Social Media and Protest Participation: Evidence from Russia*

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Abstract

Do new communication technologies, such as social media, alleviate the collective action problem? This paper provides evidence that penetration of VK, the dominant Russian online social network, led to more protest activity during a wave of protests in Russia in 2011. As a source of exogenous variation in network penetration, we use information on the city of origin of the students who studied together with the founder of VK, controlling for the city of origin of the students who studied at the same university several years earlier or later. We find that a 10% increase in VK penetration increased the probability of a protest by 4.6%, and the number of protesters by 19%. At the same time, VK penetration increased pro-governmental support, with no evidence of increased polarization. Additional results suggest that social media induced protest activity by reducing the costs of coordination rather than by spreading information critical of the government. We find that cities with higher fractionalization of network users between VK and Facebook experienced fewer protests, and the effect of VK on protests exhibits threshold behavior. Finally, we provide suggestive evidence that municipalities with higher VK penetration received smaller transfers from the central government after the occurrence of protests.

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1 Introduction

The collective action problem has traditionally been seen as one of the major barriers to achieving socially beneficial outcomes (e.g., Olson, 1965; Hardin, 1982; Ostrom, 1990). People's ability to overcome the collective action problem depends on their information environment and their ability to communicate with one another. New horizontal information exchange technologies, such as Facebook, Twitter, and other social media platforms, allow users to converse directly without intermediaries at a very low cost, thus potentially enhancing the spread of information and weakening the obstacles to coordination. However, so far there has been no systematic evidence on whether social media indeed improves people's ability to overcome the collective action problem. Our paper fills this gap in the literature by looking at the effect that the most popular online social network in Russia had on a particular form of collective action — political protests.

The rise of social media in recent years coincided with waves of political protests around the world. But did social media play any role in inducing political participation, i.e., by inciting the protests, or did its content just reflect the preferences of the population?[1] Recent theoretical work argues that social media may indeed increase the probability of political protests taking place (Edmond, 2013; Little, 2016; Barberà and Jackson, 2016). However, testing this hypothesis empirically is methodologically challenging since social media usage is endogenous to individual and community characteristics. In addition, protests are typically concentrated in one or a few primary locations, as was the case for Tahrir Square in Egypt or Maidan in Ukraine. Hence, geographic variation in protests is often very limited. Temporal variation in protest intensity can provide evidence on the association between activity and content of social media and subsequent protests (Acemoglu, Hassan, and Tahoun, 2017)[2] but does not provide evidence on the causal effect of social media availability.

To understand whether social media indeed promotes protest participation, we study an unexpected wave of political protests in Russia in December 2011 triggered by electoral fraud in parliamentary elections, coupled with the analysis of the effect of social media on the support of the government.[3] Our empirical setting allows us to overcome the problems of previous studies for two reasons. First, there was substantial geographic and time variation in protest activities and

[1] While not based on systematic empirical evidence, previous popular and academic literature disagreed even about the direction of the potential effect of social media on protests. Some have argued that the effect must be positive, as social media promotes cooperation (Shirky, 2008), fosters a new generation of people critical of autocratic leaders (Lynch, 2011), and increases the international visibility of protests (Aday et al., 2010, 2012). Others, however, have noted that social media is either irrelevant or even helps to sustain authoritarian regimes by crowding out offline actions (Gladwell, 2010), allowing governments to better monitor and control dissent (Morozov, 2011), and spread misinformation (Esfandiari, 2010).

[2] See also Hassanpour (2014) and Tufekci and Wilson (2012) for survey-based evidence on temporal variation in protests in Egypt.

[3] Electoral fraud was documented, for instance, in Enikolopov, Korovkin, Petrova, Sonin, and Zakharov (2013) and Klimek, Yegorov, Hanel, and Thurner (2012).

in the penetration of major online social networks across Russian cities. E.g., among 625 cities in our sample, 133 witnessed at least one protest demonstration after the elections in December 2011. Second, particularities of the development of VKontakte (VK), the most popular social network in Russia, allow us to exploit quasi-random variation in the penetration of this platform across cities and, ultimately, identify the causal effect of social media penetration on political protests.

Our identification is based on the information about the early stages of the VK development. VK was launched by Pavel Durov in October 2006, the same year he graduated from Saint Petersburg State University (SPbSU). Upon VK's creation, Durov issued an open invitation on an SPbSU online forum for students to apply for membership on VK. Interested students then requested access to VK, and Durov personally approved all accounts. Thus, the first users of the network were primarily students who studied at Saint Petersburg State University together with Durov. This, in turn, made their friends and relatives at home more likely to open an account, which sped up the development of VK in these cities. Network externalities magnified these effects and, as a result, the distribution of the home cities of Durov's classmates had a long-lasting effect on VK penetration. In particular, we find that the distribution of the home cities of the students who studied at SPbSU at the same time as Durov predicts the penetration of VK across cities in 2011, but the distribution of the home cities of the students who studied at SPbSU several years earlier or later does not.

We exploit this feature of VK development in our empirical analysis by using the origin of students who studied at SPbSU in the same five-year cohort as the VK founder as an instrument for VK penetration in summer 2011, controlling for the origin of the students who studied at SPbSU several years earlier and later. Thus, our identification is based on the assumption that temporal fluctuations in the number of students coming to SPbSU from different cities were not related to unobserved city characteristics correlated with political outcomes.

Using this instrument, we estimate the causal impact of VK penetration on the incidence of protests and protest participation. In the reduced form analysis, we find that the number of students from a city in the VK founder's cohort had a positive and significant effect on protest participation, while there was no such effect for the number of students from older or younger cohorts. The corresponding IV estimates indicate that the magnitude of the effect is sizable — a 10% increase in the number of VK users in a city led to a 4.6 percentage points higher probability of having a protest and a 19% increase in the number of protest participants. These results indicate that VK penetration indeed had a causal positive impact on protest participation in Russian cities in December 2011.

We also study the impact of VK on support for the government. If the effect of social media on protest participation is driven by the provision of information critical of the government, we would expect to see a negative effect on government support. However, we do not find any evidence of overwhelmingly negative content in social media posts weeks before the elections. Moreover, we find that higher VK penetration led to higher, not lower, pro-governmental vote shares in the presidential elections of 2008 and 2012, and in the parliamentary elections of 2011. We find similar results using data from a large-scale survey conducted weeks before the 2011 elections. At the same time, we do not find evidence of social media leading to increased political polarization. While respondents in cities with higher VK penetration expressed greater support for the pro-government party, there was no evidence of increased disapproval of the government or of increased support for the opposition. Moreover, respondents in cities with higher VK penetration were less likely to say that they were ready to participate in political protests. Thus, these results indicate that social media did not increase the number of people dissatisfied with the government, at least before the 2011 elections, in contrast to a common perception that social media erodes the support of autocratic leaders and leads to a higher degree of political polarization.

We perform a number of placebo tests to ensure that our results are not driven by unobserved heterogeneity. First, we show that VK penetration in 2011 does not predict protest participation in the same cities before the creation of VK using three different protest instances: anti-government protests in the end of the Soviet Union (1987-1992), labor protests in 1997-2002, and social protests in 2005. Second, we show that VK penetration in 2011 was not related to voting outcomes before the creation of VK. These findings suggest that our results are not driven by time-invariant unobserved characteristics of the cities that affect protest activity or political preferences. We also replicate our first stage regressions using information on the cities of origin of the students who studied in more than 60 other major Russian universities. We find that the coefficient for our instrument — VK founder's cohort at SPbSU — lies at the top end of the distribution of the coefficients for the same cohort in other universities, while the coefficients for younger and older cohorts lie close to the medians of the corresponding distributions, which is consistent with our identifying assumptions. The tests in the spirit of Altonji, Taber, and Elder (2005) and Oster (2016) also indicate that unobservables that are positively correlated with observables do not drive our results.

Next, we explore potential mechanisms behind the observed effects. Social media can have an impact on protests through the information channel or the collective action channel. The information channel reflects the fact that online social media can serve as an important source of information on the fundamental issues that cause protests (e.g., the quality of the government). This effect is likely to be especially strong in countries with government-controlled traditional media, such as Russia. The collective action channel relies on the fact that social media users do not only consume, but also exchange information. In particular, social media not only allows users to coordinate the logistics of the protests (logistical coordination), but also introduces social motivation and strategic considerations if users and their online friends openly announce that they are joining the protest (peer pressure and strategic coordination, respectively). Thus, the information channel increases the number of people dissatisfied with the regime, whereas the collective action channel increases the probability that dissatisfied people participate in protests.

There is an important difference between the roles social media plays in the two channels. Social media affects political outcomes through the information channel to the extent that it allows for freer protest-related content provision than in state-controlled media. Thus, in principle, any free traditional media could play a similar role. However, the role of social media in the collective action channel reflects an inherent distinction between social media and traditional forms of media, in that social media can facilitate horizontal flows of information between users. In an attempt to distinguish impact via the information versus the coordination channel, we first show that fractionalization of users between VK and Facebook,[4] conditional on the total number of users in the two networks, had a negative impact on protest participation, though this effect becomes significant only for larger cities. This finding is consistent with the collective action channel, which requires users to be in the same network, but not with the information channel, as information about electoral fraud was widely discussed in both networks. Taken together, these results are consistent with the reduction of the costs of collective action being an important mechanism of social media influence.

To derive other testable predictions, we develop a model of social media, voting, and protests in an autocracy, extending the work of Little (2016). In this theoretical framework, we show that the effect of social media on protest participation should increase with city size if it is reliant on collective action channel, but should not increase with city size if the information channel is driving the results. Empirically, we show that, indeed, the positive impact of social media on protest incidence and number of protesters increases with city size. At the same time, the positive effect of social media on voting in favor of the ruling regime does not grow with city size and stays relatively stable. In addition, there is evidence that the effect of social media on political protests exhibits threshold behavior, with VK penetration affecting both the incidence and the size of protests only above a certain critical level. These results support the predictions of the model and point towards the collective action channel being behind the baseline results.

Overall, our results indicate that social media penetration facilitates participation in political protests, and the reduction in the costs of collective action is the primary mechanism behind this effect. The positive impact of social media penetration on collective action has been predicted by theoretical literature (e.g., Edmond, 2013; Little, 2016; Barberà and Jackson, 2016) and widely discussed in the popular press (e.g., Shirky, 2011), but so far there has been no systematic empirical evidence to support this prediction. Our results imply that the availability of social media may have important consequences as political protests can affect within-regime power-sharing agreements, as well as related economic and political outcomes (Madestam, Shoag, Veuger, and Yanagizawa-Drott, 2013; Aidt and Franck, 2015; Battaglini, 2017; Passarelli and Tabellini, 2017). A broader

[4] We define fractionalization as the probability that two randomly picked social media users belong to different networks. We correct our measure for potential overlap between social media, allowing individuals to be users of both Facebook and VK, and it does not change our results.

implication of our results is that social media has the potential to reduce the costs of collective action in other circumstances.

More generally, our paper speaks to the importance of horizontal information exchange on people's ability to overcome the collective action problem. Information technologies affect collective action potential by increasing the opportunities for such exchange. In the past, technologies such as leaflets, telephones, or even coffeehouses (Pendergrast, 2010) were used to facilitate horizontal information flows. Our results imply that social media is a new technology in this line, which promotes collective action by dramatically increasing the scale of horizontal information exchange. Development of this new technology can have far-reaching implications since the collective action problem have traditionally been seen as one of the major barriers to achieving socially beneficial outcomes (e.g., Olson, 1965; Hardin, 1982; Ostrom, 1990).

Our paper is closely related to Acemoglu, Hassan, and Tahoun (2017) who study the impact of Tahrir protest participation and Twitter posts on the expected future rents of politically connected firms in Egypt. They find that the protests were associated with lower future abnormal returns of politically connected firms. They also show that the protest-related activity on Twitter preceded the actual protest activity on Tahrir Square, but did not have an independent impact on abnormal returns of connected companies. Our analysis is different from theirs in several respects. First, we focus on studying the causal impact of social media penetration across cities, rather than looking at the changes in activity in already existing social media accounts over time. Thus, we consider the long-term counterfactual effect of not having social media, rather than a short-term effect of having no protest-related content on social media. Second, we look not only at the number of protesters but also at the probability of the protests occurring, i.e., at the extensive margin of the effect. Finally, our results shed some light on the potential mechanisms behind the impact of social media on protest participation and voting in a non-democratic setting.

There are recent papers that study the association between social media usage and collective action outcomes. Qin, Strömberg, and Wu (2017) analyze the content of posts on the Chinese microblogging platform Sina Weibo and show that Sina Weibo penetration was associated with the incidence of collective action events, without interpreting these results causally. Steinert-Threlkeld, Mocanu, Vespignani, and Fowler (2015) show that the content of Twitter messages was associated with subsequent protests in the Middle East and North Africa countries during the Arab Spring. Hendel, Lach, and Spiegel (2017) provide a detailed case study of a successful consumer boycott organized on Facebook.[5]

[5] Papers that are less directly related to collective action include Bond et al. (2012) who show that that political mobilization messages in Facebook increased turnout in the U.S. elections, Qin (2013) who shows that the spread of Sina Weibo led to improvement in drug quality in China, and Enikolopov, Petrova, and Sonin (2018) who show that anti-corruption blog posts by a popular Russian civic activist had a negative impact on market returns of targeted companies and led to a subsequent improvement in corporate governance.

Our paper is also related to the literature on the impact of information and communication technologies and traditional media on political preferences and policy outcomes. A number of recent works identify the impact of broadband penetration on economic growth (e.g., Czernich, Falck, Kretschmer, and Woessmann, 2011), voting behavior (Falck, Gold, and Heblich, 2014; Campante, Durante, and Sobbrio, 2017), sexual crime rates (Bhuller, Havnes, Leuven, and Mogstad, 2013), and policy outcomes (Gavazza, Nardotto, and Valletti, 2015). However, these papers do not provide specific evidence about whether this effect is due to the accessibility of online newspapers, search engines, email, Skype communications, or social media.[6]

Recent works have also shown that traditional media has an impact on voting behavior, violence and ethnic tensions, and policy outcomes.[7] In contrast, our paper studies the impact of social media, which is becoming increasingly important in modern information flows. A number of papers also study ideological segregation online (Gentzkow and Shapiro, 2011; Gentzkow, Shapiro, and Taddy, 2015b; Halberstam and Knight, 2016). In contrast to these papers, we study the causal impact of social media rather than patterns of social media consumption. Our paper is also related to the historical literature on the impact of technology adoption (e.g., Dittmar, 2011; Cantoni and Yuchtman, 2014), though we study modern-day information technologies instead of the printing press or universities.

The rest of the paper is organized as follows. Section 2 provides background information about the environment that we study. Section 3 describes our data and its sources. Section 4 presents a theoretical framework and outlines our main empirical hypotheses. Section 5 discusses our identification strategy. Section 6 shows the empirical results. Section 7 concludes.

2 Background

2.1 Internet and Social Media in Russia

By 2011, approximately half of the Russian population had Internet access at home[8] which made Russia the largest Internet market in Europe, accounting for about 15% of all European Internet users.[9] Although more than 80 countries enjoyed higher Internet penetration rate at the

[6] There are also papers that study the impact of cellphone penetration on price arbitrage (Jensen, 2007) and civil conflict (Pierskalla and Hollenbach, 2013). In a similar vein, Manacorda and Tesei (2016) look at the impact of cellphone penetration on political mobilization and protest activity in Africa.

[7] These papers include, but are not limited to, Strömberg (2004); DellaVigna and Kaplan (2007); Eisensee and Strömberg (2007); Snyder and Strömberg (2010); Chiang and Knight (2011); Enikolopov, Petrova, and Zhuravskaya (2011); Gentzkow, Shapiro, and Sinkinson (2011); DellaVigna, Enikolopov, Mironova, Petrova, and Zhuravskaya (2014); Yanagizawa-Drott (2014); Adena, Enikolopov, Petrova, Santarosa, and Zhuravskaya (2015); Gentzkow, Petek, Shapiro, and Sinkinson (2015a).

[8] According to Internet Live Stats (`http://bit.ly/2pilVDs`).

[9] According to comScore data (`http://bit.ly/2oTnmfp`).

time, Russia started catching up rapidly, demonstrating a 23% average yearly growth rate in 2007-2011.

Social media was already popular in Russia by 2011. On average, Russians were spending 9.8 hours per month on social media websites in 2010 – more than any other nation in the world.[10] Social media penetration in Russia was comparable to that of the most developed European countries, with 88% of Russian Internet users having at least one social media account — compared, for instance, to 93% in Italy and 91% in Germany. Although Russians lost the title of the most social-media-addicted nation to Israel in October 2011, they remained third with 10.4 hours per user.[11]

Despite the increasing popularity of social media, Russia remains one of the very few markets where Facebook was never dominant. In fact, South Korea is the only other country where Facebook could not secure even the second largest share of the market for reasons other than censorship. Instead, homegrown networks VKontakte (VK) and Odnoklassniki were able to quickly take over the Russian social media market. As of August 2011, VK had the largest daily audience at 23.4m unique visitors (54.2% of the online population in Russia); Odnoklassniki was second with 16.5m unique visitors (38.1%), leaving Facebook in third place with 10.7m unique visitors (24.7%).[12]

This unusual market structure emerged because of relatively late market entry by Facebook. By the time Facebook introduced a Russian language version in mid-2008, both VK and Odnoklassniki had already accumulated close to 20m registered users.[13] Besides, VK and Odnoklassniki could offer certain services that Facebook could not, either due to legal reasons (e.g., Facebook could not provide music and video streaming services because of copyright issues) or because of a different marketing strategy (e.g., users were attracted by a lower amount of advertising on Russian platforms).

VK started off as a student- and youth-oriented website. “VKontakte” translates to “in contact”, and the original mission of VK was to help current students stay in touch later in life, with its target audience similar to that of Facebook. As a result, VK was more widespread anong younger audience than Odnoklassniki.[14] Facebook gained popularity among those who wanted to communicate with their foreign friends, and thus had a higher market share in the largest cities, especially in Moscow and St. Petersburg.[15]

As of December 2011, the Internet in general — and social media in particular — enjoyed

[10] According to comScore data (http://bit.ly/2oPqRDP).

[11] According to comScore data, reported by TheNextWeb.com (http://bit.ly/2ofKbZf).

[12] According to TNS data, reported by DreamGrow.com (http://bit.ly/2nRJlif).

[13] According to the official VK blog (https://vk.com/blog?id=92) and BBC data reported by Dni.ru (http://bit.ly/2oTDIoi).

[14] The original mission of Odnoklassniki was to help people find their former classmates and friends from the past, so the targeted audience was, on average, older relative to that of VK. According to a marketing study performed in 2010, an average VK user was 3 years older relative to an average Odnoklassniki user (http://bit.ly/2nRL5b1)

[15] According to a report by Mail.ru Group (http://bit.ly/2oToKi7).

relative freedom in Russia, as there were no serious attempts to control online content up until 2012. Centralized censorship and content manipulation in social media began after the period we focus on and, to a large extent, were consequences of the protests examined in this paper. The relative freedom made social media websites an important channel for transmitting information and enhancing political debate, taking this role away from Russian TV and major newspapers.[16]

2.2 History of VK

VK is a social media website very similar to Facebook in its functionality. A VK user can create an individual profile, add friends, converse with them, create events, write blog posts, share information (textually, and in audio and video format), etc. It was launched in October 2006. The core of the VK development team was more or less stable until 2012, consisting of Pavel Durov (philology major at SPbSU at the time), his brother Nikolai Durov (physics graduate student at SPbSU at the time, winner of the intenational programming and math contests), and their fellow students. Upon VK's creation, Durov issued an open invitation on an SPbSU online forum for students to apply for membership on VK. Interested students then requested access to VK, and Durov personally approved all accounts. Registration in VK opened to the general public at the end of November 2006. Shortly after, the number of users skyrocketed from 5 thousand users to 50 thousand in January 2007, to 3 million in November 2007, to 100 million in November 2010 (see Figure A1 in Online Appendix). By early 2008, VK became the most visited website in Russia.

VK creators held a strong position against any form of censorship. During the protests of 2011-2012 Pavel Durov was approached by the Federal Security Service (FSB) and was asked to start blocking the opposition-minded online communities, as well as protest events, some of which had more than 30,000 subscribers (Kononov, 2012). Durov refused, arguing that it would lead to a large number of people switching to VK's foreign competitors, such as Facebook.[17] VK policies regarding freedom of speech remained unchanged until Durov was forced to sell his share of VK and lost control of the firm in 2014.[18] Note that Durov himself, at least before 2013, was not directly involved in any political activity, and, in particular, did not advertise or create any politically related content in VK (Kononov, 2012).

[16]Since 2009, Freedom House has ranked mass media as "not free," and Reporters without Borders has classified Russia as a country with a "difficult situation" in terms of freedom of the press.

[17]It has been documented that VK was very reluctant to block any communities, even when it came to groups that may be linked to terrorist activity (Manrique et al., 2016). Thus, this policy was not directly supporting any particular political group, although it was disproportionately favoring groups that were underrepresented in traditional media.

[18]Durov was dismissed as the VK CEO after a similar incident two years later, in September 2014, when he refused to block groups and accounts of Ukrainian revolutionaries. He was forced to sell his shares of VK to Mail.ru earlier that year. He left VK for his new start-up Telegram. He left the country too, after obtaining Saint Kitts and Nevis citizenship.

2.3 Protest Movement of 2011-2012

A wave of protest demonstrations in 2011-2012 was triggered by electoral fraud during the parliamentary elections of December 2011. It was the first large-scale political protest movement in Russia since the collapse of the Soviet Union. Similar to other protest events in authoritarian countries (Kuran, 1991), Russian protests of December 2011 surprised everyone, including their leaders.[19] Russian society was politically inactive in the 2000s, with rapid economic growth softening any criticism of Putin's regime. Moreover, electoral fraud of an allegedly similar magnitude in the 2007 parliamentary elections did not trigger any serious protests (Treisman, 2011). In addition, traditional media had been under heavy government control in 2007-2012 (and beyond), so there was hardly any chance information on electoral fraud could have been transmitted through the main TV channels. The latter served as the primary source of information for nearly 80% of Russians at the time, ensuring steady control over the information flows.[20]

Parliamentary elections were held on December 4, 2011. During the course of that day, reports of electoral fraud were quickly grew in number, being documented both by independent observers and by regular voters. In the vast majority of cases, electoral fraud favored the incumbent party, United Russia. Videos of ballot staffing and 'carousel' voting (i.e., the same voter voting multiple times at different polling stations) started to circulate around the Web and on social media. Startling differences between exit polls and official results began to emerge; some exit polls reported 23.6% of the votes going to United Russia in Moscow, which was 20% lower relative to the official result.[21] Using statistical analysis, scholars later confirmed that the amount of fraud was sizable. For instance, Enikolopov et al. (2013) showed that the presence of a randomly assigned independent observer, on average, decreased United Russia's vote share by 11 percentage points (from 47% to 36%). Clear evidence of electoral fraud, together with absence of any reaction from the government, became a source of outrage for thousands of people and urged some of them to take to the streets.

On December 5, 2011, five to six thousand people appeared at a rally in the center of Moscow. The rally was followed by minor clashes with the police and the detention of several opposition leaders. Although the number of protesters was not particularly large, this rally set a precedent for future, more massive ones. The next anti-fraud rallies were held on December 10 and 24, and had record attendance, both in Moscow (near 100,000 participants on both dates) and across the country (more than 100 cities participated).[22] The subsequent waves of protests were less popular

[19]For instance, a day before the first protest gathered over 5,000 participants its organizers were debating whether a threshold of 500 people would be surpassed.

[20]For instance, see Levada survey in 2011 (`http://bit.ly/2nv4Nyb`, p. 135) or VTSIOM study in 2011 (`http://bit.ly/2on8h4Z`)

[21]Note that these exit poll results were later deleted from the corresponding polling agency's websites.

[22]For a map of Russian protests on December 10-11, 2011, see Figure A2 in the Online Appendix. Table A19

and involved fewer cities. Moscow and St. Petersburg, however, still hosted major rallies almost each month. The tipping point of the movement was reached on May 6, 2012, a few days before Vladimir Putin's inauguration as President. Whereas all previous demonstrations were peaceful and non-violent, the Moscow rally on May 6 broke out in a number of serious clashes with the police. Within a few days, more than 30 activists were charged with allegedly inciting mass riots and using violence against the police. Many then faced several years in prison. This trial, together with absence of any tangible achievements, marked the decline of the 2011-2012 protest movement in Russia.

2.4 VK and Protest Activity

In December 2011, online social networks, including VK, became an important source of political information in Russia, where traditional media was largely controlled by the state. Reports of electoral fraud became widely available online, often accompanied by pictures and YouTube videos. Most traditional media, however, did not cover this topic. Robertson (2015) reports that VK users were more likely to be aware of the activities of Golos, the most prominent electoral monitoring organization in Russia at the time, as compared with non-VK users. Reuter and Szakonyi (2015) show that being a user of one of the online social networks was a strong predictor of respondent's awareness of electoral fraud during the December 2011 elections. Based on an online survey of protest participants, Dokuka (2014) provides evidence that 67% of them learned about the upcoming protests from VK, while another 22% obtained this information from other online social media platforms or online newspapers.

VK was also widely used for coordinating protest activities. VK allowed users to join open online protest communities, share information about protest demonstrations in their cities, and learn organizational details. As with most user profiles on VK, these communities were open, and anyone with an account on VK could see all content posted. According to our data, out of 133 cities that had protests, 87 had VK communities or events created with the purpose of organizing protest demonstrations after the December 2011 parliamentary elections. Most of these communities were created within the first several days after the parliamentary elections.[23]

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presents the names of the cities with protests and the estimates of each protest's size.

[23] Protest communities were identified by searching for several standard keywords (e.g., "For Fair Elections") in the names of these communities, so it is possible that we underestimate the number of cities with online protest communities.

3 Data

We use several sources of data. Our sample consists of 625 Russian cities with a population over 20,000 per the 2010 Census. We exclude Moscow and Saint Petersburg from our sample as outliers.

To measure VK penetration across cities, we collect information about the city of residence for all VK users with public accounts who joined VK before the summer of 2011.[24] Only active VK users were considered, i.e., users were added to the database only if they were seen online at least once between June 21 and July 7, 2011. Based on this information, we compute the number of active VK users in each city as of early summer of 2011, i.e., before the parliamentary elections were scheduled and before the electoral campaign began.[25] More details about data sources and construction of the main variables are available in Table A18 in the Online Appendix.

We use hand-collected data on political protests that occurred between December 2011 and May 2012. When the protests began in December 2011, we started monitoring newspaper databases and online resources to record information about political protests in all the Russian cities mentioned in this context. The monitoring was repeated every week until the protests subsided in summer 2012. The main sources of information about the protests include an independent business newspaper Kommersant, a government-owned news agency RIA Novosti, an opposition-leaning independent online newspaper Ridus, various regional newspapers. Information was highly consistent across these different sources, which makes it unlikely that it was manipulated and that discrepancies across sources would have a significant impact on our results.[26]

For each protest event, we recorded the number of protesters, as reported by three alternative sources: i) the police; ii) organizers of the protest; ii) a news source that wrote about the protest.[27] As a result of this monitoring, we have collected a comprehensive city-level database on political protests in Russia in 2011-2012. We aggregate this information to city-week level by constructing

[24]Public accounts contain some basic information on VK users, such as their home city, which is then available to anyone on the Internet. The timing of the account creation could be inferred from the account ID. Note that, at the time of the data collection, more that 90% of the accounts on VK were public.

[25]In our analysis, we rely on self-reported location of VK users. This approach can potentially introduce a certain margin of error for people who move to another city and do not update their information or for people who deliberately lie about their location. However, we believe that the magnitudes of such errors would be quite limited, since Russia is notorious for its low population mobility (Andrienko and Guriev, 2004; Guriev and Vakulenko, 2015), and since there was no clear incentives to lie about one's location on this social media platform. In addition, it is unlikely that these errors would be correlated with our main variables of interest, so, even if they are present, they would be causing a measurement error bias that would be corrected in an instrumental variable specification.

[26]This is further confirmed by the fact that our numbers highly resemble those reported in an alternative source — the subsequently created Wikipedia entry devoted to the chronology of the political protests in Russia in 2011–2013 (`https://bit.ly/2oSwSOB`). The downside of the Wikipedia page, however, is its limited coverage of smaller cities.

[27]We have data on all 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. We report all these estimates separately for each city in Table A19 in the Online Appendix.

two variables: an indicator for the existence of a protest in a given city in 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.[28] 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. In this paper, we will use only data for the first week of major protests: December 10–16, 2011. See Table A19 for these data and Figure A2 for a map displaying these protests across Russian territory. We explore the dynamics of protest participation over time in a companion paper (Enikolopov et al., 2017).

We use information on the city of origin of the students who studied at Saint Petersburg State University and other top Russian universities.[29] Since, unfortunately, administrative records on the admitted students are not available, these data are based on the information on the year of birth, university attended, and years of study provided in public accounts of Odnoklassniki users. Note that, as of 2014, when these data were collected, 80% of the Russian adult population reported having an account in Odnoklassniki,[30] so the coverage of our data is reasonably large. More specifically, for each university in the sample, we calculate the number of students coming from each city in five-year cohorts. We mostly focus on three cohorts in our analysis: i) those who were born the same year as the VK founder or within two years of his birthday, either earlier or later; ii) those who were born from three to seven years earlier than the VK founder; iii) those who were born from three to seven years later than the VK founder.[31] Although using data from social media to measure the distribution of students across cities may introduce a measurement bias, the identifying assumption is that, while controlling for the number of Odnoklassniki users, this bias does not vary across cohorts in a way that is correlated with the outcomes of interest. Later on, we use various tests to provide evidence that this assumption holds.

Next, we use data on the number of Facebook users by city in 2011 and 2013. The data on Facebook penetration in 2011 was taken from Nikolai Belousov's blog.[32] The data on Facebook penetration in 2013 were collected manually for each city in our sample based on the estimates of the market size provided by Facebook to potential advertisers.[33]

We use three different sources of data for protests that occurred prior to the advent of social media. The data on protests in the late Soviet Union come from Beissinger (2002). In the analysis,

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

[29] In particular, we take all universities located in Moscow or Saint Petersburg among the top-100 Russian universities, as well as the top-20 universities from other cities. To identify the elite top-100 schools, we use the 2014 university ranking compiled by the RA Expert agency (http://bit.ly/2ofLYgU).

[30] According to Levada Center (http://bit.ly/2nv9w2C).

[31] Our results remain very similar if we use students' years of entrance to the university instead of their year of birth. For a discussion of this and other alternative ways of constructing the cohorts, see Section 6.5.2.

[32] http://bit.ly/2oWNTpg

[33] To collect this data, we created a trial targeted ad to see what, according to Facebook, is the number of users who could potentially see it for a given location target. Note that missing numbers for 2011 were imputed using the data on Facebook availability in 2013, VK availability in 2011, and VK availability in 2013 using a linear regression.

we look at all Soviet protests as a whole and the pro-democracy protests separately. The data on participants in the labor protests of 1997-2002 come from Robertson (2011). Finally, we use information on the social protests of 2005 from the website of a communist organization,[34] though we admit that this source of data is less reliable than the ones mentioned previously. For all three sources, we exploit two different measures of protest intensity: the maximum number of protesters in a city and an indicator for at least one protest in a city.

