Social Image, Networks, and Protest Participation[1]

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Social motivation plays an important role in electoral participation, political contributions, and charitable donations. We examine the role of social image concerns in the decision to participate in political protests. We develop a dynamic model of protest participation, where socially-minded individuals use protest participation to signal their type to the peers. We test predictions of the model using individual and city-level data from 2011-2012 political protests in Russia. We report several findings. First, list experiment results imply that social signaling motives indeed were important for the decision to participate in protests. Second, consistent with the model, protest participation was declining over time. Third, participation in online protest groups increased offline protest participation. Fourth, participation in protests was higher in cities with higher social capital. Finally, the importance of both online social networks and offline social capital for protest participation diminished over time, consistent with predictions of the model.

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1. Introduction

Social incentives play an important role in explaining why people turn out to vote (Gerber et al. 2008, Gerber and Rogers 2009, DellaVigna et al. 2016), make campaign contributions (Perez-Truglia and Cruces 2016), enforce regulations (Scholz and Wang 2006), or adopt new policies (e.g., Berry and Baybeck 2005). However, it is not clear whether social motivation plays a role in riskier political activities, such as political protests, when people face a threat of physical violence or arrest, and, if so, which mechanisms are involved. In this paper, we investigate this question both theoretically and empirically, using data on Russian protests in 2011-2012.

Political participation, including political protests, is a classic example of collective action, characterized by individual costs and social benefits (Olson 1965, Hardin 1982, Ostrom 1990). Intuitively, the success of a protest depends on the number of people who show up, but each person's participation is unlikely to be pivotal for the success of a protest. In such cases, participation could be driven by social motivation and depend on the observed or anticipated actions of others. One potential channel for social influence is social signaling, whereby peers infer unobservable individual traits from observable actions, and such inference affects one's status in society (Bernheim 1994), or form beliefs about prosocial attitudes of an individual from prosocial behavior, so that prosocial behavior earns honor, whereas abstention carries a stigma (Benabou and Tirole 2006).

In this paper, we focus on the role of social image concerns in political protest participation. We start by developing a micro-founded dynamic theory of protest participation as costly signaling for individuals, in the spirit of Benabou and Tirole (2006). Traditional approach implies that past protest participation could serve as a public signal of political preferences of the population at the aggregate level (Kuran 1989, Lohmann 1993, Kricheli, Livne, and Magaloni 2011). Our approach, in contrast, assumes that people can use protest participation to signal their *individual* type rather than to contribute to aggregate information. In our model prosocial individuals use costly protesting to signal their type to their peers; in other words, people go to protests partly because they care about their social image, which is similar to social pressure for turning out to vote.

Our model generates several empirical predictions: (1) protest participation, driven by social image concerns, declines over time; (2) the significance of social image and the capacity for collective action (social capital) are positively associated with the protest scale; (3) the contribution of social image concerns and social capital to the protest turnout decreases over time (in the case of image concerns – after an initial increase at an early stage of protests).

We test these predictions of the model using data on political protests in Russia in 2011-2012. The protests were triggered by electoral fraud in December 2011 parliamentary elections and were the first large-scale protests in the country since the end of the Soviet Union. There was a noticeable geographical and temporal variation in protests, which occurred in 103 towns and cities comprising our sample (out of 625 Russian cities and towns with a population over 20 thousand people), and lasted, with a varying degree of intensity, for more than six months. In the analysis, we use both aggregate city-level data and individual-level data from the survey of protest participants.

We start by providing direct evidence that social image concerns indeed play a role in individual decision to participate in political protests. In particular, in 2012, at the end of an active phase of protests, we conducted a list experiment to elicit people's social motivation for protest participation. We asked people, who indicated that they had participated in the recent political rallies, about the reasons for their participation, including options that reflected peer pressure and social image concerns. The results of the list experiment indicate that 42% of respondents went to protests because their friends were also doing so, 23% of respondents did so because they wanted to tell their friends about it, and 11% of respondents admitted that they went to protests because they wanted to blog about it in online social networks.[2] These results demonstrate that social image considerations indeed played a significant role in protest participation, consistent with the main assumptions of our model.

Using aggregate city-level data on protest intensity, we then show that protest turnout exhibited a downward trend, in agreement with the first prediction of our theory. Next, we test whether indeed stronger social image concerns lead to higher levels of protest participation. To gauge the impact of social image concerns, we study the effect of a publicly observable size of online protest groups. On VK (or *VKontakte*, Russian most popular online social network), people could openly join protest groups and/or "register" for protest events in their city. These groups provided information about the number of people as well as particular users who were planning to attend protests. Bigger online protest groups allowed protesters to signal their

[2] Note that these different motivations were not mutually exclusive.

participation to a larger number of individuals, so the size of the protest groups could be used as a proxy for the strength of the social image signaling motivation.

To identify the causal impact of the protest groups' size on protest participation, we exploit information about the early stages of the development of VK. Specifically, we use data on the city of origin of the classmates of the VK founder, Pavel Durov, as compared with the cities of origin of students of the same university in other years (similar to the approach in Enikolopov, Makarin, and Petrova, 2016). We find that both VK penetration and VK online protest group membership in a city positively depend on the number of the VK founder's classmates from the city, but do not depend on the number of students from the city in other cohorts. Using the number of the VK founder's classmates in a city as an instrumental variable, we show that, consistent with our model, size of online protest groups in a city had a positive effect on protest participation.

We also test the prediction of the model that social capital, i.e. capacity for collective action and self-organization, has a positive effect on protest activities. Using several alternative proxies for social capital in a city (number of consumer cooperatives, number of voluntary associations, and generalized trust), we demonstrate that all of them are positively related to protest participation.[3]

Finally, we test and confirm the prediction of the theory about the changes of importance of social image concerns and of social capital for protest participation over time, and we find that, after a brief initial period, the importance of both factors for generating protests declines over time.

Overall, we provide a set of empirical results that are fully consistent with the theoretical predictions. Admittedly, each of our empirical findings taken separately can be explained by some alternative logic, and some of our results are consistent with previous findings, but particular combination of the results is specific to our theory and lends to it strong empirical support.

Our paper is closely related to recent papers studying the role of social networks in protests. Enikolopov, Makarin, and Petrova (2016) provide empirical evidence that social media penetration had a causal impact on protest participation in Russia, and the reduction in the costs

[3] Cantoni et al. (2016a) show that a similar relationship holds at the individual level for participants of Hong Kong pro-democracy protests.

of collective action is a likely channel for that. However, these results do not allow for distinguishing specific mechanisms behind the effect, such as social image concerns. Larson, Nagler, Ronen, and Tucker (2016) explore theoretically and empirically the relationship between network structure and protest participation. Theoretical predictions, which are in line with Siegel (2009), are tested using data on Charlie Hebdo rallies in Paris in 2015, by comparing network structure for verified protest participants vs. non-participants. Cantoni, Yang, Yuchtman, and Zhang (2016b) use an experiment to test if expected protest participation affected actual protest participation in Hong Kong in 2015, but, in contrast to our results, they find that peer effects were negative rather than positive. Gonzalez (2016) looks at the positive spillovers in school attendance during protests in Chile in 2011, with non-attendance being an indicator of protest participation. In contrast to these papers, our empirical analysis uses both individual and city-level data, both online and offline social networks, and explores variation in protest participation over time. Our model proposes a particular mechanism for peer effects, based on signaling one's prosocial type, rather than simply assuming the existence of social motivation, which allows us to obtain new original predictions and verify them empirically.

Our paper contributes to the growing literature that studies the relationship between new communication technologies and collective action. For instance, Acemoglu, Hassan, and Tahoun (2016) show that activity in Twitter preceded spikes in protest participation in Tahrir Square in Egypt. Steinert-Threlkeld et al. (2015) arrive to a similar conclusion for protest events around the world. Hassanpour (2014) documents that temporary disruption of Internet during Tahrir Square uprising in Egypt led to an increase, not a decrease, in protest activity. Qin, Strömberg, and Wu (2017) show that Weibo penetration was associated with the spike in protest activity in China. Pierskalla and Hollenbach (2013) show that cell phone coverage increases political violence in Africa, while both Manacorda and Tesei (2016) and Christensen and Garfias (2016) find that cell phone coverage triggers political protests.

More generally, our paper is related to the extensive literature on collective action in politics. For example, a classical study of Olson (1965) examines why some groups get organized and are able to lobby for their preferred policies, while others are not. It emphasizes that the free-rider problem can prevent people with mutual interest from participating in joint activities, such as political protests. Ostrom (1990) presents a multitude of evidence for the "tragedy of the commons," or, in other words, for the collective action problem in public good provision in general. Muller and Opp (1986) find that public good approach could explain rebellion decisions.

