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Fabricating votes for Putin: new tests of fraud and electoral manipulations from Russia

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ABSTRACT

We extend the "fraud forensics" research to systematically explain precinct-level and regional variations in electoral manipulations in Russia's March 2012 presidential election. Parametric last-digit frequency tests (a multivariate extension of last-digit tests) are employed to analyze fraud heterogeneity during the vote count stage. We also utilize author-assembled data harvested from the election monitoring non-governmental organization Golos's regional reports of misconduct to explore the co-variance of last-digit fraud with other irregularities extending beyond the falsification of electoral records. We find that while higher regional education levels positively correlate with exposure of electoral malpractice, an educated populace may also incentivize regional officials to channel misconduct toward election-day fraud – perhaps because pre-electoral manipulations would be more visible to the public than tampering with ballots, and thus, more vulnerable to exposure. Furthermore, last-digit fraud is associated with (a) fake turnout counts; (b) fake votes disproportionally benefitting Putin; and (c) vote "re-distribution" whereby votes cast for some candidates are systematically miscounted. We also find that citizen reports of election-day misconduct are positively correlated with our region-specific last-digit fraud measures. The results indicate that reports by independent observers of sub-national electoral irregularities could be employed as reasonably reliable indicators of fraud, and could be utilized alongside other data to ascertain the incidence of misconduct in Russia and other settings.

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Introduction

In the winter months of 2011–2012, tens of thousands of citizens across Russia took to the streets to engage in anti-regime protests. One of their central concerns had been electoral fraud allegedly perpetrated in the December elections to the State Duma (Smyth, Sobolev, and Soboleva 2013). By many accounts, the extent of the mass uprising took the Putin–Medvedev tandem by surprise. Consequently, every effort was made to indicate to the electorate that the March 2012 presidential election that followed the State Duma race would not be tainted with fraud. The regime's protestations notwithstanding, Golos, Russia's highly respected election monitoring non-governmental organization (NGO), as indeed many other observers, reported substantial violations of electoral integrity (Gel'man 2013a; Kynev et al. 2012). As with Russia's previous elections, pronounced regional heterogeneity had been apparent in the prevalence of misconduct.

In this paper, we extend the rich "fraud forensics" research that relies on statistical procedures to detect fraud, to systematically explain both precinct-level and regional variations in electoral manipulations in

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the March 2012 presidential election. One such "forensic" procedure is the last-digit test, which allows us to ascertain, based on the prevalence of specific numbers on precinct aggregate vote records – notably last-digit zeros – whether votes had been systematically falsified. The assumption behind this analysis is that any systematic heterogeneity in the last digits of numbers entered on electoral precinct return sheets, such as systematic deviation in last-digit frequencies from a uniform benchmark, is inconsistent with clean elections and signals shortcomings in electoral integrity (Beber and Scacco 2012; Mebane and Kalinin 2009; Myagkov, Ordeshook, and Shakin 2009). We contribute to the literature on fraud heterogeneity by using last-digit frequency regression analysis (a multivariate extension of last-digit tests) to capture potential regional co-variates of fraud – notably, those related to regional ethnic composition, education, geographical distance from Moscow, and fiscal dependence on the federal center. We find in particular that education encourages exposure of electoral malpractice, yet we also observe that higher regional education levels may incentivize regional officials to channel misconduct toward election-day fraud – perhaps because pre-electoral manipulations would be more visible to the public than tampering with ballots, and thus, more vulnerable to exposure. To our knowledge, earlier research has not featured the last-digit fraud measure to capture such potential regional co-variates of fraud or of fraud substitution. In concurrent analysis, most recently, Rundlett and Svolik (2016) have pointed to an alternative mechanism of election-day fraud – the rounding of vote shares for the winner Putin to a higher multiple of five. Evidence suggests that the rounding of vote shares appeared to be more widespread in precincts with a higher vote for Putin. Unlike the analysis presented in our paper, Rundlett and Svolik (2016) do not investigate regional correlates of fraud that could make fraud more or less likely, nor do they investigate whether instances of election-day fraud are concentrated in a few individual regions or, alternatively, if fraud has "metastasized" (Lukinova, Myagkov, and Ordeshook 2011) across the country. Our paper therefore nuances our understanding of why fraud is more likely in some regions and not in others while also contributing to the growing literature on electoral malpractice in other settings. Employing electoral data for over 95,000 precincts, we identify the presence of at least three operationally distinct last-digit fraud types: (a) fake turnout counts; (b) fake votes that disproportionally benefitted the winning candidate, in our case Vladimir Putin; and (c) vote "re-distribution" where votes cast for some candidates – notably the pro-Kremlin contender Sergei Mironov – had been systematically miscounted.

The last-digit measure, however, does not allow us to test whether other types of irregularities had been occurring in particular regions, perhaps substituting for election-day last-digit type fraud (or vice versa). Manipulations going beyond the crude writing in of fabricated numbers on election return sheets, which may be detected by applying the last-digit tests, are however notoriously difficult to capture in statistical analysis. Fortunately, we possess additional data that we leverage for these purposes. On the eve of the election, Golos set up a hotline, encouraging citizens to report misconduct occurring both prior to the election and on election day. These reports were then aggregated to create a geographical map of electoral violations. We utilize author-assembled data that we harvested from these Golos records to explore the co-variance of last-digit fraud with other irregularities going beyond the falsification of electoral records. To this end, we propose a simple deviance-based measure of region-specific last-digit fraud that can be used as an explanatory variable in regression analyses of fraud reports. We are not aware of other researchers utilizing Golos-type data in this way to augment "forensic" data on fraud in Russian elections. We find that citizen reporting of election-day misconduct co-varies with last-digit fraud. These findings have important comparative, theoretical, and policy implications. In vast countries such as Russia, Brazil, Mexico, Nigeria, or India, the logistics of securing monitors for each and every polling station may present significant challenges. As Ichino and Schündeln (2012) find, spreading the monitors thinly – and sending them to only select polling stations – may only encourage fraud displacement to localities where monitors are not present. Our analysis does not allow us to establish whether citizen vigilance in fact serves to disincentivize electoral malpractice. Nevertheless, our paper suggests that local eyewitness accounts of misconduct filed by ordinary citizens can be quite accurate in establishing broader territorial patterns of irregularities and could be utilized alongside other data to ascertain the incidence of misconduct in Russia and other settings.

The paper is structured as follows. The second section (which follows) outlines our analytical framework and generates hypotheses. In Sections Methodology, Data and measures, and Analysis, we discuss our measures and data and perform statistical analysis. A sixth (concluding) section provides some reflections on the wider implications of our findings for understanding political regime dynamics in Russia and for comparative theorizing on electoral misconduct.

Theoretical framework and hypotheses

Our analysis builds on the growing body of “fraud forensics” scholarship, which develops statistical procedures for analyzing fraud and specifically for spotting the “fingerprints” of fraud (Argersinger 1985; Beber and Scacco 2012; Deckert and Myagkov 2010; Deckert, Myagkov, and Ordeshook 2011; Lukinova, Myagkov, and Ordeshook 2011; Mebane 2004, 2010, 2011; Mebane and Kalinin 2009; Myagkov, Ordeshook, and Shakin 2005, 2009). Because irregularities can take many different forms,[1] the statistical methodology employed by these studies varies, and is often conditional upon prior assumptions that researchers choose to adopt with respect to the distribution of results in hypothetical “clean” elections. For instance, Mebane (2010) applies multinomial regression analysis to vote counts – that is, vote counts reported by electoral officials – from Iran’s 2009 presidential election and uses the results of the earlier 2005 presidential elections to calibrate the baseline outcomes and to flag individual unexpected – and potentially fraudulent – outcomes. Mebane (2010) also employs the analysis that is based on second-digit Benford’s Law – a prediction as to the observed frequency of numbers in the second digits of official vote counts – that suggests that reported vote counts often deviate from their baseline expected outcomes. One shortcoming of the above vote count regressions as fraud tests, as Mebane readily admits, lies in their sensitivity to cases of strategic voting that can be mistaken for vote count fraud. Vote count regressions work well only if we are prepared to assume that the effect of political processes on voter preferences in the interim years could not in itself produce significant heterogeneity in electoral results. Similarly, the robustness of the second-digit Benford’s Law as a forensic tool when applied to election outcomes has been contested and is hotly debated (Deckert, Myagkov, and Ordeshook 2011; Mebane 2011; Medzihorsky 2015).

In another application of regression analysis that uses Russian precinct-level data, Myagkov, Ordeshook, and Shakin (2009) and Lukinova, Myagkov, and Ordeshook (2011) run region-by-region univariate regressions that help identify regions where, as turnout increases, the opposition party or candidate loses votes in absolute terms. While suggestive of fraud, this analysis has two limitations. First, the region-specific results cannot be generalized beyond the immediate region. Second, and most importantly, fraud is not the only likely explanation of the observed negative correlation between turnout and votes for the opposition candidate or parties. If voter preferences and mobilization potential are correlated – that is, if the proportion of potential pro-opposition voters who do not vote is higher in precincts dominated by pro-incumbent voters – these results can be explained by strategic voting. Finally, while fraud in vote counts is more easily distinguished from the effects of unobserved heterogeneity and strategic voting in natural and field experimental settings (Enikolopov et al. 2013; Fukumoto and Horiuchi 2011), experimental studies may require substantial research resources to set up and remain relatively rare.