The data on electoral outcomes come from the Central Election Commission of the Russian Federation. We obtained the public opinion data from the MegaFOM opinion poll conducted by the Public Opinion Foundation (Fond Obschestvennogo Mneniya, or FOM) in October-November 2011.[35] This is a regionally representative survey of 56,900 respondents in 79 regions, of which 30,669 respondents come from 519 cities in our sample.

City-level data on population, age, education, and ethnic composition come from the Russian Censuses of 2002 and 2010. Data on the average wage and municipal budgets come from the municipal statistics of RosStat, the Russian Statistical Agency. Additional city characteristics, such as latitude, longitude, year of city foundation, and the location of administrative centers, come from the Big Russian Encyclopedia. Summary statistics for each variable employed in the analysis are presented in Table A1 in the Online Appendix. In addition, Table A2 presents the summary statistics broken down by city's quartile of VK penetration.

4 Theoretical Framework

In this section, we aim at constructing a common theoretical framework that would incorporate social media with both outcomes of our study — voting and protest participation in an autocracy. Building on the work by Little (2016), we examine how, by providing more precise information about the quality of the government and protest logistics, social media can affect the number of people choosing to turn out to protest or express support for the regime. We also explore the existence of threshold behavior in the relationship between VK penetration and protests, and the way the effect of social media depends on city size.

4.1 Voting in Autocracy

First, we study how communication technology can affect the support of the government in an autocracy. Rather than examine the choice between multiple political candidates, we consider a citizen deciding whether to support a ruling party or abstain. We believe that this setup better

[34] http://trudoros.narod.ru/

[35] We are grateful to the president of FOM, Alexander Oslon, for generously sharing the data.

matches the reality of quasi-authoritarian elections in Russia.

There is a continuum of risk-neutral citizens, $i \in [0,1]$. The nature draws a common prior belief about the regime quality, ω, which is distributed as $N(0, 1/\alpha_0)$. Then the public signal about ω is drawn, $s_\omega \sim N(\mu_s, 1/\alpha_s)$. The cost of voting for citizen i is drawn as $c_{vi} \sim N(\mu_{vc}, \sigma_{vc}^2)$. Each citizen then maximizes:

$$u_v(v_i) = v_i[\bar{\omega} + \lambda_v V - c_{vi}]$$

where v_i is a voting decision indicator, which equals to one if i votes for an autocrat and zero otherwise; $\lambda_v \geq 0$ is a taste-for-conformity parameter; and V is the proportion of citizens who voted for the autocrat. In this version of the model, all citizens update their priors about the regime based on the same information, so that citizens' belief about the regime's popularity, $\bar{\omega}$, does not vary with i. However, the cost of voting, c_{vi}, is drawn at random for each individual, so their decisions to vote for the ruling party or abstain will still differ.

The citizens' updated belief about the regime's quality, ω, upon observing the public signal, s_ω, is:

$$\bar{\omega} = \mathbb{E}[\omega + s_\omega] = \frac{s_\omega \alpha_s}{\alpha_0 + \alpha_s}$$

Having updated their beliefs about the regime, citizens compare the benefits of voting with their individual costs, c_{vi}. Note that citizens with $c_{vi} < s_\omega \alpha_s/(\alpha_0 + \alpha_s)$ will vote for the ruling party no matter what others do, while citizens with $c_{vi} > s_\omega \alpha_s/(\alpha_0 + \alpha_s) + \lambda_v$ will abstain regardless of the voting decision of others. In equilibrium, there will be a cut-off value of individual cost, $\hat{c}_v$, between these two values, such that citizens with realized costs of voting below the cutoff value will vote for the incumbent, and all citizens with realized costs above this cutoff will not vote for the ruling party. To identify the voting cut-off, $\hat{c}_v$, we need to calculate the expected proportion of people voting for the government given the public signal, s_ω:

$$\mathbb{E}[V|s_\omega] = Pr[c_{vi} \leq \hat{c}_v(s_\omega)|s_\omega] = Pr\left[\frac{c_{vi} - \mu_{vc}}{\sigma_{vc}} \leq \frac{\hat{c}_v(s_\omega) - \mu_{vc}}{\sigma_{vc}}\right] = \Phi\left[\frac{1}{\sigma_{vc}}(\hat{c}_v(s_\omega) - \mu_{vc})\right] \quad (1)$$

Hence, the cut-off level, $\hat{c}_v$, is determined by the following equation:[36]

$$\hat{c}_v(s_\omega) = \frac{s_\omega \alpha_s}{\alpha_0 + \alpha_s} + \lambda_v \Phi\left[\frac{1}{\sigma_{vc}}(\hat{c}_v(s_\omega) - \mu_{vc})\right] \quad (2)$$

The comparative statics of the costs cut-off w.r.t. s_ω and α_s are as follows:

$$\frac{\partial \hat{c}_v}{\partial s_\omega} = \frac{\frac{\alpha_s}{\alpha_0 + \alpha_s}}{1 - \frac{\lambda_v}{\sigma_{vc}}\phi\left(\frac{1}{\sigma_{vc}}(\hat{c}_v - \mu_{vc})\right)} \quad (3)$$

[36]Note that in the case of $\lambda_v = 0$ the solution becomes a simple Bayesian updating.

$$\frac{\partial \hat{c}_v}{\partial \alpha_s} = \frac{\frac{s_\omega \alpha_0}{(\alpha_0+\alpha_s)^2}}{1 - \frac{\lambda_v}{\sigma_{vc}} \phi\left(\frac{1}{\sigma_{vc}}(\hat{c}_v - \mu_{vc})\right)} \tag{4}$$

We assume that the taste-for-conformity parameter, λ_v, is sufficiently small so that the denominator of the above fractions is positive. This is necessary for a meaningful equilibrium in which a positive public signal about an autocrat increases the amount of votes in favor of the regime, i.e., $\partial \hat{c}_v / \partial s_\omega > 0$.

An increase in social media penetration can be interpreted as an increase in the precision of the public signal, α_s. Thus, social media increases support for an autocrat ($\partial \hat{c}_v / \partial \alpha_s > 0$) whenever the public signal is favorable to the regime ($s_\omega > 0$) and decreases support ($\partial \hat{c}_v / \partial \alpha_s < 0$) whenever the public signal is unfavorable ($s_\omega < 0$). Hence, we draw the following empirical prediction from this part of the model:

Prediction 1. *Higher social media penetration (i.e., higher α_s) leads to higher (lower) vote share of the ruling party if the content of social media (i.e., public signal s_ω) is, on average, positive (negative).*

4.2 Protests in Autocracy

As shown in the previous section, the impact of social media on voting in favor of the ruling party naturally depends on the information content of the available social media platforms. In this section, we examine the potential ramifications of social media for protest participation. An important distinction from the case of voting is that social media can facilitate protest participation not only through the information change, but also through the coordination channel.[37]

As in the previous case, there is a continuum of risk-neutral citizens, $i \in [0,1]$. First, nature draws common priors about the regime quality, ω, and protest tactics, θ. The common priors on ω and θ are distributed as $N(0, 1/\alpha_0)$ and $N(0, 1/\beta_0)$, respectively. The public signals are then drawn as $s_\omega \sim N(\omega, 1/\alpha_s)$ and $s_\theta \sim N(\theta, 1/\beta_s)$. A random cost of protesting, which is separate from the costs of mismatching tactics, is drawn as $c_{pi} \sim N(\mu_{pc}, \sigma_{pc}^2)$. Each citizen then maximizes:

$$u_p(p_i, t_i) = p_i[-\bar{\omega} + \lambda_p P - k(t_i - \theta)^2 - c_{pi}],$$

where p_i is the protest decision indicator which equals to one if i goes out to protest and zero

[37] In this simple framework, we mostly study the effect of logistical coordination and model strategic coordination in a rudimentary fashion, by making the utility function depend on the number of participants. We refer the reader to the papers of De Mesquita (2010); Edmond (2013); Passarelli and Tabellini (2017); Barberà and Jackson (2016); Battaglini (2017) for the full-fledged theoretical models with a strategic coordination component. Note that a recent paper by Cantoni et al. (2017) suggests that individual protest participation actions could be strategic substitutes. In contrast, the effect of social media on logistical/tactical coordination is unambiguously positive, which allows us to make clear empirical predictions.

otherwise; t_i is the tactics decision of an individual; $k(t_i - \theta)$ represent the costs of mismatching tactics; P is the proportion of citizens who turn out to protest, and $\lambda_p \geq 0$ is a reduced form strategic coordination parameter, which reflects the social image parameter as in Enikolopov et al. (2017) and a number of other potential channels (e.g. safety in numbers). The main difference from the case of voting is the need to coordinate on protest tactics, which includes the decision on when, where, and how to protest against the regime, θ, which introduces an additional level of uncertainty.

Identical to the case of voting in autocracy, citizens update their beliefs about regime quality, ω, upon observing the public signal, s_ω, as follows:

$$\bar{\omega} = \mathbb{E}[\omega + s_\omega] = \frac{s_\omega \alpha_s}{\alpha_0 + \alpha_s}$$

Similarly, upon observing signal s_θ, citizens update their beliefs about the tactics of the upcoming protest:

$$\bar{\theta} = \mathbb{E}[\theta + s_\theta] = \frac{s_\theta \beta_s}{\beta_0 + \beta_s}$$

Since citizens would like to match the true θ as closely as possible, in optimum, they set $t_i = \bar{\theta}$. By definition, the expected level of the discrepancy between $\bar{\theta}$ and θ is equal to the variance of $\bar{\theta}$, i.e., formally:

$$\mathbb{E}[k(\bar{\theta} - \theta)^2] = \frac{k}{\beta_0 + \beta_s}$$

Hence, each citizen decides to participate in a protest whenever the expected benefits outweigh the expected costs:

$$-\frac{s_\omega \alpha_s}{\alpha_0 + \alpha_s} + \lambda_P \mathbb{E}[P | s_\omega, s_\theta] > \frac{k}{\beta_0 + \beta_s} + c_{pi} \tag{5}$$

As in the case of voting, citizens with $c_{pi} < -s_\omega \alpha_s / (\alpha_0 + \alpha_s) - k/(\beta_0 + \beta_s)$ are going to protest regardless of the protest participation decision of others, while citizens with $c_{pi} > \lambda_p - s_\omega \alpha_s / (\alpha_0 + \alpha_s) - k/(\beta_0 + \beta_s)$ will not participate regardless. In equilibrium, there will be a cut-off value of the individual cost of protesting, $\hat{c}_p$, in between these two values, such that citizens with a realized cost below the cutoff value will go out to protest, and citizens with a realized cost above the cutoff will abstain. We search for the cut-off level, $\hat{c}_p$, that would equalize the two sides of the equation (5) and separate participants and non-participants:

$$-\frac{s_\omega \alpha_s}{\alpha_0 + \alpha_s} + \lambda_P \Phi \left[\frac{1}{\sigma_{pc}} (\hat{c}_p(s_\omega, s_\theta) - \mu_{pc}) \right] - \frac{k}{\beta_0 + \beta_s} - \hat{c}_p(s_\omega, s_\theta) = 0 \tag{6}$$

The comparative statics of the cut-off with respect to the public signal of regime strength (s_ω) and social media (i.e., increased precision of public signals, α_s and β_s) are as follows:

$$\frac{\partial \hat{c}_p}{\partial s_\omega} = \frac{-\frac{\alpha_s}{\alpha_0+\alpha_s}}{1-\frac{\lambda_p}{\sigma_{pc}}\phi(\frac{1}{\sigma_{pc}}(\hat{c}_p-\mu_{pc}))} \tag{7}$$

$$\frac{\partial \hat{c}_p}{\partial \beta_s} = \frac{\frac{k}{(\beta_0+\beta_s)^2}}{1-\frac{\lambda_p}{\sigma_{pc}}\phi(\frac{1}{\sigma_{pc}}(\hat{c}_p-\mu_{pc}))} \tag{8}$$

$$\frac{\partial \hat{c}_p}{\partial \alpha_s} = \frac{-\frac{s_\omega \alpha_0}{(\alpha_0+\alpha_s)^2}}{1-\frac{\lambda_p}{\sigma_{pc}}\phi(\frac{1}{\sigma_{pc}}(\hat{c}_p-\mu_{pc}))} \tag{9}$$

As in the case of voting, we assume that λ_p is sufficiently small so that the denominator of the above fractions is positive. This is necessary for a meaningful equilibrium in which a positive public signal about an autocrat decreases the size of the protest. We conclude that: (i) protest size decreases with a more favorable public signal about the regime (i.e., $\partial \hat{c}_p/\partial s_\omega < 0$), (ii) protest size increases when citizens receive a more precise signal about the protest tactics (i.e., $\partial \hat{c}_p/\partial \beta_s > 0$), and (iii) protest size increases when citizens receive a more precise signal about the regime conditional on the signal being negative (i.e., $\partial \hat{c}_p/\partial \alpha_s > 0$ if $s_\omega < 0$) and decreases with signal precision if the signal provides positive information about the regime (i.e., $\partial \hat{c}_p/\partial \alpha_s < 0$ if $s_\omega > 0$). We conclude by deriving the following empirical prediction from this analysis:

Prediction 2. *Higher social media penetration (higher α_s and β_s) leads to higher protest participation against the ruling regime if the content of social media (public signal s_ω) is, on average, negative. However, even when the content online is positive, social media could increase protest participation if the gains in coordination (higher β_s) are high enough.*

Intuitively, higher social media penetration affects protest size through two different channels: by influencing the perceptions of the government quality and by decreasing the costs of coordination. The direction of the first effect depends on the content, but it works in the same direction as in the case of voting. The second effect always increases protest participation by improving tactical coordination. Thus, if the content of social media is, on average, negative, both effects work in the same direction, so that higher social media penetration unambiguously increases protest participation. If the content of social media is positive, the two forces operate in the opposite direction, and the overall effect will depend on the relative importance of learning about the regime's quality and tactical coordination.

4.3 City Size and Coordination Channel

In the previous section, we established that social media may affect protest participation along two different channels — by increasing the precision of the public signal about the quality of the regime (information channel) and by increasing the precision of the tactics signal (coordination channel). In this section, we provide an extension of the theoretical framework that yields an additional prediction: the extent to which the effect of social media depends on city size is different for these two channels.

Consider N cities of different size. Assume that the larger the city size, the more difficult it is logistically to coordinate protest activities due to the need of coordinating a larger group of people. In terms of our theoretical framework that means that the prior signal about the protest tactics is noisier in larger cities, $\beta_0^1 > \beta_0^2 > ... > \beta_0^N$ where cities are ordered monotonically in city size, from the smallest city ($i = 1$) to the largest one ($i = N$).[38] Importantly, only public signals from people from the same city are relevant for coordination, whereas for information about regime quality there is no difference between signals from the same and other cities. Thus, due to the transmission of information about regime quality across cities, which is not present for protest tactics, the baseline dispersion of the prior signal about regime quality is assumed to be the same across cities, $\alpha_0^1 = ... = \alpha_0^N = \alpha_0$.[39] Since there are no other interactions between individuals in different cities, for each city, calculations in Section 4.2 do apply.

Equation (8) implies that, if lambda is small enough, the impact of social media on protest participation via coordination exhibits diminishing returns, $\partial^2 \hat{c}_p / \partial \beta_0^i \partial \beta_s < 0$, $\forall i \in [1, N]$.[40] An immediate corollary of this result is that social media should be more important in places where coordination is harder to achieve in the absence of public signals, i.e., in cities with lower β_0^i. Although the effect of social media on protest participation via information may also exhibit diminishing returns, we would not expect it to increase in magnitude with city size, since there is little reason to believe that the ex-ante public signal regarding popularity of the federal regime is noisier in larger cities. This analysis leads to an additional prediction that the impact of social media should be greater in larger cities due to a stronger marginal effect of social media on coordination; in contrast, the impact of social media on voting should not increase with city size, as it

[38] Intuitively, this prediction can be micro-founded in the following extension of the baseline model. Suppose that there are offline word-of-mouth sources of information and online social media. The number of signals that citizens receive offline via friends and family who live in the same city, F, is independent of the city size, N. However, online, citizens can quickly communicate with an extended circle of friends and acquaintances, who can come either from the same or other cities. Suppose that the number of signals citizens receive online from other people from the same city $E(N)$ is increasing with city size, i.e. $\partial E(N)/\partial N > 0$. In this setting, the baseline precision of the public signal about the protest tactics would be more precise in smaller cities and, as a result, the importance of social media for coordination should increase with city size.

[39] For the public signal about the popularity of the regime, however, the precision of the signal does not depend on the size of the city (but does depend on the size of the whole social network).

[40] See the derivation of this result, as well as the precise condition on lambda in Section A.1 of the Online Appendix.

relies primarily on the information channel.

Prediction 3. *The impact of social media on protest participation is larger in areas where coordination is hard to achieve in the absence of public signals (low initial β_0). In particular, the effect of social media on protest participation increases with city size. In contrast, the impact of social media on voting in favor of the regime does not increase with city size.*

4.4 Social Media Penetration and the Critical Mass

In this section, we explore a natural extension of the model predicting that social media should start to matter for protest participation only after its penetration reaches a certain threshold — a prediction which we then take to the data.

Suppose all citizens fall into two categories — those who adopted social media and those who did not. The share of those who adopted social media is m. In this section, similar to the reasoning in Section 4.3, we assume that the precision of the public signal about the regime is the same for all citizens, including non-adopters. However, only adopters enjoy higher precision of the tactics signal from social media, i.e., $\beta_s^a > \beta_s^n$ where a denotes a social media adopter while n indicates that a citizen did not adopt social media. We take the adoption decision as exogenous throughout this section.

Following the calculations in Section 4.2, one can show that adopters and non-adopters would have different participation thresholds, $\hat{c}_p^a$ and $\hat{c}_p^n$, defined by the following pair of equations:

$$-\frac{s_\omega \alpha_s}{\alpha_0 + \alpha_s} + \lambda_p P = \frac{k}{\beta_0 + \beta_s^a} + \hat{c}_p^a \tag{10}$$

$$-\frac{s_\omega \alpha_s}{\alpha_0 + \alpha_s} + \lambda_p P = \frac{k}{\beta_0 + \beta_s^n} + \hat{c}_p^n \tag{11}$$

Note that the total share of protesters now consists of two different types of participants — adopters and non-adopters:

$$P = mPr[c_i \leq \hat{c}_p^a | \bar{s}_\omega, \vec{s}_\theta^a] + (1-m)Pr[c_{pi} \leq \hat{c}_p^n | \bar{s}_\omega, \vec{s}_\theta^n]$$

To understand how protest participation changes with m and whether, other things held constant, higher social media adoption could trigger a protest after reaching a certain critical mass, we study the comparative statics of the cost thresholds, $\hat{c}_p^a$, and protest participation, P, with respect to social media penetration, m. Subtracting equation (11) from equation (10), one gets:

$$\hat{c}_p^a - \hat{c}_p^n = \frac{k(\beta_s^a - \beta_s^n)}{(\beta_0 + \beta_s^a)(\beta_0 + \beta_s^n)} = K > 0$$

Note that $\hat{c}_p^a > \hat{c}_p^n$, meaning that the fraction of adopters who participate in protests is higher than the fraction of non-adopters who do, due to the higher precision of their information regarding tactics. Expressing $\hat{c}_p^a$ in terms of K and $\hat{c}_p^n$ and plugging in the result in (11), one gets:

$$-\frac{s_\omega \alpha_s}{\alpha_0+\alpha_s}+\lambda_p\left[m\Phi\left(\frac{1}{\sigma_c}(\hat{c}_p^n+K-\mu_c)\right)+(1-m)\Phi\left(\frac{1}{\sigma_c}(\hat{c}_p^n-\mu_c)\right)\right]=\frac{k}{\beta_0+\beta_s^n}+\hat{c}_p^n \tag{12}$$

For the ease of exposition, denote $\bar{c}_p^n=(\hat{c}_p^n+K-\mu_{pc})/\sigma_{pc}$ and $\underline{c}_p^n=(\hat{c}_p^n-\mu_{pc})/\sigma_{pc}$. Applying the implicit function theorem to equation (12), we derive the first derivative of the non-adopters participation, $\hat{c}_p^n$, with respect to social media penetration, m:

$$\frac{\partial \hat{c}_p^n}{\partial m}=\frac{\lambda_p\left[\Phi\left(\bar{c}_p^n\right)-\Phi\left(\underline{c}_p^n\right)\right]}{1-\frac{\lambda_p}{\sigma_{pc}}\left[m\phi(\bar{c}_p^n)+(1-m)\phi(\underline{c}_p^n)\right]}>0 \tag{13}$$

Hence, as the take-up of social media in the population grows, non-adopters go out to protest with a higher probability. As a result, the total share of protesters, P, is also monotonically increasing with m:

$$\frac{\partial P}{\partial m}=\left(\Phi\left(\bar{c}_p^n\right)-\Phi\left(\underline{c}_p^n\right)\right)\frac{\partial \hat{c}_p^n}{\partial m}\frac{1}{\sigma_{pc}}\left(m\phi\left(\bar{c}_p^n\right)+(1-m)\phi\left(\underline{c}_p^n\right)\right)>0$$

Assume now that, after citizens made their participation decisions, a protest gets organized only if the total share of citizens who would like to participate exceeds some threshold P^*.[41] Since the share of people willing to participate is monotonically increasing in m, there is a unique threshold of social media penetration m^* such that, other parameters held equal, protests are organized in cities above this threshold and are not in cities below it.[42] Hence, we conclude with the following empirical prediction:

Prediction 4. *Higher rates of social media adoption (higher m) lead to higher protest participation (higher P). Moreover, if protests take place after a certain critical mass of potential participants is accumulated, we expect protests to occur only after social media penetration reaches a certain threshold, m^*.*

[41] Such threshold behavior naturally arises if political protests are modeled in a more elaborate global game setting (e.g., as in Edmond, 2013).

[42] Note that, in this model, the location of the threshold for VK penetration depends not only on the critical mass needed for a successful protest (P^*), but also on the relative importance of strategic and logistical coordination (λ_p and k, respectively), relative importance of social media signal for believe update ($\beta_s^a-\beta_s^n$), and the within city deviation of costs distribution (σ_{pc}).

5 Identification Strategy

Our main hypothesis is that social media penetration (specifically, VK penetration) has an impact on political outcomes, whether it is protest participation, voting, or support of the government in the opinion polls. Thus, we estimate the following model:

$$\text{PoliticalOutcome}_i = \beta_0 + \beta_1 \text{VKpenetration}_i + \beta_2 \mathbf{X_i} + \varepsilon_\mathbf{i} \tag{14}$$

where $\text{PoliticalOutcome}_i$ is either a measure of protest activity — either an indicator variable for the occurrence of at least one protest in city i in the first weekend of the protests (December 10th and 11th) or the logarithm of the number of protesters in city i [43]— or of the support of the government — either through voting or support in opinion polls; VKpenetration_i is the logarithm of the number of VK users in city i in the summer of 2011; X_i is a vector of control variables that includes a fifth-order polynomial of the population, an indicator for being a regional or a subregional (rayon) administrative center, average wage in the city, the number of city residents of different five-year age cohorts, the distance to Moscow and Saint Petersburg, an indicator for the presence of a university in the city, the share of population with higher education in 2010 in each five-year age cohort, the share of the population with higher education in 2002, ethnic fractionalization, and internet penetration. In some specifications, X_i also includes the outcomes of the pre-2006 parliamentary elections to control for pre-existing political preferences of the population. Standard errors in all regressions are clustered at the regional level.[44]

5.1 Identification Strategy

The OLS estimates of the equation (5) are likely to be biased, as the unobserved characteristics that make people more (or less) likely to become VK users can also make them more likely to participate in political activities. To address this issue, we use fluctuations in the origin of the students who have studied at SPbSU as a source of exogenous variation in VK penetration that does not have an independent effect on protest participation. In particular, we exploit the fact that the distribution of the home cities of the students who studied at SPbSU at the same time as the VK founder predicts the penetration of VK across cities in 2011, but the distribution of the home cities of the students who studied at SPbSU several years earlier or later does not. Specifically, we compute the number of students from each city in three five-year student cohorts (to match the Census definition of cohorts): (i) those who have studied at the same year as Durov, as well as one or two years earlier or later, (ii) those who studied from three to seven years earlier than Durov, and

[43] We focus on the first protests to avoid a possibility of dynamic effects within and across the cities.

[44] All our baseline results are robust to spatially correlated standard errors calculated as in König et al. (2017) (see Table A6 in the Online Appendix).

(iii) those who studied from three to seven years later than Durov.[45]

The identifying assumption is that, conditional on population, education, and other observables, fluctuations of the student flows from different cities to Saint Petersburg State University in the 2000s are orthogonal to the unobserved determinants of protest participation.

Table A3 in the Online Appendix presents a full distribution of the SPbSU student cohorts by their home cities. Note that in all but one case the number of students is less than 40 students per home city, for all three cohorts. Thus, the numbers are sufficiently small to allow for random fluctuations in the distribution of students across cities.[46]

We further check whether there is enough variation in student flows across time by calculating the correlation between city rank across the three cohorts. In this analysis, we only take into account cities that sent at least one student to SPbSU in any of the three five-year cohorts. We calculate 'field' ranks of each city for each cohort by assigning rank 1 to the city with the largest outflow of students, rank 2 to the city with the second largest outflow, etc. In case of ties, the same average rank is assigned. The results provided in Table A4 in the Online Appendix show that the correlations between city ranks across cohorts are less than 0.5, which is indicative of substantial fluctuations in rankings over time. To display the variation visually, we plot the rank variables against each other in Figure A3 in the Online Appendix. The size of the marker reflects the number of cities with the same combination of ranks. As with the correlation table, these graphs illustrate considerable variation in the number of students sent to SPbSU across years. For instance, plenty of cities had more than one student in one cohort and zero in the other. Similarly, cities' ranks vary significantly at the high end of the distribution.

Note that students were coming to study at Saint Petersburg State University from all over the country. These students arrived from 73 out of 79 Russian regions included in our study. Students in the Durov's cohort came from 237 different cities (more than a third of all Russian cities), while students from an older cohort came from 222 cities and students from a younger cohort came from 214 different cities. Thus, we have sufficient variation in the student flows both over time and across cities, which allows for meaningful comparison.

5.2 Determinants of VK penetration

To show that our instrument is relevant Table 1 provides evidence on the determinants of VK penetration across Russian cities in 2011, and, in particular, on the effect of the number of Saint Petersburg State University students in different cohorts on VK adoption in their home cities. The results indicate that, once population controls are included, the five-year cohort of Pavel Durov, the VK founder, is positively and significantly (at 1% level) correlated with subsequent VK penetra-

[45] See Section 6.5.2 for the discussion of the robustness of our results to alternative definitions of cohorts.

[46] We also check that our results are robust to exclusion of cities with more than 10 students in the Durov's cohort.

tion, in contrast to the younger and older cohorts, for which the corresponding coefficients are not statistically significant. The coefficient for the number of SPbSU students in the Durov's cohort is stable across the specifications (2)-(8). In particular, it does not depend on the within-city distributions of age and education, as we control for the number of people in each of the five-year age cohorts over 20 years of age, and for the education level in each of these cohorts. The magnitude of the effect implies that a 10% increase in the size of the VK founder's cohort coming from a given city leads to a 14% increase in the number of VK users in that city in 2011. The coefficient for the size of an older cohort is much smaller in magnitude and is not statistically significant across specifications (4)-(8). The coefficient for the size of a younger cohort is consistently negative and significantly different from the effect of Durov's cohort. These results are summarized in graphical form in Figure 1.

In addition, we provide evidence that the origin of students in Durov's cohort affects VK penetration in 2011 via its effect on early adoption of the network. We look at the determinants of VK penetration at the by-invitation-only stage, i.e., for the first 5,000 users (see Table A5). While the coefficient patterns for the number of SPbSU students are similar to those in Table 1, other controls, such as population, education by cohort, or ethnic fractionalization, become insignificant, consistent with our claim that the initial VK diffusion was largely idiosyncratic. The corresponding cohort coefficients, together with their confidence intervals, are shown graphically in Figure A4 in the Online Appendix.

Overall, our results in Tables 1 and A5 suggest that the city differences in early VK penetration were, at least in part, generated by the year-to-year fluctuations in student flows from different cities, and that these small initial differences in early adoption had important long-term consequences for the later penetration of the social network. In the subsequent sections, we employ additional tests to ensure that our results are not driven by other types of unobserved heterogeneity.

6 Empirical Results

6.1 VK Penetration and Protest Participation

6.1.1 Reduced Form Estimation

We start by presenting the results of the reduced form estimation. Specifically, we look at how participation in rallies during the first weekend after the parliamentary elections is related to the number of the SPbSU students in different cohorts. Table 2 shows how the protest incidence in December 10-11, 2011 (columns (1)-(4)) and the size of these protests (columns (5)-(8)) are related to the number of the SPbSU students in different cohorts. We find that the size of the VK founder's cohort has a positive and significant effect on both the incidence and the size of the protests, while the coefficients for other cohorts are much smaller and are not statistically significant. Moreover, the sign of the coefficient for the older cohort is consistently negative across specifications. [47] The difference between coefficients for different cohorts is statistically significant for the incidence of protests in all specifications. Figures 2A and 2B report these results graphically.

To assess the possible degree of omitted variable bias, we follow the approach of Oster (2016), which is an extension of the approach of Altonji, Taber, and Elder (2005). In particular, we compute how important, in terms of explanatory power, unobservables should be relative to observables in order to fully explain the coefficient for the VK founder's cohort. We find that unobservables should be negatively correlated with observables and that their importance must be more than seven times higher to be able to explain the results for the size of the protests and three times higher to explain the results for the protest incidence. These results stand in sharp contrast to the standard assumption of equal selection, i.e., that unobservables are positively correlated with observables and are equally important (Altonji, Taber, and Elder, 2005).

Taken together, the results presented in Table 2 and Figures 2A-2B indicate that the SPbSU student cohort of the VK founder is positively and significantly associated with protest participation, in contrast to the older and younger SPbSU cohorts, and that these results are unlikely to be driven by omitted variable bias.

6.1.2 IV Results for Protest Participation

Reduced form analysis in Table 2 suggests that the SPbSU student cohort of the VK founder, through its impact on VK penetration, had a positive effect on protest activity in 2011. However, reduced form regressions do not allow us to quantify the magnitude of the effect of social media penetration on protests. In this section, we estimate equation (5) using the number of SPbSU students in the VK founder's cohort as an instrument for VK penetration in summer 2011, controlling for the number of SPbSU students in older and younger cohorts.

