Do Dictators Signal Strength with Electoral Fraud?*

Maxim Ananyev[†]

Michael Poyker[‡]

June 2021

What role does electoral fraud play in nondemocracies? In this paper, we offer an empirical test of a popular idea that authoritarian governments use elections to engineer overwhelming victories with electoral fraud 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 by other mechanisms, such as Bayesian persuasion, efficient allocation, and information gathering.

*The previous version of this paper circulated under a title "Information Acquisition and Projecting Invincibility in Authoritarian Elections." Authors are grateful to Pasha Andreyanov, Christian Dippel, Natalia Forrat, Barbara Geddes, Scott Gehlbach, Miriam Golden, Leslie Johns, Kirill Kalinin, Vasily Korovkin, Yegor Lazarev, Peter Lorentzen, Zsuzsanna Magyar, Paasha Mahdavi, Eric McGlinchey, Ben Noble, Imil Nurutdinov, Sergey V. Popov, John Reuter, Kirill Shilov, Anton Sobolev, Konstantin Sonin, Luke Sonnet, Zachary Steinert-Threlkeld, Yuan Tian, Daniel Treisman, Nico Voigtländer, Romain Wacziarg, seminar participants at SoDa Labs of Monash University, UCLA, and conference participants at APSA, MPSA, RES, and VWAR for excellent suggestions. Authors are grateful to Kirill Kalinin who generously provided region-level mixture estimates for electoral fraud in 2011, Graeme Robertson who generously provided data on actual instances of pre-electoral protests, and Anton Sobolev who generously shared data on the instances of post-election protests. All errors are ours. Correspondence at: Sir Clive Granger Building B33, School of Economics, University of Nottingham, University Park, NG7 2RD, Nottingham, UK.

[†]Ananyev: University of Melbourne, Melbourne Institute; email address: maxim.ananyev@unimelb.edu.au

[‡]Poyker: University of Nottingham, School of Economics; e-mail address: mikhail.poyker@nottingham.ac.uk

1 Introduction

Many authoritarian countries today have institutions that are commonly associated with democratic governments: multiple parties, parliaments, and elections.[1] Elections in autocracies are highly unfair to the opposition: it is outspent, harassed by the authorities, and often lacks access to media and other resources. The results of the elections themselves are also manipulated even though, given all the other restrictions, pro-regime politicians can often win without electoral manipulations (Simpser, 2013; Rundlett and Svolik, 2016).

What role does electoral manipulation play in nondemocracies? Scholars often argue that the regime needs overwhelming victories — often helped by outright manipulation of results — to convey its strength. According to Simpser (2013, p. xv): "...Manipulating elections excessively and blatantly can make the manipulating party appear strong, while failing to manipulate in this manner can convey weakness." Relatedly, Magaloni (2006, p. 46) writes, describing Mexico under the Institutional Revolutionary Party (PRI): "Ballot stuffing ... was intended to create a signal to elites that defection would be punished and that there was no hope in defying the party because it would use everything at its disposal, including fraud and force, to prevent opponents from winning." Such manipulations are used to achieve supermajorities, because, as Geddes (2005) points out, "High turnout and supermajoritarian election outcomes signal that citizens remain acquiescent."[2]

In this logic, because only regimes with high capacity to reward loyalists and punish dissenters are able to organize a widespread effective electoral manipulation, such manipulation is interpreted by regime's audiences (people, bureaucracy, potential defectors within the elite, or powerful stakeholders within civil society) as evidence of its invincibility. In this sense, a high level of electoral manipulation *signals* strength: strong regimes are able to demonstrate their high capacity in a way that weak regimes

[1] See, for example, Geddes (2005), Blaydes (2006), Gandhi (2008), Svolik (2012) as well as many others. See Brancati (2014) and Gandhi and Lust-Okar (2009) for overviews of this literature.

[2] It should be noted that Magaloni (2006) does not argue that voter fraud was the only reason for authoritarian survival of the PRI hegemonic-party regime, just that it was one of the instruments that helped achieve necessary margins and also deter potential opponents.

are unable to emulate.[3]

While this family of ideas (hereafter, the intimidation theory) is prominent in the literature, 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?[4]

Our paper answers these two questions in the context of Russian Parliamentary elections. The intimidation theory would predict that voter fraud happens in places where it is costly to conduct — otherwise, even a weak regime will be able to implement it, and no signaling goal will be achieved. In addition, conditional on the popularity of the regime, electoral fraud should deter post-election protests. The Russian institutional setting and unique combination of electoral and protest data allow us to reject the intimidation theory and provide evidence in favor of alternative theories.

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

[3]Neither Magaloni (2006) nor Simpser (2013) offer a microeconomic signaling model in a sense of Spence (1973). Magaloni (2006) chooses to make her argument informally, and Simpser (2013) offers a focal-point model where high amount of fraud serves, in one of the multiple equilibria, as a coordination device for regime's audiences to support the regime. Nevertheless, they both argue verbally in favor of the "signaling" intuitions. For instance, Magaloni (2006, p. 18) writes: "Huge margins of victory are costly to obtain because they require mobilized voters – people whose electoral participation (turnout) and/or candidate choice [are] induced by vote buying and coercion." And Simpser (2013, p. 102) writes, explaining why high manipulation serves as a deterrent: "...actors who challenge a ruling party that manipulates excessively/blatantly are likely to receive a low payoff (for example, due to punishment or reprisals by the ruling party) and therefore to become more likely to refrain from challenging when next encountering excessive/blatant manipulation."

[4]Brancati (2014) argues that the results reported in the literature can be driven by the reverse causality, since it is possible that "only popular regimes or regimes with the material capacity to win elections through strategic manipulation hold elections because the risk of their losing the elections is small."

protests). We find that the relationship between electoral manipulation and protest sentiments is the *opposite* of that which would be consistent with the intimidation theory. While the intimidation 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).[5]

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 intimidation 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 de facto rules in those elections are unfair to the opposition: it is outspent, 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 intimidation theory to apply to Russia based on its regime type.[6]

If the intimidation theory does not explain the pattern of electoral manipulation, then what does? Our results are consistent with three other related theories: (i) the Bayesian persuasion theory, (ii) the efficient allocation theory, and (iii) the information-gathering theory. The Bayesian persuasion theory (elaborated in Gehlbach and Simpser,

[5]From the theoretical point, the intimidation theory could be consistent with the inverse-U shape of the relationship between fraud and discontent, since too high levels of electoral fraud could be seen as sign of weakness. We do not observe an inverse-U relationship either. The relationship appears to be uniformly negative.

[6]Another commonly invoked example is the case of Mexico under the Institutional Revolutionary Party (PRI) (Magaloni, 2006). We do not use this example because, as Geddes (2005) points out, the relevance of the intimidation considerations for the PRI might be a result of a specific institutional feature of that regime — strictly enforced executive term limits. Thus it might be of limited external validity because this feature is unusual. In this sense, Russia's case is more relevant since it has many common features of modern "competitive autocracies" (Levitsky and Way, 2002).

2015; Little, 2015; Rozenas, 2016, and Egorov and Sonin, 2021) states that given the uncertainties involved in the process, even if the audiences are rational and understand that the government can implement manipulation, government can still improve the perception of its popularity by producing electoral manipulations.[7] The efficient allocation theory is a simple idea that given the need to show supermajorities, the fraud will happen where it is easier to conduct. Finally, the information-gathering theory is a direct corollary of a view that authoritarian governments use elections to collect data on the locations of the loyalists and the dissidents as well as on the performance of local officials (Gandhi and Lust-Okar, 2009).[8] If election results reveal that information, then they should stay relatively clean of manipulation in places with high ex-ante uncertainty. In principle, the observed negative association can be compatible with any of these theories (or all of them since they do not contradict each other).

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

[7] See Gehlbach, Sonin and Svolik (2016) for a toy model that explains this logic.

[8] 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). 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. This argument is consistent with several theories of autocracies. Specifically, Egorov, Guriev and Sonin (2009) argue that it can be in the best interest of authoritarian government to allow some media freedom to collect information about the performance of lower-level bureaucrats. Peter Lorentzen pushed the "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.

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 perceptions of discontent and indicators electoral manipulation — does not depend on which of the methods we use. We also confirm that our results remain the same if we use a measure of workplace mobilization as a dependent variable.[9]

Our main contention is that our results are inconsistent with the intimidation theory but can be consistent with Bayesian persuasion, efficient allocation, or information gathering. 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 intimidation 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. To address this concern, we control for the actual popularity of the regime, measurements of social capital, and the presence of electoral observers.[10]

One of the potential alternative explanations is that regimes tries to signal strength, but its actions get distorted because, as Rundlett and Svolik (2016) demonstrated, field agents of manipulations are likely to be overzealous if the government is popular.[11] We address this explanation by controlling for the regime's popularity. It is also possible that 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

[9] It is worth pointing out that the high level of discontent does not automatically mean that the race would be competitive since the opposition might fail to coordinate on the candidate, or the main contender could be removed from the ballot.

[10] The latter two are the proxies of the capacity of the society to organize a collective effort to prevent electoral manipulations.

