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SOCIAL MEDIA AND PROTEST PARTICIPATION: EVIDENCE FROM RUSSIA

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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 the information on the city of origin of the students who studied 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%. 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 observe that VK penetration increased pro-governmental support, with no evidence of increased polarization. We also 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.

KEYWORDS: Social media, political protests, collective action, technology adoption.

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1. INTRODUCTION

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)). In addition to the classic issue of free-riding, a group's ability to overcome a collective action problem depends on their information environment and their ability to communicate with one another. New horizontal information exchange technologies, such as Facebook and Twitter, 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. So far, there has been no systematic evidence on whether social media improves people's ability to overcome the collective action problem. Our paper fills in this gap by looking at the effect that the most popular online social network in Russia had on a particular type of collective action—political protests.

The rise of social media in the beginning of the 2010s coincided with waves of political protests around the world. But did social media play any role in inducing political participation, that is, by inciting the protests, or did its content merely reflect the preferences of the population?[1] Recent theoretical works argue that social media is likely to promote political protests (Edmond (2013), Little (2016), Barberà and Jackson (2016)). However, testing this hypothesis empirically is methodologically challenging, particularly because 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 the activity and the content on social media and subsequent protests (Acemoglu, Hassan, and Tahoun (2017)),[2] but not on the causal impact of social media availability.

To understand whether social media can indeed promote protest participation, we study an unexpected wave of political protests in Russia in December 2011 triggered by electoral fraud in parliamentary elections, coupled with an analysis of the effect of social media on support for the government. Our empirical setting allows us to overcome the limitations of previous studies for two reasons. First, there was substantial geographic and temporal variation in both protest activities and the penetration of the major online social networks across Russian cities. For example, among the 625 cities in our sample, 133 witnessed at least one protest demonstration on December 10–11, 2011, the first weekend after the elections. 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 VK's 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

[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, Farrell, Lynch, Sides, Kelly, and Zuckerman (2010)). 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.

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 each account. Thus, the first users of the network were primarily students who studied at Saint Petersburg State University together with Durov. This, in turn, made the friends and relatives in these early users' home towns more likely to open an account, which sped up the development of VK in those locations. 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, whereas 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 Russian 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 both a 4.6 percentage point increase in the probability of there being a protest and a 19% increase in the number of protest participants the first weekend after the elections. These results indicate that VK penetration indeed had a causal positive impact on protest participation in Russian cities in December 2011.

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 corresponding coefficients in other universities, while the coefficients for younger and older cohorts lie close to the medians of the corresponding distributions, consistent with our identifying assumptions.

Next, we examine the potential mechanisms behind the observed effects. To structure our analysis, we develop a theoretical framework of social media and protests in an autocracy, extending the work of Little (2016). In this framework, social media can have an impact on protests through the information channel or the collective action channel. The information channel implies 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 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).[3] 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.[4]

We start the analysis of the mechanisms by studying 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 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 for pro-government support using data from a large-scale survey conducted weeks before the 2011 elections. The analysis of all public posts on VK shows that, on average, the content on the platform was not unfavorable of the regime. 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 weeks before the elections. Thus, these results stand in contrast to a common perception that social media necessarily erodes support for autocratic leaders and leads to a higher degree of political polarization.

Another testable prediction of our theoretical framework is that the effect of social media on protest participation should increase with city size if it is reliant on the 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 instead 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.

[3]Note that 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 full-fledged theoretical models with a strategic coordination component. A recent paper by Cantoni, Yang, Yuchtman, and Zhang (2019) suggests that individual protest participation actions could be strategic substitutes due to free-ride incentives. In contrast, the effect of social media on logistical/tactical coordination is unambiguously positive, which allows us to make clear empirical predictions.

[4]There is an important conceptual difference between the roles social media plays in these two channels. Social media affects political outcomes through the information channel to the extent that it allows for more free 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 a further attempt to distinguish impact via the information versus the coordination channel, we show that fractionalization of users between VK and Facebook,[5] 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 idea that reductions in the costs of collective action are an important mechanism of social media influence.

Overall, our results indicate that social media penetration facilitates participation in political protests, and that 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 the 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 and the related economic and political outcomes (Madestam, Shoag, Veuger, and Yanagizawa-Drott (2013), Aidt and Franck (2015), Battaglini (2017), Passarelli and Tabellini (2017)). A broader 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 along this same line that promotes collective action by dramatically increasing the scale of horizontal information exchange.