In contrast to the above approaches, last-digit tests are both feasible wherever precinct-specific vote counts are publicly available and are robust to the presence of arbitrary levels of strategic voting and unobserved heterogeneity in voter preferences (Beber and Scacco 2012; Deckert, Myagkov, and Ordeshook 2011; Lukinova, Myagkov, and Ordeshook 2011). If election results are not manipulated, then the last digits in the reported election results should be randomly distributed. That is, there should be an (almost) equal proportion of 0s, 1s, 2s, … 9s. However, numerous studies have documented electoral fraud by identifying systematic deviations from these predictions. For instance, when applied to turnout counts in four consecutive Russian national elections (2003–2008), the last-digit test typically rejects the null hypothesis of uniformly distributed lasts digits (Mebane and Kalinin 2009). A similar test applied to Sweden’s 2002 parliamentary elections reveals no deviations from uniform distribution

(Beber and Scacco 2012). Widely used non-parametric last-digit fraud tests on pooled data, such as a Chi-square (henceforth Chi2) test are, however, silent on whether instances of fraud are concentrated in one or two regions or, alternatively, if fraud is spread across regions. Equally, these tests do not tell us whether last-digit fraud co-varies with region-specific developmental and political variations – for instance, those related to regional education levels or fiscal dependence on the center. We contribute to the literature, *inter alia*, by using last-digit frequency regression analysis as a multivariate extension of last-digit tests. Our strategy should help scholars test sharp and well-defined predictions firmly rooted in the micro-logic of fraud, which we shall discuss next.

While fraud can be perpetrated under a variety of political regimes (Argersinger 1985; Leemann and Bochsler 2014), recent research suggests that it is particularly widespread in autocracies, and, specifically, that autocrats are often keen to inflate turnout figures and votes for the winning candidate (Rundlett and Svolik 2016; Simpser 2013; Sjoberg 2014). Myagkov, Ordeshook, and Shakin (2009) and Lukinova, Myagkov, and Ordeshook (2011) report suspicious turnout distributions in some of Russia's regions and smaller *rayony* (sub-regional districts) where turnout is suspiciously high and/or turnout distribution is double peaked – that is, appears as having two different modes or local maxima. Consistent with Russia's slide into authoritarianism over the last decade, they find evidence that these observed empirical irregularities have gradually "metastasized" across regions in successive elections. Turnout- and vote-inflating electoral fraud may serve a number of related purposes. First, inflated turnout numbers may be used to signal to the regime's supporters the regime's legitimacy and strength. Second, inflated margins of victory can discourage the opposition and deter future challengers (Magaloni 2006; Simpser 2013). The literature on electoral clientelism suggests that the loyalties of a national regime's clients could be fragile if the regime appears weak (Hale 2007; Kitschelt and Wilkinson 2007; Rigger 2007). National officials therefore often expect grotesquely high – fraudulent – results to be delivered by their sub-national clients even if fraud is likely to be exposed. In fact, Simpser (2013) suggests that the ability to perpetrate blatant electoral fraud – and get away with it – may be intended deliberately as a signal to the autocrat's clients that the regime is invincible.

The literature on sub-national politics, however, also points to significant heterogeneity in sub-national development and regime types within one national setting and, relatedly, in the propensity of regional and local officials to perpetrate electoral misconduct (Gibson 2013; Giraudy 2013; Kitschelt and Wilkinson 2007; Lankina 2004; Lehoucq and Jiménez 2002; Magaloni, Diaz-Cayeros, and Estévez 2007; Stokes 2007; Wahman 2015). Variables related to local socioeconomic development (Lehoucq 2003; Lehoucq and Jiménez 2002; Stokes 2007), the degree of fiscal dependence of a locality on the national purse (Gervasoni 2010), regional machine politics (Eisenstadt 2004; Gel'man 2013b; Gibson 2013), or media freedom (Birch and van Ham 2014) could all affect the probability of manipulations in individual regions, or the likelihood that electoral results are marred with fraud rather than being products of voter choice or strategic voting. In our analysis, it is therefore important to perform fully parametric tests, such as multivariate regressions, that would control for these region-specific variations; non-parametric and univariate analyses of sub-national fraud heterogeneity are most likely affected by omitted variable bias and may generate spurious results.

To illustrate the above point, let us assume that precincts with characteristics $x_{1,i}, \dots, x_{K,i}$ report fraudulent results with probability $\alpha_f = \alpha_f(x_{1,i}, \dots, x_{K,i})$. Factors $X_1, \dots, X_K$ can both include precinct-specific variables (for instance, reported turnout) and region-specific (for instance, socioeconomic) variables. Assume further that the probability of last-digit zeros across precincts that report clean results is 0.1, whereas in precincts that report fraudulent results this probability is $p_f \neq 0.1$. Then the overall expected probability of last-digit zeros $0.1 + (p_f - 0.1)\,\alpha_f(x_{1,i}, \dots, x_{K,i})$ is a function of factors $X_1, \dots, X_K$ and generally deviates from the 10% benchmark. The goal of our parametric analysis, then, is to test whether we observe a systematic deviation from the uniform distribution of last digits across precincts and across regions and whether the relative probabilities of last digits and, hence, the likelihood and magnitude of last-digit fraud, co-vary with a pre-determined set of explanatory variables.

Accordingly, and with reference to the micro-logic of fraud discussed above, we propose:

H1: Sub-national last digit heterogeneity in the March 2012 presidential election is, in part, systematic. Last-digit fraud will be observed across multiple regions.

H2: Sub-national last-digit fraud will co-vary with reported turnout and with the share of votes cast for individual candidates, including the winner Putin. This effect will be observed even when we control for political and socio-economic variables that have been conventionally identified as increasing or reducing the support for national incumbents or otherwise affecting the propensity for fraud.

Election-day fraud usually refers to ballot-stuffing, tampering with vote tallies, and other forms of interference with voting results (Argersinger 1985; Calingaert 2006; Cox and Kousser 1981; Gerring and Thacker 2004; Lehoucq 2003). Researchers have therefore pointed to limited specificity of last-digit tests as a forensic tool because last-digit tests target a specific type of fraud mostly consisting of the writing in of fabricated numbers on precinct return sheets and may not detect cases of forced voting, multiple voting, and ballot stuffing (Enikolopov et al. 2013). Furthermore, a new generation of fraud literature is beginning to systematically analyze not just whether a particular fraud type is perpetrated, but whether it occurs in conjunction with, or in lieu of, other types of irregularities (Beaulieu and Hyde 2009; Ichino and Schündeln 2012; Simpser 2013; Simpser and Donno 2012; Sjoberg 2014). Research into the "menu[s] of manipulation" (Schedler 2002) conventionally distinguishes between pre-electoral manipulations and election-day fraud. Pre-electoral manipulations are widespread in settings where the electorate is dependent on the public sector for welfare payments, subsidies, or contracts; in backward rural settings; or those reliant on national fiscal transfers. Under such conditions, political machine bosses or enterprise managers routinely pressure the electorate to agree to vote for particular candidates in exchange for jobs, promises of job security, salaries, or public contracts (Frye, Reuter, and Szakonyi 2014; Gervasoni 2010; Gibson 2013; Hale 2007; Rigger 2007; Sharafutdinova 2011; Stokes 2007; Wilkinson 2007). In clientelistic settings, voters are often compliant, knowing that private rewards will accrue to them if they vote as instructed. Compliance is less likely in wealthier urban areas where the electorate might be more enlightened about the public goods advantages of fair elections, or prosperous enough not to be seduced by small cash hand-outs (Kitschelt and Wilkinson 2007; Lehoucq and Jiménez 2002; Magaloni, Diaz-Cayeros, and Estévez 2007; Stokes 2007).

We contribute to this literature by including in our analysis the Golos reports of pre-electoral manipulations and of election-day irregularities (discussed in the section on data and measures). In employing Golos election-day reports of misconduct, we opt for the term "reporting election-day misconduct" because our aggregate Golos counts of citizen witness accounts of misconduct that occurred on 4 March do not allow us to distinguish between what would be conventionally defined as fraud – for instance, tampering with vote tallies – versus, for example, election-day voter intimidation, which would be conventionally labeled as "manipulations." We believe that the term "election-day misconduct" best captures the plethora of fraudulent and manipulative activities that are detailed in the Golos report of the 2012 election (Kynev et al. 2012). Prior literature suggests that sub-national authorities in Russia tend to resort to a variety of complementary strategies of misconduct that often include both citizen manipulations (such as busing factory workers to the polling booths) and conventional election-day ballot-stuffing and other types of fraud (Hale 2007; Reisinger and Moraski 2009). Our analysis should help us more systematically ascertain the probability of resorting to manipulations going beyond the writing in of fabricated numbers on electoral return sheets.

Accordingly, we propose:

H3: Citizen reports of election-day misconduct will be positively correlated with last-digit fraud.

Since reports of election-day misconduct are aggregated by region, we test H3 by proposing two new (yet straightforward) measures of region-specific last-digit heterogeneity that are based on the concept of likelihood ratio (deviance) and are explained in detail in the methodology section.

Methodology

Last-digit frequencies

We start by observing that, in clean elections, last digits in turnout counts reported by individual precincts with at least 100 registered voters can be regarded as outcomes of identical and independent multinomial trials where individual digits $j \in \{0, 1, \dots, 9\}$ are observed with uniform probability $P_j = p = 0.1$ (Beber and Scacco 2012). The parametric analysis of last-digit fraud in this paper is based, therefore, on the multinomial logistic regression model specified for a categorical dependent variable $j_i \in \{0, 1, \dots, 9\}$ that records last digits in turnout counts reported by individual precincts *i* with at least 100 registered voters. If uniform distribution of last digits is a property shared by all precincts across the country, it follows that the observed probabilities of individual last digits should be equal and, in particular, should co-vary neither with precinct-level variables, nor with regional political and socioeconomic factors. We build on prior research that identifies precinct-specific and region-specific factors $X_1, \dots, X_K$, for which we observe realizations $x_{1,i}, \dots, x_{K,i}$, which could affect the likelihood of election fraud and hence could "skew" the relative probabilities of individual last digits from the uniform benchmark.