[11] 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.

can be more reluctant to implement manipulation. Hence, we control for the wages of those agents (teachers and administrative personnel) as a way to capture their potential grievances as well as potential rewards from the regime. Inclusion of these controls; however, does not substantially change the estimates of the effect of perceptions of discontent. We also show that our results are not driven by pre-election day 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 electoral manipulation in autocracies. We also believe that such test is informative for a broader question on the role of elections in autocracies. Our results show that achieving supermajorities by demonstrating the muscles through manipulations might not be the best explanation for their use. The role of elections might be better explained by other theories.[12]

Our paper is also relevant to the literature on the determinants and motivations of electoral fraud. In particular, Chaves, Fergusson and Robinson (2015) theorize about a trade-off between public good provision and incumbent's survival through electoral manipulation. 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 exploring if electoral fraud can be a explained by an attempt of the regime to signal high capacity. Our findings are also consistent with Rozenas (2016), who shows, using cross-country panel data, that relatively clean elections are likely to follow the events of crises interpreted as events when an incumbent is weak. Looking at the regional data from one country we show that relatively clean elections happen in places with high levels of discontent.

[12]Some of the notable theories include the following. 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. Martinez-Bravo et al. (2017) theorize that elections on the local level are needed to allow local resident better monitoring, but they also make local officials more reluctant to implement unpopular policies pushed by the center.

The strength of Rozenas (2016) is that he is able to use the panel structure of the data. The strength of our analysis is that we (i) conduct regional analysis with the country-level institutions and cultural factors being fixed, (ii) use a set of behavioral measures to quantify discontent (survey responses and actual protests), and (iii) test whether electoral manipulations are related to post-election protests.[13]

Our results also pertain to the theory of "informational autocracy" (Guriev and Treisman, 2015, 2019), 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.[14] Literature on authoritarian backsliding (Nalepa, Vanberg and Chiopris, 2018; Svolik, 2020) emphasizes that political polarization allows incumbents to subvert democratic procedures. Consistently with these findings, our paper explores a role of heterogeneity of political preferences in the 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.

[13] Kalinin and Mebane (2011) look at electoral manipulation in the Russian context and argue that regional authorities use electoral manipulation to signal loyalty to the central government.

[14] 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.

2 Background: 2011 Russian Parliamentary Elections

The 2011 parliamentary election was widely criticized by international observers for being heavily manipulated.[15] 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.[16] In another video, a cameraman demonstrates that voters' pens in a polling station were filled with erasable ink.[17] 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.[18]

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.[19] Of course, since the Kremlin had the access to the polling data, demanding those pre-specified vote shares is equivalent to demanding

[15] We provide additional background information on Russian Parliament in Online Appendix A.

[16] 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.

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

[18] 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).

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

election rigging.

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 main pro-regime party, UR. We describe our sources and construction of other variables used as covariates in Online Appendix B.

3.1 Measuring Perceptions of Discontent

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.[20]

[20] 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.

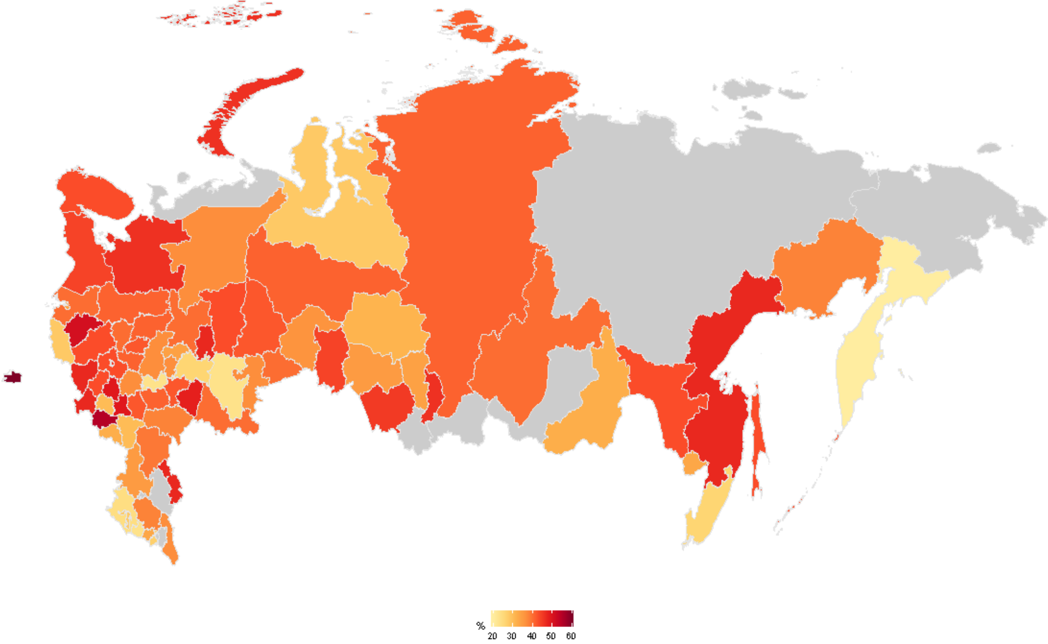


Figure 1: Map of Perceptions of Discontent in 2011

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

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 perceptions of discontent 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).[21]

In case of preference falsification, survey responses can introduce non-classical measurement error. As a validity check Figure A.3 shows that FOM's perceptions of discontent is correlated with the actual pre-election protests (because post-election protests can be influenced by the events of the elections, obviously not captured) from Robertson (2013).

[21] In Online Appendix D.1 we show robustness of our results to alternative measures of protest potential (actual instances of protests in the months before the elections) from Robertson (2013).

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 2011.[22]

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).[23] 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. We use Rozenas's *spikes* package to estimate region-level percentages of fraudulent precincts.[24]

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,

[22] 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.

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

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

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) and 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.[25]

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.

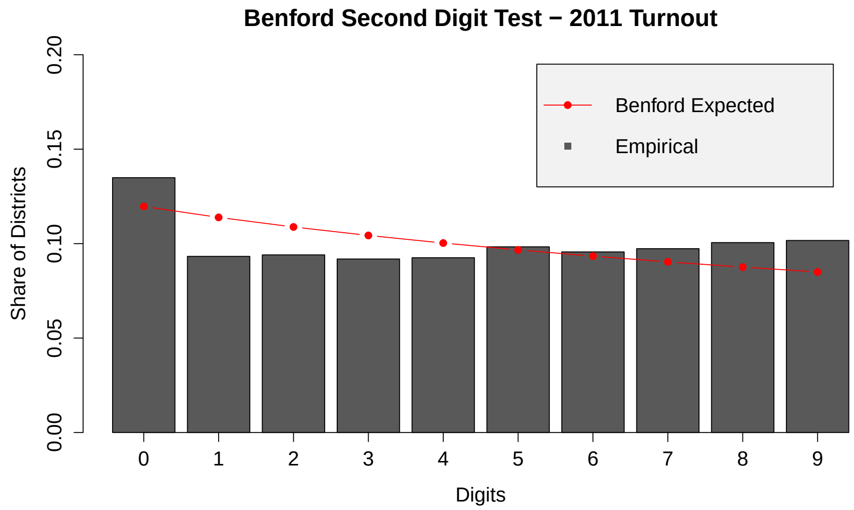
Its intuition is straightforward: if a number represents a naturally occurring phenomenon, the distribution of its second digit should follow certain empirically established distribution. See Online Appendix C for details.

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

[25]Figure A.1 shows histogram of the distribution of mixture model estimates.

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.[26] We take these concerns seriously: we computed eight types of electoral fraud estimates based on BL and compute the first principal component of all measures. 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.[27]

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.[28]

[26] 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.

[27] 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.

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

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

	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

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.

4 Empirical Specifications and Results

In this section, we offer two tests of the intimidation theory. First, we regress our region-level estimates of electoral manipulation on the survey-based estimates perceptions of discontent (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 Perceptions of Discontent

We estimate linear regressions that include 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.[29] 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: mixture model estimates, 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 perceptions of discontent in region i: the share of the Georating's respondents who say that protest inclinations are increasing.[30] 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

[29]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.

[30]In Online Appendix D.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.

such mobilization is ex-ante most likely. Thus, the intimidation theory would imply a positive effect of protest propensity on electoral fraud.

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 of electoral fraud and the level of protest potential (Enikolopov, Makarin and Petrova, 2020; Enikolopov et al., 2017; Skovoroda and Lankina, 2017).[31] 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 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. We consider an extended set of controls and other robustness checks in Online Appendix D.4.

Table 2 presents the regression results. Each column corresponds to a different measure of electoral manipulation. We use spikes as the dependent variable in col-

[31] 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.

umn 1, 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 perceptions of discontent is statistically significant and substantively large for all measures of electoral fraud.[32]

The magnitude differs across specifications. We see the largest magnitude for the mixture model estimates (column 2), and the smallest magnitude for spikes estimates (column 1). Even the smallest estimates are quantitatively large: a 10 percentage points increase in perceptions of discontent is associated with a 0.27-standard-deviation decline in spikes.[33] Coefficients for the discontent variable in columns 1 and 3 are not statistically different from each other. The same is true for coefficients in columns 2 and 4.