First, we test the hypothesis that protests are more likely to occur if social media penetration is higher. The results in columns (1)-(4) of Panel A of Table 3 indicate that social media penetration had a quantitatively large and a statistically significant effect on the incidence of protests. To be able to combine IV estimation with clustered standard errors and weak instrument tests, we use a linear probability model.[48] The results indicate that VK penetration had a positive and statistically

[47] Note that, even though we cannot reject the hypothesis that the coefficients for the VK founder and the younger cohorts are the same, that does not invalidate our exclusion restriction. This is because we can expect some spillovers of information about VK to the younger cohorts, who studied at SPbSU after the creation of the network.

[48] We show that our baseline results are robust to using non-linear models and present these results in Table A7 in the Online Appendix. In particular, we use an IV probit model for the incidence of protests and a negative binomial IV model for the number of protesters. The results remain very similar to our baseline estimates, both in terms of magnitudes and statistical significance.

significant effect on the probability that a protest occurs. A 10% increase in the number of VK users in a city leads to a 4.5-4.8 percentage points higher probability of a protest being organized.

One potentially important concern for our estimation is the weak instruments problem. Lack of a sufficiently strong first stage could lead to unreliable IV estimates and inference. The traditional Stock and Yogo (2005) thresholds for the F-statistic were derived for the case of homoscedastic errors, and thus cannot be applied to a model with clustered standard errors. For this reason, we use a recently developed methodology by Montiel Olea and Pflueger (2013) who derived a test for weak instruments similar to the one in Stock and Yogo (2005), but for the case of clustered standard errors. The corresponding effective F-statistics in our specifications take values around 10-12. Although this value is below the threshold of 23 derived by Montiel Olea and Pflueger (2013) for the case of 10% potential bias and a 5% significance, it is still above the rule-of-thumb threshold of 10 after which the weak instrument problem does not appear to affect the validity of conventional t-statistics in the case of clustered standard errors (Andrews, Stock, and Sun, 2018).[49] To be conservative, following recommendations by Andrews et al. (2018), we also report the weak-instrument robust confidence intervals for all the main coefficients, calculated without an assumption of a strong instrument. As one can see, the intervals exclude zero in all our specifications.[50]

For comparison purposes, we display the OLS estimates for the same second-stage specifications in columns (5)-(8) of Panel A of Table 3. The coefficients are still highly significant, but are much smaller in magnitude than the corresponding IV estimates. Our explanation for the difference between OLS and IV is the negative selection bias. For example, if people with higher unobserved income are more likely to become VK users, but are less likely to participate in protests, this would lead to a downward bias in the OLS estimates of the impact of VK penetration on protest participation.

Next, we examine the effect of VK penetration on the number of protest participants. According to these estimates, a 10% increase in the number of VK users leads to a 19% increase in the number of protesters. Although this effect appears to be large in relative terms, it is important to have in mind that, while VK users constituted a reasonably large share of city population (the average VK penetration in 2011 was 15 percent), protest participants in absolute terms formed only a tiny fraction of the population. Our data suggests that for the cities with protests only 0.4% of the city population participated in protests. As the average city size in our sample was 117 thousand (see

[49]In a first comprehensive overview of the best practices of dealing with weak instruments in the presence of heteroscedasticity, Andrews et al. (2018) analyzed 230 specifications from publications in the American Economic Review (AER) in 2014-2018 and document that, in contrast to specifications with the effective F-statistics below 10, overrejection problem is not present for the cases with the effective F-statistics above 10. Specifically, the behavior of t-statistics in simulations with these specifications is very similar to the one under the conventional strong-instrument assumptions.

[50]These intervals are calculated as Anderson-Rubin intervals using an implementation by Finlay et al. (2009). For the intervals calculated using other methods, such as Mikusheva et al. (2006) and Chernozhukov and Hansen (2008), see Table A8 in the Online Appendix. The results are nearly identical across these methods.

Table A1 in the Online Appendix), the aforementioned counterfactual of a 10% increase in VK penetration implies that an increase in the number of VK users by 1,000 leads to an increase in the number of protestors by approximately 50.

The results, presented in Table 3, assume a linear relationship between the number of VK users and political protests. To examine this association non-parametrically, we estimate a locally weighted regression between VK penetration and the number of protest participants. The downside of this approach is that it does not account for the endogeneity of VK penetration and does not take into account control variables. However, it provides some intuition on the functional form of the relationship. These results are presented in Figure 3. The figure indicates that there is a threshold level of VK penetration, below which there is no relation between VK penetration and protests. In other words, the effect of VK penetration on protest participation is observed only after this tipping point. The graph looks similar if we take both VK penetration and the number of protesters as a share of city population (see Figure A5 in the Online Appendix). Note, however, that, consistent with our model, there is no threshold-type dependency between pro-government voting and social media penetration (see Figure A6 in the Online Appendix).

We can also confirm the existence of a threshold level of VK penetration by estimating a non-linear threshold model in which we allow the coefficient for the effect of VK penetration on protest activity to change at some point.[51] The results of this estimation indicate that indeed, there is a threshold level of VK penetration, below which there is no significant relationship between VK penetration and protest activity and above which there is a strong positive relationship (see Table A9 in the Online Appendix). The threshold is between 23,000 and 30,000 users or 23-25% as a share of the city population.

These results are consistent with Prediction 4 of our model, as well as with the predictions of the threshold models of collective action (e.g., Granovetter, 1978; Lohmann, 1993, 1994).

6.2 VK Penetration and Pro-Governmental Support

We test whether an increase in VK penetration led to a change in electoral support for pro-governmental candidates in the elections that took place after the creation of VK.[52] Table 4 presents

[51] Note that, in these specifications, we cannot account for the endogeneity of VK penetration as we do not have an additional instrument for the threshold. Since for protest participation the results of OLS regressions are attenuated to zero compared to IV results (see Table 3) these results are still likely to be indicative of the true effect. However, for the effect on government support, this approach is not likely to work, since OLS results have a different sign compared to IV results.

[52] One may think that our setting is appropriate for mediation analysis, as dislike of the regime is a prerequisite of protest participation. Unfortunately, we cannot implement it in our setting. From Dippel et al. (2017), it follows that the general mediation IV model is not identified unless one has a separate instrument for the mediator variable which we do not have. In addition, Dippel et al. (2017) suggest a set of new assumptions about unobservables such that, if they are true, one can separately evaluate the effect of treatment T on outcome Y through and apart from the mediation variable M. In particular, one could assume that the unobservables that confound the relationship between M (in this

the results of the estimation of equation (5) with electoral support for pro-government parties and candidates after 2006 as the outcome variables. In particular, we look at the share of votes received by the government party United Russia in the parliamentary elections of 2007, 2011, and 2016, as well as the share of votes received by Dmitry Medvedev in the presidential elections of 2008 and by Vladimir Putin in 2012. The results show that higher VK penetration consistently led to higher, not lower, electoral support for the government. This effect is not statistically significant for 2007, but is positive and significant for the remaining four elections. Interestingly, OLS results for the 2007 and 2011 elections show a statistically significant negative relationship between VK penetration and electoral support for pro-governmental candidates, suggesting that people who are more likely to join VK are less likely to support the government, but that this relationship is driven by endogenous self-selection.

One possible explanation for the positive causal effect of VK penetration on electoral support for pro-governmental candidates is that, on average, there was more pro-governmental than oppositional content in the network, so that higher VK penetration actually decreased the share of people who support the opposition.[53] At the same time, reduction in the costs of collective action associated with higher VK penetration increased the probability that people supporting the opposition would go protest, and that the latter effect outweighed the former. An alternative explanation is that the availability of VK increased political polarization, so that it increased both the number of pro-government supporters and the number of people strongly opposed to the government.[54] It is also possible that the official electoral results were contaminated by electoral fraud and did not reflect the actual preferences of the population, although the results in Table 4 could be explained by electoral fraud only if higher VK penetration was associated with greater extent of electoral fraud, which does not sound plausible.

To address these potential alternative explanations, we complement our analysis of electoral outcomes with the analysis of a large-scale opinion poll conducted right before the 2011 parliamentary elections. Respondents were asked about their support of President Dmitry Medvedev,

case, voting outcomes) and T (social media penetration) can affect Y (protest participation) only through M and T (see Table 1 on Dippel et al., 2017, p.2, for illustration). We believe that, unfortunately, these assumptions are too strong for our case. It is very hard to imagine that unobservables affecting voting preferences would not also have an impact on protest participation.

[53]Note that content analysis of posts on VK before 2011 elections confirms this conjecture, as it suggest that Putin, Medvedev, and the ruling party were mentioned much more often in blog posts than the opposition candidates (see Figure A7 in the Online Appendix). According to the standard content analysis measures, most of these posts were neutral, with the majority of posts being jokes and funny stories, sometimes even poems about the ruling candidates (see Figure A8 in the Online Appendix). Very few posts were negative towards the government. Overall, our content analysis suggest that, at least on average, information in social media preceding the elections was either neutral or even positive towards the regime.

[54]Note that this alternative explanation goes against the absence of a causal impact of social media on turnout (see Table A10 in the Online Appendix), which also indicates that the results are unlikely to be driven by increased civic participation.

Prime Minister Vladimir Putin, and of the government in general on a 6-point scale. They were also asked about their voting intentions in the upcoming parliamentary elections and about their readiness to participate in a hypothetical protest demonstrations.

The IV estimates for the effect of social media on the results of this poll are presented in Table 5. They turn out to be fully consistent with the effects on voting outcomes identified in Table 4. Respondents in cities with a higher VK penetration were more likely to give the highest support to Medvedev, Putin, and the government in general. They were also more likely to report their intentions to vote for the pro-governmental party United Russia in the upcoming elections. We find no evidence of a polarizing effect of social media as there was no increase in the number of respondents with the lowest support for the President, Prime Minister, and the government as a whole.

Importantly, higher VK penetration led to a lower number of respondents who reported their readiness to participate in protests (the effect is significant at a 10% level).[55] Thus, right before the actual protests took place, the penetration of VK had a negative effect on the number of potential participants in the protest. These results suggest that the reduction in the cost of collection action is the primary channel through which social media affects political protests, despite the fact that the information mechanism is pulling in the opposite direction.[56]

Overall, the results in Tables 4 and 5 indicate that, surprisingly, social media led to *more* favorable attitudes towards the regime. This result stands contrary to the claims that social media diffusion with free exchange of information would erode the support for autocratic regimes (Shirky, 2008). Also, these results do not support the hypothesis that social media increases political polarization, contrary to the predictions that echo chambers and filter bubbles lead to a divergence in the political preferences of the population (Sunstein, 2018). Thus, our findings are consistent with the indirect evidence for a lack of internet-driven polarization reported in Boxell et al. (2017). Finally, these results suggest that the collective action channel is likely the primary mechanism through which social media affected protest participation in the context of our study. We provide further support for this claim in Section 6.4.

[55] This result is supported by the negative effect of VK penetration on the share of invalid ballots in 2011 and 2012 elections (see Table A10 in the Online Appendix). At the time of these elections, submitting invalid ballots was a common strategy of voicing discontent towards the government, and was promoted by a number of opposition leaders.

[56] It is possible, however, that only the information about the electoral fraud that appeared after the elections mattered for protest participation, so that the direction of the information effect changed its sign in a matter of days. This is not fully consistent with the nature of the protest, as the protesters were making general political claims that were not limited to the issues of electoral fraud (Greene, 2014). Moreover, the effect on pro-government vote share remains positive even for 2016 legislative elections, after the protests took place.

6.3 Identifying assumptions checks

6.3.1 Placebo Results for Earlier Protests

Table 6 presents the results of the placebo regressions in which we estimate the same IV specifications as in columns (1)-(4) of Table 3, but with the measures of pre-VK protests as dependent variables. Specifically, we look at the protests that occurred in the late Soviet Union in 1987-1992 (both total and pro-democracy as a separate category), labor protests in 1997-2002, and social protests in 2005. The results indicate that there is no significant 'causal' effect of VK penetration in 2011 on any of the placebo outcomes. Moreover, the sign of the relationship between VK penetration and protests in post-Soviet Russia is negative in all specifications. These results are consistent with the assumption that there is no time-invariant unobserved taste-for-protest heterogeneity that is driving our results. Unfortunately, we cannot reject the hypothesis for the equality of the IV coefficients for the protests of December 2011 and the pre-VK protests for the results in Panel B of Table 6 because of large standard errors. However, in Panel A, we can reject the hypothesis for the equality of the IV coefficients for the protests in December 2011 and similar coefficients for pro-democracy protests in 1987-1992 and the labor protests in 1997-2002.

6.3.2 Placebo Results for Earlier Electoral Outcomes

To ensure that our results for political preferences in Section 6.2 are not driven by unobserved heterogeneity, we replicate the results in Table 4 using various pre-VK electoral outcomes as dependent variables. These voting outcomes capture pre-existing political preferences, and the results in Table 3 suggest that they are collectively important for predicting the protest activity of 2011. Table 7 summarizes the results of the placebo tests. Each cell in this table represents the coefficient for VK penetration in an IV regression similar to that in column (1) of Table 4, but with various voting outcomes as dependent variables. The specifics of each voting outcome are outlined in the title of each column, while the election year is being reported in the row name. Overall, we find that, out of the 39 corresponding regression coefficients, only one is statistically significant at the 5% level and five are significant at the 10% level. These numbers are very close to what could have been attributed to pure chance in multiple hypotheses testing and they largely support our argument. To further ensure that our results are not driven by pre-existing political preferences, we include voting outcomes as controls for each set of results in the paper (e.g., see columns (2)-(4) of Table 4).

6.3.3 Placebo Results for Other Universities

We use the distribution of home cities for three different cohorts of the SPbSU students to overcome the problem of unobserved heterogeneity between cities. Nevertheless, it is still possible that the cohort that studied during the same years as Durov happened to be an unusual cohort, and that these people, for some reason, had a higher commitment to education, a higher demand for social media, and a higher propensity to protest at the same time. To cope with this possibility, we collect data on 64 other Russian universities of comparable quality.[57] Next, we replicate our baseline first-stage regression for each of these 64 universities. We then compare the resulting coefficients with those of the corresponding SPbSU cohorts. Figures 4A-C show the empirical cumulative distribution functions of the coefficients for Durov's cohort (Figure 4A), the older cohort (Figure 4B), and the younger cohort (Figure 4C).[58] We highlight other universities in Saint Petersburg as they could have experienced spillovers because of their proximity to SPbSU, i.e., their students could also have been more likely to join VK earlier.

Figure 4A indicates that the coefficient for Durov's cohort at SPbSU lies at the top end of the distribution and, out of four universities with higher coefficients, two are located in Saint Petersburg. At the same time, the coefficients for the younger and older cohorts at SPbSU lie close to the medians of the corresponding distributions in Figures 4B and 4C. Thus, the results in Figures 4A-C indicate that, out of all the cohorts in SPbSU, only Durov's cohort looks special for the prediction of VK penetration in 2011, relative to those in other Russian universities of similar quality. This is consistent with the idea that students from the cohort of the VK founder in Saint Petersburg State University played a special role in the subsequent penetration of the network.

6.3.4 Student Data and Odnoklassniki

One potential concern with our approach is that we do not have administrative records on student cohorts and instead rely on the information from the profiles of Odnoklassniki users to infer the number of students in each university at each point in time. As was noted in Section 3, this concern is partially mitigated by the fact that 80% of adults in Russia had an account in Odnoklassniki at the time our data collection took place. This proportion was probably even higher for younger cohorts, which further improves the representativeness of our data. Additionally, in order to correct for a possible measurement error bias due to the non-random variation in Odnoklassniki penetration, we control for the number of Odnoklassniki users in each city in all of our specifications. Finally, it is important to note that the Odnoklassniki platform had no specific relationship either to this particular age cohort, to SPbSU, or to Saint Petersburg — the founder of Odnoklassniki, Albert Popkov,

[57] See Section 3 for a discussion of how these universities were selected.

[58] Figure A9 in the Online Appendix provides the corresponding graphs for the reduced form regressions.

was born in Yuzno-Sakhalinsk on Sakhalin island, studied in Moscow in a technical college in the early 90's, and founded the network while living in London.

Despite these details, a concern may remain that people could be more likely to have an Odnoklassniki account in cities with higher VK penetration, and potentially even more likely in places with a greater number of SPbSU students in Durov's cohort. To deal with this concern, we conduct two additional tests. First, we check whether the number of Odnoklassniki users is correlated with the number of VK users in a city at different stages of VK diffusion. The results in Columns (1)-(3) of Table A11 in the Online Appendix indicate that early VK penetration (the number of users in a city among the first 5,000, 50,000, or 100,000 users of the network) is negatively, though not significantly, related to the subsequent penetration of Odnoklassniki. This is consistent with the hypotheses that the initial diffusion of VK was not driven by general preferences for social media and that there might have been a substitution effect between different social networks. VK penetration in 2011 is, however, positively related to Odnoklassniki penetration at the time of the data collection in 2014, although this effect is not statistically significant either (see column (4)), which weakly suggests that, in the long run, penetration of different social networks may be driven by the same fundamentals.

Second, we test whether Odnoklassniki penetration was related to the student flows from Russian cities to Saint Petersburg State University. The results in columns (5)-(8) indicate that there is no such association, with the standard errors being substantially larger than the coefficients for the VK founder's cohort in all specifications. We conclude that the potential selection introduced by our data collection process is unlikely to bias our results.

6.3.5 Measurement Error in Protest Data

Another potential concern with our data collection is that the measures of protests, which were calculated based on media reports, could contain a measurement error that is correlated with VK penetration. It might have been the case that political protests were less likely to be covered by mass media, if they had not been discussed in social media in the first place. This concern is likely to be more relevant for smaller cities as the probability of a non-reporting error should be substantially smaller for bigger cities. However, as documented in Section 6.4.2 below, the IV coefficients for the effect of VK penetration on both the incidence of protests and the number of participants tend to increase with city size. Thus, our results are unlikely to be driven by selective media reporting of protests in small cities.

6.4 Additional Evidence on Mechanisms

6.4.1 Protest Participation and Online Protest Communities

Before proceeding with the analysis, we provide suggestive evidence that VK was indeed used by protest participants to coordinate their activities. Our descriptive measures suggest that 87 out of 133 cities with protest activity had public VK communities directly related to the corresponding protest events. These communities were accessible to all VK users and were used for informing and coordinating offline protests. To provide evidence that availability of such communities was systematically related to offline protests, Table A12 shows that the number of VK users in protest communities was positively associated with incidence of offline protests. In particular, a 10% increase in the number of people in VK protest communities was associated with a 3% increase in the probability of having a protest demonstration in a city (columns 1-4). Similarly, a 10% increase in the number of people in protest communities was associated with a 1.2% increase in the number of protest participants (columns 5-8). Overall, these results provide suggestive evidence that coordinating activity in VK protest communities was associated with the spread of offline protests. These results, however, should be interpreted with caution since they do not have a causal interpretation and do not take into account the fact that protest communities represent only one of the channels through which VK could affect protest participation.

6.4.2 Effect of City Size

According to Prediction 3 in our theoretical framework, it may be possible to disentangle the information and coordination channels by looking at how the effect of social media changes with city size. Specifically, if social media increases protest participation primarily by making coordination easier, one would expect the effect of social media to increase with city size, as the marginal value of information from social media on protest tactics is higher in larger cities. Also, the effect caused by the information channel is not expected to be stronger in bigger cities, so that the impact of social media on voting in favor of the regime should not increase with city size.

Figure 5 presents evidence supporting this prediction. Specifically, it shows that the IV coefficients for the effect of VK penetration on both the incidence of protests and the number of participants tend to increase when we restrict our sample to larger and larger cities. The coefficients remain largely significant despite a substantial increase in standard errors caused by a reduction in sample size. In particular, the IV coefficients for the incidence of protests increases from 0.47 to 1.08 and remains significant at the 5% level when we restrict the sample to the cities with above 150,000 people.

At the same time, the effect of social media on the vote share of United Russian in 2011 and of Putin in 2012 remains stable with city size and, if anything, decrease in magnitude (see Figure 6).

This further supports the idea that the information channel is unlikely to be responsible for the positive impact of social media on protest participation and that the effect is driven by the coordination channel.[59]

6.4.3 Fractionalization

To provide further evidence on the mechanisms behind the effect of social media on protest participation, we take advantage of the fact that Facebook was a close competitor of VK and was also used in protest activities. We look at the distribution of social media users between the two networks.[60] In particular, we compute a fractionalization index, i.e., the probability that two randomly picked users of online social media in a city belong to the same network. In the simplest case of non-overlapping audiences for the two networks, it can be computed as $fract_i = 1 - \sum_j {s_{ij}}^2$, where s_{ij} is the share of users in network j in city i among all the users of online social networks in city i. Since we do not have information on the overlap in the audiences of the two social networks we compute fractionalization using this simplified formula and check that our results are robust to a change in the fractionalization index that allows for partial overlap between users from different networks.[61]

We examine how the fractionalization of social media users between the two platforms affected protest activity, conditional on the total number of social media users in any of the two networks. In particular, we estimate the following specification:[62]

$$\log(protesters)_i = \beta_0 + \beta_1 fract_i + \beta_2 \log(total\ users)_i + \beta_3 X_i + \varepsilon_{it} \tag{15}$$

The information effect depends on the total number of users in both networks and not on their sorting into the two networks, since information critical of the government was available on both platforms. Thus, if the effect of social media operates through the information channel, this implies a zero coefficient for fractionalization. The mechanisms associated with a decrease in the costs of collective actions, however, implies that the coefficient for fractionalization is negative, since both coordination and social pressure work within the same network (regardless of which one).

[59]Our approach allows us to check heterogeneity of the results with respect to the other city characteristics, not only city size. Table A15 reports our baseline IV results for various subsamples. We find that the effect comes mostly from the cities with higher incomes (columns 1-2), and with higher levels of interpersonal trust (columns 3-4). There is also evidence that the effect is observed mostly from the cities with more educated people, but this result is not statistically significant (columns 5-6). Note, however, that these results should be interpreted with caution — as we split the sample, the instrument becomes weaker, with a decreased effective F-statistics, which could lead to an overrejection problem (Andrews et al., 2018).

[60]In contrast to VK and Facebook, Odnoklassniki was not actively employed in the protest movement (Reuter and Szakonyi, 2015), so we do not include it in the analysis.

[61]See the derivations in the Section A.2 of the Online Appendix and the results in Table A13 in the Online Appendix.

[62]Note that we are forced to use OLS for this specification, as we do not have a good instrument for fractionalization.

Thus, the more divided the users are between the networks, the harder it is for the collective action channel to operate.

Table 8 displays the results of the estimation of equation (15). These estimates imply that fractionalization is negatively associated with both protest participation and the incidence of the protests. Consistent with the Prediction 3 in our theoretical framework, the negative effect of social media fractionalization on protest participation increases in magnitude with city size, so that the negative effect is statistically significant only for large cities, e.g., for a subsample of cities with a population over 100,000 (see Figure A10 in the Online Appendix for full information on how the effect depends on city size). Both of these patterns point towards the importance of the coordination function of social media in its effect on protest participation.

The results presented in column (5) of Table 8 indicate that, in larger cities, a one standard deviation increase in network fractionalization is associated with 48% lower protest participation and a 9.8 percentage points lower probability of protests occurring.[63]

Overall, these findings are consistent with the hypothesis that social media penetration affects protest participation primarily by reducing the costs of collective action and improving coordination. The finding that the effect of fractionalization is driven by the cities with populations above 100,000 suggests that in smaller cities other means of interpersonal communication may play a greater role in protest coordination.

6.5 Other Outcomes and Robustness Checks

6.5.1 Policy Outcomes

If social media penetration affects protest participation, this, in turn, can influence policy outcomes. In the context of the Russian political protests of 2011-2012, protesters' demands were directed primarily at national-level policies and appealed mainly to the federal government, which means that we do not necessarily expect to see any variation in policy outcomes at the city level. Nevertheless, in an attempt to assess whether any changes in local policy were caused by protest activity, we looked at the impact of VK penetration on municipal revenues and spending before and after the protests.[64]

[63] One may be concerned that, even controlling for the total number of VK and FB users, higher fractionalization may be negatively associated with protest participation only due to a lower *relative* VK prevalence. To assuage this concern, instead of controlling for the total number of VK and Facebook users, we condition on the number of VK and Facebook users separately and provide the corresponding estimates in Table A14 in the Online Appendix. If our fractionalization index matters only so far as it reflects a lower prevalence of VK, it would make the coefficient on the fractionalization index insignificant in such specification. However, as one can see from Table A14, our results remain robust to this exercise.

[64] Note, however, that the municipal data collection in Russia is not consistently implemented, which results in a large number of missing values.

Table 9 presents the corresponding results. In all specifications, we control for the 2008 values of the dependent variables, thus effectively focusing on the changes in the policy outcomes as opposed to their levels. Moreover, we condition on the 2007-2008 election results as they may influence the allocation of resources. Panel A tests how federal transfers to municipalities over different years depend on the level of VK penetration. We find that higher VK penetration does not translate into any significant changes in transfers before 2012, but it leads to a decrease in federal transfers in the years of 2012-2014. The magnitudes of these effects are fairly large, with a 10% increase in VK penetration leading to a 31% reduction in federal transfers in 2014. A potential explanation for this effect is that the national government punished cities for allowing protests to take place.

Panel B of Table 9 looks at a similar specification with the municipality tax revenue as an outcome variable. We find that VK penetration has a negative effect on municipal tax revenues in 2012-2014, but it becomes statistically significant only in 2014. One potential explanation for this result is that a consistent lack of transfers in previous years had reduced the tax collection capacity of the municipalities. Finally, Panel C of Table 9 checks whether a similar pattern holds for total municipal spending. Although the coefficients for VK penetration are consistently negative with relatively large magnitudes after 2011, they are not statistically significant. Thus, we do not find enough evidence that VK penetration led to lower municipal spending after 2011.

These results are consistent with the existing anecdotal evidence that federal and regional government often use municipal transfers as a political tool. A few months prior to the 2011 Parliamentary elections, several government officials were spotted arguing that their cities' municipal finances would be cut if United Russia did not receive a sufficient number of votes.[65] Furthermore, an independent mayor of Yaroslavl, Yevgeny Urlashov, after winning the 2012 elections against a United Russia candidate, faced a lack of regional funding for teacher wages. In this context, it would not be entirely surprising if cities indeed received less transfers from the federal government as a result of political protests.

A serious limitation of these results, however, is that they do not distinguish between the effect of political protests caused by higher VK penetration and the effect of other channels through which VK penetration could affect policy outcomes. A potential way to identify the effect of political protests would be to use weather shocks as an instrument for protest participation (as in Madestam et al., 2013). Unfortunately, despite using all the available weather information we were not able to find a specification with a sufficiently high predictive power in the first-stage regression even using

[65] "Sarapul received 30 mln on roads and sidewalks this summer. Glazov received only 10 mln. We ourselves, Glazov residents, refused these extra 20 mln in the previous elections. (You) refused the good roads you could have been driving on. [...] Because United Russia oversees many various projects across the country. And they determine how to work with each city." – said the head of the presidential and government administration of Udmurtia Alexander Goriyanov on 5 Nov 2011 (http://bit.ly/2ofpOKa).

sophisticated machine learning techniques.

Overall, the results in Table 9 indicate that higher VK penetration led to lower federal transfers to municipal budgets starting from 2012, the first year after the onset of the protests, which suggests that the national government punished cities for allowing the protests to occur.

6.5.2 Additional Robustness Checks

We perform several additional robustness checks to ensure that our results are not driven by our choice of specification. We check that our results are robust to using cohorts of other sizes and shapes instead of 5-year cohorts defined symmetrically around Durov's age (see Table A16 in the Online Appendix for these robustness results).[66] Note that, independent of the width of the cohort window, the main IV coefficient for protest participation is very stable and statistically significant across the board. Moreover, although we did not select our baseline specification (in bold) this way on purpose, it happens to maximize the effective F-statistics and, as such, maximizes the power of our first stage in a set of similar specifications. Our results are also robust to including two older and two younger cohorts instead of one each. In our benchmark specification, we chose to keep only one younger and one older cohorts, as our source of data for students is more complete for those cohorts. The results are also robust to using the years of study instead of the year of birth to compute different cohorts.[67]

7 Conclusion

This paper provides evidence that social media penetration had a causal effect on both the incidence and the size of the protest demonstrations in Russia in December 2011. At the same time, social media increased support of the government. Additional evidence suggests that social media affects protest activity by reducing the costs of collective action, rather than by spreading information critical of the government or by increasing political polarization. Thus, our results imply that social media can increase the ability of people to overcome the collective action problem.

[66] We believe that creating Durov's exact cohort is not an optimal approach of constructing an instrument, since, although offline connections within the same cohort mattered, VK was also extensively advertised on the SPbSU online forum, which influenced other cohorts of SPbSU students as well. Therefore, the first users were not only VK founder's classmates but also all other students who were studying at SPbSU at the time. However, in the results available upon request, we show that, when 1-year cohorts are used, the results become noisier but still point in the same direction.

[67] See Table A17 in the Online Appendix for the baseline results calculated for cohorts defined based on the years of study. Note that more people don't report their years of study on Odnoklassniki than their year of birth. Specifically, out of 22,500 people we use for construction of our instrument based on the year of birth, 3,700 (16.4%) did not report their starting year of education and 4,700 (20.8%) did not report year of graduation. Thus, when we construct our cohorts based on the starting year or graduation year, we lose student observations and increase the number of cities with zero students sent to SPbSU in different cohorts.

Our results should be generalized with caution. First, the Russian protests of 2011-2012 were unexpected and the government did not have time to prepare for them. If the threat of collective action is stable over time, governments may use various strategies to counteract social media activism (King et al., 2013, 2014). Second, as our theoretical framework highlights, while social media is expected to lower the costs of coordination, the information effects of social media could go either way, depending on whether the content of social media is, on average, positive to the government. Overwhelmingly critical content can influence political participation by diminishing support for the government and promoting protests at the same time.

We believe that our methodology can be used for studying the impact of social media penetration on other forms of collective action. For example, consumers who would like to lower tariffs or discipline companies' misbehavior through boycotts, also face the same collective action problem. Similarly, collective action is important for the fundraising campaigns of charitable or educational institutions, or for environmental activism. We expect social media to reduce the costs of collective action in all of these circumstances; at least as long as social norms imply that participation in collective action is desirable. More generally, our identification approach, which relies on social distance from the inventor to instrument for the spread of the new technology, is likely to be applicable to studying the impact of technology adoption in other settings, and can complement identification strategies based on physical distance (e.g., Dittmar, 2011; Cantoni and Yuchtman, 2014). In sum, our paper is an early step in studying how social media can change societies. More research is needed to understand whether similar results hold for other outcomes and in other contexts.