Our paper is closely related to that of Acemoglu, Hassan, and Tahoun (2017) who studied the impact of Tahrir protest participation and Twitter posts on the expected future rents of politically connected firms in Egypt. They found that the protests were associated with lower future abnormal returns of politically connected firms. They also showed 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, that is, 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) analyzed the Chinese microblogging platform Sina Weibo and showed that Sina Weibo penetration was associated

[5]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.

with the incidence of collective action events, without interpreting these results causally. Steinert-Threlkeld, Mocanu, Vespignani, and Fowler (2015) showed 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) provided a detailed case study of a successful consumer boycott organized on Facebook.[6]

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 (2018)), 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.[7]

Recent works have also shown that traditional media has an impact on voting behavior, violence, and policy outcomes.[8] In contrast, our paper studies the impact of social media, which is becoming increasingly important for modern information flows. A number of papers study ideological segregation online (Gentzkow and Shapiro (2011), Halberstam and Knight (2016), Gentzkow, Shapiro, and Taddy (2019)). 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 presents a theoretical framework and outlines our main empirical hypotheses. Section 3 provides background information about the environment that we study. Section 4 describes our data and its sources. Section 5 discusses our identification strategy. Section 6 shows the empirical results. Section 7 concludes.

2. THEORETICAL FRAMEWORK

Social media can affect protest participation both positively and negatively through a variety of forces. Building on the work of Little (2016), we present a simple theoretical framework in which social media affects protest participation by providing more precise information about the quality of the government (information channel) and the protest logistics (coordination channel). Within the same framework, we study the effect of so-

[6] Papers that are less directly related to collective action include Bond et al. (2012) who showed that that political mobilization messages on Facebook increased turnout in the U.S. elections, Qin (2013) who showed that the spread of Sina Weibo led to improvement in drug quality in China, and Enikolopov, Petrova, and Sonin (2018) who showed 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.

[7] 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) looked at the impact of cellphone penetration on political mobilization and protest activity in Africa.

[8] 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 (2015).

cial media on voting in an autocracy, which allows us to isolate the information effects of social media. Finally, we are able to shed light on the coordination channel by both analyzing how the effect of social media depends on city size and exploring the existence of threshold behavior in the relationship between VK penetration and protests. Overall, this framework provides useful micro-level foundations for our empirical analysis and yields several insightful predictions that allow us to disentangle the mechanisms. We present a concise exposition of the framework below; please see the Appendix from the Supplemental Material (Enikolopov, Makarin, and Petrova (2020)) for the full setup of the model, derivations, and other details.

2.1. *Protests in Autocracy*

There is a continuum of risk-neutral citizens. Nature draws common priors about regime quality and protest tactics. The public signals and random individual costs of protesting are drawn. Upon observing the public signals, citizens update their beliefs about regime quality and the tactics of the upcoming protest. Having updated their beliefs about the regime and the tactics, each citizen decides whether to participate in a protest or not, given the expected benefits and costs. The citizen gains zero utility if she does not participate. The utility of participation depends on the updated beliefs about the quality of the regime, the extent to which citizens' chosen protest tactics match the best cost-efficient tactics, the proportion of other citizens who turn out to protest, the (reduced form) strategic complementary parameter, and the individual costs of protest participation. Studying the decision to protest in this model, we derive the following prediction:

PREDICTION 1: *Higher social media penetration leads to higher protest participation against the ruling regime if the content of social media is*, *on average*, *negative toward the regime*. *However*, *even when the content online is positive*, *social media could increase protest participation if the gains from coordination 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 second effect always increases protest participation by improving tactical coordination. The direction of the first effect depends on social media content. If the content of social media is, on average, negative toward the regime, 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 information about the regime's quality versus tactical coordination.

2.2. *Voting in Autocracy and the Information Channel*

We examine the impact of social media on voting in autocracy by slightly modifying the previous framework. Instead of the protest decision, citizens now face individual decisions of whether to vote in favor of the regime or abstain, with a preference for conformity. The most significant difference is the absence of the matching tactics problem, as the individual voting decision does not rely on tactical coordination. Thus, only the information channel of social media is present in this version of the model. Since other features remain similar, we derive the following prediction:

PREDICTION 2: *Higher social media penetration leads to a higher* (*lower*) *vote share of the ruling party if the content of social media is*, *on average*, *positive* (*negative*) *toward the regime*.

This prediction is crucial for our empirical analysis since it illustrates why and under which assumptions we can isolate the information channel of social media by studying the impact of social media on voting and support for the regime.

2.3. *City Size and the Coordination Channel*

Next, we extend the model to the case of many cities, which allows us to show that city size affects our two channels in a different way. Specifically, we show that, if the coordination channel is at play, we should observe a larger positive impact of social media on protests in bigger cities.