Because perceptions of discontent vary from around 20 percent to around 60 percent, our model implies that the largest possible in-sample change in perceptions of discontent reduces electoral fraud by a magnitude from 1.2 standard deviation (for spikes and digit-test estimates) to 2.8 standard deviations (for 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 perceptions of discontent 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.[34] Other control variables appear to be insignif-

[32]Our results also hold for the specification without any covariates: we present scatter plots in Figure A.2. Table A8 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 A11 presents all the results for the digit tests separately.

[33]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.

[34]The goal of these specifications is to control for potential confounders of the relationship between

	Dependent variable: Electoral fraud				
	Spikes	Mixture Est.	Digit Est.	Extr. Turnout	PCA
	(1)	(2)	(3)	(4)	(5)
Perceptions of Discontent	-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 Perceptions of Discontent

icant.

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.

perceptions of discontent and electoral manipulation, not the variables that confound a relationship between perceptions of discontent and education. Thus, this particular estimate must not be interpreted causally.

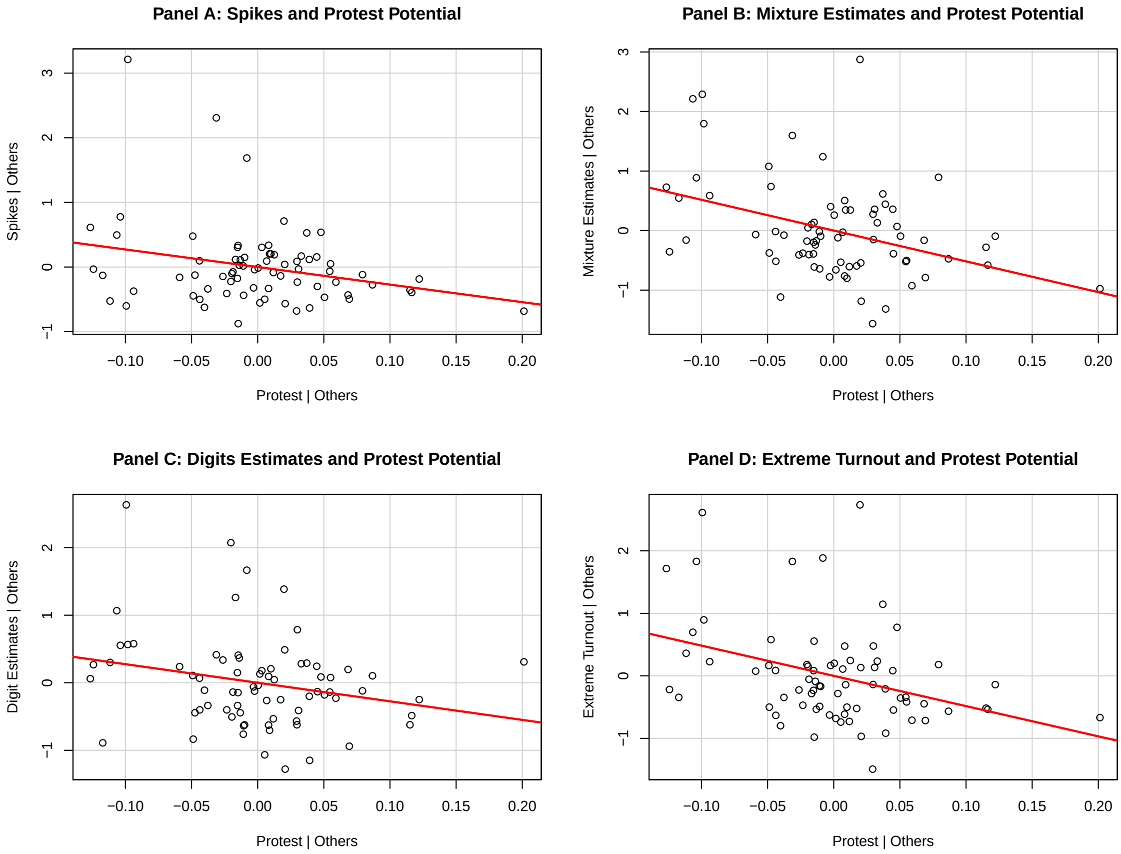


Figure 3: Electoral Fraud and Perceptions of Discontent: Added Variable Plots

Note: Panels A through D above correspond to columns (1) through (4) of Table 2.

It is worth pointing out that we are using the region-level specification because (i) according to the journalistic accounts of Russia's regime, it is the governors who are given commands from the presidential administration to achieve certain targets based on turnout and the proportion of pro-regime votes,[35] (ii) Georating survey is representative on the regional level, and not on the municipal level, (iii) measures of fraud we are using in columns 1–3 are sufficiently data-hungry and cannot be deployed on the lower levels without sufficient risk of false positive. However, as a robustness check, we divide each region into three subregions: central city, non-central urban areas, and rural areas, and estimate our baseline specification (equation 1) using the subregion-level perceptions of discontent with the subregion-level share of precincts with the extreme turnout (corresponding to baseline measure from column 4 of Table 2) and

[35]See, for example, Vedomosti, "How Many Votes Does United Russia Need": www.vedomosti.ru/politics/articles/2011/10/13/skolko_nuzhno_edinoj_rossii.

our results hold. This measure is the crudest of all other measures but is the least data-hungry. See Appendix D.2 for details. In Appendix D.7, we show that the similar pattern is observed when we use a measure of workplace mobilization from Frye, Reuter and Szakonyi (2019) as a dependent variable.

Overall, we have demonstrated that there is a negative correlation between the level of electoral manipulation and the perceptions of discontent in 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 intimidation theory, since the electoral manipulations were seemingly distributed away from the regions with high level of perceptions of discontent. In the next section, we consider another prediction of the intimidation theory: that high voting margins deter potential protests.

4.2 Ruling Party Results and Subsequent Protests

One of the key ideas of the intimidation 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). 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 intimidation 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. It is also a prediction of the intimidation theory that the intensity of manipulation should 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. It is important to note that because we control for the actual popularity of the regime, our results should be interpreted as informative about the potential effects of only the margins of victory, not the political contention or close races.[36]

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.[37]

The share of UR is not significant predictor in any of the specifications. It is negatively correlated with protest incidence, but positively correlated with protest size (conditional on the incidence of protest) as reported by the activists, and is close to

[36]For example, Kuhn (2015) discusses the effect of electoral contention on violence.

[37]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.

zero for the size of the protests reported by the authorities. We fail to reject the hypothesis that incidence/size of the protest is related to the reported result of the incumbent conditional on pre-electoral popularity of the incumbent. The estimate of the coefficient for amount of manipulation is also insignificant. Thus, we do not find evidence consistent with the intimidation theory.

5 Alternative Explanations and Robustness

In the previous sections, we find evidence against the intimidation theory. The allocation of electoral manipulation thus can be consistent with other theories: Bayesian persuasion, efficient allocation, and information gathering. It is also possible that the regime *tries* to signal with fraud, but the results end up being the opposite because of other factors. Here, we rule out a set of alternative explanations that are unrelated to the goals of the regime but might also potentially explain the negative correlation of perceptions of discontent 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. The amount of fraud and the amount of protest can both be confounded by the organizational capacity of civil society. It can contribute to election monitoring (thus decreasing fraud) and also contribute to spreading of the anti-regime ideas and organizing protests (thus increasing protest sentiments and actual protests).

We address concerns regarding electoral monitoring and social capital in Table 4. In column 1 we replicate the baseline specification from column 5 of Table 2. We add a

	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: Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 3: Results of United Russia and Subsequent Protests

control for the measure of electoral monitoring from Buzin, Brondum and Robertson (2016) in column 2. In particular, we use a dummy if the region had independent observers during the 2011 parliamentary elections.[38] The resulting coefficient of interest remained significant and even increased in magnitude. At the same time, the proxy for observers is negative and significant (regions with observers had 0.55 standard deviation less fraud) and is consistent with the predictions by Enikolopov et al. (2013), suggesting that the presence of observers decreases electoral manipulation.

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

Table 4: Alternative Explanation I: Observers and Social Capital

In columns 3–5, 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 com-

[38]For more information about the construction of variables introduced in this section, see Online Appendix B.

munity in time of need. In column 3, we add a region-level control for the number of blood donors.[39] 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 4 and 5, respectively. The estimate for protests remains significant and does not differ from the one in column 3.

5.2 Alternative Explanation II: 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 5. The first column contains the baseline regression for the comparison. In column 2, we first control for the regime's popularity 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 is associated with 0.26-standard-deviation increase in electoral fraud. 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.

[39]Those are not the only possible measures of social capital. For example, Guriev and Melnikov (2016) use an innovative measure of social capital based on pro-social internet searches. Unfortunately, we do not have access to region-level data on Internet searches from 2011.

Nevertheless, the estimate for protests remains stably negative and significant.

	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

Table 5: Alternative Explanation II: Strategic Complementarities among Field Agents

5.3 Alternative Explanation III: 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 for their salary we gauge a measure of their dissatisfaction that can be related to an effort in committing electoral fraud.

The results are presented in Online Appendix Table A9. 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 (Forrat, 2018), 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. 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.