Multinomial logistic regression models the relative probabilities (relative risks) of last digits as follows:

$$\frac{Pr_i(Last\ Digit\ =\ j)}{Pr_i(Last\ Digit\ =\ base\ outcome)} = \exp\left(\alpha^{(j)} + \sum_{k=1}^{K} \beta_K^{(j)} x_{k,i}\right). \tag{1}$$

The choice of the base outcome or base category affects the interpretation of the estimated coefficients $\alpha^{(j)}$ and $\beta_\kappa^{(j)}$, yet it does not affect the predicted probabilities for individual last digits. In clean elections, regardless of the choice of the base outcome, the estimated coefficients $\alpha^{(j)}$ and $\beta_\kappa^{(j)}$ should be (mostly) statistically insignificant. Strictly speaking, after fitting regression (1) using clean elections data, we can expect about 5% of coefficients to show "false positive" findings and *p*-values of 5% and lower due to Type I error – that is, the incorrect rejection of a true null hypothesis of clean elections. Higher proportions than this of statistically significant coefficients in clean elections are increasingly unlikely.

In fraudulent elections, where the magnitude and the exact nature of last-digit fraud generally vary with contextual variables, the proportion of statistically significant coefficients in (1) generally depends on the choice of the base outcome. In these circumstances, the joint significance tests on linear hypotheses that are invariant to the choice of the base outcome can be particularly useful. Accordingly, for all individual X_k, we test the null hypothesis that $\beta_\kappa^{(j)}$ are *jointly* equal to zero for all $j \in \{0, 1, \dots, 9\}$. This tests whether there is an association between the corresponding independent variable X_k and the 10 categories of last digits and their relative probabilities. In addition to being invariant to the choice of the base outcome, this test is agnostic to the exact nature of the last-digit fraud. In other words, this test is equally good at spotting a potential overabundance of last-digit zeros as it is good at spotting a relative scarcity of, say, 3's.

The second post-estimation test after the multinomial regression (1) draws on the results of Beber and Scacco (2012) and Mebane and Kalinin (2009), who specifically report an overabundance of zeros in last-digit frequencies in election results. The tests are focused on last-digit zeros, which may constitute a particularly "sensitive" category, and could provide statistical inference that is, potentially, sharper than the joint significance tests on all $\beta_\kappa^{(j)}$. Accordingly, our next step is to test whether there is an association between explanatory factors and the relative probabilities of last-digit categories 1 to 9, excluding last-digit zeros. The null hypothesis in this test assumes that the true population effects $\beta_\kappa^{(j)}$ are equal across categories $j = 1, \dots, 9$. If, for a particular predictor X_k, the first of the joint hypotheses $\beta_\kappa^{(j)} = 0$, for all $j \in \{0, 1, \dots, 9\}$ is rejected and the second hypothesis $\beta_\kappa^{(j1)} = \beta_\kappa^{(j2)}$, for all $j_1, j_2 \in \{1, \dots, 9\}$ is accepted, this would suggest that the corresponding X_k has a differential effect on last-digit categories and that last-digit zeros, in particular, is the category that is affected disproportionally.

The final leg of the last-digit analysis, therefore, relies on (binomial) logistic regressions that investigate the prevalence of last-digit zeros in more detail. The dependent variable equals one if the last digit in the reported turnout is zero; it is equal to zero otherwise. Considering that last-digit zeros in turnout counts are found to be over-reported in precincts that report particularly large (top quartile) turnout figures, we investigate whether the prevalence of last-digit zeros co-varies with vote counts cast for individual candidates. For this analysis, we use the ratio of the vote counts for individual candidates, as reported by precincts, to the total number of registered voters who are eligible to vote in the reporting precinct. This specification helps to distinguish among three alternative scenarios. First, if last-digit fraud is driven exclusively by the need to show higher turnout figures, which is unlikely, there is going to be no significant association between vote counts for individual candidates and last-digit zeros. Second, if fake votes that are added to the turnout figures disproportionally benefit one or two candidates, the vote counts for these candidates are likely to be positively correlated with last-digit turnout zeros. Finally, if last-digit zeros are negatively correlated with vote counts reported for some of the candidates, this would indicate that some of their votes have been (mis-) counted as if cast for other candidates.

An alternative specification to the multinomial logistic regression (1) could analyze last-digit frequencies aggregated by region using Poisson regressions with a panel-like analysis where cross-sectional index i indicates individual regions and last-digit categories $j \in \{0, 1, \dots, 9\}$ treated as individual "panels" collected across the regions. Even though the analysis based on Poisson-type count models could be informative and could potentially offer some additional insights, it can only handle voting data aggregated by region and cannot be used to analyze intra-regional fraud heterogeneity.

Citizen reports of election-day misconduct

The second part of our analysis focuses on citizen reports of election-day misconduct tallied by the NGO Golos. The report counts are available for individual regions. The aim is to test whether citizen reports of misconduct co-vary with last-digit fraud. Here, the dependent count variable, the number of Golos reports of election-day misconduct, is regressed on the variables of interest while controlling for the number of Golos reports of pre-electoral manipulations occurring during the electoral campaign in the same region. This specification allows us to control for the unobserved factors common to election-day and pre-electoral manipulations, such as region-specific propensity to report. As the count-dependent variable is characterized by overdispersion (or extra-Poisson variation), we use negative binomial regressions. We also control for the total number of polling stations in the region, as election-day reports are likely to pertain to individual polling stations where individual instances of fraud are taking place. A region with a relatively higher rate of election-day fraud, but with fewer polling stations (lower n) might have fewer total instances of reported irregularities.

Our measure of region-specific last-digit fraud – the key explanatory factor in this analysis – is based on the likelihood ratio statistic L^2 that is defined as

$$L_i^2 = 2\sum\left(O_{ij}\log\left(\frac{O_{ij}}{E_{ij}}\right)\right),$$

where O_{ij} is the observed frequency of digit j in region i, $E_{ij} = n_i/10$ is the expected frequency of digit j, and n_i is the total number of polling stations in the region. Relatively larger values of L^2, for a fixed n, indicate that last digits are distributed relatively less evenly and hence are consistent with more widespread last-digit fraud. The likelihood ratio statistic L^2 relates to the concept of *deviance* in the theory of Generalized Linear Models and this statistic and Pearson's Chi2 represent the two most commonly used measures of "goodness of fit" between the observed and the expected outcomes of categorical data (Agresti 1990). The two measures both converge to a χ^2 (in our case, $\chi^2(9)$) distribution and give very close answers in large samples where the expected frequencies E_{ij} in all categories have values of 5 or greater (our data comfortably satisfy this requirement). Between deviance L^2 and Pearson's Chi2 we prefer to use L^2, as this measure has an attractive additivity property and can be easily partitioned into independent chi-squares. Specifically, we define

$$Deviance_{0,i} = 2\left(O_{i0}\log\left(\frac{O_{i0}}{0.1n_i}\right) + (n_i - O_{i0})\log\left(\frac{n_i - O_{i0}}{0.9n_i}\right)\right),$$

and

$$Deviance_{1-9,i} = 2\left(O_{i1}\log\left(\frac{O_{i1}}{\frac{(n_i-O_{i0})}{9}}\right) + \cdots + O_{i9}\log\left(\frac{O_{i9}}{\frac{(n_i-O_{i0})}{9}}\right)\right). \quad (2)$$

It is easy to see that $Deviance_{0,i} + Deviance_{1-9,i} = L^2$ and that the total deviance (that is, heterogeneity) in last-digit frequencies is split into two parts. While $Deviance_0$ is approximately $\chi^2(1)$ and measures the part of the total heterogeneity that is due to under- or over-reported last-digit zeros, $Deviance_{1-9}$ is approximately $\chi^2(8)$ and measures the heterogeneity across digits 1 to 9. This allows us to test the independent effect of excess zeros on election-day misconduct reports, while controlling for last-digit heterogeneity that comes from digits 1 to 9.

When $Deviance_0$ and $Deviance_{1-9}$ are used in regression analysis as measures of fraud, we ought to control for (region-specific) sample size n_1 – the total number of polling stations in the region. This is due to the fact that deviance measures of fit both reflect the amount of region-specific fraud and the (region-specific) power of the statistical tests at the same time. This is easy to see: if the sample size n_1 and all frequencies O_{ij} are multiplied by a factor k, so are $Deviance_{0,i}$ and $Deviance_{1-9,i}$. Clearly, a region with relatively less fraud, but with more polling stations (larger n) might end up having higher deviance statistics than a region with more fraud and fewer polling stations (smaller n). As a result, if sample size n_1 is omitted from the regression specification and if n_1 varies systematically with any of the regressors, the estimates are likely to be biased. Accordingly, we model the expected number of citizen reports of election-day irregularities as follows:

$$\begin{aligned} E_i(\mathit{Reporting\ Election - Day\ Misconduct}) = \ & \exp(\alpha + \beta_1 \log(Deviance_{0,i}) + \beta_2 \log(Deviance_{1-9,i}) \\ & + \beta \text{controls}), \end{aligned} \quad (3)$$

where control variables include, among others, *log* (1 + *Reporting Pre-electoral Manipulations*$_i$), and log (n_i). In this specification, a 1% increase in $Deviance_0$ is associated with a β_1% increase in the rate of citizen reports of misconduct on election day, controlling for other factors, that is, "as if" all regions had equal numbers of polling stations and "as if" all regions had similar propensities to report irregularities. A 1% increase in $Deviance_{1-9}$ results in a β_2% increase in the rate of citizen and election monitor complaints.

The two parts of the analysis (the multinomial/logit analysis of last-digit frequencies on the one hand, and the analysis of citizen reports of irregularities on the other) are closely linked and should be interpreted together. If last-digit tests reveal that the frequencies of last-digit zeros are relatively more sensitive to factors such as turnout and that the frequencies of digits 1 to 9 are relatively less sensitive, hypothesis H3 would expect election-day misconduct reports to be relatively more strongly correlated with the systematic part of last-digit heterogeneity, namely $Deviance_{0,i}$, and not necessarily correlated with its relatively less systematic and more random $Deviance_{1-9,i}$.