Our paper also contributes to the literature on peer effects in social behavior (e.g. Granovetter 1973, 1978; Schelling 1978; Marwell and Oliver 1993). More recent papers in this literature are increasingly focused on the concepts of social image and social pressure. In particular, Gerber, Green, and Larimer (2008), Gerber and Rogers (2009), and DellaVigna et al. (2016) all show that social pressure is an important driver of turnout. Funk (2010) indicates that the introduction of voting by mail reduced turnout in smaller communities in Switzerland, consistent with the social motivation for turnout. Crucez and Perez-Truglia (2016) conduct a field experiment with information about donations by the neighbors and find that social pressure increases political donations. Bursztyn et al. (2016a) show that expressions of anti-Americanism in Pakistan depend on social pressure, while Bursztyn et al. (2016b) show that social pressure also matters for educational decisions.[4]

Finally, our paper is related to theoretical literature that studies the role of networks for protest participation. Recent theoretical models suggest that the decision of others to join protests might influence individual's decision through social network structure (Siegel 2009), coordination (Edmond 2013), expected costs (Kuran 1989), or information sharing (Little 2016, Jackson and Barberà 2016, Battaglini forthcoming). Glaeser, Ponzetto, and Shleifer (2007) argue that participation together with others is more valuable for protest participation when participants have higher education, while Passarelli and Tabellini (forthcoming) assume that emotional benefits from protesting are larger if more people are participating.

The rest of the paper is organized as follows. Section 2 provides some background on Russian protests of 2011-2012 and on the involved social media. Section 3 presents the theoretical model. Sections 4-5 summarize the main empirical evidence. Section 6 concludes.

2. Background

2.1 Russian Protest Movement of 2011-2012

The Russian protest movement of 2011-2012 was triggered by massive fraud in the parliamentary elections held on December 4, 2011. Evidence of fraud at polling stations

[4] See Bursztyn and Jensen (2017) for an overview of the recent literature on social image and peer effects.

(multiple voting by same individuals, ballot staffing, etc.) was widely documented by independent observers and concerned citizens, and broadly circulated through social media. Doctoring of election results caused considerable mismatch between exit polls and official data. Rigorous statistical analyses of election data (see, e.g., Klimek et al. 2012; Kobak, Shpilkin, and Pshenichnikov 2012) revealed various irregularities and biases in favor of the ruling party United Russia. For instance, Enikolopov et al. (2013) showed that United Russia received on average 36% of the votes at polling stations with randomly assigned independent observers, and 47% at stations without such observers.

Despite of the preponderance of evidence, authorities denied allegations and refused to take remedial actions. Angry citizens took to the streets. On December 5 more than 5,000 people participated in the first demonstration in Russia's capital Moscow, followed by much larger protests on December 10 and 24 with attendance around 100,000. The protest movement spread throughout the country, involving, according to our data, more than 100 cities from Khabarovsk in the Far East to Kaliningrad, Russia's westernmost exclave. The subsequent waves of protest, coordinated by the coalition movement "For Fair Elections", took place on February 4 and 26, and on March 10. The next rally in Moscow, on May 6, prior to Vladimir Putin's inauguration as president, ended in clashes with police, leading to criminal charges and significant prison sentences against several dozens of alleged rioters. The final wave of protests occurred on June 12 involving about 30 cities; it concluded the largest protest movement in Russia's post-Soviet history.

Similar to sudden spikes of protest activities under authoritarian regimes elsewhere in the world (Kuran, 1989), the scale of Russian protests took everyone by surprise, including the opposition leaders themselves. The surge cannot be explained by the electoral fraud per se – irregularities of comparable magnitude were observed at the previous parliamentary elections in 2007, with almost no reaction from the society (Treisman, 2011). According to Frye and Borisova (2016), Russians are accustomed to electoral fraud, which does not affect their attitudes to the government. A number of hypotheses could explain the difference between 2007 and 2011. First, there was higher mobilization of opposition segments in the society prior to the election, which facilitated political collective action afterwards. Second, a near decade of rapid economic growth had empowered the fledgling middle class in Russia, which, in accordance with the modernization hypothesis (Lipset, 1960), was conducive to democratic consolidation and strengthened the grassroots demand for good governance (Volkov, 2012; Polishchuk, 2014).

Third, a degree of political liberalization under president Dmitry Medvedev made citizens more prone to criticize the government (Gel'man, 2013). Finally, the protests may have occurred in 2011 and not in 2007 because of the rapid rise of the Internet and social media.

2.2 History of VK

Facebook, created in 2004 and opened to the general public in 2006, did not support Russian language until 2008. This gave a homegrown start-up an opportunity to fill in the gap. VKontakte (VK) was first launched in 2006 by a group of Saint-Petersburg State University students headed by Pavel Durov. The interface of VK was almost identical to Facebook: the profile page, the layout of the navigation bar, and even the color theme all closely resembled the American predecessor. However, the code for the website was written entirely from scratch (Kononov, 2012), and VK had a number of unique features, including the ability to share audio and video files, and fewer commercial ads.

Similar to Facebook, VK's service was first restricted to university students only. Soon thereafter the VK team allowed each user to invite a limited number of persons to join the network, and in November 2006 the registration was open to the public. After that, the number of VK users started to grow exponentially and reached 140 mln registered and 27 mln active users by 2011. Today VK is one of the largest social networking websites in the world, ranked 14th by Alexa's Top 500 Global Sites.

2.3 Online Social Media and Protest Activity

Social media could be particularly important for political mobilization when government controls traditional media outlets (Gehlbach, 2010). A lack of independent printed and electronic media in Russia made VK one of the key alternative sources of information. VK users tend to be more knowledgeable of political events in the country, and had higher awareness of a voters' rights movement `*Golos*' (Voice) and of the electoral fraud in general (Robertson, 2015; Reuter and Szakonyi, 2015). According to an online survey of 2011-2012 protest participants (Dokuka, 2014), 67% of respondents learned about the protests from VK, and another 22% from other online sources.

Social media could also allow for better coordination of any collective action, including political activities. During the Russian protests of 2011-2012, numerous online protest groups were spontaneously opened on VK in almost 90 cities by local activists. These groups advertised protests in their cities, shared relevant content, and facilitated the logistics. Similar activities took place on Facebook and Twitter, but the use of these social media in the 2011-2012 protests was mostly limited to Moscow and Saint-Petersburg. Anecdotal evidence suggests that other Russian social media sites (*Odnoklassniki*, *Moi Mir*, etc.) were not used for the purpose of organizing protests.

Pivotal role of social media, and especially VK, in the 2011-2012 protests was not left unnoticed by the Russian authorities. Various government agencies requested that VK close online protest communities (Kononov, 2012), and pressed Pavel Durov to comply. He refused to acquiesce and was eventually forced in 2014 to sell his equity in VK, which is presently under control of business interests loyal to the regime.

3. Theoretical Model

In this section, we present a dynamic model of participation in a collective action when such participation is motivated, inter alia, by social image concern, i.e. how an individual is perceived and evaluated by her peers. We assume that individuals differ from each other in their intrinsic motivation for joining political protests, which reflects their individual type. Types are private information, but protest participation is publicly observable. If peers appreciate prosocial values, individuals can participate in protests in order to improve what their peers think about them. Such signaling, in line with Benabou and Tirole (2006), can motivate protest participation: joining the action earns social praise (honor), whereas abstention carries a stigma.

Benabou and Tirole (2006) study static perfect Bayesian equilibria where the society assesses honor and stigma of engagement in or abstention from prosocial behavior based on equilibrium beliefs about the types of (non-) participating individuals. Individuals, in turn, choose their behavior to shape ex-post beliefs about their types of their peers. In equilibrium, the society's ex-post beliefs are upheld by actual individual choices. In our model, we extend Benabou and Tirole (2006) framework to a dynamic setting, where social beliefs about individuals' types are continuously updated based on (non) participation history, and hence the strength of the signaling motive also varies in time.

We demonstrate that, under mild additional assumptions, only declining participation is consistent with a signaling mechanism. Intuitively, the value of signaling diminishes over time, since peers have learned from earlier participation, and if an individual has already made a prosocial choice, there is smaller room for a further increase in perceived pro-sociality. We obtain a closed-form solution for the number of participants, in which participation asymptotically approaches a stable core. Individuals in the core have sufficiently high intrinsic motivation to continue participating in perpetuity or until the collective action process ends for exogenous reasons, e.g. due to a crackdown by authorities. However, even in the core, the signaling motive still plays a role for some individuals who would not have stayed otherwise. We show that the strength of social image concerns and appropriately defined social capital increase participation along the protest trajectory, but the marginal significance of these factors becomes less important over time (in the case of image concern the marginal significance initially rises and turns to decreasing thereafter).

3.1 Basic Setup

Consider a unit continuum of individuals whose types $a \in [0,1]$ reflect prosocial values, i.e. intrinsic payoffs from participation in collective action per unit of time; a is agent's private information and is uniformly distributed over $[0,1]$. Collective action (protest) participation carries fixed cost $c > 0$ per unit of time. Such cost is an extrinsic (de)motivation to participate (in an extension presented in the Appendix we also include extrinsic benefits of participation).