5.4 Alternative Explanation IV: Institutional Explanations

In this section, we address additional institutional concerns regarding institutional factors that may distort our results. Results are presented in Table A13 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."[40] 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 perceptions of discontent and electoral fraud are correlated with political culture (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, 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 proxy for political competition is the popularity of the governor. We have demonstrated in Table 5 earlier that inclusion of this control does not affect the main result.

To conclude, in this Section we addressed main alternative explanations. In Appendix D.1, we show that our results are robust to usage of alternative measure of protest potential. In Appendix D.3 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

[40]Table A10 shows that national republics are much more likely to have polling stations with near 100% turnout.

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 results. In Appendix D.4, we also address some additional concerns regarding possible omitted-variable bias. Appendix Table A4 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 D.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. [41]

Finally, our results are not driven by a particular subsample of the data. Appendix D.6 shows that our results are robust to outliers. Figure A.4 reports on the robustness of our preferred estimate in Column 5 of Table 2 to dropping one observation at a time. Dropping any particular observation does not affect the coefficient of interest. Similarly, Figure A.5 reports on the robustness of our preferred estimate to dropping one of eight Federal District (a set of regions) at a time. The estimated coefficient always remains significantly different from zero. Dropping Central Federal District, reduces the coefficient the most, from -4.65 to -5.59. Dropping Volga Federal District, increases the coefficient the most, from -4.65 to -2.98.

6 Discussion and Conclusion

Questions about the role of electoral manipulations 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: the intimidation theory.

The intimidation theory states 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 in a way that

[41] We also consider it unlikely that the results might by confounded by the past electoral manipulations since the literature shows evidence that electoral manipulations lead to more protests, not less (Tucker, 2007; Way, 2008; Beissinger, 2011; Wellman, Hyde and Hall, 2017).

would signal strength. We tested the association between regime popularity and perceptions of discontent 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. 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 intimidation theory.

The next natural question is, which theory would do a better job at explaining the actual geographic distribution of electoral fraud? Our results suggest that at least three theories are plausible. The first one is the Bayesian persuasion theory (elaborated in Gehlbach and Simpser, 2015; Little, 2015; Egorov and Sonin, 2021). It states that it might be useful for an incumbent to hide true results, often within a certain range of plausible outcomes. Rozenas (2016) offers a version of this argument showing that if the incumbent faces a crisis, then it is in their best interest to gamble by removing the manipulations and getting a chance of sending a cleaner signal to the public. This is a plausible theory for the variation of electoral manipulation in time. Adapting it for the geographical variation in electoral fraud is a promising direction for further analysis.

Another possible explanation is the efficient allocation theory. It is an idea that given the target vote margin, regimes tend to implement manipulations in places where it is easier. This idea is consistent with the practice of fraud in developing countries. For example, Asunka et al. (2019) analyzed the 2012 parliamentary elections in Ghana and demonstrated that electoral manipulations get relocated to precincts without observers. This is also consistent with evidence from Russia, where Enikolopov et al. (2013) found that stations with randomly assigned observers get fewer votes for a pro-regime party in 2011.

Finally, information-gathering might also be one of the goals of the regime. Results of the elections are often used in patronage-dispensation decisions: supporters get rewarded and opponents get punished (Blaydes (2011) demonstrated this mechanism using the case of Mubarak's Egypt). This dynamic suggests that the results of the elections are therefore informative regarding the locations of those supporters and opponents. If the regime uses elections to get such information — and still tries to achieve the desired margins possibly with manipulation — then the locations with the biggest ex-ante uncertainty should stay relatively clean because each additional data point from those places is too valuable. While the Russian Presidential Administration commissions regular public opinion surveys, election can still be useful for assessing whether the dissatisfaction expressed in the surveys translates into political action, such as voting for the alternative candidates. We leave the exploration of this intriguing possibility to further research.

One should also keep in mind that 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.

References

Amiram, Dan, Zahn Bozanic, and Ethan Rouen. 2015. "Financial statement errors: Evidence from the distributional properties of financial statement numbers." *Review of Accounting Studies*, 20(4): 1540–1593.

Ananyev, Maxim, and Kirill Rogov. 2018. "Public Opinion and Russian Politics." In *The New Autocracy: Information, Policy and Politics in Putins Russian.* , ed. Daniel Treisman, Chapter 8, 191–216. Washington DC:Brookings Institution Press.

Ananyev, Maxim, and Sergei Guriev. 2019. "Effect of income on trust: evidence from the 2009 economic crisis in Russia." *The Economic Journal*, 129(619): 1082–1118.

Andreyanov, Pahsa, Alec Davidson, and Vasily Korovkin. 2018. "Detecting Auctioneer Corruption: Evidence from Russian Procurement Auctions."

Asunka, Joseph, Sarah Brierley, Miriam Golden, Eric Kramon, and George Ofosu. 2019. "Electoral fraud or violence: The effect of observers on party manipulation strategies." *British Journal of Political Science*, 49(1): 129–151.

Bader, Max. 2013. "Crowdsourcing election monitoring in the 2011–2012 Russian elections." *East European Politics*, 29(4): 521–535.

Bader, Max, and Carolien van Ham. 2015. "What explains regional variation in election fraud? Evidence from Russia: a research note." *Post-Soviet Affairs*, 31(6): 514–528.

Bailey, Delia. 2008. "Caught in the act: Recent federal election fraud cases." *R. Michael Alvarez, Thad E. Hall, and Susan D. Hyde (eds.), Election Fraud: Detecting and Deterring Electoral Manipulation*, 89–98.

Baker, Peter, and Susan Glasser. 2005. *Kremlin rising: Vladimir Putin's Russia and the end of revolution.* Simon and Schuster.

Beissinger, Mark. 2011. "Mechanisms of Maidan: the structure of contingency in the making of the Orange Revolution." *Mobilization: An International Quarterly*, 16(1): 25–43.

Benford, Frank. 1938. "The law of anomalous numbers." *Proceedings of the American Philosophical Society*, 551–572.

Blaydes, Lisa. 2006. "Who votes in authoritarian elections and why? Determinants of voter turnout in contemporary Egypt."

Blaydes, Lisa. 2011. *Elections and distributive politics in Mubarak's Egypt.* Cambridge University Press.

Boix, Carles, and Milan W Svolik. 2013. "The foundations of limited authoritarian government: Institutions, commitment, and power-sharing in dictatorships." *The Journal of Politics*, 75(02): 300–316.

Brancati, Dawn. 2014. "Democratic Authoritarianism: Origins and Effects." *Annual Review of Political Science*, 17: 313–326.

Buzin, A.E., and A.Y. Lyubarev. 2008. *Crime without punishment. Administrative Technology federal elections 2007-2008.* Niccolo M.

Buzin, Andrei, Kevin Brondum, and Graeme Robertson. 2016. "Election observer effects: A field experiment in the Russian Duma election of 2011." *Electoral Studies*, 44: 184–191.

Chaves, Isaías, Leopoldo Fergusson, and James A Robinson. 2015. "He who counts elects: Economic elites, political elites, and electoral fraud." *Economics & Politics*, 27(1): 124–159.

Corazza, Marco, Andrea Ellero, and Alberto Zorzi. 2018. "The importance of being "one"(or Benford's Law)." *Lettera Matematica*, 1–7.

De Ceuster, Marc JK, Geert Dhaene, and Tom Schatteman. 1998. "On the hypothesis of psychological barriers in stock markets and Benford's Law." *Journal of Empirical Finance*, 5(3): 263–279.

Deckert, Joseph, Mikhail Myagkov, and Peter C Ordeshook. 2011. "Benford's Law and the detection of election fraud." *Political Analysis*, 19(3): 245–268.

Diekmann, Andreas. 2007. "Not the First Digit! Using Benford's Law to Detect Fraudulent Scientific Data." *Journal of Applied Statistics*, 34(3): 321–329.

Drake, Philip D, and Mark J Nigrini. 2000. "Computer assisted analytical procedures using Benford's law." *Journal of Accounting Education*, 18(2): 127–146.

Durtschi, Cindy, William Hillison, and Carl Pacini. 2004. "The effective use of Benford's Law to assist in detecting fraud in accounting data." *Journal of forensic accounting*, 5(1): 17–34.

Egorov, Georgy, and Konstantin Sonin. 2021. "Elections in Non-democracies." *The Economic Journal*, 131(636): 1682–1716.

Egorov, Georgy, Sergei Guriev, and Konstantin Sonin. 2009. "Why resource-poor dictators allow freer media: a theory and evidence from panel data." *American Political Science Review*, 103(04): 645–668.

Enikolopov, Ruben, Alexey Makarin, and Maria Petrova. 2020. "Social media and protest participation: Evidence from Russia." *Econometrica*, 88(4): 1479–1514.

Enikolopov, Ruben, Alexey Makarin, Maria Petrova, and Leonid Polishchuk. 2017. "Social image, networks, and protest participation."

Enikolopov, Ruben, Vasily Korovkin, Maria Petrova, Konstantin Sonin, and Alexei Zakharov. 2013. "Field experiment estimate of electoral fraud in Russian parliamentary elections." *Proceedings of the National Academy of Sciences*, 110(2): 448–452.