Data and measures

Outcome variables

We employ precinct data for the 2012 presidential election obtained from the Russian Electoral Commission website. The election featured five contenders (several others had been excluded from the race). Aside from the Prime Minister Vladimir Putin, there were two seasoned contenders with a long history of participation in Russia's presidential races – Gennadii Zyuganov, the candidate from the established Communist Party of the Russian Federation (CPRF); and Vladimir Zhirinovsky, the candidate from the Liberal-Democratic Party of Russia (LDPR). The two other candidates were Sergei Mironov, representing the pro-Kremlin Just Russia Party; and Mikhail Prokhorov, an independent, party-unaffiliated, candidate and one of Russia's leading industrialists, whom some analysts considered a "Kremlin project" despite his criticism of the politics of the Putin–Medvedev tandem. Putin obtained 63.6% of the total vote, while Zyuganov, Zhirinovsky, Mironov, and Prokhorov obtained 17.2, 6.2, 3.9, and 8% of the vote, respectively. In our analysis, we employ turnout and vote count statistics for each candidate that cover 95,415 precinct-level (*uchastkovye*) polling stations subordinated to the regional Territorial Electoral Commissions (*territorial'nye izbiratel'nye komissii*).

The first outcome variable is *Fraud*. The measures for this variable are last digits $j_i \in \{0, 1, \dots, 9\}$ in turnout counts reported by individual precincts *i* with at least 100 registered voters. The second (regional-level) outcome variable, *Reporting Election-Day Misconduct*, is the number of election-day reports of irregularities filed by citizens and election monitors and tallied by the NGO Golos (Kynev et al. 2012). In September 2011, Golos created a special "hotline" inviting citizens to post reports of observed pre-electoral and election-day misconduct. Subsequently, these reports served as the basis for constructing a regularly updated geographic "map of irregularities" (*karta narushenii*). The portal also has a search engine that enables analysts to obtain quantitative data on electoral misconduct by region. An example of election-day fraud reports would be election monitors or ordinary citizens supplying video footage of electoral officials tampering with ballots. An example of other types of irregularities observed on election day would be election monitors being forced out of a polling station by a police officer.

Key independent variables

Our key independent variables are *Turnout*; vote counts for individual Presidential candidates (*Putin's Vote*, *Zyuganov's Vote*, *Zhirinovsky's Vote*, *Mironov's Vote*, and *Prokhorov's Vote*) taken as ratios to the total number of registered voters who are eligible to vote in the reporting precinct; and the two measures of last-digit heterogeneity in turnout counts $Deviance_{0,i}$ and $Deviance_{1-9,i}$.

Control variables

As noted above, we use the region-level measure for *Reporting Pre-electoral Manipulations* to control for the general propensity to *report* manipulations. Examples of reported pre-electoral manipulations would be complaints that enterprise managers exert pressure on employees to cast a vote for Putin; or a student reporting being threatened with expulsion from university for canvassing for opposition candidates. Conventionally, regional variations in electoral misconduct have been explained in terms of differences in regional socioeconomic conditions; education; the degree to which regions are fiscally dependent on the federal center; ethnic structure; and strength of regional political machines. By explicitly controlling for these variables in the regression analysis, we test whether *Putin's Vote* is independently associated with last-digit fraud over and above the effects associated with regional political and socioeconomic factors. It is also important to note that, to the extent that *Reporting Election-Day Misconduct* may proxy for factors not directly related to fraud, such as citizen propensity to report manipulations and fraud, the explanatory power of last-digit fraud (deviance) measures is likely to be weakened by the inclusion of a comprehensive set of the relevant control variables. Furthermore, some scholars have suggested that pre-electoral manipulations make election-day irregularities superfluous. We therefore employ data available from Russia's yearly official statistical compilations to incorporate the variables of *Income per Capita*, geographical *Distance from Moscow* (in '000s km), the proportion of population with a *University Degree*, and *Fiscal Transfers* as a share of regional budgets. These variables capture citizen socioeconomic vulnerabilities (and corresponding propensity to succumb to pressures to deliver a pro-incumbent vote or to challenge electoral misconduct); the potential effect of geographic proximity to the national center of power; regional developmental variations, notably citizen education levels, that could capture propensity to tolerate and report misconduct; and the degree of regional financial dependence on the federal center.

In addition, we employ two variables that capture variations in regional ethnic composition and that had been in previous research linked to sub-national electoral clientelism and machine politics. Specifically, regions with the status of ethnically defined republics and those with substantial non-ethnic Russian populations tend to be more likely to produce anomalously high voting in favor of pro-Kremlin candidates and parties in national elections. These patterns have been explained with reference to

Soviet-era ethno-patronage networks whereby non-Russian groups received material transfers from the federal center in exchange for loyalty. To capture these "correlates of clientelism" (Hale 2007), we employ the variables of the share of ethnic *Russians* in regional populations and regional status (*Oblast*). Further robustness tests control for *Urbanization*, which tends to co-vary with our *Fiscal Transfers* and with *University Degree* variables, and *Media Freedom*, a variable employed in other studies of electoral malpractice (Birch and van Ham 2014; Wilkinson 2007) and which we capture by employing an index developed by scholars at the Moscow Carnegie Centre, a respected think tank (Petrov and Titkov 2013). The index encompasses regional media pluralism, censorship, and independence of media sources from municipal and regional authorities.

Analysis

We begin with non-parametric last-digit tests in turnout counts, valid vote counts, and votes cast for the winner Vladimir Putin in the March 2012 Presidential election, ignoring the differences across individual regions for now. In accordance with prior literature that applied last-digit tests to electoral fraud, we exclude polling stations with less than 100 registered voters; this reduces the sample size from 95,415 to 91,114 precincts. Table 1 reports that, based on the likelihood ratio L^2 statistics, the null hypothesis of uniformly distributed last digits is rejected for turnout counts and valid vote counts. The test results for the sub-sample of precincts that excludes ethnic republics are only marginally weaker than those for the full sample. This suggests that instances of fraud are not limited to ethnic republics. Secondly, Beber and Scacco (2012) suggest that deviations from a uniform distribution in last-digit frequencies are often caused by an overabundance of zeros. The hypothesis that assumes that the probability of last-digit zeros is 10% is tested against the sample statistics $Deviance_0$ and is rejected for turnout counts, valid vote counts, and votes cast for the winner Putin (in the full sample). Thirdly, the hypothesis of uniform distribution of digits 1 to 9 (excluding last-digit zeros) is tested against the sample statistics $Deviance_{1-9}$ and is rejected for turnout counts. Figure 1 plots the proportions of last digits in turnout counts and their 95% confidence intervals estimated after a univariate multinomial logistic regression. Overall, these results confirm the presence of last-digit fraud in the election and reveal the fact of marked over-reporting of last-digit zeros in particular.

Though informative, these non-parametric fraud tests mask important heterogeneity across regions. We illustrate this heterogeneity, first, by performing region-specific last-digit Chi2(9) tests on turnout counts reported by precincts in individual regions. The region-specific tests are based on L^2 statistics (see the sub-section on Citizen Reports of Election-Day Misconduct in the Methodology section) and

Table 1. Last-digit tests (likelihood-ratio Chi2) for last-digit frequencies in turnout counts, valid vote counts, and votes cast for Putin; March 2012 presidential elections.

	Turnout		Valid votes		Vote count, winner	
	Full sample	Excl. republics	Full sample	Excl. republics	Full sample	Excl. republics
H0: Last digits are distributed uniformly						
L^2 statistics						
Chi2(9)	52.61**	23.98**	40.70**	16.22	14.84	9.67
p-value	0	0.004	0	0.063	0.095	0.377
H0: The probability of last-digit zeros is 10%						
$Deviance_0$						
Chi2(1)	33.13**	7.82**	27.74**	4.24*	4.09*	2.98
p-value	0	0.005	0	0.04	0.043	0.084
H0: Last digits 1–9 are distributed uniformly						
$Deviance_{1-9}$						
Chi2(8)	19.48*	16.16*	12.97	11.98	10.75	6.69
p-value	0.013	0.04	0.113	0.152	0.216	0.57
N obs.	91114	72353	91114	72353	91114	72353

*Rejection at the 5% level; **Rejection of the corresponding H0 at the 1% level.

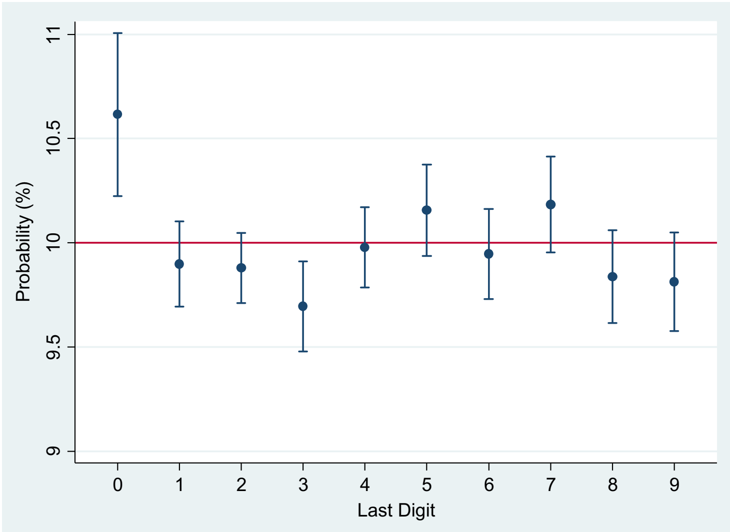

Figure 1. Proportions of last digits in turnout counts (based on univariate multinomial logistic regression) with 95% confidence intervals.