The society's posterior expectations at a given moment of time, based on an individual's (non-)participation history, are that her/his type belongs to a subset $A \subset [0,1]$. Citizens use Bayesian updating of prior believes. An individual's valuation (per unit of time) of such perception by the society is $2\mu E(a|A)$; here $\mu > 0$ is the strength of social image concerns. In the baseline version below we assume that the strength of social image motivation is the same for all individuals, but relax this assumption in the Appendix to make image concern individual-specific, similar to Bursztyn and Jensen (2017). We assume that $\mu < c < 1$, so that the cost of participation is neither too high nor too low, to ensure a separating equilibrium. Finally, denote $\delta > 0$ the discount coefficient.

3.2 Equilibrium

We look for perfect Bayesian equilibrium, in which actions are motivated inter alia by updateable beliefs, which are computed using the Bayesian rule for all events with non-zero probability. Denote ex-post belief subsets $A(t) \equiv [\hat{a}(t), 1]$ with participation threshold

$\hat{a}(t) \in [0,1]$, i.e. an individual with type a is expected to participate at moment $t \geq 0$ if and only if $a \geq \hat{a}(t)$.

Perfect Bayesian equilibrium in games with observed actions and incomplete information comprises (posterior) beliefs, which are in agreement with chosen strategies, and the latter are optimal, given the beliefs (Fudenberg and Tirole 1991). We consider beliefs about agents' participation decision as a function of their type described by subsets $A(t) \equiv [\hat{a}(t), 1]$ for some participation threshold $\hat{a}(t) \in [0,1]$, such that an individual with type a is expected to participate at moment $t \geq 0$ if $a \in A(t)$, and abstain otherwise.

Hereafter we assume that function $\hat{a}(t)$ is differentiable. Then the following proposition holds:

Proposition 1. In a perfect Bayesian equilibrium, the function $\hat{a}(t)$ is non-decreasing.

Proof: Proofs of this and other propositions, unless indicated otherwise, can be found in Section A1 of the Appendix.

Proposition 1 implies that the only possible equilibria are such in which the participation threshold increases or remains constant, which means weakly declining participation over time.

3.3 Closed-form solution

We now obtain a closed-form solution of such equilibrium with a smooth monotonically non-decreasing function $\hat{a}(t), t \geq 0$ such that:

(i) if an agent participates continuously for all $s \in [0, t]$, $0 < t \leq \infty$, and ends participation at time t, then for all $s < t$ her type is assumed $a > \hat{a}(s)$, and hence her signaling payoff at time s is $2\mu E(a|[\hat{a}(s), 1]) = \mu(1 + \hat{a}(s))$.For all $s \geq t$, her type is assumed $a = \hat{a}(t)$, and the signaling payoff is $2\mu\hat{a}(t)$.[5]

(ii) The above expectations are rational, in that given these expectations, an agent with type a, maximizing her discounted payoff, indeed participates until time t such that $a = \hat{a}(t)$ and quits thereafter (if $a \geq \sup_{t\geq 0} \hat{a}(t)$, participation continues in perpetuity).

[5] Resuming participation after an exit would be inconsistent with the beliefs and hence would not change the signaling payoff.

Up until the quitting time $t > 0$, an agent with type a earns at time $s < t$ a per unit of time payoff $a - c + \mu(1 + \hat{a}(s))$, which, as in Benabou and Tirole (2006), is a sum of intrinsic, extrinsic, and signaling (social image) payoffs. Once participation ends, the agent's signaling utility per unit of time remains $2\mu\hat{a}(t)$for all $s > t$. Hence the agent's total discounted utility is:

$$U(t, a) = \int_0^t [a - c + \mu(1 + \hat{a}(s))]e^{-\delta s} ds + \frac{e^{-\delta t}}{\delta} 2\mu\hat{a}(t). \qquad (1)$$

In equilibrium, the quitting time t maximizes the above utility.

Proposition 2. A smooth function $\hat{a}(t)$ is a perfect Bayesian equilibrium if and only if

$$\hat{a}(t) = \frac{c - \mu}{1 - \mu} - \left[\frac{c - \mu}{1 - \mu} - a_0\right] e^{-\frac{\delta}{2\mu}(1-\mu)t}, \qquad (2)$$

for some $a_0 \in \left[0, \frac{c-\mu}{1-\mu}\right]$.[6]

Proposition 2 implies that declining participation asymptotically approaches the steady-state threshold $a^* = \frac{c-\mu}{1-\mu}$. Notice that $a^* < c$, which means that signaling motivation is the reason the participants with $a \in [a^*, c]$ never exit, since their intrinsic motivation per se is not high enough to offset the cost.

3.4 Impact of Social Image Concerns and Social Capital

Initial participation $1 - a_0$ can be interpreted as a measure of the general capacity for self-organization and collective action, known as social capital, whereas μ, as indicated above, reflects the strength of social image concerns. Examination of the closed-form solution (2) shows that both of these factors increase protest participation $1 - \hat{a}(t)$ along the trajectory.

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[6] The above solution obtains as follows (for details see the Appendix). First-order condition for the maximization of the discounted utility (1) leads to a linear differential equation (taking into account that agent a quits at time t such that $a = \hat{a}(t)$). Global optimality can be established due to $\hat{a}(t)$'s monotonicity and an appropriate single-crossing condition.

Proposition 3. For any $t > 0$, participation threshold $\hat{a}(t)$ monotonically increases in a_0 and decreases in μ, and, therefore, total participation decreases in a_0 and increases in μ. ■

However, the significance of the above factors weakens over time. According to (2), social capital $1 - a_0$ matters for the initial turnout and for participation shortly thereafter, but its contribution gradually diminishes to zero, and it does not affect the asymptotic steady-state participation threshold $a^* = \frac{c-\mu}{1-\mu}$. As for the social image concerns, their marginal contribution also decreases, but this statement is subject to two caveats. First, the contribution of social image concerns to the protest turnout initially *in*creases in t, and starts declining thereafter. This can be explained by the interaction between social capital and social image considerations, whereby the former is the initial sole participation trigger, making protest a social norm to follow, whereas the latter kicks in subsequently and contributes to participation past the initial push. Notice that $a_0 < c$, since we assumed earlier that $a_0 \in \left[0, \frac{c-\mu}{1-\mu}\right]$, and $c < 1$. This means that some of the early participants (with $a < c$) would have not joined the protests without the signaling motivation, and hence initially opportunities for signaling are having increasing impact on participation. However, as explained at the beginning of this section, continued signaling carries less new information, which explains the subsequent decline of the role of image concern. Second, although the marginal contribution of social image concerns is monotonically decreasing after an initial period of time, it does not disappear completely – indeed, μ still matters for the asymptotic participation threshold $\frac{c-\mu}{1-\mu}$.

These conclusions are confirmed by direct calculations, which summarize as follows:

Proposition 4. One has $\frac{\partial^2 \hat{a}(t)}{\partial a_0 \partial t} < 0$, for all $t > 0$. Furthermore, $\frac{\partial^2 \hat{a}(t)}{\partial \mu \partial t} < 0$ for $0 < t < t_0$, and $\frac{\partial^2 \hat{a}(t)}{\partial \mu \partial t} > 0$ for $t > t_0$, where

$$t_0 = \frac{\mu}{2\delta} \frac{c - a_0}{c - a_0 - \mu(1 - a_0)}. \blacksquare \tag{3}$$

The above model can be extended to reflect some other salient features of political protests. Two such extensions are presented in the Appendix (section A1). In the first, we allow for heterogeneous reputational concerns (varying μ), and show that in such case protest dynamics remains essentially the same. Furthermore, this modification provides additional evidence that the role of image concern as a participation factor diminishes over time. In the second modification we allow for successful protest or for a government crackdown, in which cases participation at the time of protest termination carries terminal benefits or costs. Here too, the baseline comparative statics, summarized in Propositions 3 and 4, remain the same.

3.5. Empirical predictions

Our model generates three main testable predictions. First, if social image concerns matter for the decision to participate in protests, the turnout should be expected to gradually decline from a high initial level to a lower steady-state level until protests are terminated for exogenous reasons.

Second, protest turnout increases in social capital and in the strength of the social image concerns. The first of these conjectures implies that protest participation should be correlated with independently obtained measures of the capacity for collective action, and the second – that individuals are more likely to participate in a protest demonstration if they feel there are more opportunities to report own participation to their friends in the targeted reference group.[7] More specifically, the model predicts that protest participation should increase in the number of users of online social media, and that this effect is at least partially mediated through the membership in online protest groups. The intuition behind this prediction is that joining a rally with tens of thousands of participants is directly observable only by a relatively small number of the reference group members, whereas membership in online protest groups increases the "coverage" of this action.[8]

Third, the model makes very specific predictions on how the effects change over time. In particular, Proposition 4 implies that the impact of social image concerns is briefly increasing over time right after the start of the protests and is decreasing over time afterwards. The effect of social capital on protest participation should be expected to grow weaker over time, but since observable measures of social capital are at least to some extent correlated with the strength of

[7] Note that there is a difference between this and subsequent hypotheses, specific to our signaling model, and the standard peer effect conjecture that increased participation of an individual's friends increases the likelihood of his/her own decision to participate (e.g. Siegel 2009, Edmond 2013, DellaVigna et al. 2016, Barbera and Jackson 2016, Larson et al. 2016, Gonzalez 2016).