Fearon, James D. 2011. "Self-enforcing democracy." *The Quarterly Journal of Economics*, 126(4): 1661–1708.

Forrat, Natalia. 2017. "The Infrastructure of Authoritarianism: State-Society Relationships, Public Sector Organizations, and Regime Resilience in Putin's Russia." PhD diss. Northwestern University.

Forrat, Natalia. 2018. "Shock-Resistant Authoritarianism: Schoolteachers and Infrastructural State Capacity in Putin's Russia." *Comparative Politics*, 50(3): 417–449.

Frye, Timothy, Ora John Reuter, and David Szakonyi. 2014. "Political Machines at Work Voter Mobilization and electoral subversion in the Workplace." *World Politics*, 66(2): 195–228.

Frye, Timothy, Ora John Reuter, and David Szakonyi. 2019. "Hitting them with carrots: Voter intimidation and vote buying in Russia." *British Journal of Political Science*, 49(3): 857–881.

Gandhi, Jennifer. 2008. *Political institutions under dictatorship.* Cambridge University Press Cambridge.

Gandhi, Jennifer, and Ellen Lust-Okar. 2009. "Elections under authoritarianism." *Annual Review of Political Science*, 12: 403–422.

Geddes, Barbara. 2005. "Why parties and elections in authoritarian regimes?"

Geddes, Barbara. 2009. "How autocrats defend themselves against armed rivals."

Gehlbach, Scott, and Alberto Simpser. 2015. "Electoral manipulation as bureaucratic control." *American Journal of Political Science*, 59(1): 212–224.

Gehlbach, Scott, Konstantin Sonin, and Milan W Svolik. 2016. "Formal models of nondemocratic politics." *Annual Review of Political Science*, 19: 565–584.

Golden, Miriam, and Brian Min. 2013. "Distributive Politics Around the World." *Annual Review of Political Science*, 16: 73–99.

Guriev, Sergei, and Daniel Treisman. 2015. "How modern dictators survive: An informational theory of the new authoritarianism." NBER WP 21136.

Guriev, Sergei, and Daniel Treisman. 2019. "Informational autocrats." *Journal of Economic Perspectives*, 33(4): 100–127.

Guriev, Sergei, and Nikita Melnikov. 2016. "War, inflation, and social capital." *American Economic Review: Papers & Proceedings*, 106(5): 230–35.

Hale, Henry. 2007. "Correlates of clientelism: political economy, politicized ethnicity, and post-communist transition." In *Patrons, Clients, and Policies: Patterns of Democratic Accountability and Political Competition.* , ed. Herbert Kitschelt and Steven I. Wilkinson, 227–250. Cambridge University Press Cambridge, UK.

Heron, Randall A, and Erik Lie. 2007. "Does backdating explain the stock price pattern around executive stock option grants?" *Journal of Financial Economics*, 83(2): 271–295.

Hicken, Allen, and Walter R Mebane. 2015. "A Guide to Election Forensics." *U Michigan wp*.

Hill, Theodore P. 1995. "A statistical derivation of the significant-digit law." *Statistical Science*, 354–363.

Kalinin, K. 2018. "Validation of the Finite Mixture Model Using Quasi-Experimental Data and Geography." *International Journal of Elections*.

Kalinin, Kirill. 2008. "Electoral Frauds in Russia: 2004 and 2008 Presidential Elections Compared."

Kalinin, Kirill, and Walter R Mebane. 2009. "Comparative election fraud detection."

Kalinin, Kirill, and Walter R Mebane. 2011. "Understanding Electoral Frauds through Evolution of Russian Federalism: From "Bargaining Loyalty" to "Signaling Loyalty"."

Kalinin, Kirill, and Walter R Mebane. 2017. "Worst Election Ever in Russia?"

Klimek, Peter, Yuri Yegorov, Rudolf Hanel, and Stefan Thurner. 2012. "Statistical detection of systematic election irregularities." *Proceedings of the National Academy of Sciences*, 109(41): 16469–16473.

Kuhn, Patrick M. 2015. "Do contentious elections trigger violence?" In *Contentious Elections*. 103–124. Routledge.

Leemis, Lawrence M, Bruce W Schmeiser, and Diane L Evans. 2000. "Survival distributions satisfying Benford's Law." *The American Statistician*, 54(4): 236–241.

Levitsky, Steven, and Lucan Way. 2002. "The rise of competitive authoritarianism." *Journal of democracy*, 13(2): 51–65.

Lipman, Maria, Anna Kachkaeva, and Michael Poyker. 2018. "Media in Russia: Between Modernization and Monopoly." In *The New Autocracy: Information, Policy and Politics in Putin's Russian.* , ed. Daniel Treisman, Chapter 7, 159–190. Washington DC:Brookings Institution Press.

Little, Andrew T. 2015. "Fraud and monitoring in non-competitive elections." *Political Science Research and Methods*, 3(1): 21–41.

Lorentzen, Peter. 2014. "China's strategic censorship." *American Journal of Political Science*, 58(2): 402–414.

Lorentzen, Peter. 2015. "Chinas Controlled Burn: Information Management and State-Society Relations under Authoritarianism." *Book Manuscript*.

Lorentzen, Peter L. 2013. "Regularizing rioting: Permitting public protest in an authoritarian regime." *International Quarterly Journal of Political Science*, 8(2): 127–158.

Luo, Zhaotian, and Arturas Rozenas. 2018. "Strategies of Election Rigging: Trade-Offs, Determinants, and Consequences." *Quarterly Journal of Political Science*, 13(1): 1–28.

Magaloni, Beatriz. 2006. *Voting for autocracy: Hegemonic party survival and its demise in Mexico.* Cambridge University Press New York.

Mahdavi, Paasha. 2015. "Explaining the oil advantage: effects of natural resource wealth on incumbent reelection in Iran." *World Politics*, 67(2): 226–267.

Malesky, Edmund, and Paul Schuler. 2010. "Nodding or needling: Analyzing delegate responsiveness in an authoritarian parliament." *American Political Science Review*, 104(03): 482–502.

Martinez-Bravo, Monica, Gerard Padró I Miquel, Nancy Qian, and Yang Yao. 2017. "The Rise and Fall of Local Elections in China: Theory and Empirical Evidence on the Autocrat's Trade-off." National Bureau of Economic Research.

Mebane, Walter R. 2006*a*. "Detecting attempted election theft: vote counts, voting machines and Benford's Law." 20–23.

Mebane, Walter R. 2006*b*. "Election forensics: Vote counts and Benford's Law."

Mebane, Walter R. 2007*a*. "Election Forensics: Statistics, Recounts and Fraud."

Mebane, Walter R. 2007*b*. "Evaluating voting systems to improve and verify accuracy."

Mebane, Walter R. 2008*a*. "Election forensics: Outlier and digit tests in America and Russia."

Mebane, Walter R. 2008*b*. "Election forensics: the second-digit Benford's Law test and recent American presidential elections."

Mebane, Walter R. 2016. "Election forensics: Frauds tests and observation-level frauds probabilities."

Medzihorsky, Juraj. 2015. "Election fraud: A latent class framework for digit-based tests." *Political Analysis*, 23(4): 506–517.

Mellnik, Alex, John Mellnik, and Nikolay Zhelev. 2015. "Indications of vote manipulation in the 2011 Russian elections." Samarcand Analytics.

Myagkov, Mikhail G, and Peter C Ordeshook. 2008. "Russian Election: An Oxymoron of Democracy." The National Council of Eurasian and East European Research.

Myagkov, M., P. Ordershook, and D. Shakin. 2005. *The forensics of Election Fraud: Russia and Ukraine.* Cambridge University Press.

Nalepa, Monika, Georg Vanberg, and Caterina Chiopris. 2018. "Authoritarian Backsliding." *Unpublished manuscript, University of Chicago and Duke University.*

Nigrini, Mark. 2012. *Benford's Law: Applications for forensic accounting, auditing, and fraud detection.* Vol. 586, John Wiley & Sons.

OSCE. 2012. "Elections to the State Duma 4 December 2011."

Oster, Emily. 2017. "Unobservable selection and coefficient stability: Theory and evidence." *Journal of Business & Economic Statistics*, 1–18.

Pericchi, Luis Raúl, and David Torres. 2004. "La Ley de Newcomb-Benford y sus aplicaciones al referéndum revocatorio en Venezuela." *Reporte Técnico no-definitivo 2a. versión: Octubre*, 1.

Petrov, Nikolaj, and Aleksey Titkov. 2013. "Regions Democracy Ranking by Moscow Carnegie Center: 10 Years in the Ranks." Carnegie Endowment for International Peace.

Pimbley, J.M. 2014. "Benford's Law and the Risk of Financial Fraud." *Risk Professional*, 1–7.

Porter, Robert H, and J Douglas Zona. 1993. "Detection of bid rigging in procurement auctions." *Journal of Political Economy*, 101(3): 518–538.

Price, Joseph, and Justin Wolfers. 2010. "Racial discrimination among NBA referees." *The Quarterly Journal of Economics*, 125(4): 1859–1887.

Raimi, Ralph A. 1976. "The first digit problem." *American Mathematical Monthly*, 521–538.