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ONLINE APPENDIX

A.1 The Cross Partial Derivative of Protest Participation with Respect to Social Media and Baseline Coordination Signal

The cross partial derivative of the effect of social media on protests via coordination channel with respect to baseline coordination signal can be obtained by differentiating equation (8) with respect to the precision of the baseline coordination signal, β_0:

$$\frac{\partial^2 \hat{c}_p}{\partial \beta_s \partial \beta_0} = -\frac{2k}{(\beta_0+\beta_s)^3\left(1-\frac{\lambda_p}{\sigma_{pc}}\phi\left[\frac{1}{\sigma_{pc}}(\hat{c}_p-\mu_{pc})\right]\right)} + \frac{k^2\lambda_p\phi'\left[\frac{1}{\sigma_{pc}}(\hat{c}_p-\mu_{pc})\right]}{\sigma^2(\beta_0+\beta_s)^4\left(1-\frac{\lambda_p}{\sigma_{pc}}\phi\left[\frac{1}{\sigma_{pc}}(\hat{c}_p-\mu_{pc})\right]\right)^3}$$

We would like to derive the sign of this expression. First, note that, under the assumption that lambda is small enough to ensure that the denominator in (7)-(9) is positive, — more precisely, if $\lambda < \sigma_{pc}/\phi[(\hat{c}_p-\mu_{pc})/\sigma_{pc}])$ — the first part of the above expression is negative.

Second, observe that whenever the equilibrium threshold, $\hat{c}_p$, exceeds the average cost of protest participation, μ_{pc}, the second part of that expression becomes negative too (since $\phi'(x) < 0$ when $x > 0$). Thus, in this case, the cross partial derivative has a negative sign. However, the condition that $\hat{c}_p > \mu_{pc}$ is fairly restrictive and unlikely to hold in our data, as it means that more than 50% of population decide to take part in a protest.

However, we can show that, even if $\hat{c}_p < \mu_{pc}$, the cross partial derivative is negative as long as λ_p is small enough. To see this, note that, when λ_p approches zero, the second part of the expression goes to zero as well, while the first one survives and remains negative. We search for the condition on lambda more formally below. Getting rid of common multipliers and using simplified notation, the condition becomes:

$$\frac{k\lambda\phi'}{\sigma^2(\beta_0+\beta_s)\left(1-\frac{\lambda}{\sigma}\phi\right)^2} - 2 < 0$$

After a few algebraic transformations, one obtains the following inequality:

$$\lambda^2\left[-2(\beta_0+\beta_s)\phi^2\right] + \lambda\left[k\phi' + 4(\beta_0+\beta_s)\phi\sigma\right] - 2(\beta_0+\beta_s)\sigma^2 < 0$$

Under the existing restriction on lambda, $\lambda < \sigma/\phi$, there remain some values of lambda for which the above inequality does not hold. To see this, note that, when inserting $\lambda = \sigma/\phi$, the above expression becomes strictly positive:

$$-2(\beta_0+\beta_s)\sigma^2 - 2(\beta_0+\beta_s)\sigma^2 + k\sigma\frac{\phi'}{\phi} + 4(\beta_0+\beta_s)\sigma^2 = k\sigma\frac{\phi'}{\phi} > 0$$

, where $\phi' > 0$ comes from the fact that we are considering the case with $\hat{c}_p < \mu_{pc}$, and from the fact that $\phi'(x) > 0$ when $x < 0$.

Thus, the new condition on lambda is a subset of the existing condition and comes from solving the quadratic inequality above. After solving this inequality, one obtains the following condition:

$$\lambda < \frac{k\phi' + 4(\beta_0+\beta_s)\phi\sigma - \sqrt{(k\phi')^2 + 8(\beta_0+\beta_s)\phi\phi' k\sigma}}{2(\beta_0+\beta_s)\phi^2} \tag{16}$$

To conclude, if lambda is small enough, i.e., complies with condition (16), the cross partial derivative of the social media coordination effect on protest participation by precision of the baseline coordination signal has a negative sign. As a result, our theoretical framework predicts that social media should be more important in places with higher β_0^i where coordination is harder to achieve in the absence of public signals, e.g., in larger cities. Thus, if social media increases protest participation due to coordination channel, one would expect the magnitude of the effect to be increasing with city size.

A.2 Fractionalization with Arbitrary Overlap

In this section, we derive a fractionalization index formula for the case of overlapping groups. In our particular case, these are VK and Facebook users. Let us denote the number of VK users as n_1, the number of Facebook users as n_2, and their interaction as m (see Figure 1 for illustration).

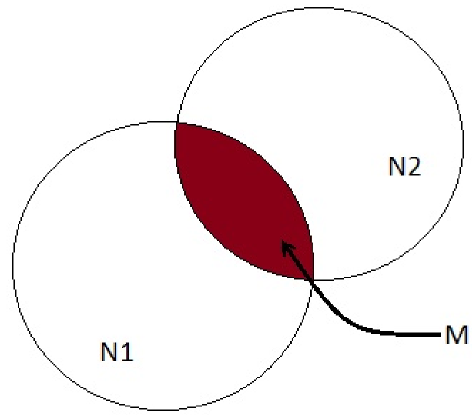


Figure 1: Overlapping groups

The usual fractionalization index measures the probability that two randomly chosen objects happen to be in different groups:

$$I = 1 - \frac{n_1^2 + n_2^2}{(n_1 + n_2)^2}$$

Suppose now that there is a non-zero overlap between the two groups, meaning that mass m now has accounts in both VK and Facebook. The probability of two randomly chosen people being from distinct social media networks is now equal to the chance that one person is drawn from n_1 but not m and the other one is drawn from n_2 but not m:[68]

$$I_1 = \frac{2(n_1 - m)(n_2 - m)}{(n_1 + n_2 - m)^2} \tag{17}$$

Now that we derived the formula for fractionalization with arbitrary overlap between groups, we can apply it to our analysis. The main issue with applying it directly is that we do not immediately observe m. However, since we want to see how a change in m affects the results of our fractionalization specification, we re-calculate our fractionalization index for 9 cases: $m = 0.1n_2, m = 0.2n_2, m = 0.3n_2, m = 0.4n_2, m = 0.5n_2$, etc. That is, we assume that 10% (20%, 30%,

[68]Similarly, one can derive this formula by computing the inverse of the probability that two randomly selected people are in the same social media platform. There could be such three cases. If one of the people is from m, they will surely be from the same platform. If the first person is from n_1 but not m, they can meet only if the other person is from n_1. Similarly, if the first person belongs to n_2 but not m, they can meet only if the other person is from n_2. Combining the probabilities of these three events, we get:

$$I_2 = 1 - \frac{m}{n_1 + n_2 - m} - \frac{(n_1 - m)n_1}{(n_1 + n_2 - m)^2} - \frac{(n_2 - m)n_2}{(n_1 + n_2 - m)^2}$$

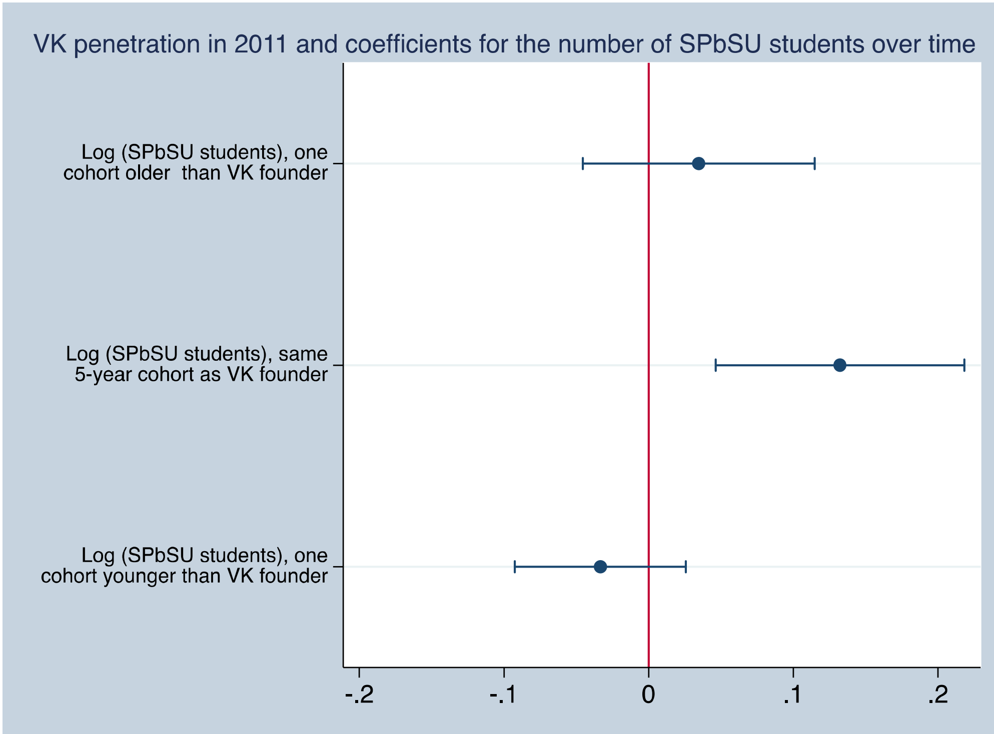
One can show that $I_1 = I_2$, so we can use either formula.

etc.) of Facebook users have a VKontakte account.[69] In Table A13 in the Online Appendix, we provide the results of the estimation for a subset of cities with large population (above 100,000). Note that the results are robust to a very high degree of overlap between the VK and Facebook users.

[69] In a survey from Enikolopov et al. (2017), we find that around 47% of regular Facebook users also use VK regularly. However, these estimates should be interpreted with caution as it heavily oversamples Moscow residents and, as such, is not representative at the city level.

FIGURES AND TABLES

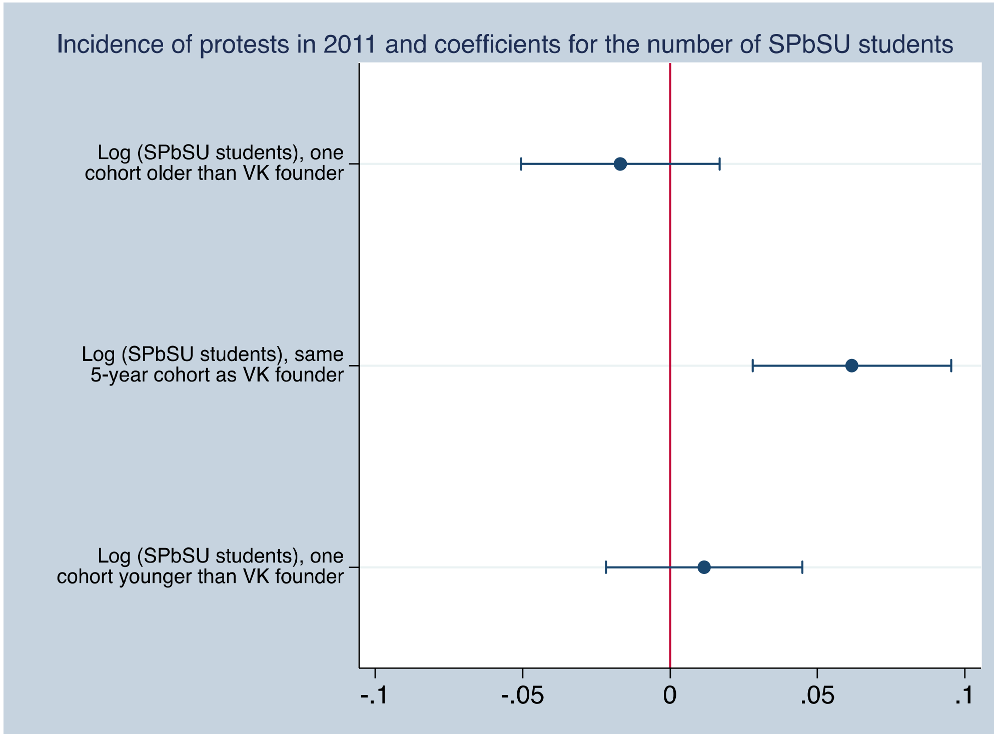
Figure 1. VK Penetration in 2011 and SPbSU student cohorts.



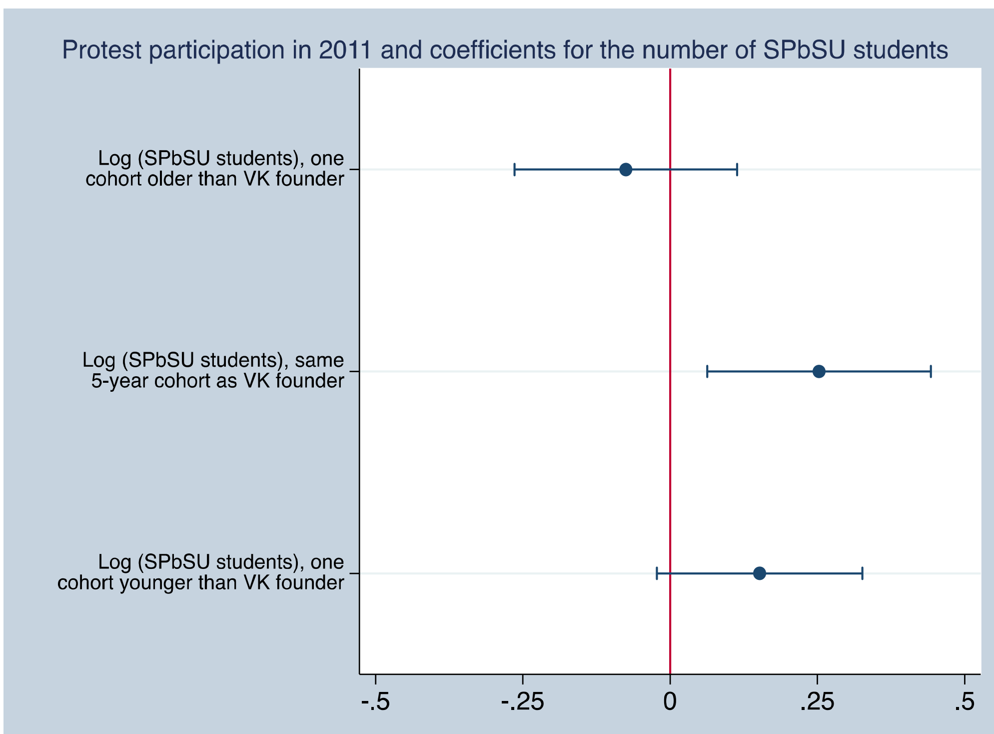
Notes: This figure presents the coefficients from column (4) of Table 1, reflecting the association between the log of the number of VK users in each city in June 2011 and the log of the number of SPbSU students who are one 5-year cohort older, of the same cohort, or one cohort younger than VK founder, respectively. Standard errors are clustered at the region level. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. For further details about this specification, see notes to Table 1.

Figure 2. Protest activity and SPbSU student cohorts

A. SPbSU Cohorts from Different Cities and The Incidence of Protests

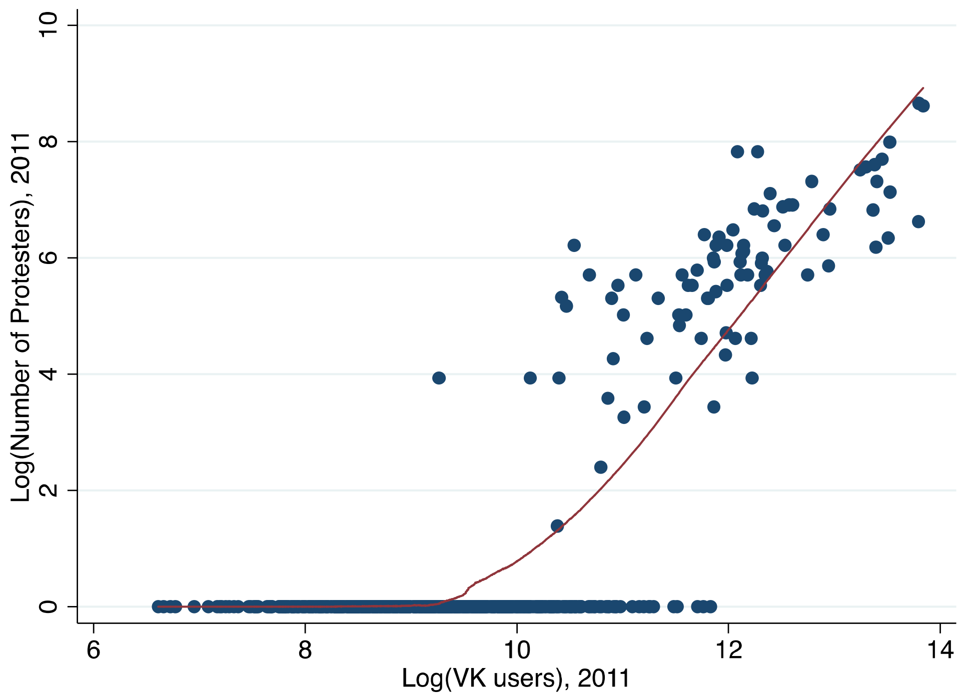


B. SPbSU Cohorts from Different Cities and Protest Participation



Notes: Figure A and Figure B present the coefficients from columns (1) and (5) of Table 2, respectively. These reflect the association between the incidence of protests (Figure A) or the log of the number of protest participants (Figure B) in each city during the first week of protests in December 2011 and the number of SPbSU students who are one 5-year cohort older, of the same cohort, or one cohort younger than VK founder, respectively. Standard errors are clustered at the region level. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. For further details about this specification, see notes to Table 2.

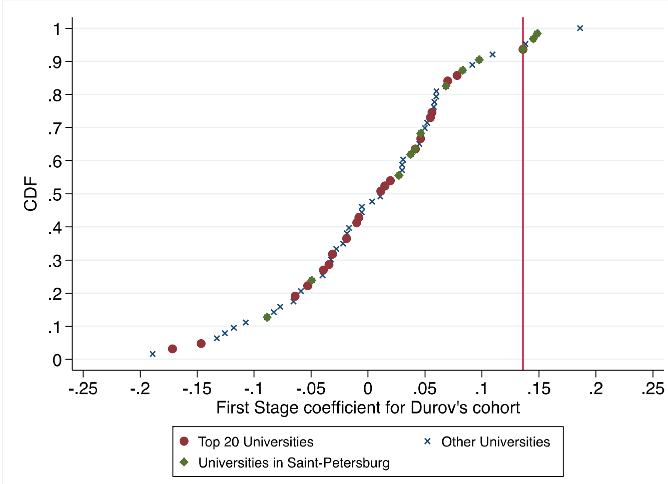
Figures 3. Nonparametric Relationship Between VK Penetration and Number of Protesters.



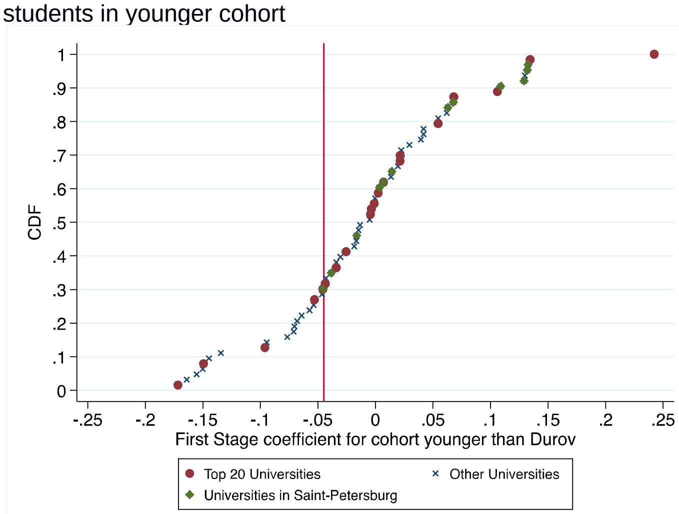
Notes: This figure displays the association between the log of the number of protesters in each city during the first week of protests in December 2011 and the log of the number of VK users in these cities as of June 2011. Logarithm of any variable is calculated with 1 added inside. Blue dots illustrate raw city-level data. Red line represents a non-parametric relationship between the two variables.

Figure 4. First Stage Coefficients for 65 Universities in Russia.

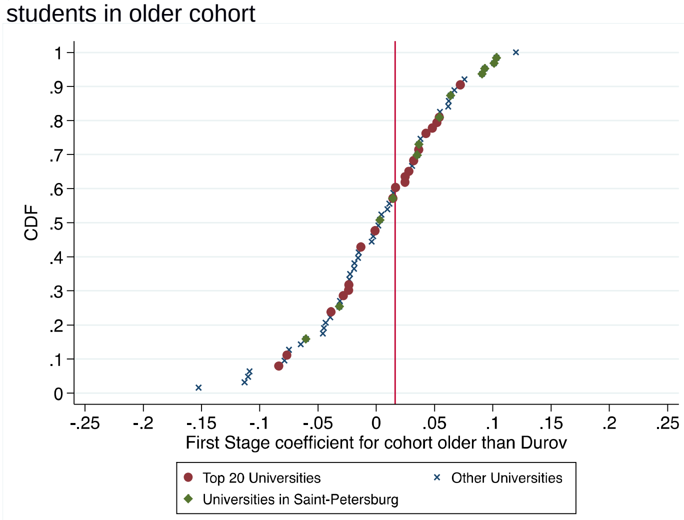
A: Distribution of students in Durov's cohort (+- 2 years from Durov).



B: Distribution of students in younger cohort

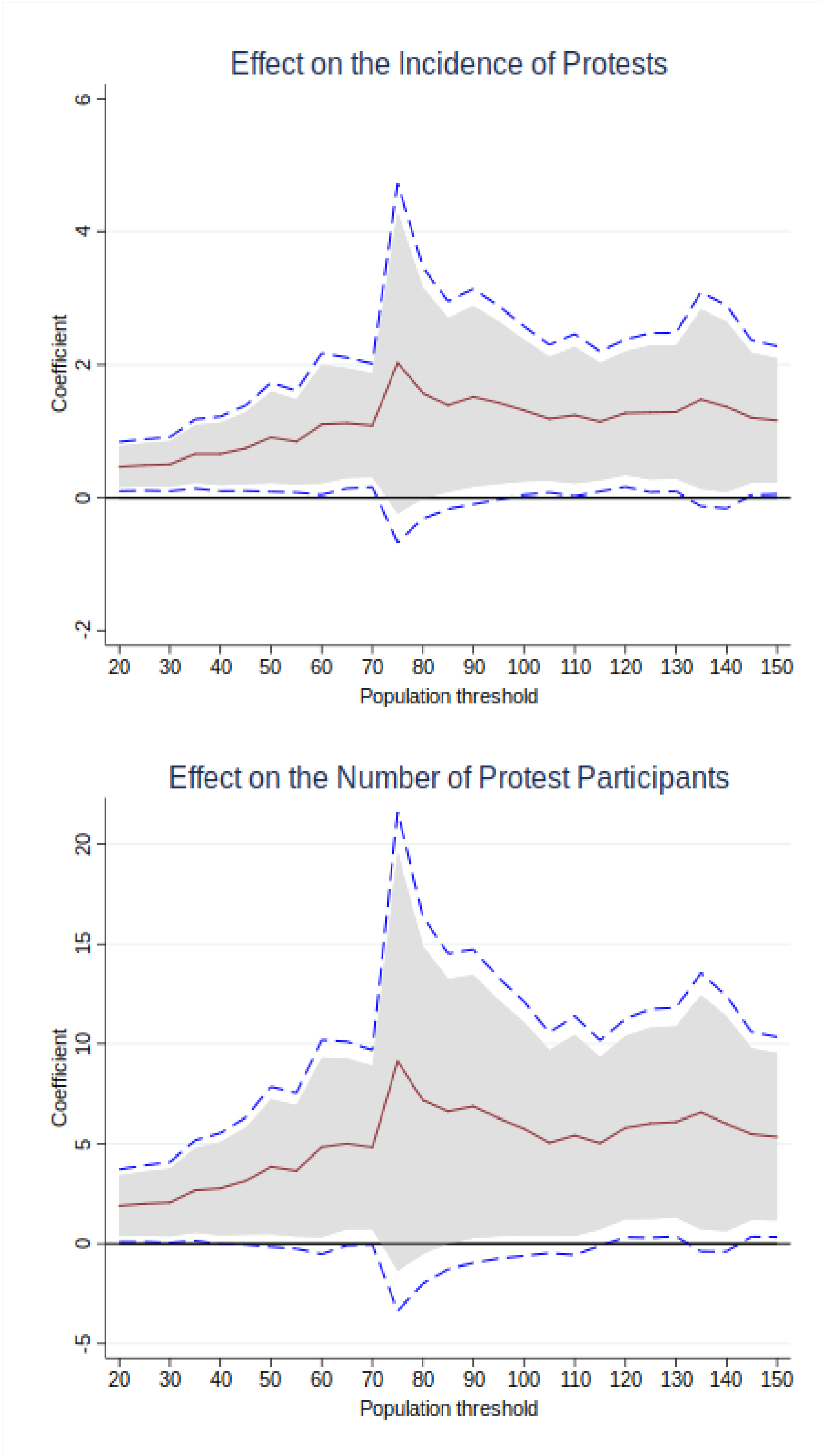


C: Distribution of students in older cohort



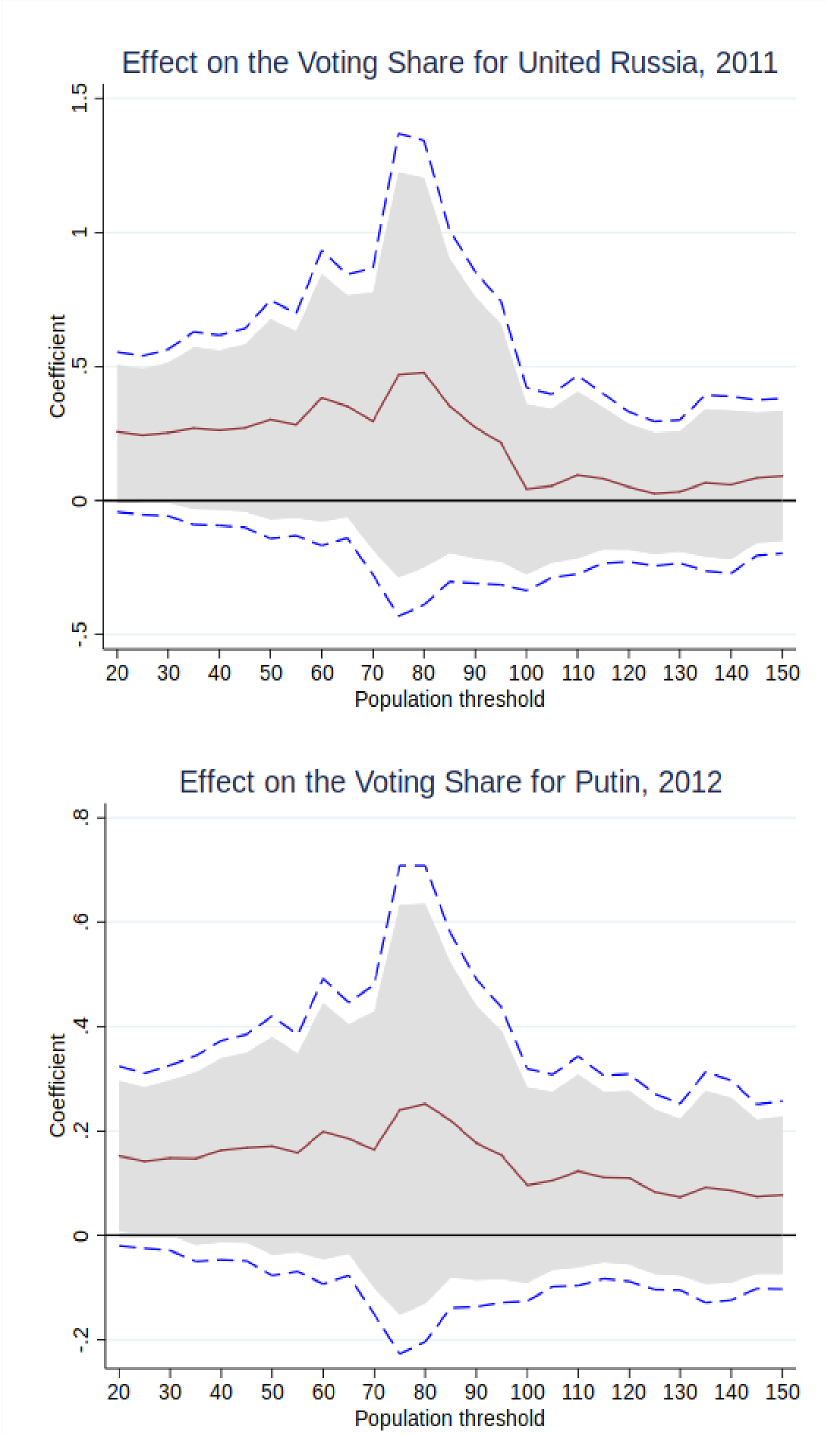
Notes: These figures draw comparisons between the first stage coefficients displayed on Figure 1 and the coefficients from the same specification, but estimated with the log of the number of students from other 65 top Russian universities, as opposed to SPbSU. Red vertical lines indicate the SPbSU coefficients from Figure 1. Red dots represent first stage coefficients for top-20 universities, such as MSU, SPbSPU, etc. Green dots represent first stage coefficients for top-65 Russian universities that are located in St. Petersburg. Blue crosses represent first stage coefficients for other top-65 universities.

Figure 5. Magnitude of the Effect of Social Media on Protest Participation as a Function of Population Threshold.



Notes: The graphs show the magnitude of the coefficients for the causal effect of VK penetration on Protest Incidence and Log (protesters in December 2011) for cities to the right of a given population threshold (in thousands). Grey areas show the 10% confidence intervals. Dashed lines display the 95% confidence intervals.

Figure 6. Magnitude of the Effect of Social Media on Voting Outcomes as a Function of Population Threshold.



Notes: The graphs show the magnitude of the coefficients for the causal effect of VK penetration on Vote Share for United Russia in 2011 and Vote Share for Putin in 2012 for cities to the right of the given population threshold (in thousands). Grey areas show the 10% confidence intervals. Dashed lines display the 95% confidence intervals.

Table 1. Determinants of VK penetration in 2011 (first stage regression).