[8] See Bursztyn and Jensen (2017) on using variations in observability of behavior to identify the image concern effect.

social image concerns, we could expect that the marginal impact of such independent variables could also be increasing for a period of time right after the start of the protests.

4. List experiment

We start by presenting evidence that social image concerns and signaling were indeed prominent in the Russian 2011-2012 political protests. At the end of the wave of protests we conducted a survey of protest participants to shed light on the role of social motivation in their participation decision. Since protest participants might not be willing to admit openly that peer pressure or social image concerns played a role in their decision, we have performed a list experiment, which is considered to be one of the main methods to elicit truthful answers to sensitive survey questions (Glynn 2013).

4.1. Sample

The survey was conducted in Russia in early June of 2012 using two different sampling approaches.[9] First, we posted the links to our primary survey at Slon.ru and Forbes.ru, popular Russian online news outlets, along with a neutrally colored advertising text.[10] The number of respondents in this sample was 2,368. This sample was not representative by design, and survey participation was heavily biased in favor of protest participants, with most respondents being from Moscow. The goal of this approach was to provide evidence on the importance of peer pressure and social signaling for protest participation. Second, a professional marketing firm Tiburon Research conducted a survey of 996 respondents from 91 cities on a representative panel of urban Internet users in Russia. Although this sample contained fewer protest participants, it provided a benchmark comparing the first sample to a representative one.

4.2. Experimental Design

To elicit social image concerns in protest participation, survey respondents were first asked if they had participated in the recent political protests. Participants that answered this

[9] The survey took place in between two large-scale protests of May 6, 2012 and of June 12, 2012. See full chronology of the events in Section 2.

[10] Slon.ru - https://slon.ru/russia/a_vy_khodite_na_mitingi-794916.xhtml, Forbes.ru - http://www.forbes.ru/sobytiya-column/lyudi/82978-chto-vyvodit-lyudei-na-ploshchad (both in Russian).

question positively were randomly divided into four groups: one control group and three treatment groups. In the control group they were asked the following question:

"Why did you participate in protests? You can find a list of possible motives below. Please, tell us how many of them were important for your decision.

(1) *I wanted to show my attitude to what is going on in the country;*

(2) *We needed to show there are many of us;*

(3) *I wanted to influence the situation in my country;*

(4) *It was just interesting to go and watch it."*

In each of three treatment groups, the set of options included one additional entry that reflected potentially sensitive motive related to peer pressure or social signaling.[11] In particular, we included the following three additional options:

Treatment Q1: *Many of my friends and acquaintances were participating;*

Treatment Q2: *I wanted to tell my friends and acquaintances about it.*

Treatment Q3: *I wanted to post about it on social media;*

Treatment option 1 reflected whether protests were perceived as a social norm, making participation imperative and laying the ground for signaling responding to such pressure. Treatment option 2 was included to examine if opportunities for reporting protest participation, which corresponds to social signaling in our model, indeed played a role in individual participation decisions. Finally, treatment option 3 aimed at capturing peer pressure and image concerns in their modern form, where "peers" are not necessarily friends and acquaintances, but also the users of online social media. Option 1 is consistent with any mechanism for peer effects, similar to existing literature (Siegel 2009, Larson et al. 2016, Cantoni et al. 2016b, Gonzalez 2016). Choosing options 2 or 3 would be broadly consistent with the assumption that specifically social signaling plays a role in protest participation decision and that individual participation is higher when there are more opportunities to report one's participation to a larger group of peers.

After being asked the experimental question, treatment group respondents were asked directly about the importance of the motivation that was added as the respective additional

[11] Each list of motives, for both control and treatment groups, was shown in randomized order, to prevent order effects.

option.[12] Respondents in the control group were randomly assigned to face a direct question regarding one of the three potentially sensitive motivations. The goal of this exercise was to assess whether these questions were indeed sensitive.

Figure 1 shows the breakdown of the sample into treatment groups. Randomization was performed without stratification. Out of 1,661 protest participants that we surveyed, 414 did not face any additional "sensitive" motivations in the list experiment question (control group). The remaining 1,247 respondents were split between groups facing additional treatment motivation Q1, Q2, and Q3 (417, 414, and 416 respondents respectively).

4.3. Estimation

Given randomized treatment, comparison of the mean number of positive answers between treatment and control group provides a valid estimate of the percentage of respondents having a sensitive motivation, described in the respective treatment (Imai, 2011). We can also use regression method to get more precise estimates and account for a potential systematic difference in treatment response associated with recruiting respondents from different sources. Finally, as one can see from Table 2, some variables (specifically, income levels and federal districts) were not perfectly balanced across treatment groups, and it is important to control for these characteristics.

Formally, we estimate the following model:

$$y_i = \alpha + \sum_{j=1}^{3} \beta_j T_{ij} + X_i \gamma + \varepsilon_i \,, \tag{4}$$

where y_i is the number of motivations entered, T_{ij} is the indicator that respondent i belongs to treatment group j, and X_i is the matrix of respondent $i's$ covariates.

[12] A direct question was asked after the main list experiment question, phrased as follows: "Why did you participate in protests? How important or not important for you was the following motive:" (treatment motive Q1, Q2, or Q3 is listed) "1 – very important, 2 – rather not important, 3 – rather not important, 4 – not at all important". We then code the answers "very important" and "rather important" as "yes" or 1, while "rather not important" and "not at all important" were interpreted as "no" or 0.

4.4. Results

Figure 2 presents the results of the simple mean comparison. These estimates suggest that 42% of our respondents went to protest (partly) because their friends and acquaintances were going; 23% participated (partly) because they wanted to tell their friends and acquaintances about it; while 11% of the respondents went out to protest (partly) because they wanted to tell about it on social media.

Table 2 presents the regression results with groups of controls added sequentially. The results are very similar to the difference-in-means estimator, both regarding coefficients' size and statistical significance.[13] Our full specification (column 5) includes fixed effects for gender, age, education income, occupation, and region. In this specification, 39% of our respondents went to protest (partly) because their friends were going, while 20% report that telling their friends about it was an important motivation for their participation. However, after taking all observables into account, the coefficient for the motivation related to posting on online social media decreases down to 9% and loses statistical significance.

As was noted above, we also included direct questions regarding potentially sensitive motivations to check whether they were indeed considered as "sensitive" by the respondents. Figure 3 shows that direct questions yield remarkably similar estimates for the importance of the treatment motivations as compared to the results of list experiment for all three options. The lack of significant difference is confirmed by the methodology of Blair and Imai (2012). Thus, the results indicate that our respondents did not consider the questions about social motivation in protest participation as sensitive and were willing to admit them even if asked directly (at least in the case of these particular protests in Russia). Although this finding goes against our expectations, it further confirms the importance of social motivation. Social motivation not only was salient for a sizable share of protest participants, but also was viewed as socially acceptable reason for protest participation. In Section A3 of the Appendix, we present evidence in favor of identifying assumptions for list experiments (Imai 2011).

Overall, the results of the list experiment indicate that both social pressure and social signaling motives were important determinants of the decision to participate in political protests.

[13] We find that federal districts and income level fixed effects do not appear to be jointly important in explaining the variation in the number of motivations reported. This is a sign that randomization imbalances do not appear to affect our results substantially.

5. City-level analysis

In this section, we use city-level information on political protests to test empirical predictions of the model. First, we provide evidence that the overall protests dynamics is consistent with the theoretical predictions (subsection 5.2). Next, we study how protest participation is affected by the penetration of online social media (subsection 5.3) and preexisting social capital (subsection 5.4). Finally, we analyze how the effect of online social media and social capital changes over time (subsection 5.5).

5.1 Data

We use several sources of data for the city-level analysis. Our sample consists of 625 Russian cities with populations over 20,000 according to the 2010 Census. We exclude Moscow and Saint Petersburg from the cross-city analysis as outliers since they are clearly not comparable to the rest of the sample.

We use hand-collected data on political protests that occurred between December 2011 and July 2012. When the protests began in December 2011, we started monitoring newspaper databases and online resources to record information about political protests in any Russian city mentioned in this context. The monitoring was repeated every week until the protests subsided in summer 2012. For each event, we recorded the number of protesters, as reported by three alternative sources: (i) the police; (ii) organizers of the protest; and (iii) a news source that wrote about the protest.[14] As a result of this monitoring, we have collected a unique, comprehensive city-level database on political protests in Russia in 2011-2012. We aggregate this information to city-week level constructing two variables: an indicator for existence of a protest in a given city during a given week, and the number of protesters computed by taking the average number of protesters as reported by the police, organizers, and the news source.[15] If there were more than one protest event in a city during the same week, we take the number of protesters at the biggest event.

[14] We have data on all the three estimates in 9.5% of the cases. Only one estimate is available in 64% of the cases. As a result, we primarily use the estimates reported by journalists in various news sources.

[15] Our estimates remain practically unchanged if we use a median value of the available estimates instead of a mean.