R Development Core Team. 2008. "R: A Language and Environment for Statistical Computing." Vienna, Austria, R Foundation for Statistical Computing, ISBN 3-900051-07-0.

Reisinger, William M, and Bryon J Moraski. 2017. *The regional roots of Russia's political regime.* University of Michigan Press.

Reuter, Ora John. 2017. *The Origins of Dominant Parties: Building Authoritarian Institutions in Post-Soviet Russia.* Cambridge University Press.

Robertson, Graeme. 2013. "Protesting putinism: the election protests of 2011-2012 in broader perspective." *Problems of Post-Communism*, 60(2): 11–23.

Rozenas, Arturas. 2016. "Office Insecurity and Electoral Manipulation." *The Journal of Politics*, 78(1): 232–248.

Rozenas, Arturas. 2017. "Detecting Election Fraud from Irregularities in Vote-Share Distributions." *Political Analysis*, 25(1): 41–56.

Rundlett, Ashlea, and Milan W Svolik. 2016. "Deliver the vote! Micromotives and macrobehavior in electoral fraud." *American Political Science Review*, 110(1): 180–197.

Shen, A. 2012. "Elections and Statistics: The Case of "United Russia" (2009-2012)." Working Paper.

Shpilkin, S. 2009. "Statistical research of Russian elections 2007 – 2009." *Troitzkij variant*, 40: 2–27.

Simpser, Alberto. 2013. *Why governments and parties manipulate elections: Theory, practice, and implications.* Cambridge University Press.

Simpser, Alberto, and Daniela Donno. 2012. "Can international election monitoring harm governance?" *The Journal of Politics*, 74(2): 501–513.

Skovoroda, Rodion, and Tomila Lankina. 2017. "Fabricating votes for Putin: New tests of fraud and electoral manipulations from Russia." *Post-Soviet Affairs*, 33(2): 100–123.

Sobolev, Anton. 2019. "Can Independent Media Help Autocrats Suppress Collective Action?" *Unpublished Manuscript*.

Spence, Michael. 1973. "Job Market Signaling." *The Quarterly Journal of Economics*, 87(3): 355–374.

Svolik, Milan W. 2012. *The politics of authoritarian rule.* Cambridge University Press.

Svolik, Milan W. 2020. "When Polarization Trumps Civic Virtue: Partisan Conflict and the Subversion of Democracy by Incumbents." *Quarterly Journal of Political Science*, 15(1): 3–31.

Tam Cho, Wendy K, and Brian J Gaines. 2007. "Breaking the (Benford) Law: Statistical fraud detection in campaign finance." *The American Statistician*, 61(3): 218–223.

Treisman, Daniel. 2001. *After the deluge: Regional crises and political consolidation in Russia.* University of Michigan Press.

Truex, Rory. 2017. "Consultative Authoritarianism and Its Limits." *Comparative Political Studies*, 50(3): 329–361.

Tucker, Joshua A. 2007. "Enough! Electoral fraud, collective action problems, and post-communist colored revolutions." *Perspectives on Politics*, 5(3): 535–551.

Voigtländer, Nico, and Hans-Joachim Voth. 2014. "Highway to Hitler." Department of Economics - University of Zurich Working Paper 156.

Vorobyev, D. 2011. "Towards Detecting and Measuring Ballot Stuffing."

Way, Lucan. 2008. "The real causes of the color revolutions." *Journal of Democracy*, 19(3): 55–69.

Wellman, Elizabeth Iams, Susan D Hyde, and Thad E Hall. 2017. "Does fraud trump partisanship? The impact of contentious elections on voter confidence." *Journal of Elections, Public Opinion and Parties*, 1–19.

Zitzewitz, Eric. 2012. "Forensic economics." *Journal of Economic Literature*, 50(3): 731–769.

Online Appendix

to

"Do Dictators Signal Strength with Electoral Fraud?"

A 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.[42] 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%.

B 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.[43] Source: ICSID.
- 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.

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

[43]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.

- 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.
- 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).

C 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.[44] 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 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):

[44] 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.

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

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.[45] 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 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

[45]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.

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.

D Additional Robustness and Sensitivity Checks

D.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.

	(1)	(2)	(3)
	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 A1: Regressions with Protest Data from Robertson (2013)

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 A1. 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.

D.2 Robustness to Division Into Subregions

In this section, we expand our analysis of the estimations from Table 2 with the extreme turnout as a dependent variable if the regions are divided into subregions: central city of the region, non-central urban area, and rural area. This method allows us to increase the number of observations because Georating data has the question about the urban/rural status of the respondent. Hence this is the finest level of aggregation we can achieve with Georating data (see Ananyev and Guriev (2019) for details). The drawback of this method is that we can only use extreme turnout as the measure of electoral fraud because three other measures of electoral manipulations require a substantial number of observations per location. In addition, Georating data is not representative on municipal level or even district level. Overall, while this method has considerable drawbacks it is important to show the robustness of our coefficient of interest to estimation on a different sample.

Table A2 presents the results. Column 1 replicates baseline estimates for the measure of electoral fraud based on the share of precincts with the extreme turnout from column 4 of Table 2. Column 2 shows results for the same regression measured on a subregional level. The coefficient of interest remains negative and significant. Results hold when column 3 replaces region-level measures of GRP and education with respondents' income and education measured on the sub-regional level using Georating survey.[46] Column 4 adds subregional fixed effects. Finally, column 5 uses the most conservative specification from column 4 but with standard errors clustered on the regional level. Our results hold.

D.3 Alternative Explanation V: 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. Pre-election day fraud is not unusual in authoritarian regimes (Simpser and Donno, 2012). For example, Frye, Reuter and Szakonyi (2014, 2019) 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 A3.

[46] Income is measured as a median subregional self-reported income and education is measured as a proportion of people with university degrees.

	Dependent variable: Extreme Turnout				
	Baseline	(2)	(3)	(4)	(5)
Protest	-4.837^{***}	-3.021^{***}	-3.270^{***}	-2.974^{***}	-2.974^{***}
	(1.508)	(0.713)	(0.725)	(0.719)	(0.928)
GRP	-0.021	-0.238^{**}			
	(0.183)	(0.116)			
Educ	0.033	0.061^{***}			
	(0.026)	(0.016)			
Internet	2.295	1.315	1.878^{**}	1.493^{*}	1.493
	(1.970)	(0.882)	(0.862)	(0.852)	(0.997)
Income (Survey)			-0.078^{***}	-0.078^{***}	-0.078
			(0.025)	(0.025)	(0.047)
Educ (Survey)			2.063^{**}	5.636^{***}	5.636^{**}
			(0.921)	(1.510)	(2.30)
Pop. Density	-0.132	-0.173	-0.024	-0.078	-0.078
	(0.113)	(0.107)	(0.101)	(0.100)	(0.040)
Dist. to Moscow	-0.001	-0.124^{*}	-0.025	-0.059	-0.059
	(0.113)	(0.070)	(0.074)	(0.074)	(0.076)
Treaty	0.091	-0.018	-0.014	-0.002	-0.002
	(0.186)	(0.120)	(0.121)	(0.119)	(0.175)
Subregion FEs				✓	✓
Observations	74	216	216	216	216
R^2	0.352	0.275	0.258	0.296	0.296

Note: (*a*) Column 1 replicates column 4 from Table 2. (*b*) In columns 2–5 observation is a subregion: central city of the region, non-central urban area, and rural area. (*c*) In columns 1–4, robust standard are errors in parentheses. In column 5, robust clustered by region standard are errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A2: Robustness to Division Into Subregions

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 perceptions of discontent. Moreover, the size of the point-estimate for the pre-election day fraud is insignificant. In column 3, we use perceptions of discontent 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 perceptions of discontent means that protests do not depend on pre-electoral fraud.

	(1)	(2)	(3)
	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 A3: Alternative Explanation V: Pre-Electoral Fraud

D.4 Additional Robustness Checks

In this section, we address some additional concerns regarding possible omitted-variable bias. The results are presented in Table A4, 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

	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 A4: Additional Robustness Checks

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 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.

D.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 A5. 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 A5: Selection on Unobservables

D.6 Robustness to Outliers

Table A6 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 A6.

	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 A6: Robustness to Outliers

D.7 Workplace Mobilization and Perceptions of Discontent

The intimidation theory also predicts that the regime will use mobilization tactics to achieve supormajority (Geddes, 2005; Magaloni, 2006). Here we test these additional implications using Levada Center's survey data on political workplace mobilization. The survey happened right after the 2011 election. In particular, we use the fact that one of surveys contained the question whether respondent was pressured by the employer to vote (possibly specifying, to vote for the United Russia) at the upcoming Parliamentary elections. The intimidation theory would predict a positive association between discontent and workplace mobilization.