PREDICTION 3: *The impact of social media on protest participation is larger in areas where coordination is harder to achieve in the absence of public signals*. *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*.

The intuition behind this result is that the larger the city size, the more logistically difficult it is to coordinate protest activities due to the need for organizing a larger group of people. At the same time, if anything, a larger city size would predict better quality of information about the regime. We formalize this intuition in the Appendix and derive the conditions under which the effect of social media on protest participation via the coordination channel decreases with city size.

2.4. *Social Media Penetration and the Critical Mass*

Finally, we explore a natural extension of the model in which protests take place only if participation is above some threshold level of participants.

PREDICTION 4: *Higher rates of social media adoption lead to higher protest participation*. *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*.

In this extension, we separate all citizens into adopters and non-adopters of social media. 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 accuracy of the tactics signal from social media. In this setup, as the adoption of social media in the population grows, both adopters and non-adopters go out to protest with a higher probability. As a result, the total share of protesters is monotonically increasing with the share of social media users. A corollary of this statement is that if a protest is organized if and only if the number of potential participants crosses a certain threshold, there is a threshold level of social media participation that can trigger protest incidence. In what follows, we apply these predictions to the data.

3. BACKGROUND

3.1. *Internet and Social Media in Russia*

By 2011, approximately half of the Russian population had access to the Internet,[9] making Russia the largest Internet market in Europe (15% of all European Internet users).[10]

Social media was also already quite 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.[11] 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.

Despite the increasing popularity of social media, Russia remains one of the very few markets where Facebook was never dominant. Instead, homegrown networks VKontakte (VK) and Odnoklassniki took over. 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] Additionally, VK and Odnoklassniki could offer certain services that Facebook could not, due either to legal reasons (e.g., Facebook could not provide music and video streaming services because of copyright restrictions) or a different marketing strategy (e.g., Russian platforms had a lower amount of advertising).

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

3.2. *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 and converse with them, create events, write blog posts, share information (textually and in audio or video format), etc. VK was launched in October 2006. The core of the VK development team was stable until 2012, consisting of Pavel Durov (a philology major at SPbSU at the time), his brother Nikolai Durov (a physics graduate student at SPbSU at the time, and a winner of international programming and math contests), and fellow students. Upon VK's creation, Durov issued an open invitation on an SPbSU online forum for students to apply for membership on VK.

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

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

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

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

[13] According to the official VK blog (https://bit.ly/32rZWPy) and BBC data reported by Dni.ru (http://bit.ly/2oTDIoi).

Interested students then requested access to VK, and Durov personally approved each account. Registration in VK opened to the general public in 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, and to 100 million in November 2010 (see Figure A1 in the Supplemental Material (Enikolopov, Makarin, and Petrova (2020))). By early 2008, VK became the most visited website in Russia.

VK creators maintained 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 opposition-minded online communities and 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).[14] VK policies regarding freedom of speech remained unchanged until Durov lost control of the firm in 2014.[15] Note that Durov himself, at least before 2013, was not directly involved in any political activity and did not advertise or create any politically related content on VK (Kononov (2012)).

3.3. *Protest Movement of 2011–2012*

A wave of protest demonstrations in 2011–2012 was triggered by electoral fraud during the parliamentary elections held on December 4, 2011. During the course of that day, reports of electoral fraud quickly grew in number, 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 the exit polls and the official results began to emerge; some exit polls reported 23.6% of the votes going to United Russia in Moscow, which was 20% lower than the official electoral results. Clear evidence of electoral fraud together with the 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.[16]

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).[17] The subsequent waves of protests were less popular and involved fewer cities. Moscow

[14]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.

[15]Durov was dismissed as the VK CEO 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 and left the country after obtaining Saint Kitts and Nevis citizenship.

[16]Using statistical analysis, scholars later confirmed that the amount of fraud was indeed sizable. For instance, Enikolopov, Korovkin, Petrova, Sonin, and Zakharov (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%).

[17]It was the largest political protest movement in Russia since the collapse of the Soviet Union. For a map of Russian protests on December 10–11, 2011, see Figure A2 in the Supplemental Material. Table A23 presents the names of the cities with protests and the estimates of each protest's size.

and St. Petersburg, however, hosted major rallies almost every 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 years in prison. This trial, together with absence of any tangible achievements, marked the decline of the 2011–2012 protest movement in Russia.