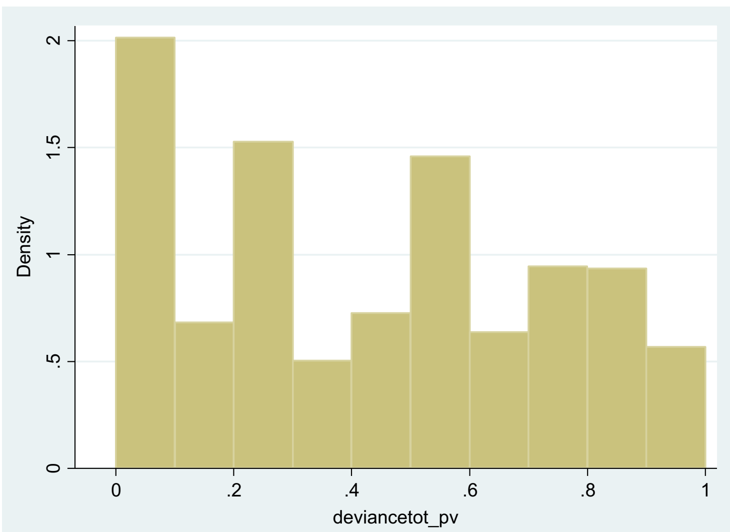

Figure 2. Region-specific last-digit tests: the histogram of Chi2(9) *p*-values that correspond to region-specific L^2 statistics in voter turnout counts.
Note: The Kolmogorov–Smirnov test weakly rejects the hypothesis that *p*-values are uniformly distributed (K–S *p*-value 0.053), suggesting that regions differ in their propensity to generate statistically unlikely last digits in turnout counts.

each yields a *p*-value. Figure 2 reports the *p*-values histogram, which shows a significant degree of *p*-value heterogeneity. In individual tests, we usually reject the null hypothesis of no fraud if the corresponding *p*-value is below the 5 or 10% cut-off level. This approach would not be adequate here, however. With 79 tests corresponding to the 79 regions for which data are available (out of Russia's 83 constituent regions),[2] we can expect a number of regions to fall into the rejection area purely by chance. Indeed, if turnout counts across individual regions had been generated by a fair vote count, the *p*-values would be distributed uniformly. Similarly, if last-digit fraud affects only a small number of regions, the distribution of *p*-values would be nearly uniform. In contrast, any significant deviation from a uniform distribution would signal that last-digit fraud affects a significant proportion of individual regions. We test whether the *p*-values come from a uniform distribution by performing the Kolmogorov–Smirnov (K–S) test, which ascertains the extent of equality of distributions. The test weakly rejects the hypothesis that the *p*-values are uniformly distributed (K–S *p*-value 0.053), suggesting that (a) regions differ in their propensity to generate statistically unlikely last digits in turnout counts; and (b) last-digit fraud seems to be affecting a significant proportion of individual regions.

If deviations from a uniform distribution in last-digit frequencies are caused by an overabundance of zeros (Beber and Scacco 2012), the Chi2(1) tests against sample statistics $Deviance_0$, focused on last-digit zeros, should be sharper than Chi2(9) tests against L^2. Accordingly, Figure 3 shows the histogram of *p*-values after region-specific Chi2(1) tests based on $Deviance_0$. Again, the results show considerable variation in the *p*-values, with lower *p*-values favoring the fraud hypothesis. In particular, the probability of last-digit zeros in turnout counts appears to be significantly different from 10% in Bashkortostan, Dagestan, Kabardino-Balkaria, Karachay-Cherkessia, Kemerovo, Magadan, North Ossetia, Sakhalin, Stavropol,' and Tatarstan. As before, we employ the Kolmogorov–Smirnov test that, this time, strongly rejects the hypothesis of uniform distribution (K–S *p*-value 0.001), confirming that the *p*-value heterogeneity is, in part, systematic. Since fraud is the most likely causal mechanism that could generate the systematic component in the *p*-value heterogeneity, our analysis confirms hypothesis H1 about the incidence of fraud in the election. The strong results of the Kolmogorov–Smirnov test also suggest that last-digit fraud was not a problem specific to one or two individual regions (if this were the case, the K–S statistics would not have detected it). The results suggest instead that the number of regions across Russia that were affected by last-digit fraud was sufficiently high for the test to reject the null hypothesis of a uniform distribution.

Regression analysis of last digits: fake votes and vote "re-distribution"

We now proceed with regression analysis. In this section, we test whether last-digit fraud co-varies with turnout and with vote counts for individual candidates (hypothesis H2), controlling for conventional

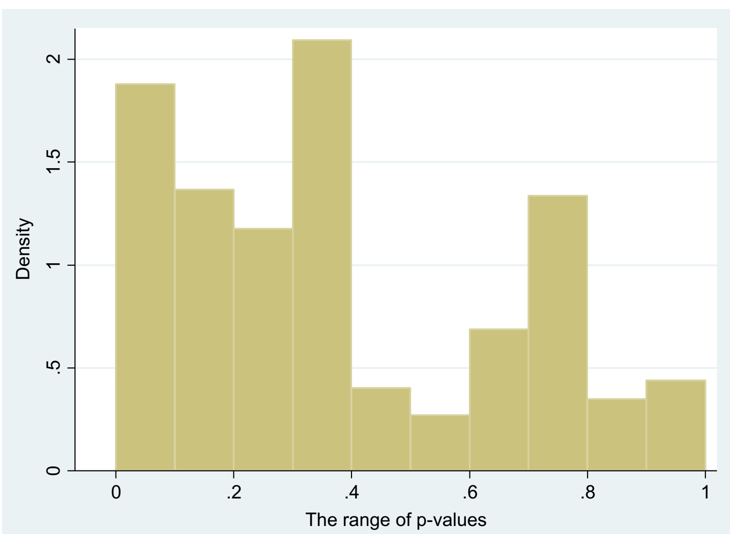

Figure 3. Region-specific last-digit zero tests: the histogram of Chi2(1) *p*-values that correspond to region-specific $Deviance_0$ statistics in voter turnout counts.

Note: The Kolmogorov–Smirnov test strongly rejects the hypothesis that the *p*-values are uniformly distributed (K–S *p*-value 0.001), suggesting the incidence of, and considerable regional variation in, last-digit fraud.

correlates of electoral misconduct. The Dagestan region stands out as a statistical "outlier" in terms of last-digit fraud. The expected number of last-digit zeros in Dagestan under a uniform distribution is 170.7 versus the observed 322, which yields a remarkable Chi2(1) statistic of 121.53. We therefore exclude Dagestan from the regression analysis and report results for the remaining 78 regions. Including Dagestan strengthens the key results of our regression analysis, and yet, on balance, we do not want the results to be influenced by this idiosyncratically fraudulent region. Descriptive statistics for all variables used in the regression analysis and the correlation matrix are presented in the Appendix (Tables A1 and A2).

Table 2 reports results of the multivariate logit regression, where we regress last-digit categories in turnout counts on four quartiles of *Turnout*, and on the control variables *University Degree*, *Distance from Moscow*, *Fiscal Transfers*, and *Russians*. Turnout quartiles control for the possible effect of non-linearity. Cluster-robust standard errors are used to allow for intragroup correlations in 78 regions. Figure 4 plots predicted probabilities of last digits across turnout quartiles and illustrates the key result that last-digit zeros are significantly over-reported in precincts reporting turnout levels in the fourth quartile (that is, *Turnout* of at least 79% or greater). The graph illustrates that the *Turnout* effect on over-reported zeros is mostly concentrated in the fourth quartile, although the overall linear effect, when *Turnout* is entered as a continuous variable, is positive and statistically significant (unreported). Tables 3 and 4 report post-estimation tests. Table 3 reports that the fourth quartile *TURNOUT DUMMY* is jointly statistically significant in all categories of last digits, rejecting the hypothesis of no association between last-digit frequencies and the fourth quartile (versus the first quartile) turnout. Among other effects, *University Degree* and *Distance from Moscow* are statistically significant, further suggesting that last-digit heterogeneity is partly systematic and non-random. Based on the results in Table 4, on the other hand, we cannot reject the hypothesis of no association between last-digit frequencies 1 to 9 (excluding last-digit zeros) and the fourth quartile (vs. first quartile) turnout, which suggests that a systematic component associated with *Turnout* is mostly carried by last-digit zeros. Last-digit zeros also seem to be carrying a systematic component associated with *Distance from Moscow*. These results are robust to the use of alternative control variables and do not change when *Oblast*, *Income*, and *Media Freedom* are included (*Russians* and *Fiscal Transfers* are excluded due to potential multicollinearity issues). *Oblast*, *Income*, and *Media Freedom* do not emerge as statistically significant.

Table 2. Last-digit fraud in turnout counts, multinomial logistic regression[a]; Dagestan is excluded.

Categories (last digits):	0 (base)	1 vs. 0	2 vs. 0	3 vs. 0	4 vs. 0	5 vs. 0	6 vs. 0	7 vs. 0	8 vs. 0	9 vs. 0
Turnout[b]										
2nd quartile		−.018	.028	−.076	−.026	−.009	−.010	.002	−.028	−.016
		(.039)	*(.040)*	*(.042)*	*(.040)*	*(.032)*	*(.029)*	*(.036)*	*(.030)*	*(.027)*
3rd quartile		.001	.015	−.071	−.021	−.022	−.047	−.047	−.013	−.025
		(.041)	*(.045)*	*(.047)*	*(.046)*	*(.039)*	*(.044)*	*(.040)*	*(.036)*	*(.039)*
4th quartile		−.115**	−.100*	−.210**	−.197**	−.111**	−.135**	−.124*	−.142**	−.090*
		(.044)	*(.046)*	*(.050)*	*(.042)*	*(.042)*	*(.041)*	*(.050)*	*(.044)*	*(.042)*
University Degree		−.157	−.536*	−.698**	−.539*	−.583*	−.537	−.554*	.047	−.497
		(.208)	*(.261)*	*(.234)*	*(.230)*	*(.265)*	*(.284)*	*(.252)*	*(.242)*	*(.379)*
Distance from Moscow		−.023*	−.038**	−.030**	−.020	−.017	−.025*	−.020*	−.018	−.010
		(.011)	*(.010)*	*(.011)*	*(.011)*	*(.011)*	*(.011)*	*(.009)*	*(.011)*	*(.010)*
Fiscal Transfers		.042	−.023	.080	−.098	.196	−.036	.084	−.007	−.053
		(.152)	*(.153)*	*(.153)*	*(.142)*	*(.148)*	*(.164)*	*(.148)*	*(.150)*	*(.128)*
Russians		.076	−.019	.152	−.022	.124	.094	.138	−.002	.072
		(.085)	*(.101)*	*(.094)*	*(.118)*	*(.108)*	*(.082)*	*(.118)*	*(.084)*	*(.099)*
Constant		−.024	.131	.055	.197	−.002	.083	.028	.001	.041
		(.091)	*(.118)*	*(.119)*	*(.120)*	*(.130)*	*(.115)*	*(.150)*	*(.078)*	*(.107)*
N obs.	87720									
Wald $\chi^2(63)$	476.42									

[a]Cluster-robust standard errors in parentheses allow for intragroup correlations in 78 regions.
[b]Quartile categories represent dummy variables, where first quartile is treated as the reference outcome.
*Significance at the 5% level; **Indicates significance at the 1% level.

