

One possible concern is related to the fact that the FOM's survey took place nine months before the election. It would create a measurement error. In case of a classical measurement error we would have attenuation of the coefficient of interest what would be against us finding negative effect of protest potential on electoral fraud. However, if the measurement error is not classical, the direction of bias may be ambiguous.

To address this concern we use the data from Robertson (2013) who counted actual number of protests in Russian regions in 2011. While the theory suggest that we need to use protest potential rather then actual protests, number of protests in November 2011 provide us a good snapshot of protest activity just before the December's election.

We present our results in Table A6. In column 1, we report the baseline results with the protest potential computed on FOM's data. In column 2, we use number of protest in November 2011 as the main explanatory variable. The coefficient of interest remains significant, suggesting that we indeed measure protest potential. Column 3, where we use total number of protests during September, October, and November yield similar results.

	Baseline	One Month	Three Months
Protest Sentiments	-4.65^{***}		
	(1.31)		
Nov. Protests.		-0.21^{*}	
		(0.92)	
Sep., Oct., Nov. Protests			-0.32^{**}
			(0.12)
Controls	✓	✓	✓
R^2	0.36	0.30	0.33
Observations	74	74	74

Note: (*a*) In all columns, we take specification from the baseline results, i.e., Table 2, and extend it by adding further controls. (*b*) The main dependent variable is a first principal component of the four measures of electoral fraud: spikes, mixture estimator, BL, and extreme turnout. (*c*) Robust standard are errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A6: Regressions with Protest Data from Robertson (2013)

F.2 Alternative Explanation VI: Pre-election Day Fraud

Another possible alternative explanation is related to the possibility of the pre-election day fraud. For example, if the government is afraid of the protests that can be caused by the electoral manipulations during the election day, they may substitute it with pre-election day manipulations. In this case we would make us see less fraud in regions with high protest potential (thus supporting the Information theory against the Influence theory.

Pre-election day fraud is not unusual in authoritarian regimes (Simpser and Donno, 2012). For example, Frye, Reuter and Szakonyi (2014, 2018) document the most widespread type of such manipulations in Russia: voter intimidation through work-place mobilization. They estimate the measure of work-place mobilization in Russian regions as a share of the total number workers who were intimidated to vote divided by the total number of workers in employed in companies with ties to the government during Russian elections of 2011-2012. We use this data to address this important alternative explanation in Table A7.

We present our baseline results in column 1 for comparison. In column 2, we add measure of pre-election day fraud as control variable. The coefficient of interest did not change much suggesting that channel between pre-election and election day manipulations goes not through the protest potential. Moreover, the size of the point-estimate for the pre-election day fraud is insignificant. In column 3, we use protest potential as the dependent variable, and pre-election day fraud as the main explanatory variable and omit the measure of electoral day fraud. Absence of the correlation between the work-place mobilization and the protest potential means that protests do not depend on pre-electoral fraud.

	Baseline	Fraud	Protest
Protest	-4.65^{*}	-4.43^{*}	
	(1.31)	(1.50)	
Pre-Elec. Fraud		0.10	0.02
		(0.20)	(0.01)
Controls	✓	✓	✓
R^2	0.36	0.36	0.46
Observations	74	73	73

Note: (*a*) First column shows the baseline result. The second column controls for pre-electoral fraud. The third column uses protest sentiment as dependent variable and shows that it does not depend on pre-electoral fraud. (*b*) In all columns, we take specification from the baseline results, i.e., Table 2, and extend it by adding further controls. (*c*) The main dependent variable is a first principal component of the four measures of electoral fraud: spikes, mixture estimator, BL, and extreme turnout. (*d*) Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A7: Alternative Explanation VI: Pre-Electoral Fraud

F.3 Alternative Explanation: VII: Signaling with Nation-Wide Results

Russian Parliament is a federal legislative organ. So, one might suggest that even if the elections are used to signal strength, the focal results used for ”signaling” are not the regional results, but the federal results, and the government implements manipulation in the places where it is easier to do (e.g. in places where the regime is popular) to boost the aggregate results.

F.4 Additional Robustness Checks

In this section, we address some additional concerns regarding possible omitted-variable bias. The results are presented in Table A8, where column 1 contains the baseline specification for a comparison.

In unlikely case that there is an improvisational dynamic built into how the Kremlin and its regional clients react to information about the extent of regime support available from regions that have already returned their first voting results we add latitude and longitude as controls. Nevertheless, inclusion of these variables in column 2 does not affect our results.