3.4. *VK and Protest Activity*

In December 2011, online social networks, including VK, became an important source of political information in Russia, whereas 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 the topic. Robertson (2017) reported 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. Reuter and Szakonyi (2015) showed that being a user of one of the online social networks was a strong predictor of a respondent's awareness of electoral fraud during the December 2011 elections. Based on an online survey of protest participants, Dokuka (2014) provided evidence that 67% 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.[18]

4. DATA

We use several sources of data. Our sample consists of 625 Russian cities with populations over 20,000 according to the 2010 Census, excluding Moscow and Saint Petersburg 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.[19] Only active VK users were considered, that is, 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, that is, before the parliamentary elections were scheduled and before the electoral

[18] 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.

[19] 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 than 90% of the accounts on VK were public.

campaign began.[20] More details about data sources and construction of the main variables are available in Table A22 in the Supplemental Material.

We use hand-collected data on political protests that occurred between December 2011 and May 2012. When the protests began in December 2011, we began monitoring newspaper databases and online resources so as to record information about political protests in each of the Russian cities mentioned in this context. This monitoring was repeated every week until the protests subsided in summer 2012. The primary sources of information about the protests include independent business newspaper Kommersant, government-owned news agency RIA Novosti, opposition-leaning independent online newspaper Ridus, and various regional newspapers. Information was highly consistent across these different sources, making it unlikely that information was manipulated and that discrepancies across these sources would have a significant impact on our results.[21]

For each protest event, we recorded the number of protesters, as reported by three alternative sources: (i) the police; (ii) organizers of the protest; and (iii) a news source that wrote about the protest.[22] 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 the city-week level by constructing 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.[23] If there were more than one protest event in a city during the same week, we take the number of protesters at the largest event. In this paper, we will use only data for the first week of major protests: December 10–16, 2011. See Table A23 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, Makarin, Petrova, and Polishchuk (2017)).

We also rely on information on the city of origin of the students who studied at Saint Petersburg State University and other top Russian universities.[24] Because, unfortunately, administrative records on admitted students are not available, these data are based 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 who use social media reported having an account in Odnok-

[20]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)), and since there were 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 cause a measurement error bias that would be corrected in an instrumental variable specification.

[21]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/2oSwS0B). The downside of the Wikipedia page, however, is its limited coverage of smaller cities.

[22]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 A23 in the Supplemental Material.

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

[24]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).

lassniki,[25] 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.[26] Although using data from social media to measure the distribution of students across cities may introduce 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 were taken from Nikolai Belousov's blog.[27] 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.[28]

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, 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,[29] though we admit that this source of data is less reliable than those 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.[30] This is a regionally representative survey of 56,900 respondents from 79 regions, of which 30,669 respondents come from 519 cities in our sample.[31]

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 of the Supplemental

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

[26] 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 6.3.6.

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

[28] To collect these 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.

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

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

[31] On average, every 0.0024 VK user has been sampled, with some variation across cities (0.0033 sd). In the results available upon request, we tested that weighting observations by this ratio does not significantly alter our estimates.

Material. In addition, Table A2 presents the summary statistics broken down by each city's quartile of VK penetration.

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:

$$\text{Political Outcome}_i = \beta_0 + \beta_1 \text{VKpenetration}_i + \beta_2 X_i + \varepsilon_i, \tag{1}$$

where Political Outcome$_i$ is either a measure of protest activity—an indicator for the occurrence of at least one protest in the first weekend of the protests (December 10th and 11th) or the logarithm of the number of protesters in city i[32]—or of support for 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 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, internet penetration in 2011, and logarithm of the number of Odnoklassniki users in 2014. In some specifications, X_i also includes the outcomes of the pre-2006 parliamentary elections to control for the pre-existing political preferences of the local population. Standard errors in all regressions are clustered at the regional level.[33]

5.1. *Identification Strategy*

The OLS estimates of the equation (1) 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 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 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 who have studied at SPbSU in three five-year student cohorts (so as to match the Census definition of cohorts): (i) those who were born in the same year as Durov, as well as one or two years earlier or later, (ii) those who were born from three to

[32]We focus on the first protests to avoid the possibility of dynamic effects within and across the cities. For the panel results and the detailed analysis of the dynamic protest participation, see our companion paper, Enikolopov et al. (2017). One concern may be that the protests that took place on Sunday of the first protest weekend, as opposed to Saturday, could also be affected by the dynamic considerations. As can be seen from Table A23, only four took place on Sunday, December 11, 2011. Table A6 in the Supplemental Material shows that our baseline results are robust to focusing on Saturday protests (December 10, 2011) only.