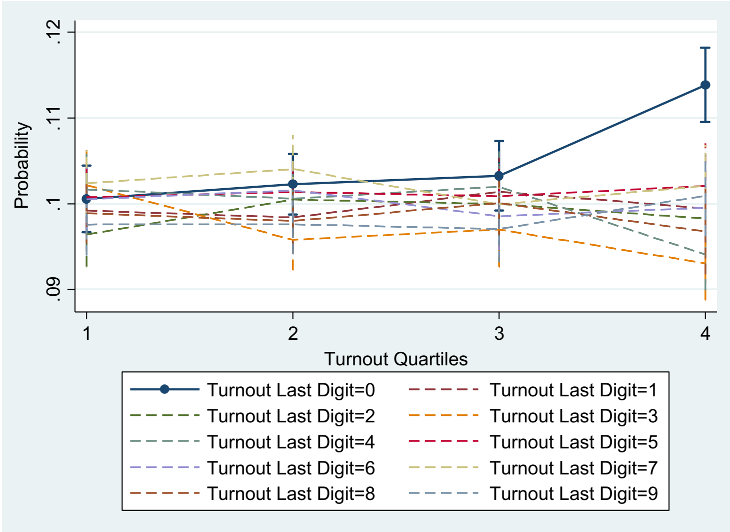

Figure 4. Predicted probabilities of turnout last digits by turnout quartiles (based on Table 2) with 95% confidence intervals.
Notes: Other explanatory variables are taken at their means. Turnout quartiles: first – 58.7% of registered voters or less; second – between 58.7 and 66.0%; third – between 66.0 and 79.3%; fourth – 79.3% or greater.

Table 3. Wald tests of composite hypothesis (all digits) after multivariate logit reported in Table 2.

H0: There is no association between the corresponding explanatory variable and the 10 categories of last digits. *H0* assumes that the true population effects in categories 0 to 9 in Table 2 are *jointly* equal to zero.

Independent variables	Chi2(9)	*p*-value
Turnout		
2nd quartile	7.51	.5839
3rd quartile	6.25	.7145
4th quartile	31.63**	.0002
University Degree	24.86**	0.0031
Distance from Moscow	19.32*	0.0226
Fiscal Transfers	9.71	0.3748
Russians	6.23	0.7162

*Rejection at the 5% level; **Indicates the rejection of the corresponding H0 at the 1% level.

Table 4. Wald tests of composite hypotheses (digits 1 to 9) after multivariate logit reported in Table 2.

H0: There is no association between the corresponding explanatory variable and the relative frequencies of last-digit categories 1 to 9 (that is, excluding last-digit zeros). *H0* assumes that the true population effects in categories 1 to 9 in Table 2 are equal.

Independent variables	Chi2(8)	*p*-value
Turnout		
2nd quartile	7.51	.4825
3rd quartile	5.57	.6958
4th quartile	13.03	.1109
University Degree	19.87*	0.0109
Distance from Moscow	10.07	0.2603
Fiscal Transfers	9.6	0.2942
Russians	5.52	0.7007

*Rejection at the 5% level; **Indicates the rejection of the corresponding H0 at the 1% level.

Table 5. Last-digit zeros in turnout counts, logistic regressions[a]; Dagestan is excluded.

Variables	M2	St. Err.	M3	St. Err.
Turnout[b]				
2nd Quartile	.017	(.025)		
3rd Quartile	.026	(.032)		
4th Quartile	.135**	(.033)		
Putin's vote[b]				
2nd Quartile			.001	(.036)
3rd Quartile			.023	(.041)
4th Quartile			.138**	(.045)
Zyuganov's vote[b]				
2nd Quartile			-.002	(.041)
3rd Quartile			-.006	(.035)
4th Quartile			.010	(.035)
Zhirinovsky's vote[b]				
2nd Quartile			.014	(.038)
3rd Quartile			.039	(.039)
4th Quartile			.006	(.039)
Mironov's vote[b]				
2nd Quartile			-.032	(.036)
3rd Quartile			-.049	(.036)
4th Quartile			-.115**	(.036)
Prokhorov's vote[b]				
2nd Quartile			.006	(.041)
3rd Quartile			.047	(.043)
4th Quartile			.044	(.049)
University degree	.448*	(.211)	.510*	(.231)
Distance from Moscow	.022**	(.007)	.020**	(.007)
Fiscal transfers	-.027	(.122)	-.021	(.125)
Russians	-.068	(.081)	-.063	(.084)
Constant	-2.25**	(.091)	-2.26**	(.101)
Obs	87,720		87,720	
Clusters (regions)	78		78	
Wald Chi2	45.15		69.62	

[a]Cluster-robust standard errors in parentheses allow for intragroup correlations in 78 regions.
[b]Quartile categories represent dummy variables where the first quartile is treated as the reference outcome.
*Significance at the 5% level;
**Indicates significance at the 1% level.

Table 5 reports the results of a (binomial) logit model that explores last-digit zeros in detail. The dependent variable in Table 5 is a dummy variable for which last-digit zeros in turnout counts are coded as "1" and the other last-digit categories are coded as "0." While the model M2 in Table 5 uses a specification that is identical to the one used earlier in Table 2 and reports similar results, model M3 introduces vote counts for individual candidates (*Putin's Vote*, *Zyuganov's Vote*, *Zhirinovsky's Vote*, *Mironov's Vote*, and *Prokhorov's Vote*) as new explanatory variables in place of *Turnout*. Vote counts for individual candidates are taken as a ratio to the number of registered voters and are split into quartiles to control for possible effects of non-linearity. *Putin's Vote* yields statistically significant results – we observe a 0.138 increase in predicted log-odds of last-digit zeros in the fourth quartile of *Putin's Vote* (that is, *Putin's Vote* is at least 56% of registered voters or greater) relative to the first quartile (*Putin's Vote* is 33.5% of registered voters or less). This, together with the earlier results for turnout strongly suggests that turnout counts include fake votes that produce over-reported last-digit zeros, and that fake votes disproportionally benefit Putin.

Figure 5 illustrates this by plotting the predicted probabilities of last-digit zeros across four quartiles of *Putin's Vote*. Controlling for the effect of *Putin's Vote*, vote counts reported for candidate Mironov are *negatively* correlated with over-reported last-digit zeros in turnout counts. This suggests that fraudulent activities encompassed a number of strategies. In addition to propping up Putin's vote and turnout counts with fake votes, some election officials were actively stealing and re-distributing the actual votes. The evidence suggests that *Mironov's Vote* (a pro-Kremlin candidate) was particularly badly affected by this vote "re-distribution." Figure 6 illustrates this by plotting the predicted probabilities of last-digit

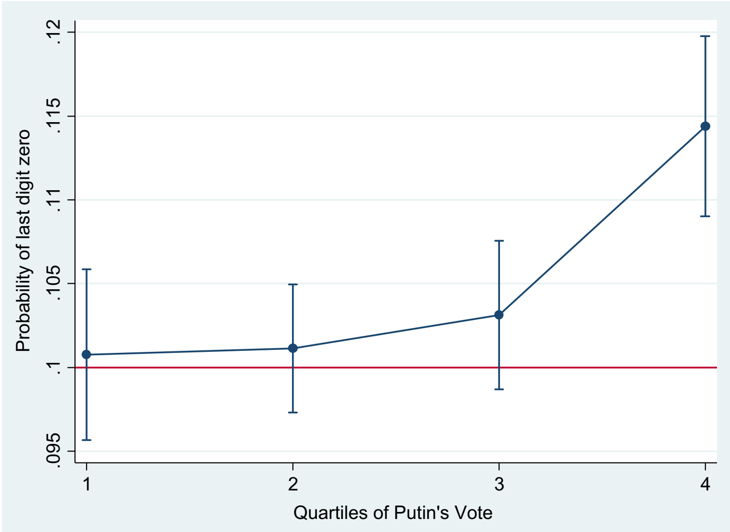

Figure 5. Predicted probabilities of turnout last-digit zeros by quartiles of *Putin's Vote* (based on model M3 in Table 5) with 95% confidence intervals.

Notes: Other explanatory variables are taken at their means. *Putin's Vote* quartiles: first – 33.5% of registered voters or less; second – between 33.5 and 41.8%; third – between 41.8 and 56%; fourth – 56% or greater.

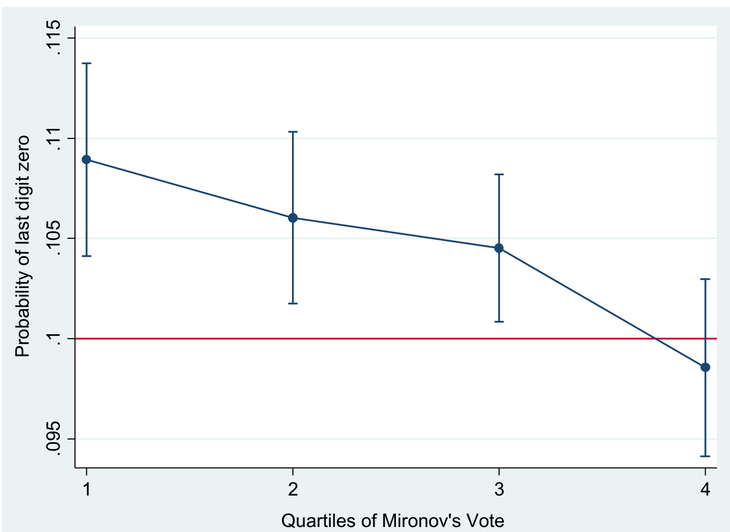

Figure 6. Predicted probabilities of turnout last-digit zeros by quartiles of *Mironov's Vote* (based on M3 in Table 5) with 95% confidence intervals.