The literature also suggests (Lipman, Kachkaeva and Poyker, 2018) that regional media less affected by the federal propaganda machine may induce protest sentiments while negatively affecting electoral fraud. Thus, in column 3, we add a control for the number of regional newspapers published in 2011. As expected, the coefficient for regional media is negative and significant. Moreover, the estimate for electoral manipulation also moved in the expected direction, in line with the existing literature.

Some analysts have suggested that dependence on oil sector may affect subnational regime dynamics (Mahdavi, 2015). We add a control in column 4 for the share of oil and gas in the regional GRP; however, find that it does not correlate with electoral fraud and did not affect the coefficient of interest. In column 5, we control for regional unemployment rates, which may potentially it can positively affect protest sentiments and be correlated with electoral fraud. However, adding unemployment rates as a

	Dependent variable: Electoral fraud (PCA)					
	Baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Protest	-4.65^{***}	$--4.69^{***}$	-5.07^{***}	-4.25^{***}	-4.83^{***}	-4.45^{***}
	(1.39)	(1.38)	(1.35)	(1.19)	(1.35)	(1.43)
Latitude		-0.041				-0.03
		(0.03)				(0.24)
Longitude		-0.006				0.001
		(0.010)				(0.007)
Newspapers			-0.24^{**}			-0.10
			(0.10)			(0.08)
Oil				0.002		0.0002
				(0.002)		(0.002)
Unemployment					0.12^{**}	0.08
					(0.06)	(0.076)
Controls	✓	✓	✓	✓	✓	✓
Observations	74	74	74	64	74	64
R^2	0.358	0.399	0.411	0.297	0.400	0.388

Note: (*a*) In all columns, we take specification from the baseline results, i.e., Table 2, and extend it by adding further controls. (*b*) The main dependent variable is a first principal component of the four measures of electoral fraud: spikes, mixture estimator, BL, and extreme turnout. (*c*) Robust standard are errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A8: Additional Robustness Checks

control does not change our results.

Finally, in column 6, we employ all our controls together. The coefficient for protests remains significant, while decreasing slightly in magnitude: a 10 percentage point increase in protest sentiments decreases electoral manipulations by 0.44 of its standard deviation.

F.5 Exploring Selection on Unobservables

Despite the rich set of control variables, some unobserved heterogeneity may still bias the estimate of interest if an omitted variable is correlated with both anti-government protests and electoral fraud. To address the concern about the effect of unobservables, we follow Oster (2017) by evaluating the likelihood that the coefficient estimate is biased by omitted variables. This procedure suggests adopting the conservative bounding value for the R-squared (R_{max}) from the hypothetical regression with all observable and unobservable controls all together, and then finding the value of the coefficient of proportionality (δ) for which the estimator would produce a treatment effect of zero. Thus, intuitively, the coefficient of interest can be expressed as a function of δ and R-squared movements ($\beta = \beta(\delta, R_{max})$), and by setting $\beta = 0$ we can calculate how big the effect of unobservables δ given R_{max} should be.

The results of the robustness test are shown in Table A9. In Columns 1–5, we present results for all five measures of electoral fraud. Each column reports δ for different values of $\overline{R_{max}}$. Following Oster (2017), we use the value of $\overline{R_{max}} = 1.3R^{UR}$. For the baseline specification in Column 5, $R^{UR} = 0.36$, thus $\overline{R_{max}} = 0.47$. The value of δ for the baseline measure of electoral manipulation suggests that the unobservables would need to be 1.16 times as important as the observables to completely explain away the effect of protest sentiments. Similarly, all other values of δ are above 1, suggesting that our results are robust to potential confounding by unobservables.

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable:				
	Spikes	Mixture Est.	Digit Est.	Extr. Turnout	PCA
Delta	1.26	1.17	1.27	1.12	1.16
$\overline{R_{max}}$	0.369	0.488	0.332	0.457	0.467

Note: (*a*) The first row reports the coefficient of proportionality δ computed by using the psacalc STATA code (Oster, 2017). (*b*) The $\overline{R_{max}}$ is computed as $1.3R^{UR}$, where R^{UR} is an R-squared of the regression with the full set of controls. (*c*) See Table 2 for the list of controls.