Here, we use replication dataset from Frye, Reuter and Szakonyi (2019) studying the issue of voter intimidation in the context of Russian Parliamentary elections of 2011. Hence, we follow the authors by using the following question: "Did you notice during the campaign any kind of pressure or coercion by your employer, trying to get you to participate in the elections and support a particular candidate?" We create variable $Pressured_i$ equal to unity if the respondent i answered "Yes" and zero otherwise.[47]

We estimate linear-probability model with $Pressured_i$ as a dependent variable and a measure of perceptions of discontent as an explanatory variable. Because perceptions of discontent may correlate with individual characteristics, most notably age and education, we choose to run our baseline specification on the respondent level. We add controls for respondent's age, gender, employment status, and education. Because the main explanatory variable — perceptions of discontent — is measured on

[47] Approximately, 8% of employed voters answered "yes." See summary statistics in Frye, Reuter and Szakonyi (2019).

the province level, we cluster standard errors on the same level. The main issue with the data, is that it has only 1,600 observation in 43 Russian regions, thus severely reducing the identifying variation. Thus, all results for this specification are marginally significant and should be interpreted with caution as a suggestive evidence that the coefficient of interest is negative.

Table A7 contains results. First column reports results for our baseline measure of perceptions of discontent. Because of the number of regions and clusters (43) the specification is very demanding; however, the coefficient of interest appears to be marginally significant. Respondents living in regions with higher perceptions of discontent were less likely to be pushed to vote in the elections. One standard deviation increase in perceptions of discontent is correlated with 14.5% smaller probability of workforce mobilization. Columns 2 and 3 uses number of protests in November 2011 and September, October, and November of 2011 from Robertson (2013). Negative correlation holds; however, the coefficient becomes insignificant for the specification in column 3.

	(1)	(2)	(3)
	Baseline perceptions of discontent	Robertson's Nov. protests	Robertson's Sep.–Nov. protests
Pressured	-0.145^{*}	-0.010^{*}	-0.004
	(0.088)	(0.005)	(0.008)
Individual Controls	✓	✓	✓
Regional Controls	✓	✓	✓
R^2	0.031	0.031	0.029
Observations	1,600	1,600	1,600

Note: (*a*) First column reports results for the baseline measure of perceptions of discontent (from Table 2). The explanatory variable in the second column is the number of protests in November 2011 from Robertson (2013). The explanatory variable in the third column is the number of protests in September, October, and November of 2011 from Robertson (2013). (*b*) In all columns, we take specification from the baseline results, i.e., Table 2, and extend it by adding further controls. (*c*) Following Frye, Reuter and Szakonyi (2019) individual-level controls include log of age, log of income, gender, dummy for single-company towns (*monogorod*), town size dummies, and education dummies. (*d*) Robust clustered by region standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Online Appendix Table A7: Perceptions of Discontent and Workplace Mobilization

E Additional Tables and Figures

	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 A8: Measures of Electoral Manipulation and perceptions of discontent (w/o Studentizing the Dependent Variable)

	Dependent variable: Electoral fraud (PCA)					
	(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. Sector						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 A9: Alternative Explanation III: Unreliable Field Agents

	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 A10: Ethnic Republics vs. Other Regions

	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 A11: Digit Tests

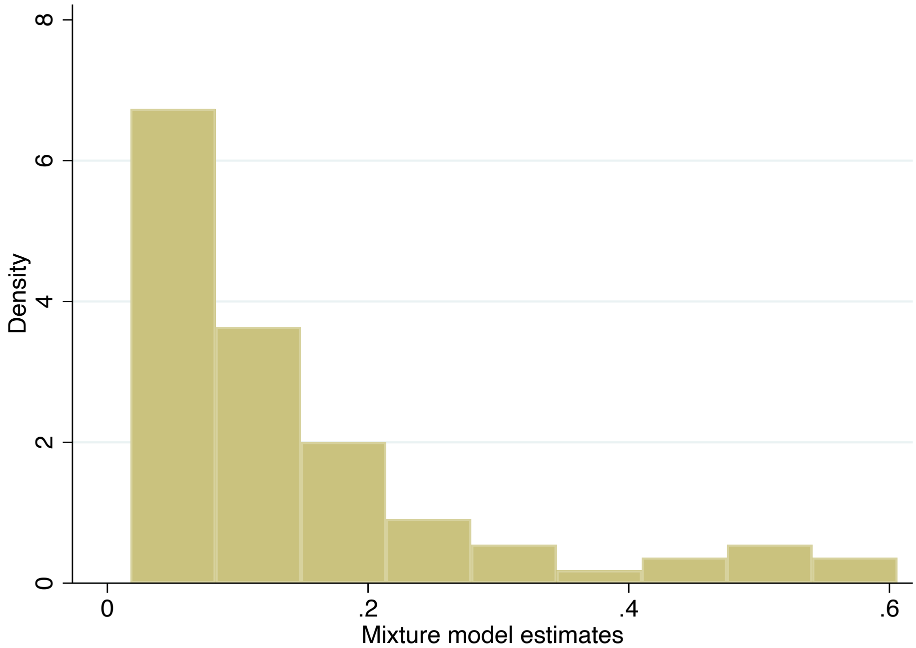
	Dependent variable: Electoral fraud (PCA)	
	Baseline	
	(1)	(2)
Protest	-4.651^{***}	-4.444^{***}
	(1.387)	(1.316)
Population		-0.350^{***}
		(0.120)
Controls	✓	✓
Observations	74	74
R^2	0.358	0.432
Note:		*p<0.1; **p<0.05; ***p<0.01

Online Appendix Table A12: Electoral Manipulation, perceptions of discontent, and Population

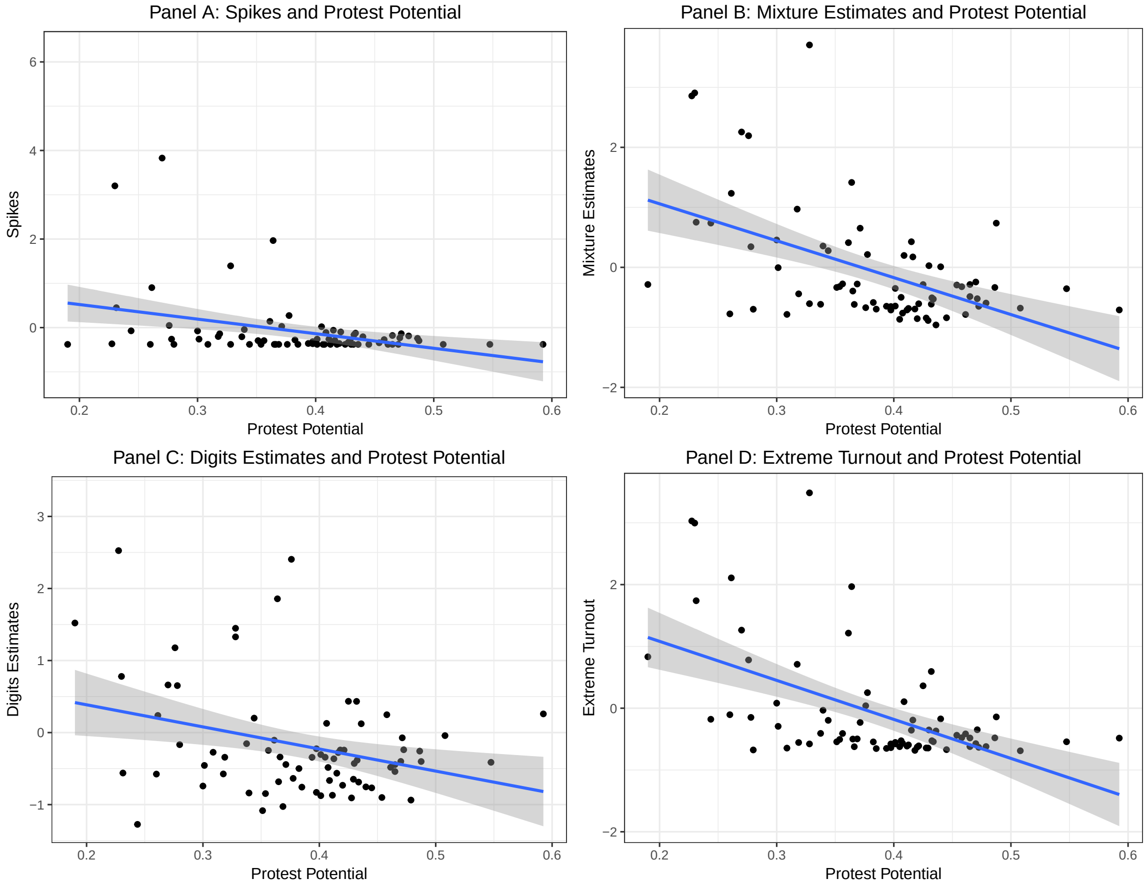
	Dependent variable: Electoral fraud (PCA)				
	(1)	(2)	(3)	(4)	(5)
Protest	-4.651***	-2.836**	-4.403***	-3.873***	-2.559**
	(1.311)	(1.105)	(1.259)	(1.287)	(1.087)
Ethnic Republic		1.069***			0.949***
		(0.287)			(0.265)
Political Competition			-0.209		-0.115
			(0.143)		(0.124)
Urbanization				-0.0281**	-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 A13: Alternative Explanation IV: Additional Institutional Explanations