Notes: Other explanatory variables are taken at their means. *Mironov's Vote* quartiles: first – 1.3% of registered voters or less; second – between 1.3 and 2.2%; third – between 2.2 and 3.1%; fourth – 3.1% or greater.

zeros across four quartiles of *Mironov's Vote*, holding other variables at their means. *University Degree* and *Distance from Moscow* are positively associated with last-digit fraud and emerge as statistically significant, while *Fiscal Transfers* and *Russians* do not seem to have an independent effect on fraud. The result for the *University Degree* variable may be interpreted as follows. In regions with educated populations, regional officials may opt for election-day fraud in lieu of pre-electoral manipulations – such as pressuring citizens to cast a vote for a particular party or candidate – because better-educated voters are less likely to succumb to such pressures. The *Distance from Moscow* variable may capture the effects of fraud in, for instance, the North Caucasus regions, which are notoriously associated with delivering implausibly high results for Kremlin-supported parties and presidential candidates. It could also capture distance from the West and from diffusion processes associated with proximity to democratic countries and the EU, which in previous studies have been found to positively affect regional democracy (Lankina and Getachew 2006, 2008; Obydenkova and Libman 2012, 2015). Overall, the evidence supports Hypothesis 2. The results are robust to the inclusion of the alternative control variables *Oblast*, *Media Freedom*, *Urbanization*, and *Income*.

Reports of election-day misconduct

In this section, we investigate whether our measures of last-digit fraud co-vary with Golos's regional reports of misconduct (H3). Models M4–M11 in Table 6 report the results of a series of negative binomial regressions. Dagestan is excluded as an outlier. In the benchmark model M4, the dependent variable *Reporting Election-Day Misconduct* is regressed on a set of control variables, excluding our measures of fraud. As expected, *Reporting Election-Day Misconduct* is found to be larger in those regions that reported more pre-electoral manipulations (*Reporting Pre-electoral Manipulations*), which, in part, controls for unobserved heterogeneity in general propensity to report across individual regions. Pre-electoral manipulation reports are likely to proxy both for the electorate that values fair elections and also for the pressure on regional authorities to deliver the desired result on election day. The observed positive correlation between pre-electoral and election-day reports is consistent with both of these effects. Second, as expected, regions with more polling stations tend to generate more reports of election-day irregularities. Finally, as expected, education (*University Degree*) is positively and significantly associated

Table 6. Reports of election-day misconduct, Golos data, negative binomial regressions[a]; Dagestan is excluded.

	M4	M5	M6	M7	M8	M9	M10	M11
Log (1+*Reporting Pre-electoral Manipulations*)	.256**	.257**	.259**	.259**	.247**	.251**	.246**	.251**
	(.087)	(.080)	(.088)	(.081)	(.090)	(.081)	(.091)	(.081)
Log *Total Number of Polling Stations in the Region*	.621**	.579**	.616**	.575**	.611**	.561**	.611**	.561**
	(.214)	(.200)	(.216)	(.201)	(.179)	(.166)	(.180)	(.166)
Log ($Deviance_0$)[b]		.140**		.140**		.155**		.155**
		(.041)		(.041)		(.040)		(.040)
Log ($Deviance_{1-9}$)[c]			−.037	−.034			.017	.009
			(.191)	(.185)			(.193)	(.183)
University Degree	8.33**	7.08**	8.27**	7.03**	9.00**	6.90*	9.01**	6.90*
	(2.87)	(2.59)	(2.88)	(2.61)	(3.46)	(3.25)	(3.46)	(3.25)
Distance from Moscow	−.137*	−.165**	−.139*	−.167**	−.150*	−.189**	−.149*	−.188**
	(.056)	(.054)	(.057)	(.055)	(.068)	(.061)	(.069)	(.062)
Fiscal Transfers	−.681	−.424	−.710	−.450				
	(.698)	(.679)	(.715)	(.695)				
Russians	−1.04	−.471	−1.06	−.487				
	(.539)	(.540)	(.546)	(.548)				
Oblast					−.080	.050	−.078	.051
					(.254)	(.249)	(.256)	(.250)
Income					−.007	.003	−.007	.003
					(.022)	(.020)	(.022)	(.020)
Constant	−.837	−.750	−.698	−.624	−1.72	−1.12	−1.76	−1.14
	(1.65)	(1.53)	(1.80)	(1.67)	(1.26)	(1.15)	(1.34)	(1.23)
N obs.	78	78	78	78	78	78	78	78
LR Chi2	100.3	109.97	100.33	110	96.57	109.2	96.58	109.21
Log pseudo-likelihood	−432.7	−427.87	−432.68	−427.85	−434.57	−428.25	−434.56	−428.25
Pseudo-R^2	0.1039	0.1139	0.1039	0.1139	0.1	0.0031	0.1	0.1131

[a]Dependent variable is *Reporting Election-Day Misconduct* (number of reports of election-day misconduct per region). Standard errors in parentheses.
[b]*Last-Digit Fraud Index* based on observed frequencies of last-digit zeros.
[c]*Last-Digit Index* based on relative frequencies of last digits 1 to 9.
*Significance at the 5% level; **Indicates significance at the 1% level.

with election-day reports *ceteris paribus*, while *Distance from Moscow* is negatively associated with election-day reports. *Russians* emerges as only weakly statistically significant, suggesting, counterintuitively, that regions with a higher proportion of ethnically Russian populations tend to show a lower likelihood of exposing election-day misconduct than do those with larger non-ethnically Russian populations. This effect, however, disappears when we include the last-digit fraud variable in the regression.

Model M5 introduces our preferred measure of fraud prevalence *Log* ($Deviance_0$), which is found to be positively and significantly correlated with fraud reports in support of hypothesis H3. A 10% increase in $Deviance_0$ is associated with a $1.1^{0.140} - 1 \approx 1.3\%$ increase in fraud reports. This is an important finding. We show in the previous section that last-digit zeros are not entirely random and that variance in last-digit zeros is partly systematic. Fake turnout counts and over-reported zeros produce higher values of $Deviance_0$ ("fingerprints of fraud"), which are found to be associated with fraud reports. Here, we do not claim that the empirical relationship between last-digit fraud and fraud reports is necessarily causal.

As discussed earlier, last-digit fraud measures such as $Deviance_0$ might not detect all instances of forced voting and ballot stuffing that could be more readily observed and reported by monitors. Our results, therefore, are consistent with the view that regional authorities, eager to "deliver," resort to a variety of complementary election-day strategies. Models M6 and M7 report that the relatively less systematic and more random part of last-digit heterogeneity $Deviance_{1-9}$ measured across digits 1 to 9 is not associated with misconduct reports, neither on its own nor when the effect of last-digit zeros is being controlled for. The association between last-digit fraud and misconduct reports is robust to the inclusion of alternative controls. Models M8 to M11 report results that include *Oblast* and *Income*, while *Fiscal Transfers* and *Russians* are excluded due to potential multicollinearity. The effect of last-digit fraud on misconduct reports is somewhat stronger in this specification. The *Oblast* and *Income* variables are not statistically significant.

Discussion

Our analysis of last-digit fraud in Russia's presidential election points to a significant degree of sub-national fraud heterogeneity. The evidence confirms that fraud tended to be higher in regions with a history of "deference" (Moraski and Reisinger 2010) to the Kremlin – for instance, the North Caucasus republics. Last-digit fraud is associated with: (a) fake turnout counts; (b) fake votes that disproportionally benefitted Vladimir Putin; and (c) vote "re-distribution" whereby votes cast for some candidates appear to have been systematically miscounted. We document further that Golos's regional reports of election-day irregularities are correlated with last-digit fraud, suggesting that regional authorities use a menu of complementary strategies to produce the desired outcome.

The parametric last-digit frequency regressions employed in this paper could be extended to study fraud heterogeneity in further detail. For instance, we could ask questions such as: "Is the association between turnout and over-reported last-digit zeros stronger/weaker in relatively larger precincts with higher numbers of registered voters?" Consistent with recent analyses of strategic selection of fraud location in different settings (Sjoberg 2014), it could be argued that the most efficient way to use fraud to win a plurality of votes in direct elections would be to channel fraud efforts to larger, more consequential, precincts. Systematic resort to fraud would, then, produce stronger turnout – fraud links in larger precincts – this could be easily tested by including appropriate interaction terms in last-digit frequency regressions.

The systematic evidence that we present of election officials strategically re-allocating votes from one of the pro-Kremlin contenders in favor of the winner-apparent is also significant in terms of possibilities for further research. Specifically, we find that votes for Mironov, the pro-Kremlin candidate, had been particularly vulnerable to such manipulative tactics. These practices suggest that having a number of contenders ostensibly representing the political opposition serves a wider purpose beyond simply seeking to create the impression of a genuinely competitive political process. In fact, we conjecture that such politicians may be deliberately planted into the electoral race to generate votes that could be reallocated to the winner-apparent without the risk of being challenged by the "loser" in the courts, the media, etc.

Our findings, based on an analysis of Golos data, also tentatively suggest that last-digit fraud occurs even in settings where pre-electoral manipulations are widespread. Intuitively, one might expect that election-day fraud would be unnecessary where, for instance, manipulations such as vote-buying would have ensured citizen commitment to vote for a particular candidate prior to the day of the election (Magaloni, Diaz-Cayeros, and Estévez 2007; Stokes 2007). Thus, Susan Stokes, an expert on political clientelism in various national contexts, writes how after "a long day of handing out goods and favors at Children's Day celebrations" one Argentinian party activist boasted: "Votes will come. I don't have to go and look for them . . . votes will come anyway" (Stokes 2007, 7). Nevertheless, what we find is more in line with alternative arguments that the two types of misconduct co-vary – both are perpetrated to augment a pro-regime result (Hale 2007).