	Log (number of VK users), June 2011							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (SPbSU students), same 5-year cohort as VK founder	0.5006***	0.1715***	0.1749***	0.1332***	0.1323**	0.1369**	0.1392***	0.1371***
	[0.1381]	[0.0441]	[0.0442]	[0.0503]	[0.0517]	[0.0526]	[0.0505]	[0.0517]
Log (SPbSU students), one cohort younger than VK founder	0.5612***	-0.0267	-0.0323	-0.0195	-0.0333	-0.0331	-0.0419	-0.0354
	[0.1040]	[0.0508]	[0.0522]	[0.0359]	[0.0355]	[0.0364]	[0.0369]	[0.0369]
Log (SPbSU students), one cohort older than VK founder	0.3687**	0.1040**	0.0945**	0.0351	0.0347	0.0292	0.0223	0.0232
	[0.1726]	[0.0459]	[0.0448]	[0.0476]	[0.0482]	[0.0487]	[0.0451]	[0.0460]
Regional center			0.1992*	0.2946**	0.1860	0.1925	0.2102	0.1795
			[0.1115]	[0.1279]	[0.1393]	[0.1390]	[0.1344]	[0.1360]
Distance to Saint Petersburg, km				-0.0000	-0.0001	-0.0001	-0.0001	-0.0002
				[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0001]
Distance to Moscow, km				-0.0001	-0.0000	0.0000	-0.0001	0.0001
				[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Rayon center (county seat)				-0.0104	-0.0200	-0.0299	-0.0387	-0.0271
				[0.0735]	[0.0683]	[0.0665]	[0.0715]	[0.0647]
Log (average wage), city-level, 2011				0.1604	0.1179	0.1141	0.0369	0.0586
				[0.1493]	[0.1501]	[0.1569]	[0.1482]	[0.1525]
Presence of a university in a city, 2011					0.1229	0.1416	0.1265	0.1585
					[0.0963]	[0.0966]	[0.0948]	[0.0982]
Internet penetration, region-level, 2011					0.1958	0.2025	0.1615	0.2012
					[0.2254]	[0.2153]	[0.2351]	[0.2212]
Log (number of Odnoklassniki users), 2014					0.0887	0.1024	0.1096	0.1360*
					[0.0851]	[0.0829]	[0.0818]	[0.0807]
Ethnic fractionalization, 2010					0.3894*	0.3449	0.5086**	0.3901*
					[0.2205]	[0.2342]	[0.2323]	[0.1966]
Observations	625	625	625	625	625	625	625	625
R-squared	0.4428	0.8606	0.8614	0.9031	0.9063	0.9098	0.9094	0.9110
Mean of the dependent variable	9.536	9.536	9.536	9.536	9.536	9.536	9.536	9.536
SD of the dependent variable	1.334	1.334	1.334	1.334	1.334	1.334	1.334	1.334
Population controls		Yes***	Yes***	Yes*	Yes**	Yes**	Yes*	Yes*
Age cohort controls				Yes***	Yes***	Yes***	Yes***	Yes***
Education controls				Yes***	Yes***	Yes***	Yes***	Yes***
Electoral controls, 1995						Yes**		
Electoral controls, 1999							Yes*	
Electoral controls, 2003								Yes**
p-value for equality of coefficients for three cohorts	0.706	0.044**	0.038**	0.033**	0.025**	0.026**	0.019**	0.028**
p-value for equality of coefficients of Durov's and younger cohort	0.762	0.014**	0.011**	0.011**	0.009***	0.008***	0.006***	0.009***
p-value for equality of coefficients of Durov's and older cohort	0.583	0.367	0.279	0.229	0.231	0.201	0.144	0.160

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year.

Table 2. Student cohorts and protest participation in 2011. Reduced form estimation.

	Incidence of protests, dummy, Dec 2011				Log (number of protesters), Dec 2011			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (SPbSU students), same 5-year cohort as VK founder	0.062***	0.062***	0.064***	0.066***	0.253**	0.256**	0.264**	0.276**
	[0.020]	[0.020]	[0.020]	[0.020]	[0.114]	[0.113]	[0.115]	[0.115]
Log (SPbSU students), one cohort younger than VK founder	0.012	0.011	0.009	0.013	0.152	0.147	0.134	0.159
	[0.020]	[0.020]	[0.020]	[0.020]	[0.105]	[0.104]	[0.105]	[0.106]
Log (SPbSU students), one cohort older than VK founder	-0.017	-0.016	-0.018	-0.014	-0.075	-0.072	-0.082	-0.068
	[0.020]	[0.020]	[0.020]	[0.020]	[0.113]	[0.113]	[0.112]	[0.114]
Regional center	-0.015	-0.011	-0.007	-0.013	0.287	0.304	0.333	0.291
	[0.099]	[0.097]	[0.096]	[0.098]	[0.488]	[0.480]	[0.480]	[0.490]
Distance to Saint Petersburg, km	0.000	0.000	0.000	0.000	-0.000	0.000	-0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Distance to Moscow, km	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Rayon center (county seat)	-0.001	0.001	-0.007	-0.010	0.003	0.007	-0.031	-0.045
	[0.009]	[0.009]	[0.010]	[0.011]	[0.044]	[0.046]	[0.048]	[0.054]
Log (average wage), city-level, 2011	0.021	0.041	0.009	-0.013	0.100	0.171	0.009	-0.066
	[0.034]	[0.037]	[0.036]	[0.034]	[0.176]	[0.186]	[0.193]	[0.182]
Presence of a university in a city, 2011	0.196**	0.194*	0.193**	0.198**	0.870**	0.869**	0.852**	0.892**
	[0.098]	[0.098]	[0.097]	[0.098]	[0.423]	[0.424]	[0.420]	[0.430]
Internet penetration, region-level, 2011	-0.013	0.007	-0.003	-0.011	0.138	0.204	0.172	0.132
	[0.045]	[0.046]	[0.054]	[0.049]	[0.243]	[0.237]	[0.276]	[0.256]
Log (number of Odnoklassniki users), 2014	0.032*	0.024	0.039*	0.031	0.104	0.078	0.147	0.124
	[0.017]	[0.019]	[0.020]	[0.019]	[0.109]	[0.119]	[0.120]	[0.117]
Ethnic fractionalization, 2010	-0.089	-0.084	-0.079	-0.088	-0.580*	-0.549	-0.511	-0.583*
	[0.059]	[0.061]	[0.063]	[0.062]	[0.321]	[0.331]	[0.342]	[0.346]
Observations	625	625	625	625	625	625	625	625
R-squared	0.776	0.780	0.781	0.781	0.823	0.826	0.828	0.826
Mean of the dependent variable	0.134	0.134	0.134	0.134	0.773	0.773	0.773	0.773
SD of the dependent variable	0.341	0.341	0.341	0.341	2.024	2.024	2.024	2.024
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*
Electoral controls, 1995		Yes**				Yes**		
Electoral controls, 1999			Yes*				Yes**	
Electoral controls, 2003				Yes**				Yes**
p-value for equality of coefficients for three cohorts	0.078*	0.071*	0.058*	0.068*	0.271	0.277	0.250	0.246
p-value for equality of coefficients of Durov's and younger cohort	0.089*	0.072*	0.064*	0.076*	0.528	0.488	0.416	0.474
p-value for equality of coefficients of Durov's and older cohort	0.031**	0.032**	0.025**	0.028**	0.115	0.114	0.099*	0.100

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year.

Table 3. VK penetration and protest participation in 2011.

Panel A. Probability of protests

	Incidence of protests, dummy, Dec 2011							
	IV	IV	IV	IV	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (number of VK users), June 2011	0.466**	0.451**	0.458***	0.479***	0.060***	0.057***	0.055***	0.065***
	[0.189]	[0.177]	[0.175]	[0.181]	[0.018]	[0.018]	[0.019]	[0.018]
Weak IV Robust 95% Confidence Interval	*(0.20; 1.77)*	*(0.20; 1.56)*	*(0.20; 1.44)*	*(0.20; 1.53)*				
Log (SPbSU students), one cohort younger than VK founder	0.027	0.026	0.028	0.030	0.029	0.028	0.026	0.030
	[0.024]	[0.024]	[0.025]	[0.025]	[0.021]	[0.020]	[0.021]	[0.020]
Log (SPbSU students), one cohort older than VK founder	-0.033	-0.029	-0.028	-0.026	0.003	0.005	0.003	0.007
	[0.031]	[0.029]	[0.027]	[0.029]	[0.018]	[0.017]	[0.017]	[0.018]
Observations	625	625	625	625	625	625	625	625
Mean of the dependent variable	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
SD of the dependent variable	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341
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**
Kleibergen-Paap F-stat	6.554	6.779	7.591	7.031				
Effective F-stat (Montiel Olea and Pflueger 2013)	10.97	12.03	12.30	12.17				

Panel B. Number of protesters

	Log (number of protesters), Dec 2011							
	IV	IV	IV	IV	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (number of VK users), June 2011	1.911**	1.872**	1.894**	2.013**	0.377***	0.359***	0.351***	0.393***
	[0.924]	[0.872]	[0.872]	[0.889]	[0.098]	[0.102]	[0.104]	[0.103]
Weak IV Robust 95% Confidence Interval	*(0.23; 7.31)*	*(0.29; 6.56)*	*(0.29; 6.10)*	*(0.41; 6.46)*				
Log (SPbSU students), one cohort younger than VK founder	0.216*	0.209*	0.213*	0.230*	0.221**	0.217**	0.207*	0.233**
	[0.117]	[0.115]	[0.119]	[0.119]	[0.107]	[0.106]	[0.108]	[0.107]
Log (SPbSU students), one cohort older than VK founder	-0.141	-0.127	-0.124	-0.115	-0.004	0.004	-0.002	0.013
	[0.151]	[0.145]	[0.135]	[0.144]	[0.093]	[0.092]	[0.090]	[0.094]
Observations	625	625	625	625	625	625	625	625
Mean of the dependent variable	0.773	0.773	0.773	0.773	0.773	0.773	0.773	0.773
SD of the dependent variable	2.024	2.024	2.024	2.024	2.024	2.024	2.024	2.024
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*
Kleibergen-Paap F-stat	6.554	6.779	7.591	7.031				
Effective F-statistics (Olea Montiel and Pflueger 2013)	10.97	12.03	12.30	12.17				

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014). Weak IV robust 95% confidence intervals are Anderson-Rubin confidence sets calculated using software in Finlay and Magnusson (2009), which accommodates heteroskedasticity.

Table 4. VK penetration and Voting Outcomes.

	IV	IV	IV	IV	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Voting share for United Russia, 2007								
Log (number of VK users), June 2011	0.055	0.048	0.064	0.022	-0.020	-0.025**	-0.019	-0.030***
	[0.057]	[0.053]	[0.055]	[0.045]	[0.013]	[0.011]	[0.012]	[0.010]
Weak IV Robust 95% Confidence Interval	*(-0.04; 0.36)*	*(-0.04; 0.32)*	*(-0.02; 0.34)*	*(-0.06; 0.24)*				
Log (SPbSU students), one cohort younger than VK founder	-0.008	-0.005	-0.007	-0.007	-0.008	-0.004	-0.007	-0.007
	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]	[0.007]	[0.007]
Log (SPbSU students), one cohort older than VK founder	0.001	0.001	-0.001	-0.003	0.009	0.008	0.006	0.001
	[0.009]	[0.008]	[0.009]	[0.007]	[0.007]	[0.006]	[0.007]	[0.005]
Voting share for Medvedev, 2008	IV	IV	IV	IV	OLS	OLS	OLS	OLS
Log (number of VK users), June 2011	0.143*	0.140*	0.156*	0.118*	-0.003	-0.009	-0.005	-0.014
	[0.079]	[0.077]	[0.080]	[0.068]	[0.011]	[0.010]	[0.011]	[0.009]
Weak IV Robust 95% Confidence Interval	*(0.02; 0.68)*	*(0.04; 0.64)*	*(0.04; 0.64)*	*(0.02; 0.52)*				
Log (SPbSU students), one cohort younger than VK founder	-0.006	-0.004	-0.006	-0.005	-0.005	-0.003	-0.005	-0.004
	[0.010]	[0.009]	[0.010]	[0.008]	[0.007]	[0.006]	[0.007]	[0.006]
Log (SPbSU students), one cohort older than VK founder	-0.002	-0.002	-0.005	-0.005	0.012*	0.011*	0.008	0.006
	[0.011]	[0.010]	[0.011]	[0.010]	[0.007]	[0.006]	[0.007]	[0.006]
Voting share for United Russia, 2011	IV	IV	IV	IV	OLS	OLS	OLS	OLS
Log (number of VK users), June 2011	0.257*	0.217*	0.259*	0.198	-0.035*	-0.039**	-0.031*	-0.045***
	[0.152]	[0.131]	[0.147]	[0.128]	[0.018]	[0.017]	[0.017]	[0.014]
Weak IV Robust 95% Confidence Interval	*(0.04; 1.40)*	*(0.04; 1.12)*	*(0.06; 1.20)*	*(0.02; 1.00)*				
Log (SPbSU students), one cohort younger than VK founder	-0.006	-0.000	-0.004	-0.003	-0.003	0.002	-0.003	-0.001
	[0.015]	[0.014]	[0.016]	[0.013]	[0.012]	[0.010]	[0.012]	[0.011]
Log (SPbSU students), one cohort older than VK founder	-0.003	0.003	-0.003	-0.005	0.024**	0.026**	0.020*	0.016
	[0.020]	[0.017]	[0.018]	[0.016]	[0.012]	[0.011]	[0.011]	[0.011]
Voting Share for Putin, 2012	IV	IV	IV	IV	OLS	OLS	OLS	OLS
Log (number of VK users), June 2011	0.152*	0.144*	0.155*	0.114	-0.011	-0.013	-0.010	-0.020**
	[0.088]	[0.085]	[0.084]	[0.073]	[0.011]	[0.010]	[0.011]	[0.008]
Weak IV Robust 95% Confidence Interval	*(0.04; 0.80)*	*(0.04; 0.72)*	*(0.04; 0.68)*	*(0.02; 0.58)*				
Log (SPbSU students), one cohort younger than VK founder	-0.001	0.001	0.000	-0.001	0.000	0.002	0.001	0.000
	[0.010]	[0.009]	[0.010]	[0.008]	[0.008]	[0.007]	[0.007]	[0.007]
Log (SPbSU students), one cohort older than VK founder	0.003	0.004	0.001	0.000	0.018**	0.018**	0.015**	0.011*
	[0.013]	[0.012]	[0.012]	[0.010]	[0.007]	[0.007]	[0.007]	[0.006]
Voting share for United Russia, 2016	IV	IV	IV	IV	OLS	OLS	OLS	OLS
Log (number of VK users), June 2011	0.214**	0.171*	0.205**	0.134*	0.007	0.009	0.017	0.002
	[0.108]	[0.098]	[0.097]	[0.072]	[0.019]	[0.017]	[0.018]	[0.012]
Weak IV Robust 95% Confidence Interval	*(0.04; 0.92)*	*(0.00; 0.72)*	*(0.06; 0.74)*	*(0.02; 0.52)*				
Log (SPbSU students), one cohort younger than VK founder	-0.002	0.004	0.000	0.001	0.000	0.006	0.001	0.001
	[0.012]	[0.011]	[0.012]	[0.009]	[0.011]	[0.010]	[0.010]	[0.009]
Log (SPbSU students), one cohort older than VK founder	0.004	0.010	0.003	0.004	0.024**	0.024**	0.019*	0.015*
	[0.016]	[0.015]	[0.015]	[0.011]	[0.011]	[0.011]	[0.010]	[0.009]
Population, Age cohorts, Education, and 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
Kleibergen-Paap F-stat	6.554	6.779	7.591	7.031				
Effective F-statistics (Olea Montiel and Pflueger 2013)	10.97	12.03	12.30	12.17				

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Since the outcomes are shares of population, population weights are applied. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014). Weak IV robust 95% confidence intervals are Anderson-Rubin confidence sets calculated using software in Finlay and Magnusson (2009), which accommodates heteroskedasticity.

Table 5. VK Penetration and Political Attitudes.

	How do you assess the work of president Dmitry Medvedev					
	Good and getting better	Good and remains the same	Good and getting worse	Bad, but getting better	Bad and remains the same	Bad and getting worse
	(1)	(2)	(3)	(4)	(5)	(6)
Log (number of VK users), June 2011	0.255**	-0.069	-0.060	-0.094	-0.026	0.026
	[0.127]	[0.130]	[0.062]	[0.059]	[0.076]	[0.061]
Log (SPbSU students), one cohort younger than VK founder	-0.013	0.010	0.001	0.013**	0.003	0.005
	[0.016]	[0.009]	[0.007]	[0.005]	[0.009]	[0.008]
Log (SPbSU students), one cohort older than VK founder	-0.016	-0.017	-0.001	0.006	-0.011	-0.006
	[0.019]	[0.014]	[0.010]	[0.008]	[0.009]	[0.008]
	How do you assess the work of prime minister Vladimir Putin					
	Good and getting better	Good and remains the same	Good and getting worse	Bad, but getting better	Bad and remains the same	Bad and getting worse
Log (number of VK users), June 2011	0.205*	-0.072	0.004	-0.061	-0.068	-0.016
	[0.124]	[0.124]	[0.047]	[0.042]	[0.075]	[0.056]
Log (SPbSU students), one cohort younger than VK founder	-0.019	0.012	-0.000	0.008**	0.007	0.004
	[0.016]	[0.009]	[0.006]	[0.003]	[0.009]	[0.007]
Log (SPbSU students), one cohort older than VK founder	-0.011	-0.021	-0.007	0.005	-0.002	-0.002
	[0.018]	[0.016]	[0.007]	[0.006]	[0.011]	[0.007]
	How do you assess the work of the government					
	Good and getting better	Good and remains the same	Good and getting worse	Bad, but getting better	Bad and remains the same	Bad and getting worse
Log (number of VK users), June 2011	0.313**	0.100	-0.124*	-0.078	-0.075	-0.027
	[0.133]	[0.129]	[0.074]	[0.079]	[0.104]	[0.091]
Log (SPbSU students), one cohort younger than VK founder	-0.017	0.015	0.004	0.013**	-0.001	0.001
	[0.018]	[0.013]	[0.008]	[0.006]	[0.012]	[0.009]
Log (SPbSU students), one cohort older than VK founder	-0.019	-0.026	0.007	0.006	-0.014	0.001
	[0.020]	[0.018]	[0.012]	[0.010]	[0.012]	[0.011]
	Which party are you planning to vote for in December elections					
	United Russia	Just Russia	LDPR	KPRF	Patriots of Russia	Yabloko
Log (number of VK users), June 2011	0.260*	0.050	-0.056	-0.041	-0.002	-0.005
	[0.155]	[0.055]	[0.055]	[0.067]	[0.009]	[0.013]
Log (SPbSU students), one cohort younger than VK founder	-0.006	-0.000	0.006	0.003	0.001	0.002
	[0.016]	[0.005]	[0.005]	[0.005]	[0.001]	[0.001]
Log (SPbSU students), one cohort older than VK founder	-0.043*	-0.004	0.005	0.002	0.000	-0.002
	[0.023]	[0.007]	[0.009]	[0.008]	[0.001]	[0.002]
	Do you personally admit or exclude a possibility to take part in any protests					
	Admit	Exclude	Difficult to answer			
Log (number of VK users), June 2011	-0.278*	0.101	0.186			
	[0.164]	[0.184]	[0.146]			
Log (SPbSU students), one cohort younger than VK founder	-0.001	-0.002	0.002			
	[0.014]	[0.015]	[0.012]			
Log (SPbSU students), one cohort older than VK founder	0.027	-0.024	-0.005			
	[0.021]	[0.025]	[0.022]			

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is an individual respondent. Logarithm of any variable is calculated with 1 added inside. The table presents results of 27 separate IV regressions. In all regressions the number of observations is 31,728 and the effective F-statistics (Olea Montiel and Pflueger 2013) is 30,415. All regressions include the following city-level controls:5th polynomial of population, the number of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50 and older years, the share of population with higher education in each of the age cohorts separately, dummy for regional and county centers , distances to Moscow and St Petersburg, log (average wage), share of population with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table 6. VK Penetration and pre-VK Protests.

Panel A. Incidence of earlier protests

	Incidence of protests, 1987-1992				Incidence of pro-democracy protests, 1987-1992			
Log (number of VK users), June 2011	0.009	0.006	-0.012	0.023	-0.011	-0.011	-0.022	0.012
	[0.281]	[0.287]	[0.267]	[0.281]	[0.194]	[0.193]	[0.189]	[0.197]
P-value for equality of coefficients with that in Table 3	0.182	0.200	0.151	0.186	0.094*	0.100	0.080*	0.094*
	Incidence of labor protests, 1997-2002				Incidence of social protests, 2005			
Log (number of VK users), June 2011	-0.070	-0.080	-0.164	-0.052	-0.056	-0.060	-0.022	-0.000
	[0.239]	[0.217]	[0.225]	[0.241]	[0.238]	[0.226]	[0.226]	[0.232]
P-value for equality of coefficients with that in Table 3	0.042**	0.037**	0.017**	0.040**	0.108	0.095*	0.120	0.121

Panel B. Participation in earlier protests

	Log (number of protesters), 1987-1992				Log (pro-democracy protesters), 1987-1992			
Log (number of VK users), June 2011	0.533	0.494	0.295	0.495	0.144	0.119	0.022	0.220
	[1.904]	[1.953]	[1.851]	[1.937]	[1.494]	[1.487]	[1.474]	[1.564]
P-value for equality of coefficients with that in Table 3	0.482	0.497	0.412	0.453	0.298	0.301	0.267	0.302
	Log (participants in labor protests), 1997-2002				Log (participants in social protests), 2005			
Log (number of VK users), June 2011	-0.562	-0.604	-1.326	-0.537	-0.312	-0.335	-0.083	0.100
	[1.850]	[1.740]	[1.772]	[1.862]	[1.625]	[1.532]	[1.540]	[1.584]
P-value for equality of coefficients with that in Table 3	0.194	0.182	0.085*	0.179	0.268	0.244	0.303	0.319
Population, Age cohorts, Education, and 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

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. "Yes" indicates inclusion of a corresponding group of controls. Significance level is NOT reported after each group of controls for the purpose of brevity. 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 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. Electoral controls include vote 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. Other controls include dummy for regional and county centers , distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014). P-values for equality of coefficients are calculated relative to a corresponding coefficient in columns (1)-(4) of Tables 4 and 5, using a 3sls framework.

Table 7. VK Penetration and Pre-VK Voting Results.

Panel A. Parliamentary elections

	Dependent variable					
	Pro-government vote share	Yabloko vote share	Communists vote share	LDPR vote share	Turnout	Against all share
Voting results in 1995, IV with SPbSU cohorts	-0.018	-0.012	0.093	0.034	0.025	-0.010
	[0.029]	[0.022]	[0.072]	[0.057]	[0.039]	[0.008]
Voting results in 1999, IV with SPbSU cohorts	0.031	0.006	0.053	-0.008	-0.088	-0.000
	[0.051]	[0.017]	[0.049]	[0.011]	[0.062]	[0.007]
Voting results in 2003 IV with SPbSU cohorts	0.088	-0.017	-0.005	-0.002	-0.019	-0.016
	[0.056]	[0.011]	[0.024]	[0.025]	[0.050]	[0.012]

Panel B. Presidential elections

Year 1996, 1st round	Yeltsin vote share	Yavlinsky vote share	Zyuganov vote share	Lebedev vote share	Turnout	Against all share
Voting results, IV with SPbSU cohorts	-0.135	0.014	0.127	-0.007	0.008	-0.002
	[0.086]	[0.018]	[0.091]	[0.042]	[0.025]	[0.003]
Year 1996, 2nd round	Yeltsin vote share		Zyuganov vote share		Turnout	Against all share
Voting results, IV with SPbSU cohorts	-0.122	-	0.136	-	0.004	-0.006
	[0.092]	-	[0.095]	-	[0.031]	[0.009]
Year 2000	Putin vote share	Yavlinsky vote	Zyuganov vote	Tuleev vote share	Turnout	Against all share
Voting results, IV with SPbSU cohorts	0.125	-0.028*	-0.042	-0.006	0.005	-0.012**
	[0.081]	[0.015]	[0.055]	[0.031]	[0.031]	[0.005]
Year 2004	Putin vote share	Hakamada vote	Haritonov vote	Glaziev vote share	Turnout	
Voting results, IV with SPbSU cohorts	0.109*	-0.025*	0.000	-0.034*	-0.027	
	[0.063]	[0.014]	[0.034]	[0.019]	[0.053]	

Table 8. Fractionalization of Networks and Protest Participation.

Panel A. Network fractionalization and the incidence of protest

	Incidence of protests, dummy, Dec 2011							
	Whole sample				Cities with more than 100 000 inhabitants			
Fractionalization of social media networks (Facebook+Vkontakte)	-0.135	-0.153	-0.155	-0.133	-0.983**	-0.883**	-0.910**	-1.046**
	[0.143]	[0.148]	[0.141]	[0.146]	[0.435]	[0.424]	[0.430]	[0.417]
Log (number of users in both networks)	0.265***	0.262***	0.252***	0.265***	0.072	0.099	0.108	0.140
	[0.074]	[0.072]	[0.073]	[0.073]	[0.122]	[0.122]	[0.125]	[0.124]
Observations	625	625	625	625	158	158	158	158
Mean of the dependent variable	0.134	0.134	0.134	0.134	0.500	0.500	0.500	0.500
SD of the dependent variable	0.341	0.341	0.341	0.341	0.502	0.502	0.502	0.502
Population, Age cohorts, Education, and 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
R-squared	0.783	0.787	0.786	0.786	0.768	0.789	0.786	0.799

Panel B. Network fractionalization and protest participation.

	Log (number of protesters), Dec 2011							
	Whole sample				Cities with more than 100 000 inhabitants			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fractionalization of social media networks (Facebook+Vkontakte)	-0.894	-1.007	-1.010	-0.922	-4.797**	-4.731**	-4.453**	-5.311**
	[0.744]	[0.771]	[0.741]	[0.754]	[2.140]	[2.238]	[2.195]	[2.044]
Log (number of users in both networks)	1.896***	1.874***	1.823***	1.889***	1.233**	1.269*	1.497**	1.490**
	[0.373]	[0.367]	[0.373]	[0.370]	[0.618]	[0.665]	[0.639]	[0.649]
Observations	625	625	625	625	158	158	158	158
Mean of the dependent variable	0.773	0.773	0.773	0.773	2.926	2.926	2.926	2.926
SD of the dependent variable	2.024	2.024	2.024	2.024	3.065	3.065	3.065	3.065
Population, Age cohorts, Education, and 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
R-squared	0.838	0.841	0.842	0.841	0.821	0.836	0.838	0.840

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table 9. VK Penetration and Municipal Budgets.

	2009	2010	2011	2012	2013	2014
Panel A. VK penetration and federal transfers to municipalities						
			Log (transfers to municipality)			
Log (number of VK users), June 2011	-0.190	-0.903	-1.275	-3.458**	-2.826**	-3.161**
	[0.865]	[0.942]	[1.026]	[1.495]	[1.431]	[1.473]
Population controls	Yes	Yes	Yes	Yes	Yes**	Yes**
Age cohort controls	Yes	Yes	Yes	Yes*	Yes***	Yes
Education controls	Yes***	Yes	Yes	Yes	Yes	Yes
Observations	325	347	347	351	352	323
Effective F-statistics (Olea Montiel and Pflueger 2013)	12.53	13.48	13.88	12.92	11.23	11.03
Panel B. VK penetration and municipality's tax revenues						
			Log (municipal tax revenues)			
Log (number of VK users), June 2011	-0.157	-0.105	0.040	-0.382	-0.498	-0.677**
	[0.198]	[0.269]	[0.233]	[0.287]	[0.303]	[0.341]
Population controls	Yes	Yes	Yes	Yes	Yes	Yes
Age cohort controls	Yes**	Yes*	Yes	Yes	Yes	Yes
Education controls	Yes*	Yes*	Yes	Yes**	Yes	Yes
Observations	496	513	502	501	499	483
Effective F-statistics (Olea Montiel and Pflueger 2013)	12.65	14.17	14.27	13.92	12.26	11.97
Panel C. VK penetration and municipal spending						
			Log (municipal total spending)			
Log (number of VK users), June 2011	-0.094	0.138	-0.030	-0.306	-0.304	-0.365
	[0.186]	[0.203]	[0.167]	[0.267]	[0.273]	[0.283]
Population controls	Yes	Yes	Yes	Yes	Yes	Yes
Age cohort controls	Yes**	Yes	Yes	Yes	Yes	Yes
Education controls	Yes*	Yes	Yes	Yes	Yes	Yes
Observations	436	448	467	458	477	456
Effective F-statistics (Olea Montiel and Pflueger 2013)	17.27	19.63	22.99	21.62	17.07	16.22

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. IV estimates are reported. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014). All specifications control for the initial 2008 values of the corresponding dependent variable and election results of 2007 parliamentary elections.

ONLINE APPENDIX

A.1 The Cross Partial Derivative of Protest Participation with Respect to Social Media and Baseline Coordination Signal

The cross partial derivative of the effect of social media on protests via coordination channel with respect to baseline coordination signal can be obtained by differentiating equation (8) with respect to the precision of the baseline coordination signal, β_0:

$$\frac{\partial^2 \hat{c}_p}{\partial \beta_s \partial \beta_0} = -\frac{2k}{(\beta_0+\beta_s)^3\left(1-\frac{\lambda_p}{\sigma_{pc}}\phi\left[\frac{1}{\sigma_{pc}}(\hat{c}_p-\mu_{pc})\right]\right)} + \frac{k^2\lambda_p\phi'\left[\frac{1}{\sigma_{pc}}(\hat{c}_p-\mu_{pc})\right]}{\sigma^2(\beta_0+\beta_s)^4\left(1-\frac{\lambda_p}{\sigma_{pc}}\phi\left[\frac{1}{\sigma_{pc}}(\hat{c}_p-\mu_{pc})\right]\right)^3}$$

We would like to derive the sign of this expression. First, note that, under the assumption that lambda is small enough to ensure that the denominator in (7)-(9) is positive, — more precisely, if $\lambda < \sigma_{pc}/\phi[(\hat{c}_p-\mu_{pc})/\sigma_{pc}])$ — the first part of the above expression is negative.

Second, observe that whenever the equilibrium threshold, $\hat{c}_p$, exceeds the average cost of protest participation, μ_{pc}, the second part of that expression becomes negative too (since $\phi'(x)<0$ when $x>0$). Thus, in this case, the cross partial derivative has a negative sign. However, the condition that $\hat{c}_p > \mu_{pc}$ is fairly restrictive and unlikely to hold in our data, as it means that more than 50% of population decide to take part in a protest.

However, we can show that, even if $\hat{c}_p < \mu_{pc}$, the cross partial derivative is negative as long as λ_p is small enough. To see this, note that, when λ_p approches zero, the second part of the expression goes to zero as well, while the first one survives and remains negative. We search for the condition on lambda more formally below. Getting rid of common multipliers and using simplified notation, the condition becomes:

$$\frac{k\lambda\phi'}{\sigma^2(\beta_0+\beta_s)\left(1-\frac{\lambda}{\sigma}\phi\right)^2} - 2 < 0$$

After a few algebraic transformations, one obtains the following inequality:

$$\lambda^2\left[-2(\beta_0+\beta_s)\phi^2\right] + \lambda\left[k\phi' + 4(\beta_0+\beta_s)\phi\sigma\right] - 2(\beta_0+\beta_s)\sigma^2 < 0$$

Under the existing restriction on lambda, $\lambda < \sigma/\phi$, there remain some values of lambda for which the above inequality does not hold. To see this, note that, when inserting $\lambda = \sigma/\phi$, the above expression becomes strictly positive:

$$-2(\beta_0+\beta_s)\sigma^2-2(\beta_0+\beta_s)\sigma^2+k\sigma\frac{\phi'}{\phi}+4(\beta_0+\beta_s)\sigma^2=k\sigma\frac{\phi'}{\phi}>0$$

, where $\phi'>0$ comes from the fact that we are considering the case with $\hat{c}_p<\mu_{pc}$, and from the fact that $\phi'(x)>0$ when $x<0$.