For identification, we use information on the city of origin of the students who studied at Saint Petersburg State University (SPbSU). We use information on the year of birth of these students and the city where they finished high school, to create measures for the number of students from a given city who studied with Pavel Durov, VK founder, and the number of students from a city who have been studying several years earlier or later. To avoid the influence of outliers, we take the natural logarithm of both the number of students in each cohort and the number of protest participants.

To measure online protest group membership, we first collected information on online protest groups. We used two sources of information: (i) public lists of online protest groups and events provided by *Yandex*, the leading Russian search engine, and (ii) manual online search using keywords common in the protest community (e.g., "for fair elections" + the name of the city). We collect information on the number of public members of these groups. More details on data collection are available in Section A4 of the Appendix.

To measure social capital at the city level, we use information on the number of voluntary associations per city, which is often used as a proxy for social capital (e.g. see Keefer, and Knack 2008, Guiso, Sapienza, and Zingales 2016). This information comes from the registrar of nonprofit organizations by the Russian Ministry of Justice.[16] Following Menyashev (2014), we also use a specific type of voluntary associations – consumer cooperatives – as a proxy for social capital at the city level. Since this data is very noisy in smaller cities, we restrict the analysis to cities with a population above 50,000. As an alternative measure of social capital, we use answers to a question about generalized trust. This measure comes from an extensive survey of more than 34,000 respondents in 66 regions conducted in 2007 by the Public Opinion Foundation (FOM). This survey was regionally representative and covered 219 cities in our sample. Trust is measured as a response to a question "Generally speaking, do you believe that most people can be trusted or can't you be too careful in dealing with people?"

The city-level data on population, age, education, and ethnic composition comes from the Russian Censuses of 2002 and 2010. The data on the average wage and municipal budgets comes from the Russian Federal State Statistics Service (or *Rosstat*). Additional city characteristics (latitude, longitude, year of city foundation, and the location of administrative centers) come

[16] Available at http://unro.minjust.ru/NKOs.aspx.

from the national encyclopedia of Russian cities and regions.[17] Summary statistics for the variables employed in the analysis are presented in Table A4 in the Appendix.

5.2 Protest dynamics

Figure 4 depicts how aggregate protest turnout was changing over time in eight largest cities in our sample, as well as on average across all cities in the sample. The graph covers the period from protests inception at the beginning of December 2011 until late July 2012, when the regular protests across the country died out. Participation data is reported for every two weeks. Data for the period around May 1, 2012, is not included because protest demonstrations over that period overlapped with the "conventional" May 1 rallies held as a tradition continued from the Soviet times and it was not possible to fully differentiate different types of rallies. Figure 4 contains a scatter plot of protest participation, combined with a smoothed approximation constructed using the locally weighted scatterplot smoothing technique. Presented dynamics is consistent with the second prediction of the model – it exhibits a gradual decline towards a temporary stable lower level, continuing until the end of mass protests.

5.3 Online protest groups and protest participation

According to empirical predictions of the model from subsection 3.5, we expect protest participation to increase in the number of users of online social media. Moreover, we expect this effect to be at least partially mediated through the membership in highly visible public online protest groups, in which people could make their participation publicly observable.

Empirical results in Enikolopov, Makarin, and Petrova (2016) show that political participation was indeed higher in cities with higher penetration of the online social media. To identify the causal effect of social media penetration, the above paper exploits an IV approach, in which the number of users of VK in a given city is instrumented with the number of students from this city who studied at SPbSU in the same cohort as the founder of VK, Pavel Durov. Importantly, this method also includes controlling for the number of students from the same city who studied at SPbSU several years earlier or later. The intuition behind this approach is that Durov's classmates at SPbSU were the first adopters of VK and, therefore, were the earliest to bring VK to their home cities. This idiosyncratic shock, in turn, due to network externalities, positively influenced later VK penetration in those cities and, finally, the visible size of online

[17] Available at http://www.mojgorod.ru/.

protest groups. Note that unobserved city characteristics that make certain cities more prone to sending students to SPbSU would likely affect all cohorts of students the same way; thus, identification rests upon an unexpected quasi-random city-level shock to student flows in one particular student cohort.

In this paper, we check if membership in online protest groups was one of the channels through which VK penetration affected the protests. We employ the same source of exogenous variation, but use the number of users registered in online protest groups, rather than the total number of VK users, as the explanatory variable. In particular, we estimate the following model:

$$Protests_i = \beta_0 + \beta_1 Protest\_groups\_membership_i + \beta_2 \mathbf{X_i} + \varepsilon_i, \qquad (5)$$

where $Protests_i$ is one of the two measures of protest activity – either the logarithm of the number of protesters in city i in the first weekend of the protests plus one or an indicator variable for the occurrence of at least one protest in city i on the first weekend of the protests.[18] $VKProtest\_groups\_membership\_Penetration_i$ is the logarithm of the number of online protest group members on VK in city i ; $\mathbf{X_i}$ is a vector of control variables that includes a fifth-order polynomial of population, an indicator for whether city i is a regional or a sub-regional (rayon) administrative center, average wage, number of city residents of different five-year age cohorts, distance to Moscow and Saint Petersburg, an indicator for whether city i has a university, a share of population with higher education in 2010 for each age cohort separately, the average share of population with higher education in 2002, ethnic fractionalization, and the regional internet penetration. In some specifications, $\mathbf{X_i}$ also includes the outcomes of the pre-2006 parliamentary elections, to account for pre-existing political preferences in city i. Standard errors in all models are clustered at the regional level.

Figure 5 shows that the number of online protest group participants was higher in places with a higher number of students in Durov's cohort as compared to other cohorts. Note that the corresponding Kleibergen-Paap statistics from the first-stage regression (reported in Table 3) is above 50 in all the specifications, which indicates that our results are not likely to be biased because of a weak instrument problem.

Table 3 reports the results of our IV estimation, in which we examine the effect of membership in online protest groups on the size and incidence of protests. Columns 1-4 show

[18] We focus on the first weekend of mass protests to avoid a possibility of dynamic effects within and across the cities. These effects are examined separately in subsection 5.5.

that the size of online protest groups significantly increased the number of protest participants, with a 10% increase in the size of a group leading to an approximately 10% increase in the number of protest participants. Similarly, columns 5-8 show that a similar result holds for the protest incidence, with a 10% increase in the size of an online protest group leading to a 2.5 percentage point increase in the probability of a protest. Both of these results are consistent with a theoretical prediction that an enhanced visibility of protest participation increases the likelihood of individual participation.

5.4 Social capital and protest participation

Next, we test if cities with a higher stock of social capital featured higher protest turnouts, as predicted by the theory. In particular, we estimate the following model:

$$Protests_i = \beta_0 + \beta_1 Social\_capital_i + \beta_2 \mathbf{X_i} + \varepsilon_i, \qquad (6)$$

where $Social\_capital_i$ is one of the four different measures of social capital – (i) the number of voluntary associations, (ii) the number of consumer cooperatives, (iii) share of people who agreed with the statement that most people can be trusted, and (iv) summary index of social capital based on all the first three measures, which was constructed using the approach of Kling, Liebman, and Katz (2007) by taking the equally weighted average of z-scores of the individual indicators.[19] Due to limitations of data availability for the measures of social capital, our sample is substantially smaller than in Table 3, and our set of controls is more parsimonious.

The results indicate that, indeed, places with higher stocks of social capital, on average, had more protest participants and a higher probability of protest participation (see Table 4). The magnitudes of the results imply that a one standard deviation increase in the summary measure of social capital was associated with a 2% higher protest participation and a 3 percentage point higher probability of having a protest in a city.

Overall, the above results are consistent with the predictions of our theoretical model and indicate that that social capital increases protest turnout.

[19] The z-scores are calculated by subtracting the mean from each observation-value and dividing it by the standard deviation of each respective measure.

5.5 The effect of online social networks and social capital over time

Finally, we turn to the last prediction of the model that the importance of social image concerns and social capital on protest participation declines over time. To test this prediction, we conduct panel data analysis with city fixed effects, exploiting the fact that protests of 2011-2012 continued for more than six months. The unit of observation is city-week. Our main specification is as follows:

$$protest\_variable_{it} = \beta_0 + \beta_1 social_i \times t + \beta_2 \boldsymbol{X_i} \times t + \beta_3 t + \delta_i + \varepsilon_{it}, \qquad (7)$$

where $protest\_variable_{it}$ is protest participation in city i in week t, measured by either the logarithm of the number of protest participants or a dummy for having a protest in a city; $social_i$ is either a measure of online social media penetration, which proxies for social image concerns, or a measure of social capital; $\boldsymbol{X_i}$ is a vector of controls, and δ_i is a city fixed effect. The effect of online social media penetration is estimated using 2SLS in which the interaction between the number of users of VK and the time trend is instrumented with the interaction of the number of students from this city who studied at SPbSU in the same cohort as the founder of VK with the time trend. The effects of social image concerns are estimated using OLS regressions.

To capture the prediction that the dynamics of the effects is different right after the start of protests and in the subsequent periods we estimate these regressions separately for two periods: i) the first two weeks of the protests; ii) the period starting from the second week of protests until the end of the protest wave in the end of July 2012.