The analysis presented in this paper has wider implications for understanding Russia's center-regional relations, regional electoral dynamics, and the effects of sub-national variations in socioeconomic conditions and regime types on national electoral outcomes. Despite Putin's recentralization reforms – which had the effect of undermining political pluralism in the hitherto more democratic regions – we observe inter-temporal continuity in the reproduction of regional patterns of electoral malpractice. In what dovetails with earlier research, we find that these variations are in turn to a certain extent conditioned by variables such as levels of regional modernization and specifically education (Hale 2007; Lankina 2012, 2016; Lankina and Getachew 2008; Saikkonen 2015). Despite the Kremlin's protestations to the effect that fawning governors in some regions are simply "trying too hard" to please the national regime in delivering implausibly high results, our analysis is more suggestive of the fact that fraud and other irregularities are perpetrated where regional authorities feel that they can get away with them and where they possess significant levers of influence over citizens. In other words, capacity to deliver, not so much the extent of loyalty to the Kremlin, is what drives the extent of electoral malpractice under a regime where in any case most of the regional assemblies and governorships are controlled by the Kremlin.

Thus, during the December 2011 parliamentary elections, the mere presence of independent observers at Moscow's polling stations reportedly decreased the vote for the Kremlin-supported United Russia party by 11% (Enikolopov et al. 2013). True, on the eve of the 2012 presidential election, Russia's leaders made a conscious effort to give the impression of striving for electoral integrity, not least because of citizen anger at fraud perpetrated in the State Duma elections in December 2011. Web-cameras were introduced at polling stations, and pronouncements were made encouraging citizens to show vigilance in exposing fraud. Yet, we also know that governors were punished for failing to deliver a robust result in favor of the Kremlin-supported parties in the 2011 elections, and that every effort was made to secure Putin's victory in the first round of the presidential election that followed. A number of governors – in Vologda, Arkhangel'sk, and Volgograd – arguably had been dismissed because of a "weak" result in December 2011. The Golos report contains evidence that regional governors, perhaps conscious of these pressures from above, are likely to have directed the process of securing the desired vote: they threatened to cut funding to the *rayony* unless precinct officials delivered at least a 50%, and as high as a 60–70% vote for Putin; fired officials who failed to deliver a sufficiently high result for the United Russia "party of power" in December 2011; and promoted officials in the *rayony* in which allegations of fraud – and court cases – in the previous elections featured prominently, in other words, signaling that fraudsters would be rewarded rather than punished (Kynev et al. 2012). There are also numerous cases of precinct officials resigning in protest over pressures by governors to commit fraud. Furthermore, Golos had been subjected to state-sponsored harassment both before and after the March 2012 presidential election. Against this background, and given the findings of our own statistical analysis, the Kremlin's protestations about a desire to ensure a transparent vote ring hollow.

Our findings also dovetail with other, longer term, analyses of electoral dynamics in Russia. Reisinger and Moraski (2009) find that high levels of regional "deference" to the Kremlin have in recent years tended to extend even to the traditionally less "deferential" regions, while Lukinova, Myagkov and

Ordeshook (2011) use the metaphor of "metastasized" fraud to describe the cancer-like spread of electoral malpractice across Russia. Generally, it is well known that there has been a significant erosion of sub-national democratic institutions and electoral competition under Putin (Golosov 2011; Panov and Ross 2013; Reddaway and Orttung 2005; Reuter and Buckley 2015; Reuter and Remington 2009; Reuter and Robertson 2012; Rochlitz 2014). Yet, this unfavorable national context notwithstanding, in these various studies, some regions consistently feature as among the worst abusers of citizens' right to cast a vote, whereas others continue to feature greater levels of electoral integrity.

Similar to other autocratic regimes, Putin's Kremlin has shown remarkable ingenuity in skewing the electoral playing field in its favor – through blatant fraud and other, more "subtle" techniques (such as potential vote redistribution between pro-Kremlin candidates and the winner-apparent) that we have uncovered. Yet, the electorate in many regions continues to show a certain degree of vigilance in exposing both pre-electoral and election-day misconduct. Likewise, NGOs such as Golos and its regional activists, as indeed local election monitoring NGOs and other civil society groups, continue to fulfill their civic duties despite the very difficult and hostile climates in which they operate. The reproduction of such spatial variations in democratic practices and processes despite authoritarian consolidation under Putin in turn suggests that longer term sub-national developmental trajectories, which condition regional resilience to national autocracy, matter (Lankina, Libman, and Obydenkova 2016a,b). Careful attention to sub-national democratic practices, transcending the preoccupation with national-level authoritarian retrenchment, is therefore essential for nuancing our understanding of the nature of Russia's current regime, and indeed for appreciating the potential for future political change in Russia.

Notes

1. Wahman (2015) identifies at least 13 types of manipulations in the 2014 Malawi general election.
2. Chechnya and regions with autonomous okrug status are conventionally excluded from cross-regional statistical analyses because of missing data.

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Table A1. Variables, definitions, and descriptive statistics; Dagestan is excluded.

	Definition	*N*	Mean	St. dev	Min	Median	Max
(1) *Turnout*	The number of votes cast divided by the number of people eligible to vote (registered voters)	87,720	0.68	0.14	0.05	0.65	1
(2) *Putin's Vote*	The number of votes cast for Putin divided by the number of registered voters	87,720	0.46	0.17	0	0.41	1
(3) *Zyuganov's Vote*	The number of votes cast for Zyuganov divided by the number of registered voters	87,720	0.11	0.05	0	0.11	0.55
(4) *Zhirinovsky's Vote*	The number of votes cast for Zhirinovsky divided by the number of registered voters	87,720	0.04	0.02	0	0.04	0.52
(5) *Mironov's Vote*	The number of votes cast for Mironov divided by the number of registered voters	87,720	0.02	0.01	0	0.02	0.69
(6) *Prokhorov's Vote*	The number of votes cast for Prokhorov divided by the number of registered voters	87,720	0.04	0.03	0	0.03	0.35
(7) *Total Number of Polling Stations*	Total number of polling stations in the region with at least 100 registered voters	78	1125	791	52	940	3390
(8) *University Degree*	Share of people with university degree, 2010	78	0.21	0.04	0.15	0.20	0.41
(9) *Distance from Moscow*	Geographical distance from Moscow, '000s km	78	1.81	1.84	0	1.16	6.43
(10) *Income*	Income per capita, 2010	78	16.3	6.06	7.54	14.7	43.9
(11) *Fiscal Transfers*	Share of fiscal transfers in regional public expenditures, 2009	78	0.34	0.20	0.04	0.28	1.35
(12) *Media Freedom*	Index of regional media freedom for 2006–2010	78	2.91	0.96	1	3	5
(13) *Russians*	Share of ethnic Russians in the regional populations	78	0.79	0.24	0.01	0.89	0.97
(14) *Oblast*	Regions with oblast status	78	0.74	0.44	0	1	1
(15) *Reporting Election-Day Misconduct*	Number of reports of election-day misconduct in the region, 4 March 2012	78	204	396	0	58	2190
(16) *Reporting Pre-electoral Manipulations*	Number of reports of pre-electoral manipulations in the region, September 2011–3 March 2012	78	86.6	182	0	38.5	1185
(17) *Deviance*$_0$	Last-digit fraud index based on observed frequencies of last-digit zeros and the likelihood ratio statistics	78	1.71	2.27	0.00	0.92	12.4
(18) *Deviance*$_{1-9}$	Last-digit index based on relative frequencies of last digits 1 to 9 and the likelihood ratio statistics	78	8.66	4.35	2.29	7.94	23.1

Table A2. Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) *Turnout*	1.00																
(2) *Putin's Vote*	0.90	1.00															
(3) *Zyuganov's Vote*	−0.06	−0.40	1.00														
(4) *Zhirinovsky's Vote*	−0.06	−0.27	0.20	1.00													
(5) *Mironov's Vote*	−0.17	−0.39	0.21	0.16	1.00												
(6) *Prokhorov's Vote*	−0.26	−0.49	0.12	0.08	0.44	1.00											
(7) *Total Number of Polling Stations*	0.05	0.04	−0.07	−0.18	−0.05	0.22	1.00										
(8) *University Degree*	−0.13	−0.21	−0.01	−0.07	0.16	0.54	0.32	1.00									
(9) *Distance from Moscow*	−0.04	−0.02	−0.04	0.19	−0.10	−0.10	−0.30	−0.07	1.00								
(10) *Income*	−0.12	−0.18	−0.11	−0.06	0.14	0.52	0.21	0.58	0.32	1.00							
(11) *Fiscal transfers*	0.12	0.14	0.05	0.02	−0.11	−0.28	−0.55	−0.21	0.34	−0.27	1.00						
(12) *Media freedom*	−0.35	−0.35	−0.03	0.03	0.18	0.28	0.35	0.18	−0.14	0.12	−0.36	1.00					
(13) *Russians*	−0.43	−0.49	0.15	0.33	0.19	0.24	0.24	0.06	−0.06	0.17	−0.59	0.39	1.00				
(14) *Oblast*	−0.40	−0.46	0.16	0.29	0.17	0.20	0.29	0.07	−0.06	0.16	−0.48	0.38	0.85	1.00			
(15) *Reporting Election-Day Misconduct*	−0.11	−0.18	−0.03	−0.11	0.14	0.49	0.61	0.73	−0.27	0.41	−0.33	0.24	0.13	0.18	1.00		
(16) *Reporting Pre-electoral Manipulations*	−0.14	−0.21	0.00	−0.07	0.12	0.48	0.63	0.68	−0.25	0.45	−0.31	0.17	0.15	0.17	0.83	1.00	
(17) *Deviance*$_0$	0.29	0.35	−0.11	−0.22	−0.17	−0.18	0.07	0.09	0.05	−0.05	0.14	−0.24	−0.45	−0.29	0.11	−0.08	1.00
(18)*Deviance*$_{1–9}$	0.02	0.01	0.03	0.01	0.05	−0.04	−0.01	−0.04	−0.01	−0.15	−0.06	0.05	−0.05	−0.10	0.07	0.09	0.05