Thus, the new condition on lambda is a subset of the existing condition and comes from solving the quadratic inequality above. After solving this inequality, one obtains the following condition:

$$\lambda<\frac{k\phi'+4(\beta_0+\beta_s)\phi\sigma-\sqrt{(k\phi')^2+8(\beta_0+\beta_s)\phi\phi'k\sigma}}{2(\beta_0+\beta_s)\phi^2} \tag{16}$$

To conclude, if lambda is small enough, i.e., complies with condition (16), the cross partial derivative of the social media coordination effect on protest participation by precision of the baseline coordination signal has a negative sign. As a result, our theoretical framework predicts that social media should be more important in places with higher β_0^i where coordination is harder to achieve in the absence of public signals, e.g., in larger cities. Thus, if social media increases protest participation due to coordination channel, one would expect the magnitude of the effect to be increasing with city size.

A.2 Fractionalization with Arbitrary Overlap

In this section, we derive a fractionalization index formula for the case of overlapping groups. In our particular case, these are VK and Facebook users. Let us denote the number of VK users as n_1, the number of Facebook users as n_2, and their interaction as m (see Figure 1 for illustration).

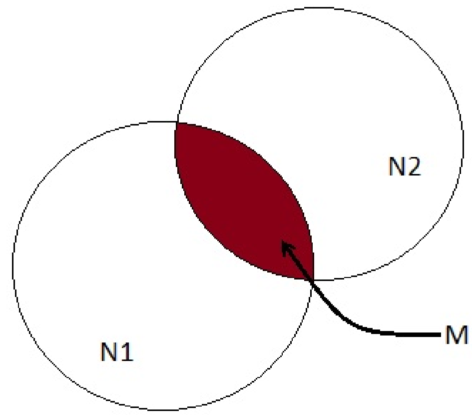


Figure 1: Overlapping groups

The usual fractionalization index measures the probability that two randomly chosen objects happen to be in different groups:

$$I = 1 - \frac{n_1^2 + n_2^2}{(n_1 + n_2)^2}$$

Suppose now that there is a non-zero overlap between the two groups, meaning that mass m now has accounts in both VK and Facebook. The probability of two randomly chosen people being from distinct social media networks is now equal to the chance that one person is drawn from n_1 but not m and the other one is drawn from n_2 but not m:[68]

$$I_1 = \frac{2(n_1 - m)(n_2 - m)}{(n_1 + n_2 - m)^2} \tag{17}$$

Now that we derived the formula for fractionalization with arbitrary overlap between groups, we can apply it to our analysis. The main issue with applying it directly is that we do not immediately observe m. However, since we want to see how a change in m affects the results of our fractionalization specification, we re-calculate our fractionalization index for 9 cases: $m = 0.1n_2, m = 0.2n_2, m = 0.3n_2, m = 0.4n_2, m = 0.5n_2$, etc. That is, we assume that 10% (20%, 30%,

[68] Similarly, one can derive this formula by computing the inverse of the probability that two randomly selected people are in the same social media platform. There could be such three cases. If one of the people is from m, they will surely be from the same platform. If the first person is from n_1 but not m, they can meet only if the other person is from n_1. Similarly, if the first person belongs to n_2 but not m, they can meet only if the other person is from n_2. Combining the probabilities of these three events, we get:

$$I_2 = 1 - \frac{m}{n_1 + n_2 - m} - \frac{(n_1 - m)n_1}{(n_1 + n_2 - m)^2} - \frac{(n_2 - m)n_2}{(n_1 + n_2 - m)^2}$$

One can show that $I_1 = I_2$, so we can use either formula.

etc.) of Facebook users have a VKontakte account.[69] In Table A13 in the Online Appendix, we provide the results of the estimation for a subset of cities with large population (above 100,000). Note that the results are robust to a very high degree of overlap between the VK and Facebook users.

[69] In a survey from Enikolopov et al. (2017), we find that around 47% of regular Facebook users also use VK regularly. However, these estimates should be interpreted with caution as it heavily oversamples Moscow residents and, as such, is not representative at the city level.

ONLINE APPENDIX

Figure A1. VK penetration over time. Number of users (vertical axis, in 100 mln accounts) and the date of the first post (horizontal axis) are shown.

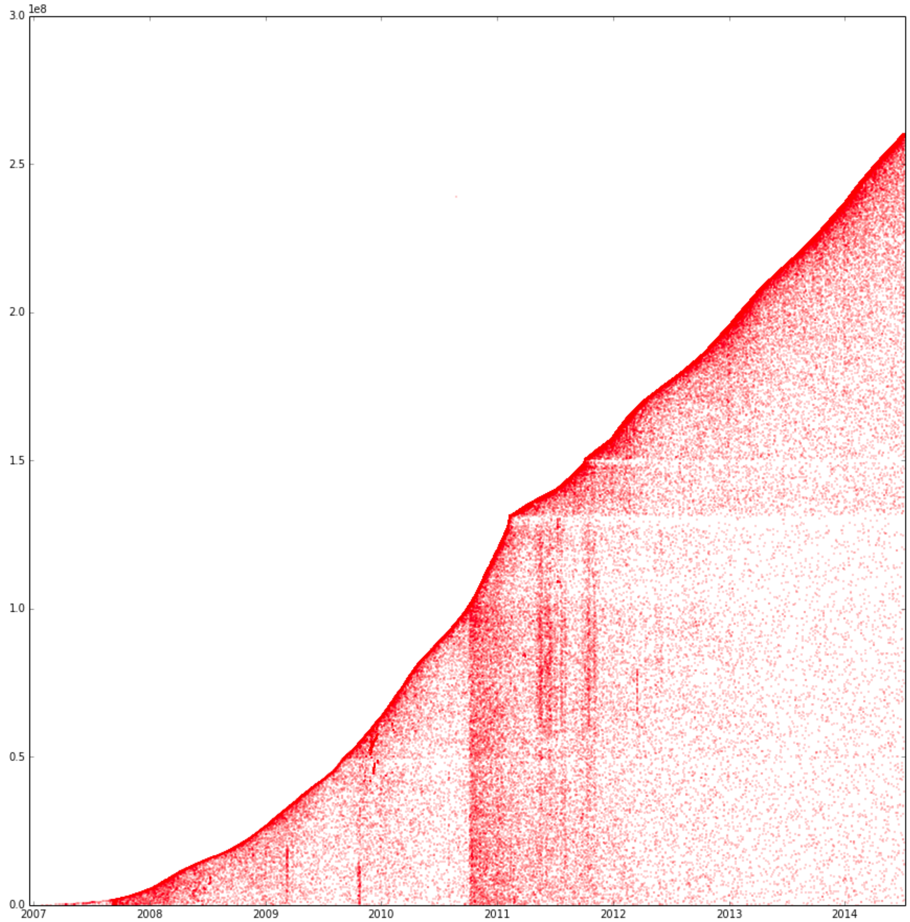
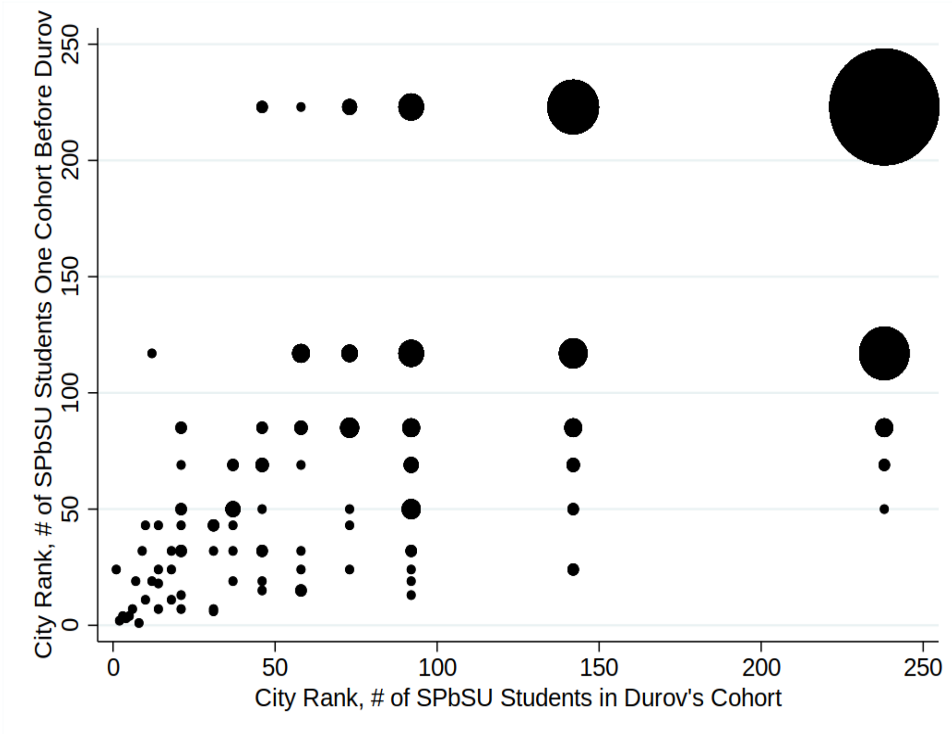


Figure A2. Map of Protests across Russian Territory, Dec 10-11, 2011

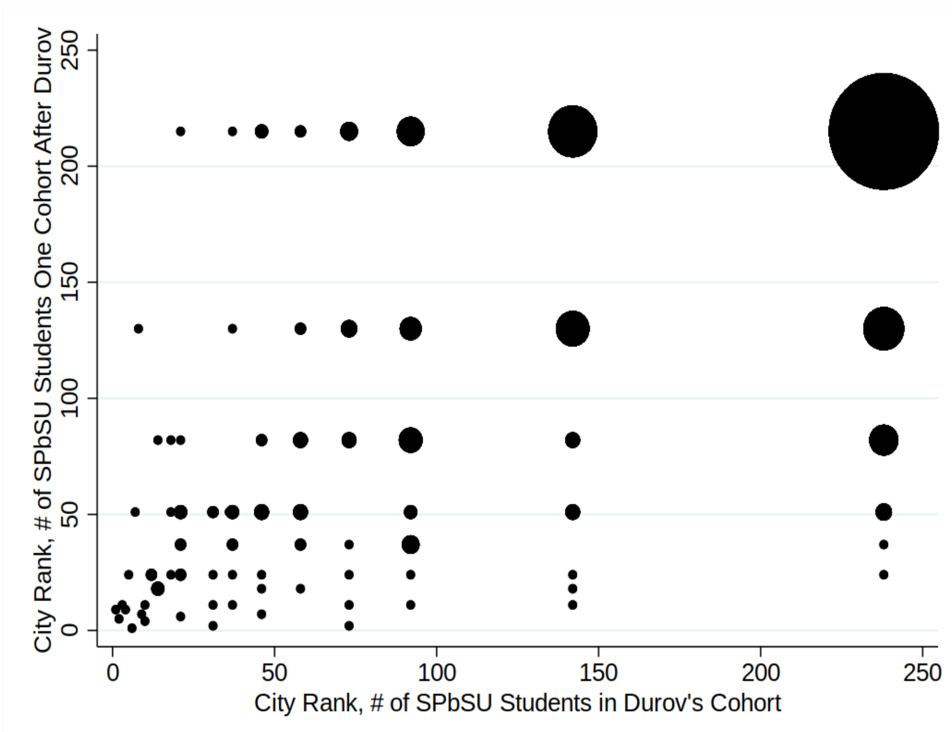
Notes: The graphs displays geographic location of the Russian cities that held protests on Dec 10-11, 2011. The size of the markers reflects the number of protest participants in each city. The number of protest participants for each city can be found in Table A19.

Figure A3. Fluctuations of City Ranks Across Cohorts.

Panel A: VK founder's (Durov's) cohort and one cohort older

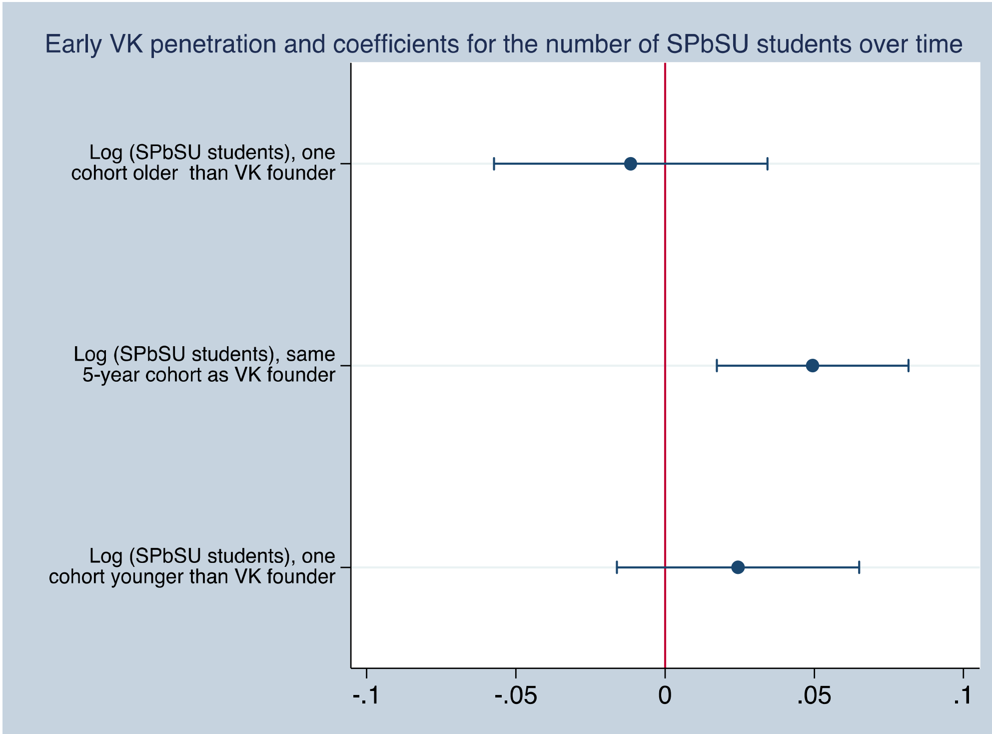


Panel B: VK founder's (Durov's) cohort and one cohort younger



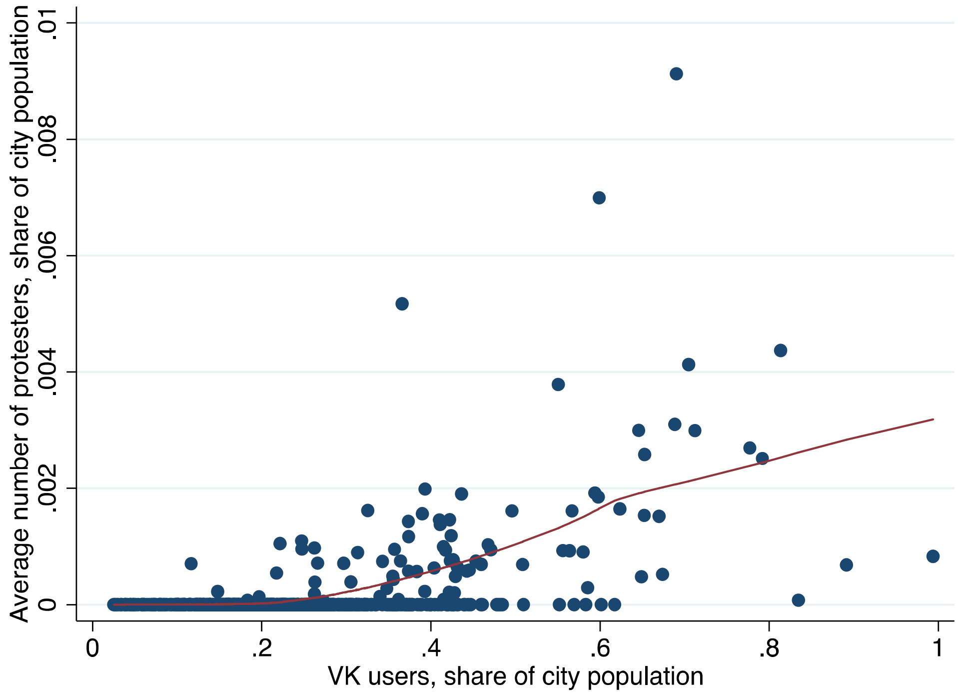
Notes: City rank is calculated with the highest value ranked 1 and assigning the same average rank in case of ties. The size of the dots reflects the number of cities with a given combination of ranks across cohorts.

Figure A4. VK Penetration in November 2006 and SPbSU student cohorts.



Notes: This figure presents the coefficients from column (4) of Table A5, reflecting the association between the log of the number of VK users in each city in November 2006 and the log of the number of SPbSU students who are one 5-year cohort older, of the same cohort, or one cohort younger than VK founder, respectively. Standard errors are clustered at the region level. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. For further details about this specification, see notes to Table A5.

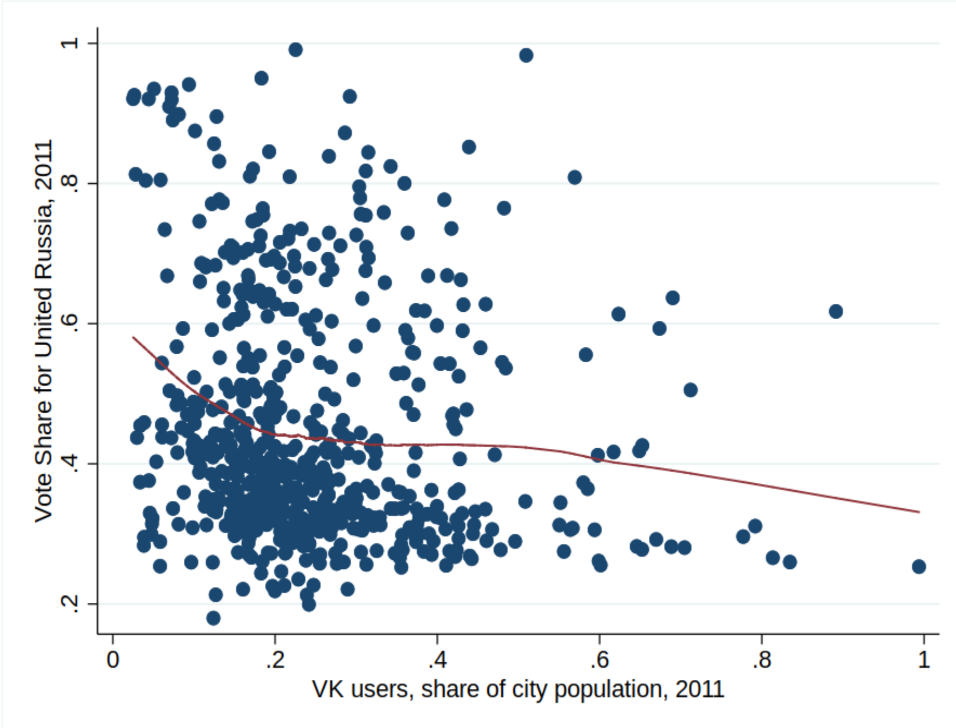
Figure A5. Nonparametric Relationship between VK Penetration and Number of Protesters (in shares).



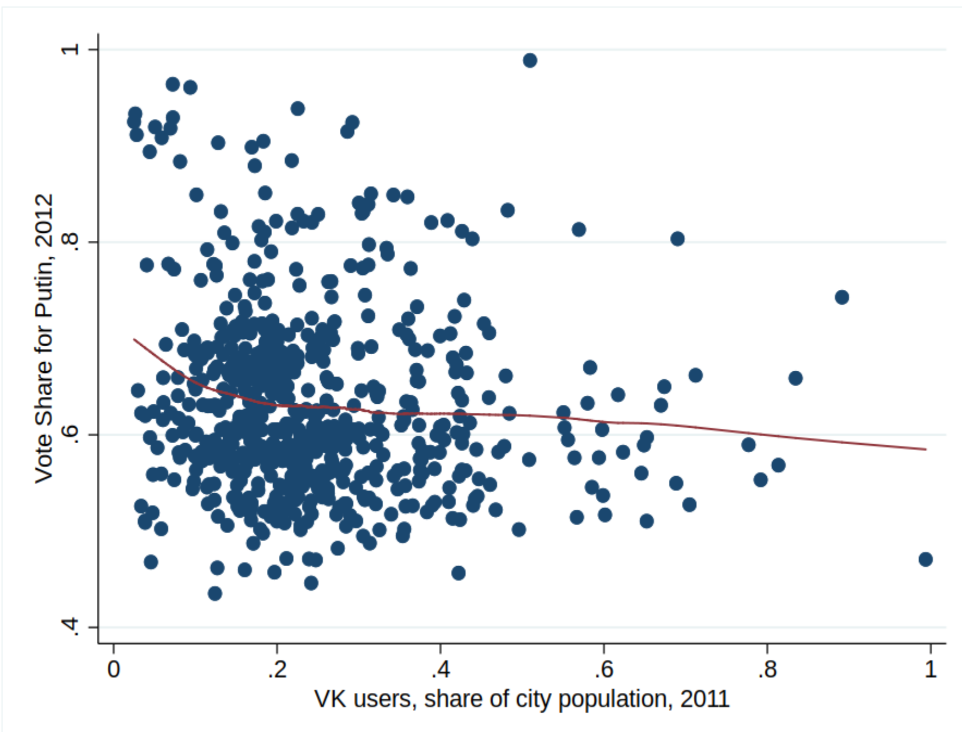
Notes: This figure displays the association between the average number of protesters in each city during the first week of protests in December 2011 and the number of VK users in these cities as of June 2011, both variables are per capita. Logarithm of any variable is calculated with 1 added inside. Blue dots illustrate raw city-level data. Red line represents a non-parametric relationship between the two variables.

Figure A6. Nonparametric Relationship between VK Penetration and Pro-Government Vote

Panel A: Vote Share for United Russia on December 4, 2011

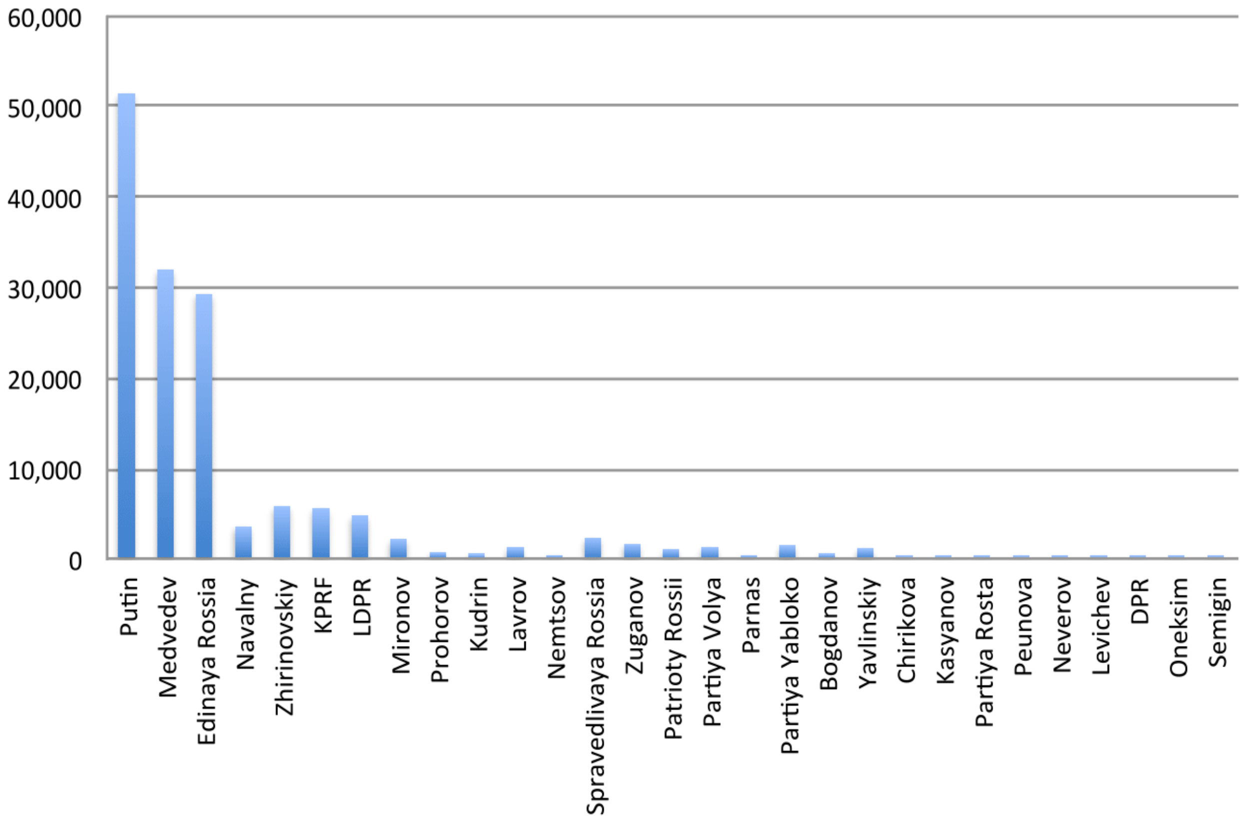


Panel B: Vote Share for Vladimir Putin on March 4, 2012



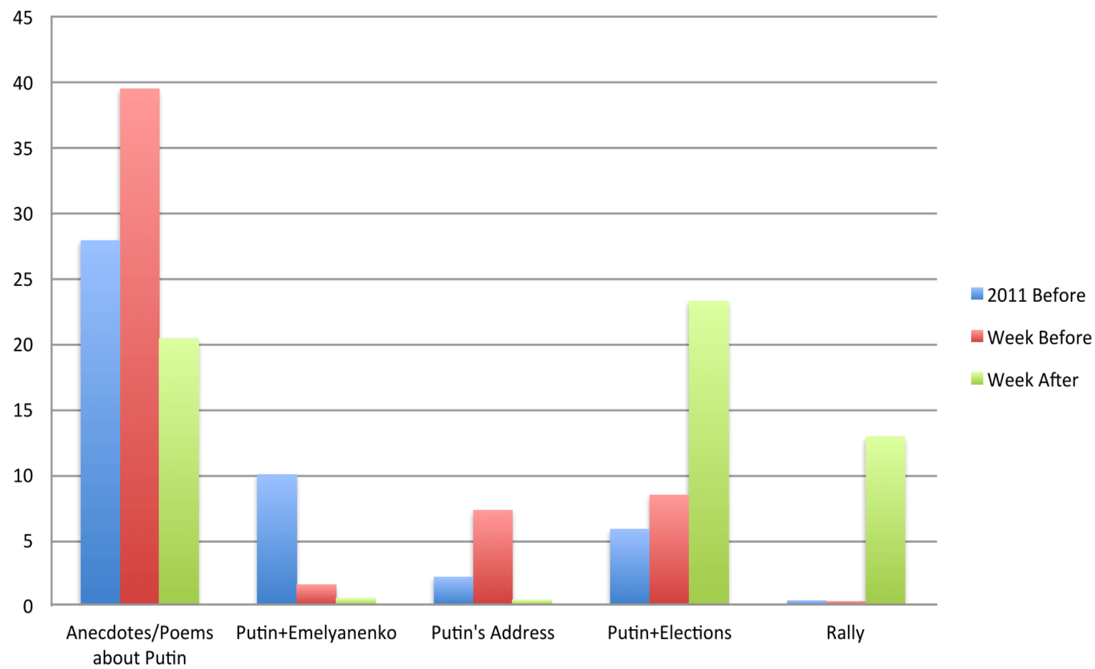
Notes: This figure displays the association between the pro-government vote share in each city in 2011 and 2012 and VK penetration in these cities as of June 2011. Blue dots illustrate raw city-level data. Red line represents a non-parametric relationship between the two variables.

Figure A7. Mentions of Politicians and Parties on VK in November 2011



Notes: The graph displays the raw number of politician mentions in the universe of posts on VK in November 2011, the month before the protests. Vladimir Putin, Dmitry Medvedev, and Political Party "Edinaya Rossia" ("United Russia") represented the status quo government. Alexey Navalny, Political Party "Parnas" with its leaders Boris Nemtsov and Mikhail Kasyanov, and Political Party "Yabloko" with its leader Grigory Yavlinskiy were in strong opposition to the government and were one of the most important figures during the protests. KPRF (Communist Party of Russia) with its leader Zuganov, LDPR with its leader Zhirinovskiy, Spravedlivaya Rossia with its leader Mironov, and a few others were the official opposition parties and candidates during the December 2011 Parliamentary elections but had limited importance during the protests. Data were retrieved on March 2017.

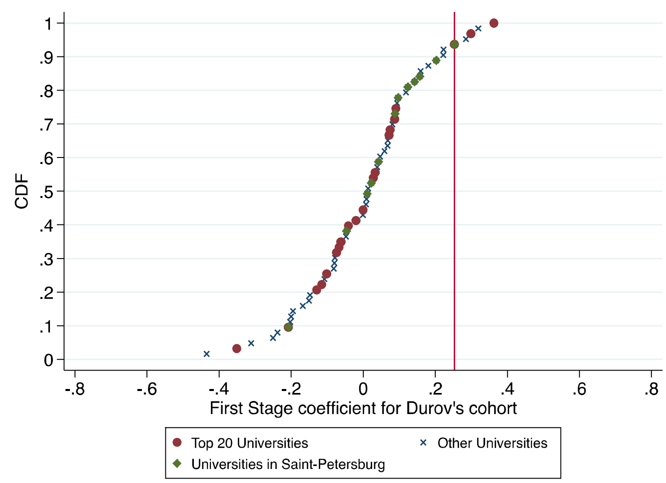
Figure A8. Mentions of Putin and Protests on VK in 2011



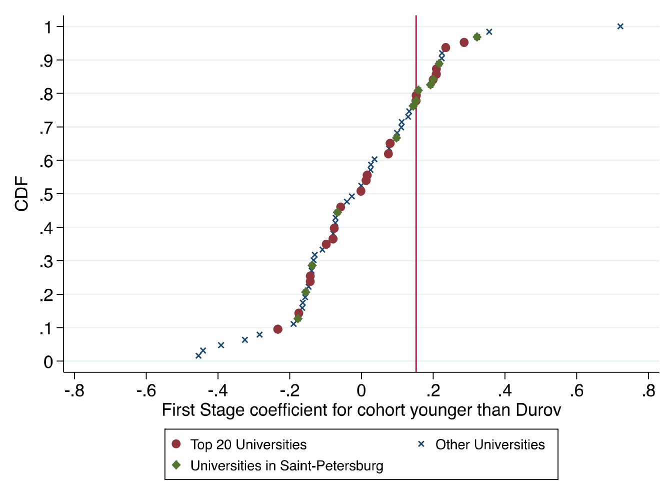
Notes: The graph analyzes the universe of all posts on VK mentioning Vladimir Putin, grouping them by date and topic. Blue bars (to the left) present data for all posts written in 2011 before the legislative elections on December 4, 2011; red bars (center) display data for all posts written a week before December 4, 2011; and green bars (to the right) represent all posts written a week after December 4, 2011. The bar height represents the percentages of all posts devoted to a given topic. “Putin+Emelyanenko” topic refers to an incident on November 20, 2011, when Putin was booed during an award ceremony of the MMA fighter Fedor Emelyanenko. “Putin’s Address” refers to the Putin’s pre-election address on Dec 1, 2011, in which he calls to vote for United Russia. “Putin+Elections” category refers to all posts that include words “Putin” and “elections” but which are not anecdotes/poems, are not about Putin’s address, and do not include mentions of Emelyanenko. Finally, the “Rally” category includes posts that mention both Putin and protest demonstrations. Data were retrieved on March 2017.