The results presented in Table 5 indicate that the importance of online social networks in generating protests was increasing in the first two weeks of the protest and has been declining over time afterwards. Both effects, predicted by the theory, are statistically significant. Similarly, Table 6 shows that the importance of social capital for generating protests was slightly increasing in the first two weeks of the protests, and declining afterwards.[20] The initial increase of the marginal effect of social capital measures is not predicted by the theory (unlike the eventual decline), and is likely an artifact of the used measures, possibly also capturing to some extent social image concern (for which such initial increase is predicted).[21]

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[20] If we estimate regressions for the whole sample the second effect dominates and the results are declining over time (see Tables A6 and A7 in the Appendix).

[21] Notice also that the initial increase of the social capital impact is statistically insignificant in most specifications, while the predicted eventual decline is always significant.

Overall, the results in both Table 5 and Table 6 are consistent with our prediction that the effects of social image concerns and social capital on political protests should decrease over time after the initial phase of the protest, during which the role of social image concerns is increasing.[22]

6. Conclusion

Existing literature suggests that social motivation is important for political behavior and political collective action. Our paper identifies a specific potential mechanism for this relationship. We argue that costly protest participation allows pro-socially minded individuals to signal their type, and we show how participation supported by this mechanism evolves over time. We build a micro-founded dynamic model of protest participation that takes into account this mechanism and provides a number of testable predictions.

We then test the predictions of the model using data on protest activity during the wave of political protests in Russia in 2011-2012. Using an original survey and data on the dynamics of political protest in Russian cities, we provide a set of empirical results, all of which are consistent with the predictions of our theoretical model. Taken together, these results indicate that both online social networks and offline social capital played a significant role in generating political protests, but their effect was declining over time. More generally, our results demonstrate that both online and offline social networks are important in explaining participation in political collective action.

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[22] Possible explanation of the difference between our results and the results in Cantoni et al. (2016b) is that they study political protests in Hong Kong, which already lasted for several years by the time the research has been conducted, and the peer pressure motive could have substantially weakened by that time.

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Figures and Tables

Figure 1. Treatment Allocation, Including Randomization of Direct Questions

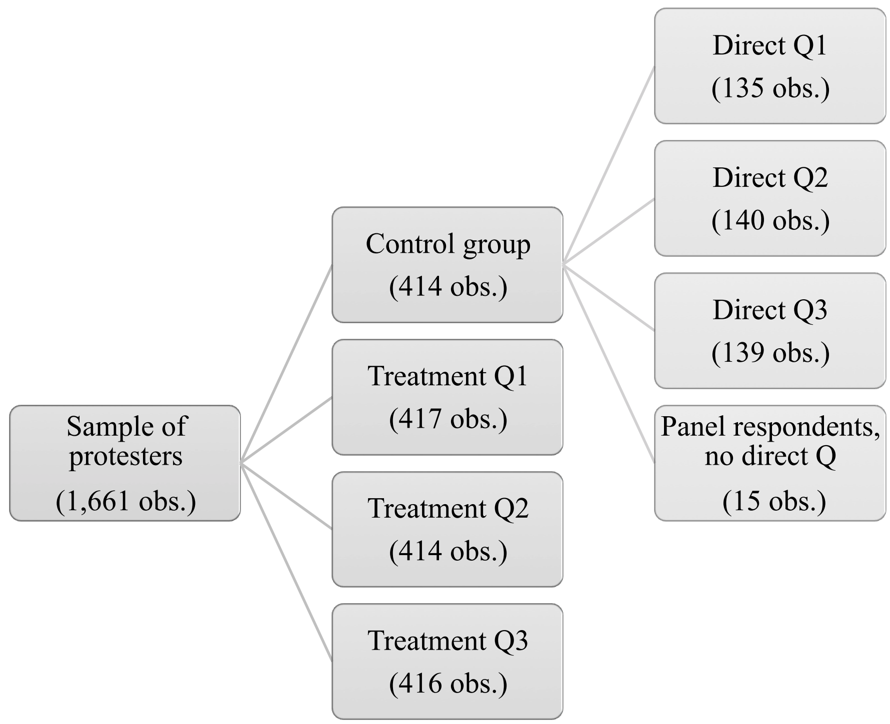
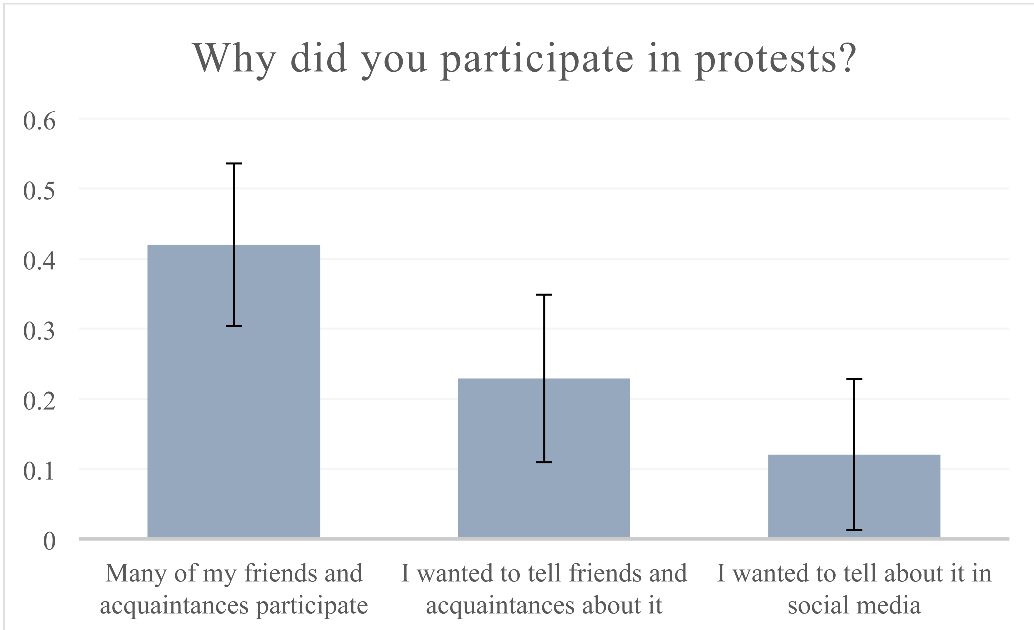
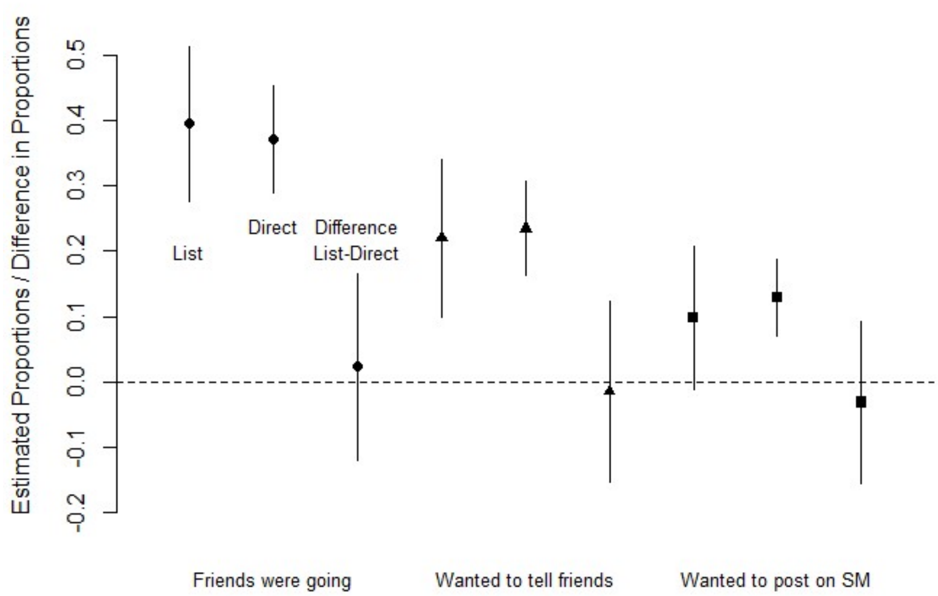


Figure 2. List Experiment Estimates of Peer Pressure in Protest Participation. Difference-in-Means Estimator



Notes: Based on data from 1,661 respondents (Slon.ru, Forbes.ru, and the panel respondents are pooled). Bars represent the 95% confidence intervals. Difference-in-means estimates are obtained from a pooled regression without control variables.

Figure 3. Comparison between List Experiment and Direct Question Estimates (Slon.ru and Forbes.ru Respondents Only)



Notes: Direct question results are available only for the Slon.ru and Forbes.ru respondents (n=1,607). Panel respondents were excluded. Results were obtained using R package "*list*" by Blair and Imai (2012).