Online Appendix Table A9: Selection on Unobservables

F.6 Robustness to Outliers

Table A10 presents the results of our efforts to ensure that our results are not driven by a handful of outliers. We start by reporting the baseline specification in column 1. In column 2, we omit two largest Russian cities, Moscow and Saint Petersburg. The coefficient of interest remains significant and does not change. In column 3, we similarly omit three observations with the strongest protest sentiments (Kaliningradskaya Oblast, Kurskaya Oblast, and Novgorodskaya Oblast). The protest sentiment coefficient remains significant and even increases in magnitude. Then, in column 4, we drop three observations with the largest share of electoral manipulation (Republic of Kabardino-Balkaria, Republic of Karachayevo-Cherkessia, and Republic of Mordovia). While the point-estimate for protest sentiment decreases in magnitude, it remains negative and significant. Finally, in column 5, we omit the three ethnic republics with the largest population (Bashkortostan, Daghestan, and Tatarstan). The estimate for protest sentiment decreases slightly but remains significant. Overall, this table suggests that our results are not caused by statistical artifacts in the data. We also use robust regression with the automated deletion of observations that have a Cook's distance (a statistic that combines leverage and residual) larger than one. However, this method chooses to drop only Moscow from the sample, yielding results similar to the specification in column 2 of Table A10.

	Dependent variable: Electoral fraud (PCA)				
	(1)	(2)	(3)	(4)	(5)
Protest	-4.651^{***}	-4.841^{***}	-5.299^{***}	-3.798^{***}	-4.032^{***}
	(1.387)	(1.387)	(1.607)	(1.084)	(1.403)
w/o Capitals		✓			
w/o Largest Protests			✓		
w/o Largest Fraud				✓	
w/o Largest Rep					✓
Observations	74	72	71	71	71
R^2	0.358	0.379	0.363	0.270	0.339

Note: (*a*) In all columns, we take specification from the baseline results, i.e., Table 2, and extend it by adding further controls. (*b*) The main dependent variable is a first principal component of the four measures of electoral fraud: spikes, mixture estimator, BL, and extreme turnout. (*c*) Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A10: Robustness to Outliers

G Additional Tables and Figures

	2003		2007		2011	
Total Turnout (%)	54.7		59.0		60.2	
Share of UR (%)	37.6		64.3		49.3	
	Ethnic Republics	Oblasts	Ethnic Republics	Oblasts	Ethnic Republics	Oblasts
Turnout (%)	68.8	53.4	79.3	61.0	76.1	57.3
Share of UR (%)	35.2	18.4	62.6	37.1	54.2	25.1
Number of polling stations	17,360	77,622	17,897	78,349	17,734	77,423
100% turnout	1,695	2,538	2,383	2,549	1,532	2,229
of than 100% for UR	72	37	310	92	124	68
90-100 % turnout	3,627	2,561	6,729	6,015	6,311	4,305
> 90% for UR	714	22	3,367	431	2,500	437
80-90 % turnout	2,555	5,087	2,666	9,101	2,614	6,293
> 80% for UR	71	7	239	145	389	85

Note: (*a*) Turnout is a share of voters who reportedly voted in a parliamentary elections in a given year. *Share of UR* is a share of ballots cast in support of the major pro-government political party UR. (*b*) Source: Central Election Commission of the Russian Federation.

Online Appendix Table A12: Ethnic Republics vs. Other Regions

	Dependent variable:		
	Spikes	Mixture Est.	Extr. Turnout
	(1)	(2)	(3)
Protest	-10.679^{**}	-0.647^{***}	-1.135^{***}
	(4.812)	(0.192)	(0.354)
GRP	-1.320^{**}	-0.012	-0.005
	(0.583)	(0.023)	(0.043)
Education	0.198^{**}	0.005	0.008
	(0.083)	(0.003)	(0.006)
Internet	0.011	0.245	0.539
	(6.284)	(0.250)	(0.462)
Pop. Density	-0.463	-0.018	-0.031
	(0.359)	(0.014)	(0.026)
Distance to Moscow	-0.204	-0.023	-0.0003
	(0.362)	(0.014)	(0.027)
Treaty	0.502	0.008	0.021
	(0.592)	(0.024)	(0.044)
Constant	-2.306	0.037	-0.042
	(5.482)	(0.218)	(0.403)
Observations	74	74	74
R^2	0.281	0.376	0.352
Note:			*p<0.1; **p<0.05; ***p<0.01