Figure A9. Reduced Form Coefficients for 65 Universities in Russia.

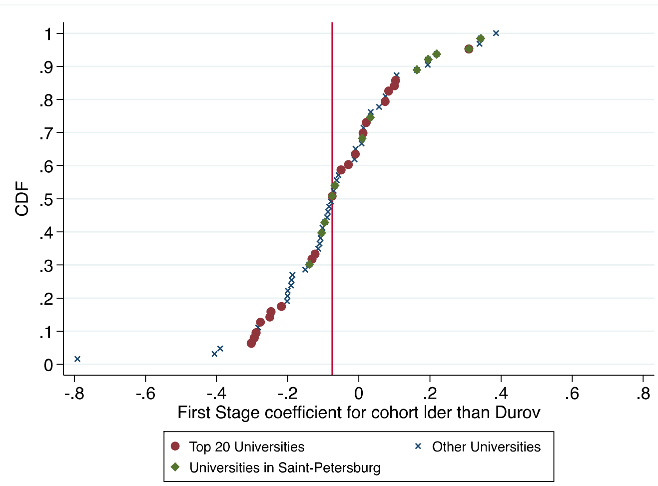
Panel A: Distribution of students in Durov's cohort (+- 2 years from Durov).



Panel B: Distribution of students in younger cohort

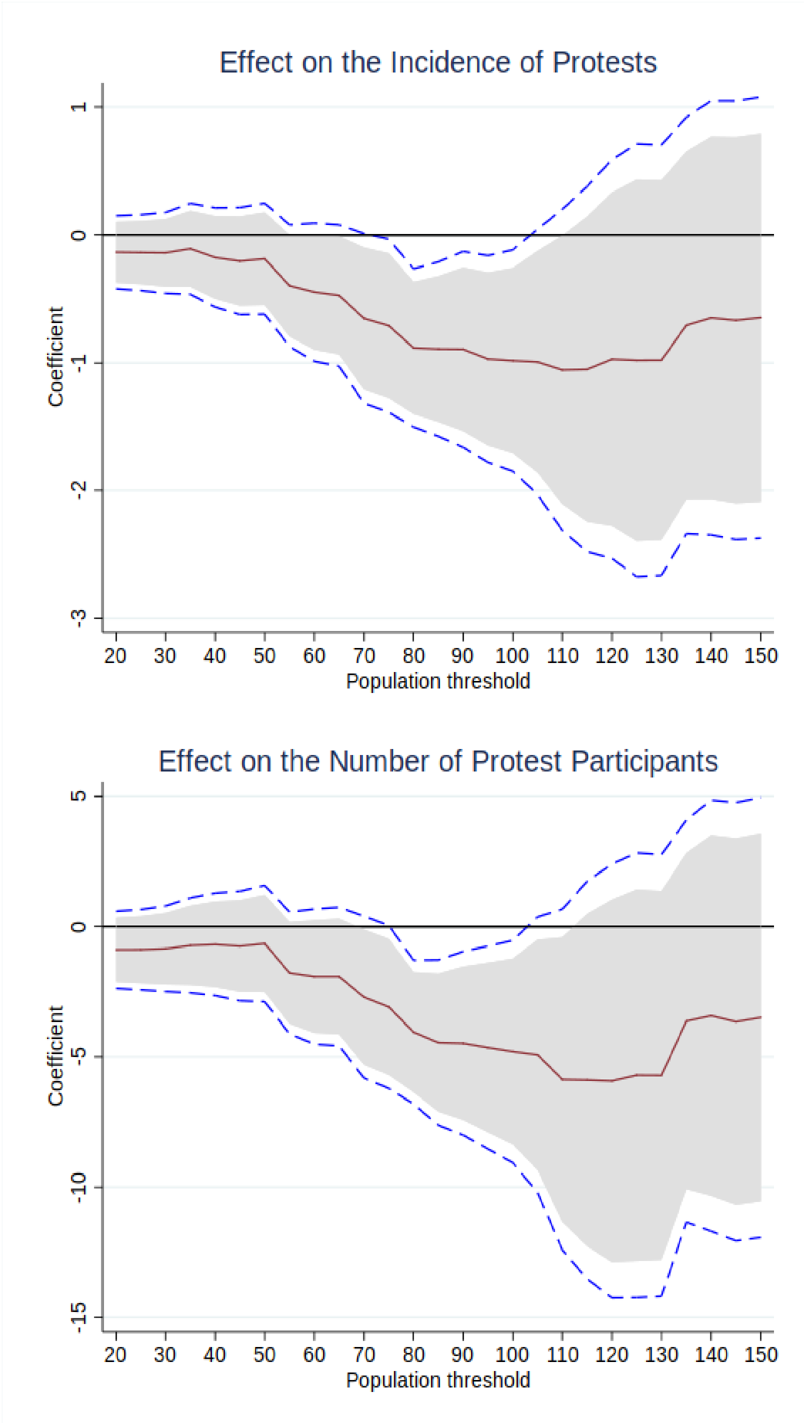


Panel C: Distribution of students in older cohort



Notes: These figures draw comparisons between the reduce form coefficients displayed on Figure 2B and the coefficients from the same specification, but estimated with the log of the number of students from other 65 top Russian universities, as opposed to SPbSU. Red vertical lines indicate the SPbSU coefficients from Figure 2B. Red dots represent first stage coefficients for top-20 universities, such as MSU, SPbSPU, etc. Green dots represent first stage coefficients for top-65 Russian universities that are located in St. Petersburg. Blue crosses represent first stage coefficients for other top-65 universities.

Figure A9. Magnitude of the Association between Social Media Fractionalization and Protest Participation as a Function of Population Threshold.



Notes: The graphs show the magnitude of the coefficients for the association between social media fractionalization and protest participation for cities to the right of the given population threshold (in thousands). Grey areas show the 10% confidence intervals. Dashed lines display the 95% confidence intervals.

Table A1. Summary statistics.

	Observations	Mean	Standard deviation	Median	Min	Max
Incidence of protests, Dec 2011	625	0.13	0.34	0	0	1
Incidence of protests, USSR, 1987-1992	625	0.22	0.41	0	0	1
Incidence of pro-democratic protests, USSR, 1987-1992	625	0.18	0.38	0	0	1
Incidence of anti-monetization protests, 2005	625	0.19	0.39	0	0	1
Incidence of labor protests, 1997-2000	625	0.61	0.49	1	0	1
Log (number of protest participants), Dec 2011	625	0.77	2.02	0	0	8.66
Log (number of protest participants), USSR, 1987-1992	625	1.41	2.77	0	0	12.99
Log (number of participants in pro-democratic protests), USSR, 1987-1992	625	1.38	3.08	0	0	13.93
Log (number of participants in anti-monetization protests), 2005	625	1.28	2.7	0	0	9.21
Log (number of participants in labor protests), 1997-2000	625	3.8	3.42	4.39	0	11.76
Log (number of VK users), June 2011	625	9.54	1.33	9.31	6.61	13.84
Log (number of early VK users), Nov 2006	625	0.08	0.3	0	0	3.5
Log (number of VK users), 2013	625	10.13	1.27	9.84	7.65	14.3
Log (number of Odnoklassniki users), 2014	625	10.72	1.12	10.45	7.94	14.36
Log (number of Facebook users), 2013	625	6.9	2.06	6.76	0	12.3
Log (SPbSU students, same 5-year cohort as VK founder)	625	0.49	0.75	0	0	4.64
Log (SPbSU students, one cohort younger than VK founder)	625	0.4	0.63	0	0	2.77
Log (SPbSU students, one cohort older than VK founder)	625	0.44	0.7	0	0	3.53
Internet penetration, region-level, 2011	625	0.27	0.17	0.22	0.01	0.63
Population, in thousands, 2010	625	117.68	189.63	52.7	20	1393.5
Regional center	625	0.12	0.32	0	0	1
Rayon center (county seat)	625	0.79	0.41	1	0	1
Distance to Saint Petersburg, km	625	1481.62	839.41	1419	21.7	4646
Distance to Moscow, km	625	1152.76	875.97	1014	15.75	4174
Log (average wage), 2011	625	9.89	0.35	9.83	9.08	11.19
Log (number of people with age 20-24), 2010	625	8.46	1.07	8.19	6.79	11.83
Log (number of people with age 25-29), 2010	625	8.53	1.02	8.28	6.83	11.84
Log (number of people with age 30-34), 2010	625	8.47	1	8.21	6.8	11.69
Log (number of people with age 35-39), 2010	625	8.41	0.99	8.16	6.84	11.59
Log (number of people with age 40-44), 2010	625	8.27	0.99	8.03	6.78	11.41
Log (number of people with age 45-49), 2010	625	8.42	0.97	8.21	6.79	11.52
Log (number of people with age 50 and older), 2010	625	9.93	0.97	9.71	8.27	13.08
% with higher education, 2002	625	0.15	0.06	0.13	0.05	0.45
% with higher education among age 20-24, 2010	625	0.18	0.06	0.17	0.05	0.37
% with higher education among age 25-29, 2010	625	0.34	0.1	0.33	0.11	0.67
% with higher education among age 30-34, 2010	625	0.31	0.1	0.3	0.12	0.67
% with higher education among age 35-39, 2010	625	0.28	0.08	0.26	0.13	0.58
% with higher education among age 40-44, 2010	625	0.25	0.08	0.23	0.12	0.6
% with higher education among age 45-49, 2010	625	0.23	0.08	0.21	0.09	0.62
% with higher education among age 50-54, 2010	625	0.17	0.07	0.15	0.07	0.55
Presence of a university in a city, 2011	625	0.15	0.35	0	0	1
Ethnic fractionalization, 2010	625	0.2	0.17	0.14	0.01	0.85

Table A1 (cont'd). Summary statistics. Voting outcomes.

Vote share for "Our Home – Russia" party, 1995	625	0.09	0.05	0.08	0.02	0.46
Vote share for "Unity" party, 1999	625	0.25	0.1	0.25	0	0.56
Vote share for "United Russia" party, 2003	625	0.36	0.1	0.34	0.16	0.92
Vote share for "United Russia" party, 2007	625	0.63	0.1	0.61	0.42	1
Vote share for "United Russia" party, 2011	625	0.45	0.17	0.4	0.18	0.99
Vote share for "United Russia" party, 2016	625	0.49	0.15	0.44	0.26	0.97
Vote share for Eltsin, 1996	625	0.33	0.12	0.31	0.1	0.7
Vote share for Eltsin, 1996 (2nd round)	625	0.53	0.14	0.52	0.21	0.89
Vote share for Putin, 2000	625	0.53	0.12	0.52	0.17	0.95
Vote share for Putin, 2004	625	0.69	0.09	0.68	0.42	0.99
Vote share for Medvedev, 2008	625	0.68	0.09	0.67	0.49	0.99
Vote share for Putin, 2012	625	0.63	0.1	0.61	0.44	0.99
Vote share for "Yabloko" party, 1995	625	0.06	0.04	0.05	0	0.23
Vote share for "Yabloko" party, 1999	625	0.06	0.03	0.05	0	0.19
Vote share for "Yabloko" party, 2003	625	0.04	0.02	0.04	0	0.14
Vote share for Communist party, 1995	625	0.23	0.11	0.21	0.03	0.72
Vote share for Communist party, 1999	625	0.25	0.08	0.24	0	0.51
Vote share for Communist party, 2003	625	0.13	0.05	0.12	0	0.31
Vote share for "LDPR" party, 1995	625	0.13	0.06	0.12	0	0.37
Vote share for "LDPR" party, 1999	625	0.07	0.02	0.06	0	0.16
Vote share for "LDPR" party, 2003	625	0.13	0.04	0.13	0	0.26
Vote share for Yavlinsky, 1996	625	0.07	0.03	0.07	0.01	0.21
Vote share for Yavlinsky, 2000	625	0.05	0.03	0.04	0	0.17
Vote share for Hakamada, 2004	625	0.03	0.02	0.03	0	0.14
Vote share for Zyuganov, 1996	625	0.32	0.14	0.31	0.05	0.83
Vote share for Zyuganov, 1996 (2nd round)	625	0.41	0.14	0.42	0.06	0.76
Vote share for Zyuganov, 2000	625	0.3	0.1	0.3	0.02	0.58
Vote share for Haritonov, 2004	625	0.15	0.07	0.14	0	0.38
Vote share for Lebed, 1996	625	0.16	0.06	0.15	0	0.39
Vote share for Tuleev, 2000	625	0.04	0.09	0.02	0	0.6
Vote share for Glaziev, 2004	625	0.04	0.03	0.04	0	0.28
Vote share against all parties/candidates, 1995	625	0.03	0.01	0.03	0	0.07
Vote share against all parties/candidates, 1996	625	0.02	0	0.02	0	0.04
Vote share against all parties/candidates, 1996 (2nd round)	625	0.05	0.02	0.05	0	0.1
Vote share against all parties/candidates, 1999	625	0.03	0.01	0.03	0	0.13
Vote share against all parties/candidates, 2000	625	0.02	0.01	0.02	0	0.06
Vote share against all parties/candidates, 2003	625	0.05	0.02	0.05	0	0.12
Turnout, 1995	625	0.63	0.07	0.63	0.41	0.98
Turnout, 1996	625	0.69	0.06	0.7	0.5	0.96
Turnout, 1996 (2^{nd} round)	625	0.68	0.06	0.68	0.49	0.99
Turnout, 1999	625	0.6	0.07	0.6	0.28	0.93
Turnout, 2000	625	0.68	0.06	0.67	0.54	0.97
Turnout, 2003	625	0.54	0.1	0.52	0.33	0.95
Turnout, 2004	625	0.54	0.1	0.52	0.33	0.95

Table A2. Variable Means by Quartile of VK Penetration.

	VK users, share of population, Aug 2011			
	Q1 (lowest)	Q2	Q3	Q4 (highest)
Incidence of protests, Dec 2011	0.01	0.01	0.06	0.45
Incidence of protests, USSR, 1987-1992	0.1	0.12	0.16	0.48
Incidence of pro-democratic protests, USSR, 1987-1992	0.07	0.1	0.12	0.41
Incidence of anti-monetization protests, 2005	0.06	0.12	0.16	0.42
Incidence of labor protests, 1997-2000	0.63	0.56	0.51	0.73
Log (number of protest participants), Dec 2011	0.06	0.04	0.32	2.66
Log (number of protest participants), USSR, 1987-1992	0.77	0.78	1.01	3.08
Log (number of participants in pro-democratic protests), USSR, 1987-1992	0.57	0.76	0.84	3.34
Log (number of participants in anti-monetization protests), 2005	0.38	0.76	1.07	2.89
Log (number of participants in labor protests), 1997-2000	3.98	3.23	3.1	4.91
Log (number of VK users), June 2011	8.29	9.19	9.65	11.01
Log (number of early VK users), Nov 2006	0	0.02	0.06	0.23
Log (number of VK users), 2013	9.04	9.77	10.19	11.49
Log (number of Odnoklassniki users), 2014	10.22	10.49	10.61	11.54
Log (number of Facebook users), 2013	5.8	6.4	6.81	8.59
Log (SPbSU students, same 5-year cohort as VK founder)	0.18	0.2	0.43	1.13
Log (SPbSU students, one cohort younger than VK founder)	0.2	0.22	0.3	0.89
Log (SPbSU students, one cohort older than VK founder)	0.16	0.2	0.36	1.01
Internet penetration, region-level, 2011	0.23	0.29	0.28	0.26
Population, in thousands, 2010	46.67	66.41	87.79	268.87
Regional center	0.02	0.03	0.03	0.38
Rayon center (county seat)	0.74	0.72	0.8	0.92
Distance to Saint Petersburg, km	1711.24	1493.21	1435.87	1287.41
Distance to Moscow, km	1423.68	1057.1	1081.88	1049.04
Log (average wage), 2011	9.79	9.8	9.9	10.06
Log (number of people with age 20-24), 2010	7.89	8.19	8.4	9.37
Log (number of people with age 25-29), 2010	7.97	8.27	8.48	9.4
Log (number of people with age 30-34), 2010	7.92	8.23	8.42	9.31
Log (number of people with age 35-39), 2010	7.86	8.17	8.36	9.22
Log (number of people with age 40-44), 2010	7.72	8.03	8.23	9.09
Log (number of people with age 45-49), 2010	7.86	8.18	8.4	9.25
Log (number of people with age 50 and older), 2010	9.38	9.76	9.9	10.69
% with higher education, 2002	0.13	0.14	0.14	0.18
% with higher education among age 20-24, 2010	0.16	0.17	0.18	0.2
% with higher education among age 25-29, 2010	0.29	0.33	0.34	0.4
% with higher education among age 30-34, 2010	0.26	0.3	0.31	0.38
% with higher education among age 35-39, 2010	0.23	0.27	0.28	0.33
% with higher education among age 40-44, 2010	0.22	0.24	0.25	0.3
% with higher education among age 45-49, 2010	0.2	0.22	0.23	0.27
% with higher education among age 50-54, 2010	0.15	0.16	0.17	0.21
Presence of a university in a city, 2011	0.02	0.06	0.06	0.45
Ethnic fractionalization, 2010	0.18	0.15	0.21	0.27

Table A2 (cont'd). Variable Means by Quartile of VK Penetration. Voting Outcomes.

	VK users, share of population, Aug 2011			
	Q1 (lowest)	Q2	Q3	Q4 (highest)
Vote share for "Our Home – Russia" party, 1995	0.08	0.08	0.1	0.12
Vote share for "Unity" party, 1999	0.27	0.24	0.25	0.24
Vote share for "United Russia" party, 2003	0.37	0.35	0.36	0.37
Vote share for "United Russia" party, 2007	0.66	0.63	0.62	0.62
Vote share for "United Russia" party, 2011	0.49	0.45	0.42	0.43
Vote share for "United Russia" party, 2016	0.49	0.5	0.48	0.48
Vote share for Eltsin, 1996	0.29	0.32	0.34	0.37
Vote share for Eltsin, 1996 (2nd round)	0.48	0.51	0.53	0.58
Vote share for Putin, 2000	0.52	0.51	0.53	0.55
Vote share for Putin, 2004	0.68	0.67	0.68	0.71
Vote share for Medvedev, 2008	0.68	0.67	0.68	0.69
Vote share for Putin, 2012	0.65	0.64	0.62	0.62
Vote share for "Yabloko" party, 1995	0.05	0.06	0.07	0.07
Vote share for "Yabloko" party, 1999	0.05	0.06	0.06	0.07
Vote share for "Yabloko" party, 2003	0.03	0.04	0.04	0.05
Vote share for Communist party, 1995	0.26	0.24	0.22	0.19
Vote share for Communist party, 1999	0.28	0.26	0.24	0.21
Vote share for Communist party, 2003	0.15	0.14	0.13	0.11
Vote share for "LDPR" party, 1995	0.14	0.13	0.12	0.1
Vote share for "LDPR" party, 1999	0.07	0.06	0.07	0.06
Vote share for "LDPR" party, 2003	0.14	0.13	0.13	0.12
Vote share for Yavlinsky, 1996	0.06	0.06	0.07	0.09
Vote share for Yavlinsky, 2000	0.04	0.05	0.05	0.06
Vote share for Hakamada, 2004	0.03	0.03	0.03	0.04
Vote share for Zyuganov, 1996	0.37	0.34	0.32	0.27
Vote share for Zyuganov, 1996 (2nd round)	0.46	0.43	0.41	0.35
Vote share for Zyuganov, 2000	0.33	0.31	0.29	0.27
Vote share for Haritonov, 2004	0.16	0.16	0.14	0.12
Vote share for Lebed, 1996	0.15	0.17	0.16	0.16
Vote share for Tuleev, 2000	0.03	0.05	0.04	0.03
Vote share for Glaziev, 2004	0.04	0.04	0.05	0.04
Vote share against all parties/candidates, 1995	0.03	0.03	0.03	0.03
Vote share against all parties/candidates, 1996	0.02	0.01	0.02	0.02
Vote share against all parties/candidates, 1996 (2nd round)	0.05	0.05	0.05	0.06
Vote share against all parties/candidates, 1999	0.03	0.03	0.03	0.03
Vote share against all parties/candidates, 2000	0.01	0.02	0.02	0.02
Vote share against all parties/candidates, 2003	0.04	0.05	0.05	0.05
Turnout, 1995	0.63	0.64	0.64	0.62
Turnout, 1996	0.69	0.69	0.7	0.69
Turnout, 1996 (2^{nd} round)	0.68	0.68	0.69	0.68
Turnout, 1999	0.6	0.59	0.61	0.61
Turnout, 2000	0.68	0.67	0.68	0.68
Turnout, 2003	0.53	0.52	0.54	0.56
Turnout, 2004	0.53	0.52	0.54	0.56

Table A3. Distribution of size of SPbSU student cohorts

Number of SPbSU students from a city in VK founder's cohort	Frequency	Number of SPbSU students from a city one cohort older than VK founder	Frequency	Number of SPbSU students from a city one cohort younger than VK founder	Frequency
0	389	0	404	0	412
1	96	1	106	1	85
2	50	2	32	2	48
3	19	3	16	3	31
4	15	4	19	4	14
5	12	5	7	5	13
6	9	6	11	6	6
7	1	7	8	7	7
8	5	8	5	8	2
9	10	9	1	9	2
10	3	10	3	10	1
11	4	11	2	12	1
12	2	12	2	13	1
13	2	13	4	14	2
14	1	14	1	15	1
15	1	20	2		
16	1	21	1		
17	1	29	1		
20	1	33	1		
23	1				
25	1				
29	1				
103	1				

Note: all the results in the paper are robust to exclusion of a city with 103 people in VK founder cohorts (if anything, results get stronger without this outlier).

Table A4. Correlation Between City Ranks across Cohorts

		City Rank in # of SPbSU Students		
		One Cohort After Durov	In Durov's Cohort	One Cohort Before Durov
City Rank in # of SPbSU Students	One Cohort After Durov	1		
	In Durov's Cohort	0.4217	1	
	One Cohort Before Durov	0.3860	0.4645	1

Note: City rank is calculated with the highest value ranked 1 and no correction for ties.

Table A5. Determinants of Early VK Penetration.

	Log (number of early VK users), Nov 2006							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (SPbSU students), same 5-year cohort as VK founder	0.0925***	0.0523***	0.0510***	0.0517***	0.0495**	0.0512***	0.0485**	0.0504***
	[0.0206]	[0.0191]	[0.0190]	[0.0182]	[0.0193]	[0.0186]	[0.0193]	[0.0189]
Log (SPbSU students), one cohort younger than VK founder	0.0756**	0.0147	0.0170	0.0194	0.0244	0.0275	0.0216	0.0246
	[0.0378]	[0.0246]	[0.0247]	[0.0228]	[0.0244]	[0.0247]	[0.0242]	[0.0242]
Log (SPbSU students), one cohort older than VK founder	0.0343	-0.0152	-0.0113	-0.0071	-0.0116	-0.0142	-0.0134	-0.0148
	[0.0324]	[0.0211]	[0.0223]	[0.0276]	[0.0275]	[0.0272]	[0.0279]	[0.0278]
Regional center			-0.0806	-0.1068	-0.1348	-0.1195	-0.1285	-0.1431
			[0.0619]	[0.0706]	[0.0874]	[0.0887]	[0.0867]	[0.0865]
Distance to Saint Petersburg, km				0.0001	0.0001	0.0001	0.0001	0.0000
				[0.0000]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Distance to Moscow, km				-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
				[0.0000]	[0.0000]	[0.0000]	[0.0001]	[0.0000]
Rayon center (county seat)				-0.0132	-0.0088	-0.0146	-0.0170	-0.0076
				[0.0131]	[0.0120]	[0.0138]	[0.0124]	[0.0131]
Log (average wage), city-level, 2011				0.0523	0.0365	0.0036	0.0183	0.0503
				[0.0323]	[0.0315]	[0.0309]	[0.0302]	[0.0341]
Presence of a university in a city, 2011					0.0951	0.1034	0.0959	0.1009
					[0.0631]	[0.0635]	[0.0615]	[0.0630]
Internet penetration, region-level, 2011					0.0341	0.0241	0.0201	0.0243
					[0.0456]	[0.0440]	[0.0473]	[0.0468]
Log (number of Odnoklassniki users), 2014					-0.0194	-0.0051	-0.0102	-0.0093
					[0.0200]	[0.0181]	[0.0213]	[0.0198]
Ethnic fractionalization, 2010					-0.0862	-0.0740	-0.0814	-0.0841
					[0.0816]	[0.0880]	[0.0806]	[0.0784]
Observations	625	625	625	625	625	625	625	625
R-squared	0.1805	0.5159	0.5185	0.5333	0.5387	0.5470	0.5427	0.5452
Mean of the dependent variable	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
SD of the dependent variable	0.301	0.301	0.301	0.301	0.301	0.301	0.301	0.301
Population controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age cohort controls				Yes	Yes	Yes	Yes	Yes
Education controls				Yes	Yes	Yes	Yes	Yes*
Electoral controls, 1995						Yes		
Electoral controls, 1999							Yes	
Electoral controls, 2003								Yes*
p-value for equality of coefficients for three cohorts	0.298	0.113	0.175	0.288	0.220	0.163	0.215	0.178
p-value for equality of coefficients of Durov's and younger cohort	0.726	0.313	0.364	0.354	0.495	0.508	0.460	0.478
p-value for equality of coefficients of Durov's and older cohort	0.122	0.050*	0.080*	0.117	0.099*	0.068*	0.093*	0.077*

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year.

Table A6. VK penetration and protest participation in 2011 (spatial standard errors).

	Incidence of protests, dummy, Dec 2011				Log (number of protesters), Dec 2011			
	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Log (number of VK users), June 2011	0.466**	0.451**	0.458**	0.479**	1.911**	1.872**	1.894**	2.013**
	[0.200]	[0.190]	[0.190]	[0.202]	[0.924]	[0.872]	[0.872]	[0.889]
Log (SPbSU students), one cohort younger than VK founder	0.027	0.026	0.028	0.030	0.216*	0.209*	0.213*	0.230*
	[0.023]	[0.022]	[0.022]	[0.022]	[0.117]	[0.115]	[0.119]	[0.119]
Log (SPbSU students), one cohort older than VK founder	-0.033	-0.029	-0.028	-0.026	-0.141	-0.127	-0.124	-0.115
	[0.025]	[0.025]	[0.024]	[0.025]	[0.151]	[0.145]	[0.135]	[0.144]
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
Kleibergen-Paap F-stat	9.597	9.730	11.604	9.843	9.597	9.730	11.604	9.843

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in brackets are adjusted for spatial correlations as in Konig, Rohner, Thoenig, and Zilibotti (2017). Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A7. IV Probit and Negative Binomial Models.

	Incidence of protests, dummy, Dec 2011				Number of protesters in '000s, Dec 2011			
	IV Probit	IV Probit	IV Probit	IV Probit	IV Neg Bin	IV Neg Bin	IV Neg Bin	IV Neg Bin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (number of VK users), June 2011	0.055*	0.063**	0.062**	0.171**	2.343**	2.580***	2.899***	2.729**
	[0.030]	[0.025]	[0.026]	[0.077]	[0.975]	[0.959]	[0.918]	[1.112]
Log (SPbSU students), one cohort younger than VK founder	0.008	0.005	0.009	0.066***	0.356***	0.369***	0.509***	0.392***
	[0.007]	[0.009]	[0.009]	[0.023]	[0.101]	[0.104]	[0.124]	[0.118]
Log (SPbSU students), one cohort older than VK founder	-0.020*	-0.024**	-0.035***	-0.038***	-0.310	-0.369*	-0.564***	-0.365
	[0.011]	[0.010]	[0.011]	[0.012]	[0.224]	[0.218]	[0.186]	[0.223]
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

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in Columns (1)-(4) are clustered at the region level. Standard errors in Columns (5)-(8) are obtained with a bootstrap procedure. The IV negative binomial model in Columns (5)-(8) is estimated using a control function approach. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. "Yes" indicates inclusion of a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A8. Weak IV Robust Confidence Intervals.

Panel A. Protest Participation

	Incidence of protests, Dec 2011				Log (# of protesters), Dec 2011			
	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (number of VK users), June 2011	0.466**	0.428***	0.459***	0.466***	1.911**	1.787**	1.900**	1.951**
	[0.189]	[0.161]	[0.176]	[0.174]	[0.924]	[0.809]	[0.872]	[0.866]
95% CIs Robust to Weak IV								
Chernozhukov and Hansen (2008)	(0.19; 1.58)	(0.19; 1.45)	(0.20; 1.31)	(0.22; 1.45)	(0.33; 6.61)	(0.37; 6.07)	(0.38; 5.61)	(0.50; 6.18)
Finlay and Magnusson (2009)	(0.20; 1.77)	(0.20; 1.56)	(0.20; 1.44)	(0.20; 1.53)	(0.23; 7.31)	(0.29; 6.56)	(0.29; 6.10)	(0.41; 6.46)
Mikusheva (2010)	(0.22; 1.13)	(0.22; 1.03)	(0.22; 1.04)	(0.24; 1.08)	(0.70; 4.68)	(0.71; 4.37)	(0.75; 4.36)	(0.84; 4.59)
Baseline 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

Panel B. Pro-Government Voting

	Voting share for United Russia, 2011				Voting Share for Putin, 2012			
	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (number of VK users), June 2011	0.257*	0.217*	0.259*	0.198	0.152*	0.144*	0.155*	0.114
	[0.152]	[0.131]	[0.147]	[0.128]	[0.088]	[0.085]	[0.084]	[0.073]
95% CIs Robust to Weak IV								
Chernozhukov and Hansen (2008)	(0.06; 1.27)	(0.04; 1.02)	(0.07; 1.11)	(0.03; 0.96)	(0.04; 0.73)	(0.03; 0.67)	(0.05; 0.63)	(0.02; 0.55)
Finlay and Magnusson (2009)	(0.05; 1.41)	(0.05; 1.11)	(0.05; 1.20)	(0.03; 1.02)	(0.05; 0.81)	(0.02; 0.72)	(0.05; 0.69)	(0.02; 0.57)
Mikusheva (2010)	(0.07; 0.74)	(0.08; 0.66)	(0.08; 0.66)	(0.04; 0.56)	(0.04; 0.43)	(0.04; 0.38)	(0.05; 0.39)	(0.02; 0.32)
Baseline 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

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted for clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A9. Threshold Model. Protest Participation as a Function of VK Penetration.