Figure 4. Total Number of Protestors for Bi-Weekly Intervals Between December 4, 2011 and July 31, 2012

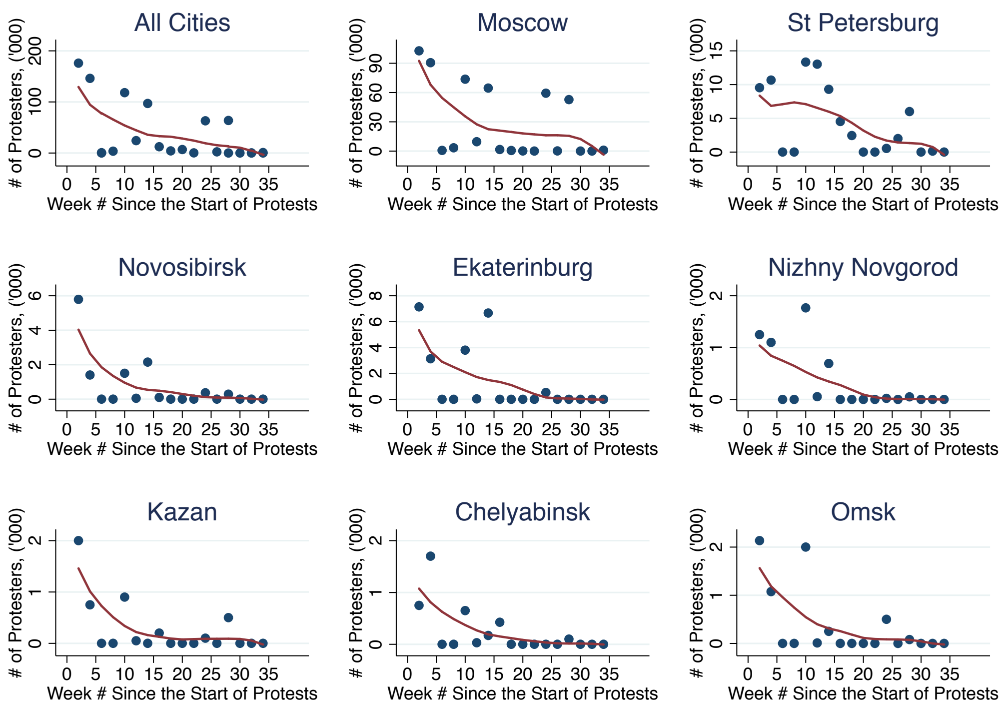
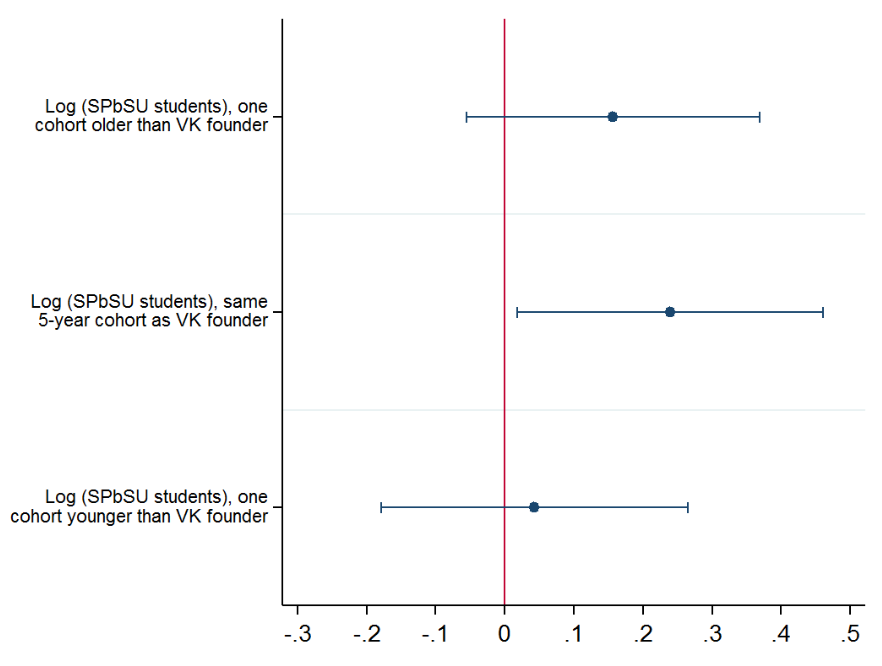


Figure 5. Online Protest Group Membership and Saint Petersburg State University Student Cohorts



Note: The figure shows the coefficients from a regression of the number of registered members of the online protest groups on VK in a city on the number of students from that city that studied in each of the three 5-year cohorts in Saint Petersburg State University.

Table 1. Summary Statistics and Balance on Covariates for List Experiment.

VARIABLES	N	Mean	SD	Mean (Control)	Mean (TQ 1)	Mean (TQ 2)	Mean (TQ 3)	P-value (equality of means)		
								TQ1=Control	TQ2=Control	TQ3=Control
Sex: 1 = Woman, 2 = Man	1,661	1.613	0.487	1.590	1.606	1.640	1.618	0.385	0.721	0.527
Age	1,661	32.80	10.41	32.55	32.46	32.81	33.39	0.242	0.201	0.409
Moscow	1,661	0.780	0.415	0.801	0.796	0.749	0.773	0.348	0.404	0.302
Saint Petersburg	1,661	0.045	0.208	0.043	0.039	0.036	0.063	0.212	0.108	0.082*
Region: Central	1,661	0.854	0.353	0.866	0.877	0.843	0.831	0.171	0.048**	0.808
Region: Northwestern	1,661	0.055	0.228	0.058	0.046	0.044	0.073	0.396	0.100	0.081*
Region: South	1,661	0.013	0.114	0.005	0.019	0.022	0.007	0.666	0.134	0.069*
Region: Volzhsky	1,661	0.037	0.188	0.029	0.019	0.053	0.046	0.203	0.028	0.535
Region: Uralian	1,661	0.014	0.119	0.012	0.017	0.012	0.017	0.557	0.979	0.635
Region: Siberian / Far Eastern	1,661	0.027	0.161	0.031	0.022	0.027	0.027	0.670	0.638	0.874
Voted for a Communist Party	1,661	0.167	0.373	0.173	0.178	0.152	0.164	0.738	0.608	0.613
Voted for a Socialist Party	1,661	0.182	0.386	0.168	0.212	0.181	0.169	0.952	0.120	0.655
Voted for a Liberal Party	1,661	0.379	0.485	0.386	0.327	0.401	0.401	0.636	0.028**	0.902
Voted for a Pro-Government Party	1,661	0.008	0.091	0.000	0.012	0.010	0.012	0.015**	0.915	0.812
Knew which parties made it to the Parliament	1,661	0.884	0.321	0.871	0.882	0.901	0.882	0.573	0.944	0.472
Education: High school / Specialized high school	1,661	0.059	0.236	0.053	0.063	0.058	0.063	0.605	0.929	0.957
Education: Incomplete higher education	1,661	0.150	0.357	0.146	0.144	0.159	0.150	0.882	0.828	0.729
Education: Higher education	1,661	0.675	0.468	0.695	0.673	0.650	0.684	0.749	0.762	0.229
Education: PhD or Doctorate Degree	1,661	0.110	0.312	0.096	0.118	0.128	0.097	0.950	0.318	0.168
Income: Enough money for food, but not for clothes	1,661	0.049	0.215	0.041	0.060	0.041	0.053	0.402	0.666	0.385
Income: Enough money for clothing, but not for durables	1,661	0.207	0.405	0.223	0.245	0.174	0.186	0.176	0.039**	0.738
Income: Enough money for durables, but not for a car	1,661	0.368	0.482	0.353	0.387	0.353	0.379	0.431	0.812	0.415
Income: Enough money for a car, but not for an apartment	1,661	0.296	0.457	0.295	0.252	0.350	0.287	0.838	0.263	0.058*
Income: Financial difficulties are not experienced at all	1,661	0.075	0.264	0.082	0.048	0.077	0.094	0.517	0.010**	0.383
Job: Head, director, deputy head	1,661	0.067	0.251	0.082	0.051	0.075	0.063	0.307	0.445	0.525
Job: Head of a unit (department, shift, etc.)	1,661	0.129	0.336	0.110	0.115	0.159	0.133	0.325	0.453	0.293
Job: Specialist with higher education (doctor, teacher, etc.)	1,661	0.357	0.479	0.376	0.361	0.336	0.355	0.535	0.861	0.520
Job: Owner	1,661	0.084	0.277	0.082	0.096	0.070	0.087	0.762	0.627	0.342
Job: Creative profession	1,661	0.135	0.342	0.134	0.139	0.121	0.147	0.572	0.745	0.227
Job: Student	1,661	0.113	0.317	0.110	0.118	0.128	0.097	0.536	0.318	0.173

Notes: Summary statistics are presented for protest participants only. All variables except for sex and age are in terms of a share of respondents.

Table 2. List Experiment Estimates for Peer Pressure in Protest Participation.