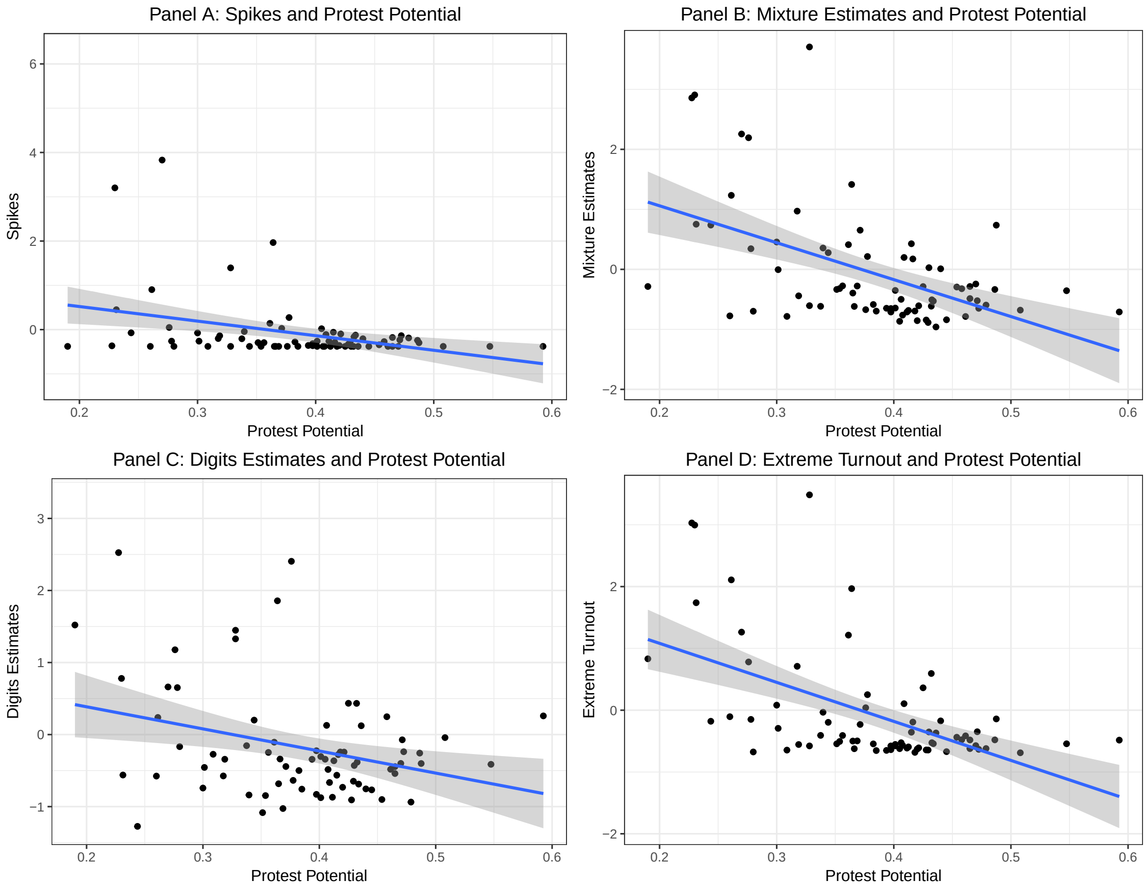
Online Appendix Table A11: Measures of Electoral Manipulation and Protest Potential (w/o Studentizing the Dependent Variable)

	Model	Coefficient	Std.Error
1	2BL Turnout Count	-0.09	0.11
2	2BL Turnout Percentage	-0.74	0.32
3	2BL UR Percentage	-0.34	0.16
4	2BL UR Count	-0.13	0.08
5	Last Digit UR Count Deviation From Uniform	28.44	39.81
6	Last Digit Vote Count Deviation from Uniform	-0.02	0.09
7	Last Digit Vote Count Deviation of Frequency of Zeros	-0.00	0.04
8	Last Digit UR Count Deviation of Frequency of Zeros	-0.04	0.01

Online Appendix Table A13: Digit Tests

	Dependent variable: Electoral fraud (PCA)	
	Baseline	
	(1)	(2)
Protest	-4.651^{***}	-4.444^{***}
	(1.387)	(1.316)
Population		-0.350^{***}
		(0.120)
Controls	✓	✓
Observations	74	74
R^2	0.358	0.432
Note:		*p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A14: Electoral Manipulation, Protest Potential, and Population



Note: (*a*) Panels A through D above correspond to columns (1) through (4) of Table 2. (*b*) All four measures of electoral fraud exhibit very strong negative correlation with protest sentiments, even without controls. Measures of spikes (A) and extreme turnout (D) capture mostly extreme fraud, thus many observations have many near-zero values of electoral fraud. Meanwhile, mixture (B) and digit-test (C) estimators can catch more subtle electoral manipulations and have more regional variation.

Online Appendix Figure A.2: Electoral Fraud and Protest Potential: Scatter Plots