PANEL A. Threshold model with VK penetration as a share of city population

	Incidence of protests, dummy, Dec 2011				Log (number of protesters), Dec 2011			
	NLS	NLS	NLS	NLS	NLS	NLS	NLS	NLS
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Share of city population with VK accounts, before the threshold	-0.027	-0.067	-0.053	0.020	-0.126	-0.534	-0.265	0.029
	(0.144)	(0.152)	(0.145)	(0.148)	(0.713)	(0.658)	(0.723)	(0.770)
Share of city population with VK accounts, extra effect after the threshold	0.549**	0.607**	0.554**	0.510**	3.629***	4.055***	3.648***	3.480***
	(0.190)	(0.203)	(0.185)	(0.190)	(0.975)	(0.972)	(0.951)	(0.983)
Threshold, share of city population with VK accounts	0.233***	0.233***	0.233***	0.231***	0.251***	0.239***	0.251***	0.250***
	(0.0446)	(0.0425)	(0.0460)	(0.0466)	(0.0358)	(0.0279)	(0.0356)	(0.0363)

PANEL B. Threshold model with VK penetration as a share of city population

	Incidence of protests, dummy, Dec 2011				Log (number of protesters), Dec 2011			
	NLS	NLS	NLS	NLS	NLS	NLS	NLS	NLS
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Share of city population with VK accounts, before the threshold	0.0265*	0.0227	0.0212	0.0293*	0.158*	0.135	0.128	0.171*
	(0.0126)	(0.0134)	(0.0126)	(0.0131)	(0.0761)	(0.0817)	(0.0783)	(0.0801)
Share of city population with VK accounts, extra effect after the threshold	0.227**	0.232**	0.223**	0.233**	1.757***	1.786***	1.740***	1.785***
	(0.0780)	(0.0776)	(0.0752)	(0.0754)	(0.430)	(0.427)	(0.419)	(0.419)
Threshold, share of city population with VK accounts	10.07***	10.07***	10.05***	10.04***	10.29***	10.30***	10.29***	10.29***
	(0.176)	(0.174)	(0.179)	(0.162)	(0.148)	(0.149)	(0.151)	(0.147)
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

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in brackets are clustered at the region level. Threshold model is estimated using non-linear least squares. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. "Yes" indicates inclusion of a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A10. VK penetration, Turnout, and Invalid Votes

	Turnout, % 2007				Invalid Ballots, % 2007			
	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (number of VK users), June 2011	-11.390*	-11.835**	-7.741	-13.133**	-0.217	-0.210	-0.225	-0.134
	[6.190]	[5.241]	[5.009]	[5.480]	[0.229]	[0.190]	[0.199]	[0.199]
Log (SPbSU students), one cohort younger than VK founder	-1.164	-0.739	-1.172	-0.703	-0.045	-0.044	-0.042	-0.041
	[0.983]	[0.784]	[0.828]	[0.866]	[0.035]	[0.032]	[0.034]	[0.032]
Log (SPbSU students), one cohort older than VK founder	0.878	0.773	0.177	0.444	0.003	0.012	0.011	0.004
	[1.066]	[1.084]	[0.929]	[0.959]	[0.031]	[0.028]	[0.031]	[0.027]
	Turnout, % 2008				Invalid Ballots, 2008			
	IV	IV	IV	IV	IV	IV	IV	IV
Log (number of VK users), June 2011	8.121	3.826	9.061	4.994	-1.144	-1.198*	-1.266*	-1.111
	[8.243]	[6.749]	[7.326]	[6.442]	[0.706]	[0.688]	[0.746]	[0.708]
Log (SPbSU students), one cohort younger than VK founder	0.030	0.280	0.175	0.305	-0.046	-0.013	-0.049	-0.043
	[1.094]	[0.857]	[1.069]	[0.930]	[0.057]	[0.058]	[0.062]	[0.056]
Log (SPbSU students), one cohort older than VK founder	-1.606*	-1.100	-1.671*	-1.585**	0.082	0.097	0.080	0.059
	[0.960]	[0.759]	[0.895]	[0.806]	[0.096]	[0.098]	[0.095]	[0.084]
	Turnout, % 2011				Invalid Ballots, 2011			
	IV	IV	IV	IV	IV	IV	IV	IV
Log (number of VK users), June 2011	5.581	2.249	6.292	2.920	-0.683**	-0.602***	-0.595**	-0.588**
	[8.282]	[6.670]	[7.619]	[6.775]	[0.276]	[0.218]	[0.254]	[0.243]
Log (SPbSU students), one cohort younger than VK founder	-0.404	-0.086	-0.494	0.065	-0.023	-0.013	-0.016	-0.022
	[1.097]	[0.941]	[1.085]	[0.944]	[0.047]	[0.047]	[0.048]	[0.044]
Log (SPbSU students), one cohort older than VK founder	0.987	1.231	0.603	0.615	0.024	0.018	0.020	0.015
	[1.139]	[0.982]	[1.073]	[1.005]	[0.052]	[0.046]	[0.044]	[0.044]
	Turnout, % 2012				Invalid Ballots, 2012			
	IV	IV	IV	IV	IV	IV	IV	IV
Log (number of VK users), June 2011	-1.248	-3.273	-0.832	-2.767	-0.418**	-0.358**	-0.408**	-0.316*
	[6.302]	[5.506]	[5.796]	[5.060]	[0.211]	[0.166]	[0.189]	[0.165]
Log (SPbSU students), one cohort younger than VK founder	-0.747	-0.389	-0.774	-0.421	-0.008	-0.002	-0.008	-0.004
	[0.938]	[0.799]	[0.884]	[0.849]	[0.023]	[0.021]	[0.024]	[0.020]
Log (SPbSU students), one cohort older than VK founder	1.034	1.175	0.739	0.690	0.002	0.000	0.002	-0.001
	[0.974]	[0.934]	[0.948]	[0.851]	[0.030]	[0.026]	[0.028]	[0.024]
	Turnout, % 2016				Invalid Ballots, 2016			
	IV	IV	IV	IV	IV	IV	IV	IV
Log (number of VK users), June 2011	12.608	6.478	13.106	5.595	-0.154	-0.089	-0.161	0.006
	[10.785]	[8.760]	[9.745]	[7.182]	[0.274]	[0.236]	[0.245]	[0.215]
Log (SPbSU students), one cohort younger than VK founder	-0.833	-0.234	-0.560	-0.558	0.011	0.000	0.009	0.010
	[1.576]	[1.203]	[1.448]	[1.195]	[0.034]	[0.031]	[0.031]	[0.028]
Log (SPbSU students), one cohort older than VK founder	1.281	1.759	1.014	0.806	-0.009	-0.005	0.003	0.005
	[1.360]	[1.190]	[1.301]	[1.034]	[0.032]	[0.029]	[0.032]	[0.030]
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
Kleibergen-Paap F-stat	6.554	6.779	7.591	7.031	6.554	6.779	7.591	7.031
Effective F-statistics (Olea Montiel and Pflueger 2013)	10.97	12.03	12.30	12.17	10.97	12.03	12.30	12.17

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A11. VK and penetration of Odnoklassniki

	Log (number of Odnoklassniki users), 2014							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (early VK users, from first 5,000 users)	-0.042							
	[0.059]							
Log (early VK users, from first 50,000 users)		-0.045						
		[0.034]						
Log (early VK users, from first 100,000 users)			-0.024					
			[0.037]					
Log (number of VK users), June 2011				0.074				
				[0.074]				
Log (SPbSU students), same 5-year cohort as VK founder					0.028	0.018	0.015	0.017
					[0.048]	[0.045]	[0.043]	[0.045]
Log (SPbSU students), one cohort younger than VK founder					0.084	0.072	0.073	0.068
					[0.052]	[0.050]	[0.052]	[0.051]
Log (SPbSU students), one cohort older than VK founder					-0.049	-0.032	-0.034	-0.028
					[0.043]	[0.042]	[0.042]	[0.040]
Regional center	0.259**	0.269**	0.267**	0.252**	0.261**	0.228**	0.256**	0.254**
	[0.123]	[0.119]	[0.119]	[0.115]	[0.116]	[0.110]	[0.111]	[0.110]
Distance to Saint Petersburg, km	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Distance to Moscow, km	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Rayon center (county seat)	0.053	0.051	0.053	0.054	0.046	0.071	0.073	0.067
	[0.077]	[0.078]	[0.078]	[0.075]	[0.078]	[0.083]	[0.086]	[0.077]
Log (average wage), city-level, 2011	0.111	0.115	0.115	0.104	0.124	0.250**	0.205**	0.181*
	[0.106]	[0.105]	[0.106]	[0.105]	[0.104]	[0.097]	[0.100]	[0.104]
Presence of a university in a city, 2011	0.029	0.042	0.035	0.011	0.026	-0.011	-0.029	-0.015
	[0.097]	[0.098]	[0.097]	[0.097]	[0.095]	[0.088]	[0.082]	[0.087]
Internet penetration, region-level, 2011	-0.479**	-0.469**	-0.467**	-0.492**	-0.471**	-0.354*	-0.287	-0.354*
	[0.204]	[0.204]	[0.205]	[0.211]	[0.203]	[0.197]	[0.185]	[0.197]
Ethnic fractionalization, 2010	-0.231	-0.237	-0.231	-0.261	-0.259	-0.205	-0.247	-0.303**
	[0.166]	[0.167]	[0.167]	[0.162]	[0.168]	[0.162]	[0.163]	[0.151]
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***
Observations	625	625	625	625	625	625	625	625
R-squared	0.892	0.892	0.892	0.892	0.893	0.899	0.903	0.902

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Results in columns (1)-(4) are robust to inclusion of electoral controls, but corresponding specifications are not shown to save space.

Table A12. Online protest communities and protest participation. OLS estimates.

	Log (number of protesters), Dec 2011				Incidence of protests, dummy, Dec 2011			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (# of members in VK protest community in a city)	0.121**	0.120**	0.119**	0.121**	0.030***	0.030***	0.030***	0.030***
	[0.050]	[0.050]	[0.050]	[0.050]	[0.009]	[0.009]	[0.009]	[0.009]
Observations	625	625	625	625	625	625	625	625
R-squared	0.824	0.827	0.829	0.826	0.783	0.786	0.787	0.786
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
Electoral controls, 1995		Yes**				Yes*		
Electoral controls, 1999			Yes**				Yes	
Electoral controls, 2003				Yes*				Yes**

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers , distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A13. Robustness of Fractionalization Results to Partial Overlap

Panel A. Network fractionalization and the incidence of protests (in cities with population > 100,000).

	Incidence of protests, dummy, Dec 2011									
% of FB users who have a VK account	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Fractionalization of social media networks (Facebook+VK)	-0.983**	-0.851**	-0.703**	-0.561**	-0.439**	-0.341*	-0.267*	-0.211*	-0.172*	-0.158*
	[0.435]	[0.380]	[0.322]	[0.266]	[0.217]	[0.174]	[0.139]	[0.111]	[0.090]	[0.081]
Log (number of users in both networks)	0.072	0.096	0.119	0.137	0.151	0.160	0.166	0.170	0.171	0.171
	[0.122]	[0.119]	[0.117]	[0.117]	[0.117]	[0.117]	[0.118]	[0.118]	[0.118]	[0.118]
Population, Age cohorts, Education, and Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	158	158	158	158	158	158	158	158	158	158
R-squared	0.768	0.768	0.767	0.766	0.765	0.765	0.764	0.764	0.764	0.763

Panel B. Network fractionalization and protest participation (in cities with population > 100,000).

	Log (number of protesters), Dec 2011									
% of FB users who have a VK account	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Fractionalization of social media networks (Facebook+VK)	-4.797**	-4.209**	-3.518**	-2.834**	-2.233**	-1.742*	-1.356*	-1.062*	-0.847*	-0.746
	[2.140]	[1.864]	[1.589]	[1.335]	[1.108]	[0.910]	[0.741]	[0.602]	[0.497]	[0.454]
Log (number of users in both networks)	1.233**	1.348**	1.457**	1.548***	1.616***	1.663***	1.694***	1.712***	1.719***	1.717***
	[0.618]	[0.599]	[0.585]	[0.578]	[0.575]	[0.575]	[0.576]	[0.577]	[0.578]	[0.578]
Population, Age cohorts, Education, and Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	158	158	158	158	158	158	158	158	158	158
R-squared	0.821	0.821	0.820	0.820	0.820	0.819	0.819	0.819	0.818	0.818

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in brackets are adjusted for clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. Only cities with population greater than 100,000 are in the sample. "Yes" is added to indicate inclusion of a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A14. Fractionalization of Networks and Protest Participation.

Panel A. Network fractionalization and the incidence of protest

	Incidence of protests, dummy, Dec 2011							
	Whole sample				Cities with more than 100 000 inhabitants			
Fractionalization of social media networks (Facebook+Vkontakte)	-0.727***	-0.726***	-0.712***	-0.742***	-0.992**	-0.948**	-0.948**	-1.079**
	[0.239]	[0.238]	[0.233]	[0.233]	[0.440]	[0.416]	[0.416]	[0.434]
Log (number of FB users), predicted, 2011	-0.037	-0.034	-0.043	-0.065	-0.033	-0.019	-0.038	-0.067
	[0.052]	[0.052]	[0.053]	[0.050]	[0.118]	[0.123]	[0.121]	[0.110]
Log (number of VK users), 2011	0.135***	0.132***	0.128***	0.143***	0.077	0.083	0.107	0.145*
	[0.033]	[0.032]	[0.033]	[0.032]	[0.077]	[0.074]	[0.080]	[0.083]
Population, Age cohorts, Education, and 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	158	158	158	158
R-squared	0.785	0.788	0.788	0.789	0.769	0.788	0.787	0.794

Panel B. Network fractionalization and protest participation.

	Log (number of protesters), Dec 2011							
	Whole sample				Cities with more than 100 000 inhabitants			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fractionalization of social media networks (Facebook+Vkontakte)	-4.734***	-4.730***	-4.647***	-4.792***	-6.380***	-6.435***	-6.229***	-6.876***
	[1.183]	[1.186]	[1.155]	[1.168]	[2.073]	[2.059]	[1.980]	[2.025]
Log (number of FB users), predicted, 2011	0.293	0.306	0.261	0.177	0.296	0.316	0.247	0.098
	[0.298]	[0.303]	[0.309]	[0.302]	[0.644]	[0.731]	[0.662]	[0.626]
Log (number of VK users), 2011	0.839***	0.819***	0.801***	0.866***	0.782*	0.762*	1.004**	1.080**
	[0.160]	[0.158]	[0.162]	[0.160]	[0.412]	[0.388]	[0.412]	[0.453]
Population, Age cohorts, Education, and 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	158	158	158	158
R-squared	0.837	0.839	0.840	0.839	0.822	0.836	0.839	0.838

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A15. Heterogeneity of the VK penetration effect on protests.

	Log (number of protesters), Dec 2011					
	Wage lower than median	Wage higher than median	Trust lower than median	Trust higher than median	Education lower than median	Education higher than median
	(1)	(2)	(3)	(4)	(5)	(6)
Log (number of VK users), June 2011	1.252	2.021**	0.144	3.843**	0.139	4.448
	[1.602]	[0.995]	[1.830]	[1.558]	[0.210]	[2.789]
Log (SPbSU students), one cohort younger than VK founder	0.031	0.314**	0.152	-0.076	-0.032	0.117
	[0.159]	[0.158]	[0.141]	[0.335]	[0.049]	[0.275]
Log (SPbSU students), one cohort older than VK founder	-0.094	-0.210	0.213	-0.675*	-0.040	-0.348
	[0.171]	[0.210]	[0.237]	[0.362]	[0.045]	[0.344]
Population controls	Yes**	Yes***	Yes***	Yes***	Yes***	Yes***
Age cohort controls	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes***	Yes	Yes	Yes
Observations	315	310	231	231	313	312
Effective F-statistics (Olea Montiel and Pflueger 2013)	3.753	6.492	1.333	6.918	9.959	2.527

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. Specification is the same as Table 4A, column (1) (only baseline controls included). When "Yes" is added to indicate inclusion of a group of controls, a significance level is reported immediately after for this group of controls. Flexible controls for population (5th polynomial) are included in all specifications. Education controls include 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. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A16. Baseline Results with Alternative Cohort Definitions.

	Incidence of protests, dummy, Dec 2011														
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Cohort Definition	*(-1,+2)*	*(-1,+3)*	*(-1,+4)*	*(-2,+1)*	*(-2,+2)*	*(-2,+3)*	*(-2,+4)*	*(-3,+1)*	*(-3,+2)*	*(-3,+3)*	*(-3,+4)*	*(-4,+1)*	*(-4,+2)*	*(-4,+3)*	*(-4,+4)*
Log (number of VK users), June 2011	0.687*	0.385*	0.579*	0.547**	0.466**	0.357**	0.415**	0.562*	0.535**	0.365*	0.381**	0.452*	0.442*	0.269	0.374**
	[0.383]	[0.210]	[0.312]	[0.241]	[0.189]	[0.171]	[0.173]	[0.312]	[0.239]	[0.201]	[0.188]	[0.261]	[0.229]	[0.174]	[0.187]
Log (SPbSU students), one cohort younger than VK founder	-0.006	0.008	0.015	0.033	0.027	0.023	0.029	0.016	0.023	0.028	0.047**	0.036	0.054**	0.044**	0.054***
	[0.031]	[0.020]	[0.025]	[0.026]	[0.024]	[0.021]	[0.020]	[0.027]	[0.023]	[0.019]	[0.018]	[0.024]	[0.022]	[0.019]	[0.019]
Log (SPbSU students), one cohort older than VK founder	-0.036	-0.008	-0.063	-0.041	-0.033	-0.024	-0.043	-0.028	-0.042	-0.026	-0.039	-0.025	-0.047	-0.016	-0.042
	[0.044]	[0.030]	[0.044]	[0.037]	[0.031]	[0.029]	[0.030]	[0.040]	[0.036]	[0.032]	[0.032]	[0.036]	[0.036]	[0.028]	[0.033]
Observations	625	625	625	625	625	625	625	625	625	625	625	625	625	625	625
Mean of the dependent variable	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
SD of the dependent variable	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341
Population controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age cohort controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	2.882	4.838	3.351	5.097	6.554	7.062	8.492	3.211	5.183	5.801	6.960	3.979	4.902	5.806	6.375
Effective F-statistics (Olea Montiel and Pflueger 2013)	4.788	7.585	3.720	6.439	10.97	10.18	9.354	4.053	8.045	8.399	7.588	5.365	7.559	9.094	6.817

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in brackets are adjusted by clusters within regions. Cohort definition changes across columns according to the following rule: (-x, +y) means that VK founder cohort is defined as all SpbSU graduates who were born x years earlier or y years later than VK founder. A cohort younger and a cohort older are defined with the same length. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A17. Baseline Results with Cohorts Defined Based on Starting Year of Study at SpbSU.

	Incidence of protests, dummy, Dec 2011				Log (number of protesters), Dec 2011			
	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (number of VK users), June 2011	0.513**	0.496***	0.494**	0.542***	2.087**	2.036**	1.970**	2.225**
	[0.199]	[0.188]	[0.195]	[0.197]	[1.017]	[0.973]	[0.989]	[1.008]
Log (SPbSU students), one cohort younger than VK founder	0.054*	0.053*	0.056**	0.055*	0.365***	0.364***	0.377***	0.381***
	[0.029]	[0.029]	[0.028]	[0.029]	[0.140]	[0.138]	[0.136]	[0.138]
Log (SPbSU students), one cohort older than VK founder	-0.070*	-0.065*	-0.064*	-0.063*	-0.333*	-0.318*	-0.307*	-0.312**
	[0.036]	[0.034]	[0.033]	[0.034]	[0.172]	[0.164]	[0.157]	[0.159]
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
Kleibergen-Paap F-stat	9.819	11.28	10.15	10.25	9.819	11.28	10.15	10.25
Effective F-statistics (Olea Montiel and Pflueger 2013)	9.536	10.46	9.559	9.807	9.536	10.46	9.559	9.807

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in brackets are adjusted by clusters within regions. The VK founder's cohort includes all SPbSU students in our sample who started studying at SPbSU at some point from 2000 to 2004. A cohort younger and a cohort older are defined accordingly with the same length. Unit of observation is a city. Logarithm of any variable is calculated with 1 added inside. When "Yes" is added to indicate inclusion of a group of controls, a 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 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. Electoral controls include vote for Yabloko party, Communist Party (KPRF), LDPR party, the ruling party (Our Home is Russia in 1995, Unity in 1999, United Russia in 2003), and electoral turnout for a corresponding year. Other controls include dummy for regional and county centers, distances to Moscow and St Petersburg, log (average wage), share of people with higher education in 2002, internet penetration in 2011, log (Odnoklassniki users in 2014).

Table A18. Data Description and Sources

Variable	Description
Protest participation in December 2011	The number of people in a given city participating in protests against electoral fraud in December 10-16, 2011, i.e., during the first wave of massive protests after the legislative elections of December 4, 2011. Data were gathered manually from open sources on the Internet. Where possible, three estimates of the number of protest participants were collected - an estimate from the Ministry of Internal Affairs, an estimate from the activists themselves, and an estimate from journalists. Whenever more than one estimate was present, an average estimate was used. See Table A19 for all of our collected data.
Incidence of protests in December 2011	1 = at least one protest occurred in a city in December 10-16, 2011; 0 = no protests that week
Protest participation in USSR in 1987-1992	The number of people who participated in protests in the USSR in 1987-1992. Data were obtained from Mark Beissenger's website (http://www.princeton.edu/~mbeissin/research1.htm). This variable does not distinguish between different protest agendas — e.g., pro-democratic and pro-communist protests are treated equally. For protests with more than one estimate, an average number of participants was taken. For cities with multiple protests during that period, we use median participation.
Incidence of protests in USSR in 1987-1992	1 = at least one protest occurred in the city in 1987-1992, regardless of the protest's agenda; 0 = no protests occurred in 1987-1992
Participation in pro-democratic protests in USSR in 1987-1992	The number of people who participated in anti-Soviet or pro-democratic protests in the USSR in 1987-1992. Data were obtained from Mark Beissenger's website (http://www.princeton.edu/~mbeissin/research1.htm). We identified 75 various demands in the dataset which we considered either anti-Soviet or pro-democratic. Examples of such demands are "Against Communist Party Privileges", "Decentralize Economic Administration", "Democratization of Political institutions", etc. A full list of anti-Soviet/pro-democratic demands is available upon request. For protests with more than one estimate of participation, an average number of participants was taken. For cities with multiple protests during that period, we use median participation.
Incidence of pro-democratic protests in USSR in 1987-1992	1 = at least one anti-Soviet or pro-democratic protest occurred in the city in 1987-1992; 0 = no anti-Soviet or pro-democratic protests occurred in 1987-1992
Number of VK users in 2013	The number of registered VK users living in a given city, as of 2013. Manually collected data.
Number of VK users in 2011	The number of valid and active VK users in 2011, who picked a given city as their hometown. By "valid," we mean "not blocked." By "active," we mean that they were seen online at least once between June 21 and July 7, 2011. Data were collected by a professional programmer. Full description of the gathering process can be found at http://habrahabr.ru/post/123856/ (in Russian).
Number of early 5,000 VK users	The number of VK users with id<5,000, who picked a given city as their hometown. In other words, those were the first 5,000 users ever registered in VK. They were registered within less than a month in November 2006.
Number of Odnoklassniki users in 2014	Number of all registered Odnoklassniki users living in a given city, as of 2014. Manually collected data.

Number of Facebook users in 2013	Number of all registered Facebook users living in a given city, as of 2013. Manually collected data.
Population in 2001, in thousands	Collected from mojgorod.ru, which in turn stores data collected from Russian Federal State Statistics Service.
Distance to Saint Petersburg	Spherical distance from a given city to Saint Petersburg, in km
Distance to Moscow	Spherical distance from a given city to Moscow, in km
Administrative center	1 = city is the administrative center of its region; 0 = not. Data collected from Wikipedia.
Rayon center (county seat, dummy)	1 = city is the administrative center of its district (rayon); 0 = not. Data collected from Wikipedia.
Average wage in 2011	Data gathered from Russian Federal State Statistics Service.
Number of people with age xx-xx in 2010	Data gathered from Russian Federal State Statistics Service. Based on Russian census in 2010.
Presence of university	1 = city has at least one university; 0 = not. Data collected from Wikipedia.
Percentage with higher education in 2010	Percentage of adults with at least one university degree. Data gathered from Russian Federal State Statistics Service. Based on Russian census in 2010.
Internet penetration in 2011, region-level	Number of unique users in a region divided by its population according to the 2010 census. Data collected from liveinternet.com
Number of SPbSU students, same 5-year cohort as VK founder	Number of Odnoklassniki users who studied in Saint Petersburg State University in classes of 2004-2008, i.e. in the same age 5-year cohort together with Pavel Durov, former CEO of VK. Data manually collected from OK.ru.
Number of SPbSU students, one cohort younger than VK founder	Number of Odnoklassniki users who studied in Saint Petersburg State University in classes of 1999-2003, i.e. one 5-year cohort earlier than Pavel Durov, former CEO of VK. Data manually collected from OK.ru.
Number of SPbSU students, one cohort older than VK founder	Number of Odnoklassniki users who studied in Saint Petersburg State University in classes of 2009-2013, i.e. one 5-year cohort after Pavel Durov, former CEO of VK. Data manually collected from OK.ru.

Table A19. Data on Protest Participation across Russian Cities

Date	City	OKATO	# according to police	# according to organizers	# according to journalists	Average # of protesters
12/10/2011	Barnaul	01401	300	1500	.	900
12/10/2011	Krasnodar	03401	250	1500	1000	917
12/10/2011	Anapa	03403	.	500	.	500
12/10/2011	Sochi	03426	150	300	.	225
12/10/2011	Krasnoyarsk	04401	400	4000	.	2,200
12/10/2011	Vladivostok	05401	150	1000	.	575
12/11/2011	Stavropol	07401	.	.	30	30
12/10/2011	Pyatigorsk	07427	150	300	300	250
12/10/2011	Khabarovsk	08401	70	150	.	110
12/10/2011	Komsomolsk-on-Amur	08409	80	100	430	203
12/10/2011	Blagoveshchensk	10401	.	50	.	50
12/10/2011	Arkhangelsk	11401	.	3000	2000	2,500
12/10/2011	Belgorod	14401	100	.	.	100
12/10/2011	Stary Oskol	14440	.	.	30	30
12/10/2011	Bryansk	15401	300	1000	.	650
12/10/2011	Vladimir	17401	.	.	300	300
12/10/2011	Volgograd	18401	1000	2000	.	1,500
12/10/2011	Vologda	19401	500	1300	1000	933
12/11/2011	Cherepovets	19430	.	.	300	300
12/10/2011	Voronezh	20401	300	1500	1000	933
12/10/2011	Nizhny Novgorod	22401	500	2000	.	1,250
12/10/2011	Ivanovo	24401	250	400	.	325
12/10/2011	Irkutsk	25401	400	1000	.	700
12/10/2011	Angarsk	25405	15	60	30	35
12/10/2011	Bratsk	25414	.	.	150	150
12/10/2011	Kaliningrad	27401	200	500	.	350
12/10/2011	Tver	28401	400	500	.	450
12/10/2011	Kaluga	29401	.	.	250	250
12/10/2011	Obninsk	29415	50	300	.	175
12/10/2011	Kemerovo	32401	200	500	400	367
12/10/2011	Novokuznetsk	32431	.	50	.	50
12/10/2011	Kostroma	34401	50	200	.	125
12/10/2011	Samara	36401	900	5000	.	2,950
12/10/2011	Tolyatti	36440	.	.	1000	1,000
12/10/2011	Mound	37401	.	100	.	100
12/10/2011	Kursk	38401	.	.	100	100
12/10/2011	Vyborg	41417	.	300	.	300
12/10/2011	Lipetsk	42401	.	300	.	300
12/10/2011	Murmansk	47401	500	1500	.	1,000
12/10/2011	Velikiy Novgorod	49401	.	400	200	300
12/10/2011	Novosibirsk	50401	3500	8000	.	5,750
12/10/2011	Omsk	52401	1000	2500	2000	1,833
12/10/2011	Orenburg	53401	.	300	.	300
12/11/2011	Orsk	53423	.	.	300	300
12/10/2011	Orel	54401	300	700	.	500
12/10/2011	Penza	56401	300	500	.	400
12/11/2011	Permian	57401	850	3000	.	1,925
12/10/2011	Pskov	58401	.	.	600	600
12/10/2011	Rostov-na-Donu	60401	250	700	500	483
12/10/2011	Volgodonsk	60412	.	.	10	10
12/10/2011	Taganrog	60437	.	.	200	200
12/10/2011	Ryazan	61401	.	500	.	500
12/10/2011	Saratov	63401	200	1000	.	600
12/10/2011	Balakovo	63407	200	200	.	200
12/10/2011	Yuzhno-Sakhalinsk	64401	.	70	.	70
12/10/2011	Ekaterinburg	65401	1500	10000	5000	5,500
12/10/2011	Kachkanar	65448	.	.	50	50
12/10/2011	Nizhny Tagil	65476	.	.	150	150
12/10/2011	Smolensk	66401	.	.	200	200
12/10/2011	Tambov	68401	150	250	.	200
12/10/2011	Tomsk	69401	1500	4000	2000	2,500
12/10/2011	Tula	70401	250	500	.	375
12/10/2011	Khanty-Mansiysk*	71131	.	.	3	3

Table A19 (cont'd). Data on Protest Participation across Russian Cities

Date	City	OKATO	# according to police	# according to organizers	# according to journalists	Average # of protesters
12/10/2011	Nizhnevartovsk	71135	.	.	50	50
12/10/2011	Surgut	71136	.	.	250	250
12/10/2011	Tyumen	71401	.	1500	.	1,500
12/10/2011	Ulyanovsk	73401	400	1500	1000	967
12/10/2011	Chelyabinsk	75401	1000	3000	.	2,000
12/10/2011	Magnitogorsk	75438	.	.	500	500
12/10/2011	Chita	76401	100	200	.	150
12/10/2011	Yaroslavl	78401	650	2000	1000	1,217
12/10/2011	Ufa	80401	200	1000	500	567
12/10/2011	Sterlitamak	80445	.	.	250	250
12/10/2011	Ulan-Ude	81401	50	100	.	75
12/10/2011	Makhachkala	82401	.	25	.	25
12/10/2011	Gorno-Altaisk	84401	.	50	.	50
12/10/2011	Petrozavodsk	86401	300	600	400	433
12/10/2011	Syktyvkar	87401	250	500	.	375
12/10/2011	Yoshkar-Ola	88401	.	.	400	400
12/10/2011	Kazan	92401	500	1000	.	750
12/10/2011	Naberezhnye Chelny	92430	.	350	150	250
12/10/2011	Izhevsk	94401	.	500	.	500
12/10/2011	Abakan	95401	.	100	.	100
12/10/2011	Cheboksary	97401	230	420	300	317

* Removing this small-scale protest from our sample does not change our results. For geographic distribution of protests across Russian territory, see Figure A2. Sources include, but are not limited to, an independent business newspaper Kommersant, a government owned new agency RIA Novosti, and an opposition-leaning independent online newspaper Ridus, various regional newspapers, etc. OKATO is the official all-Russian classifier of cities and other populated localities.