	Why did you participate in protests? The number of motives				
	(1)	(2)	(3)	(4)	(5)
Treatment Q1: Many of my friends and acquaintances participate	0.421***	0.419***	0.418***	0.418***	0.391***
	[0.060]	[0.060]	[0.060]	[0.060]	[0.061]
Treatment Q2: I wanted to tell friends and acquaintances about it	0.234***	0.238***	0.232***	0.224***	0.203***
	[0.062]	[0.062]	[0.061]	[0.062]	[0.062]
Treatment Q3: I wanted to tell about it in social media	0.114**	0.115**	0.117**	0.113**	0.088
	[0.055]	[0.056]	[0.056]	[0.056]	[0.057]
Respondent: Forbes.ru			-0.212*	-0.209*	-0.233**
			[0.112]	[0.113]	[0.118]
Respondent: Panel			-0.399***	-0.315*	-0.253
			[0.153]	[0.162]	[0.171]
Observations	1,661	1,661	1,661	1,661	1,661
Federal district Fixed Effects		Yes	Yes	Yes	Yes
Income level Fixed Effects		Yes	Yes	Yes	Yes
Occupation Fixed Effects				Yes	Yes
Sex Fixed Effects					Yes
Age Fixed Effects					Yes
Education Fixed Effects					Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets. "Fixed effects" stand for a set of indicator variables for each value of a categorical variable.

Table 3. VK Online Protest Groups and Protest Participation (First Week of Protests).

	Log (Number Of Protesters)				Dummy for Incidence of Protests			
	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (size of online protest group on VK), Dec 2011	1.051*	1.103*	1.028*	1.175*	0.256*	0.264*	0.248**	0.281*
	[0.589]	[0.656]	[0.544]	[0.685]	[0.139]	[0.151]	[0.126]	[0.160]
Log (SPbSU students), one cohort younger than VK founder	0.249**	0.267**	0.244**	0.263**	0.035	0.039	0.035	0.037
	[0.121]	[0.130]	[0.119]	[0.132]	[0.029]	[0.031]	[0.029]	[0.032]
Log (SPbSU students), one cohort older than VK founder	-0.150	-0.164	-0.150	-0.156	-0.035	-0.038	-0.035	-0.036
	[0.176]	[0.195]	[0.170]	[0.196]	[0.042]	[0.045]	[0.039]	[0.046]
Population controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age cohort controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Electoral controls, 1995		Yes				Yes		
Electoral controls, 1999			Yes				Yes	
Electoral controls, 2003				Yes				Yes
Observations	625	625	625	625	625	625	625	625
F-statistics (Kleibergen-Paap)	56.74	56.16	56.16	56.16	56.74	56.16	56.16	56.16

calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a joint significance level is reported immediately after for this group of controls. Flexible controls for population (5th polynomial) are included in all specifications. Age cohort controls include the number of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50 and older years, in each city according to 2010 Russian Census. Education controls include an indicator for university presence, as well as the share of population with higher education overall according to 2002 Russian Census and separately in each of the age cohorts according to 2010 Russian Census, to account for both the levels and the change in education within each five-year cohort. Electoral controls include the vote shares for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), vote against all, and the electoral turnout for a corresponding year. Other controls include dummies for regional and county centers, distances to Moscow and St Petersburg, the logarithm of the average wage, oblast-level internet penetration in 2011, the logarithm of the number of Odnoklassniki users in 2014, and ethnic fractionalization in 2010.

Table 4. Protest Participation and Social Capital (First Week of Protests).

	Log (Number Of Protesters)				Dummy for Incidence of Protests			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Number of Consumer Cooperatives)	0.138**				0.025*			
	(0.068)				(0.013)			
Log (Number of Voluntary Associations)		0.093**				0.021		
		(0.047)				(0.016)		
Generalized Trust			0.916**				0.113*	
			(0.355)				(0.059)	
Social capital, summary measure				0.290**				0.046**
				(0.110)				(0.021)
Log (Average wage), city-level, 2011	0.330	0.352	0.370	0.298	0.036	0.046	0.043	0.037
	(0.276)	(0.265)	(0.277)	(0.276)	(0.035)	(0.035)	(0.041)	(0.036)
Population with higher education, 2010 (%)	2.911	3.206	2.912	3.674	0.599	0.603	0.321	0.720
	(3.056)	(3.044)	(3.221)	(2.975)	(0.463)	(0.455)	(0.395)	(0.493)
Population with higher education, 2002 (%)	-1.435	-1.400	0.895	-2.086	-0.244	-0.317	0.275	-0.420
	(4.353)	(4.280)	(4.941)	(4.139)	(0.616)	(0.580)	(0.524)	(0.650)
Internet penetration 2011, region-level	-1.132*	-0.958	-1.508**	-1.047*	-0.154*	-0.134	-0.166*	-0.136
	(0.611)	(0.583)	(0.669)	(0.581)	(0.089)	(0.085)	(0.093)	(0.085)
Ethnic fractionalization, 2010	-0.534	-0.545	-0.130	-0.527	-0.072	-0.088	-0.010	-0.084
	(0.448)	(0.450)	(0.559)	(0.456)	(0.072)	(0.072)	(0.076)	(0.075)
Population controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	321	321	269	321	321	321	269	321

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are clustered at the region level. Unit of observation is a city. A logarithm of any variable is calculated with 1 added inside. Flexible controls for population (5th polynomial) are included in all specifications. Because of data availability, the sample is limited to the cities with population above 50,000 people.

Table 5. VK penetration effect over time, 2011-2012. Panel IV.

	Log (Number Of Protesters)							
	The First Two Weeks of Protests				Following the First Two Weeks of Protest			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (VK users in 2011) x Time	1.8244*	1.7943*	1.8067*	1.9490*	-0.0191*	-0.0187**	-0.0189*	-0.0198**
	[1.0149]	[0.9894]	[1.0109]	[1.0212]	[0.0098]	[0.0093]	[0.0096]	[0.0099]
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls Interacted with Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5th Polynomial of Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Voting Controls 1995, Interacted with Time		Yes				Yes		
Voting Controls 1999, Interacted with Time			Yes				Yes	
Voting Controls 2003, Interacted with Time				Yes				Yes
Observations	1,250	1,250	1,250	1,250	23,125	23,125	23,125	23,125
	Dummy for Incidence of Protests							
	The First Two Weeks of Protests				Following the First Two Weeks of Protest			
Log (VK users in 2011) x Time	0.4469**	0.4312**	0.4379**	0.4657**	-0.0042**	-0.0041**	-0.0041**	-0.0043**
	[0.1965]	[0.1890]	[0.1916]	[0.1981]	[0.0020]	[0.0019]	[0.0019]	[0.0020]
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls Interacted with Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5th Polynomial of Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Voting Controls 1995, Interacted with Time		Yes				Yes		
Voting Controls 1999, Interacted with Time			Yes				Yes	
Voting Controls 2003, Interacted with Time				Yes				Yes
Observations	1,250	1,250	1,250	1,250	23,125	23,125	23,125	23,125

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are clustered at the region level. Unit of observation is a city. The interaction between the number of users of VK and the time trend is instrumented with the interaction of the number of students from the city who studied at SPbSU in the same cohort as the founder of VK with the time trend. Baseline controls include 5th polynomial of population, the number of students from the city who studied at SPbSU in the same cohorts younger and older than the founder of VK, age cohorts (the number of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50 and older), dummies for regional and county centers, distances to Moscow and St Petersburg, the logarithm of the average wage, % with higher education, region-level internet penetration in 2011, the logarithm of the number of Odnoklassniki users in 2014. Electoral controls include the vote shares for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), vote against all, and electoral turnout for a corresponding year.

Table 6. Protest Participation Over Time and Social Capital.

	Log (Number Of Protesters)							
	The First Two Weeks of Protests				Following the First Two Weeks of Protest			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Number of Consumer Cooperatives) x Time	0.1351*				-0.0015**			
	[0.0742]				[0.0007]			
Log (Number of Voluntary Associations) x Time		0.0683				-0.0018***		
		[0.0474]				[0.0006]		
Generalized Trust x Time			0.7435**				-0.0139***	
			[0.3584]				[0.0037]	
Social capital, Summary Measure x Time				0.1995				-0.0050***
				[0.1302]				[0.0012]
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls Interacted with Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5th Polynomial of Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	642	642	538	642	11,877	11,877	9,953	11,877
	Dummy for Incidence of Protests							
	The First Two Weeks of Protests				Following the First Two Weeks of Protest			
Log (Number of Consumer Cooperatives) x Time	0.0189				-0.0003*			
	[0.0133]				[0.0001]			
Log (Number of Voluntary Associations) x Time		0.0084				-0.0003***		
		[0.0097]				[0.0001]		
Generalized Trust x Time			0.0965				-0.0025***	
			[0.0702]				[0.0008]	
Social capital, Summary Measure x Time				0.0234				-0.0010***
				[0.0245]				[0.0002]
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls Interacted with Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5th Polynomial of Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	642	642	538	642	11,877	11,877	9,953	11,877

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are clustered at the region level. Unit of observation is a city. Baseline controls include 5th polynomial of population, age cohorts (the number of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50 and older), dummies for regional and county centers, distances to Moscow and St Petersburg, the logarithm of the average wage, % with higher education, region-level internet penetration in 2011, the logarithm of the number of Odnoklassniki users in 2014. Electoral controls include the vote shares for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), vote against all, and electoral turnout for a corresponding year. Because of data availability, the sample is limited to the cities with population above 50,000 people.