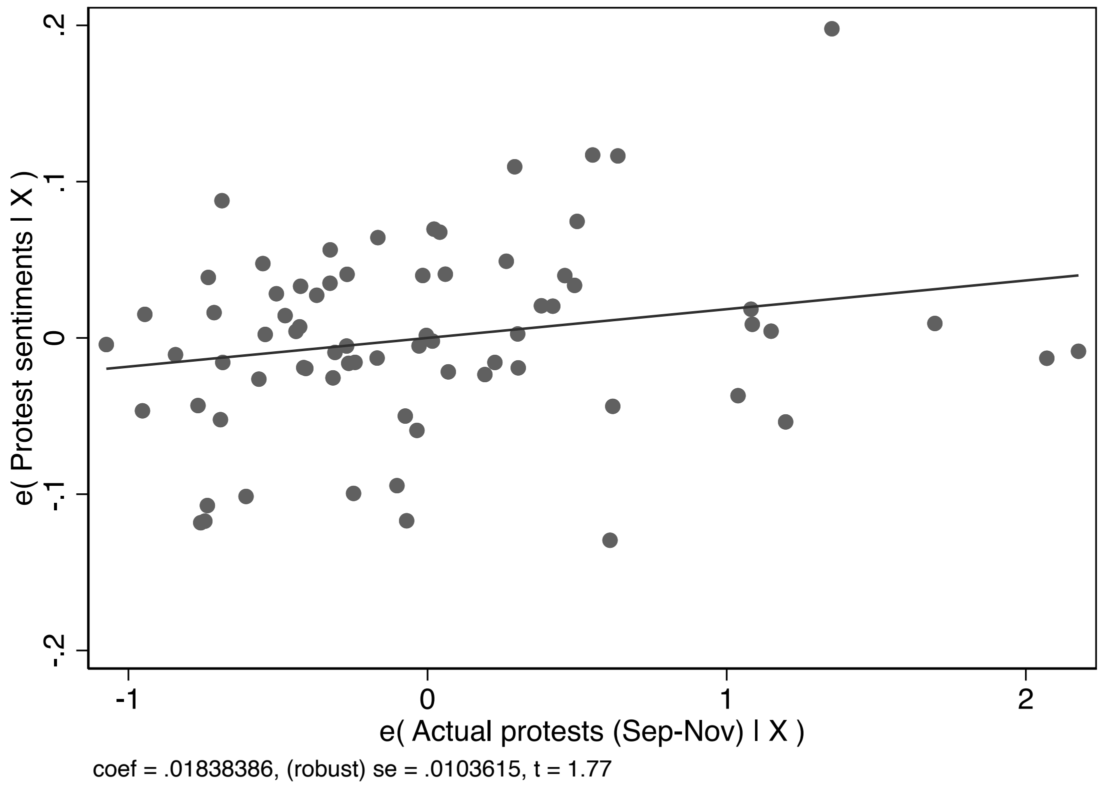


Online Appendix Figure A.1: Histogram of Mixture Model Estimates



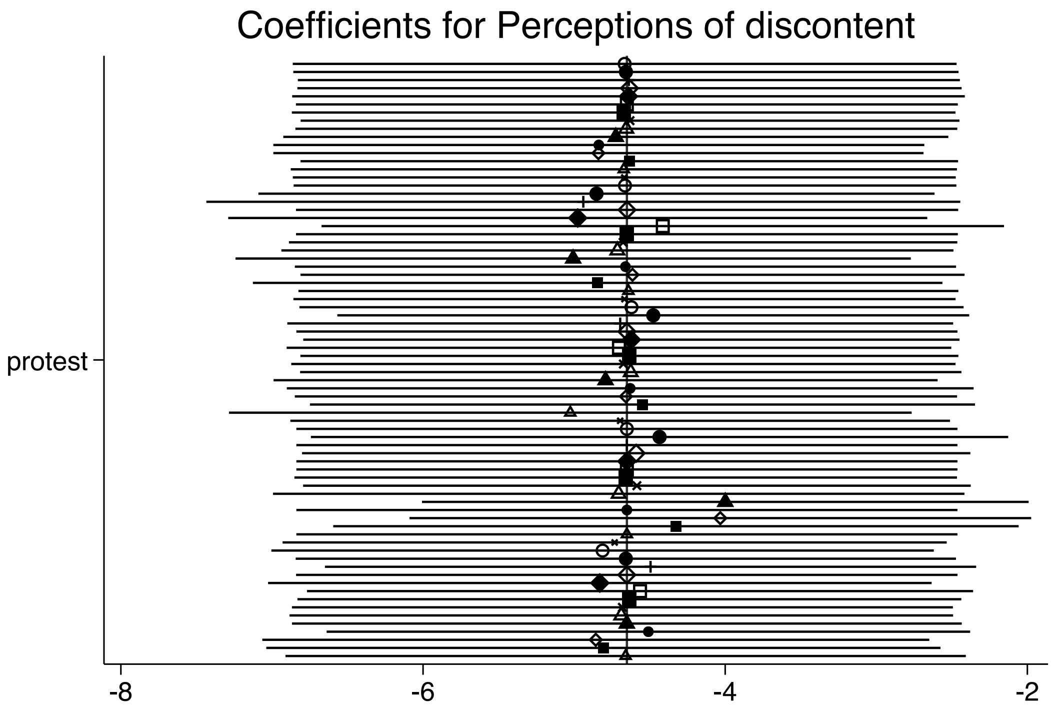
Note: (*a*) Panels A through D above correspond to columns (1) through (4) of Table 2. (*b*) All four measures of electoral fraud exhibit very strong negative correlation with protest sentiments, even without controls. Measures of spikes (A) and extreme turnout (D) capture mostly extreme fraud, thus 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 perceptions of discontent: Scatter Plots



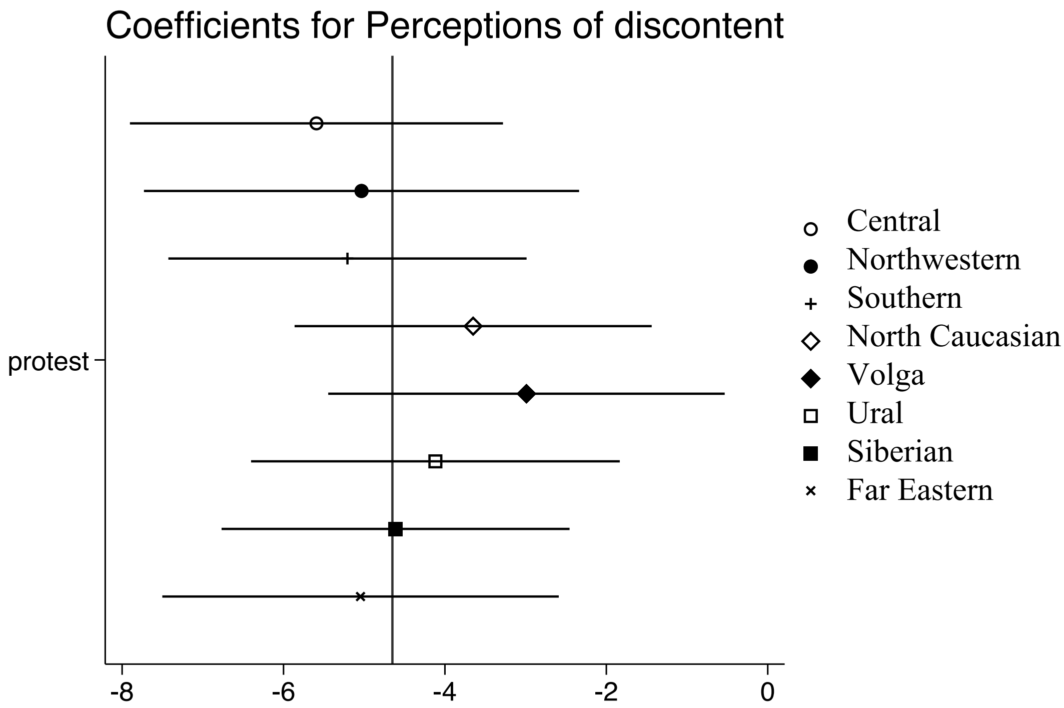
Note: This Figure depicts residual plots of from the regression of the number of actual protests in September-November of 2011 from Robertson (2013) and Georating's protest sentiments (conditional on the baseline set of controls from Table 2).

Online Appendix Figure A.3: Correlation of the Protest Sentiments from Georating with Actual Protests from Robertson (2013)



Note: (*a*) This figure reports on the results of estimating the baseline specification from Column 5 of Table 2. The black vertical line is the point-estimate of β. We then report the point-estimates and confidence bands that result from re-estimating equation (1) but dropping one observation (oblast) at a time (in oblast's vehicle registration plates order, omit Republic of Adygea (BDI), then Republic of Bashkortostan, and etc.). (*b*) 90% confidence intervals are shown.

Online Appendix Figure A.4: Robustness to an omission of an oblast (observation)



Note: (*a*) This figure reports on the results of estimating the baseline specification from Column 5 of Table 2. The black vertical line is the point-estimate of β. We then report the point-estimates and confidence bands that result from re-estimating equation (1) but dropping one Federal District at a time (in west-to-east order, omit Central Federal District, then Northwestern Federal District, and etc.), as indicated in the legend. (*b*) 90% confidence intervals are shown.

Online Appendix Figure A.5: Robustness to an omission of a federal district (observation)