[33]All our baseline results are robust to spatially correlated standard errors calculated as in König, Rohner, Thoenig, and Zilibotti (2017) (see Table A7 in the Supplemental Material).

seven years earlier than Durov, and (iii) those who were born from three to seven years later than Durov.[34]

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 Supplemental Material 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.[35] Thus, the numbers are sufficiently small to allow for random fluctuations in the distribution of students across cities.[36]

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 Durov's cohort came from 237 different cities (more than one 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 to allow for a meaningful comparison.

5.2. *Determinants of VK Penetration*

To show that our instrument is relevant, Table I provides evidence on the determinants of VK penetration across Russian cities in 2011, and, in particular, on the effect of the number of SPbSU 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 the VK founder is positively and significantly (at a 1% level) correlated with subsequent VK penetration, 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 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 1.3–1.4% 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.

[34]See Section 6.3.6 for the discussion of the robustness of our results to alternative definitions of cohorts.

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

[36]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 Supplemental Material 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 Supplemental Material. 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.

TABLE I

DETERMINANTS OF VK PENETRATION IN 2011 (FIRST STAGE REGRESSION)[a]

	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

[a]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" 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.

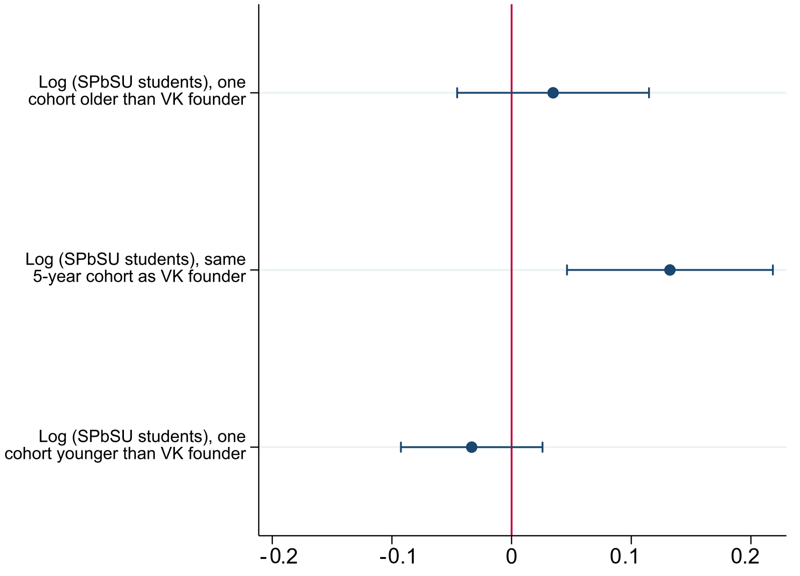

FIGURE 1.—VK penetration in 2011 and the number of SPbSU students over time. *Notes*: This figure presents the coefficients from column (5) of Table I, reflecting the association between the log of the number of VK users in each city in June 2011 and the log of the number of SPbSU students who are one 5-year cohort older, of the same cohort, or one cohort younger than the 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 I.

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, that is, for the first 5,000 users (see Table A5 in the Supplemental Material). While the coefficient patterns for the number of SPbSU students are similar to those in Table I, other controls, such as population, education by cohort, and ethnic fractionalization, become insignificant, consistent with our claim that the initial VK diffusion was largely idiosyncratic. The corresponding cohort coefficients and their confidence intervals are shown graphically in Figure A4 in the Supplemental Material.

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 SA.I in the Appendix shows how protest incidence on 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, whereas the coefficients for other cohorts are much smaller and not statistically significant. Moreover, the sign of the coefficient for the older cohort is consistently negative across specifications.[37] The difference between coefficients for different cohorts is statistically significant for the incidence of protests in all specifications. Figures 2(A) and 2(B) report these results graphically.

6.1.2. *IV Results for Protest Participation*

Reduced form analysis in Table SA.I 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 (1) 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 II indicate that social media penetration had a quantitatively large and a statistically significant effect on the incidence of protests. To combine IV estimation with clustered standard errors and weak-instrument tests, we use a linear probability model.[38] The results indicate that VK penetration had a positive and statistically 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 methodology recently developed by Montiel Olea and Pflueger (2013) who derived a test for weak instruments similar to that in Stock and Yogo (2005), but for the case of clustered standard errors. The corresponding effective F-statistic in our specifications takes 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 (2019)).[39] So as to be conservative, following recommendations by Andrews, Stock, and Sun (2019), we also report the weak-instrument robust confidence intervals for each main coefficient,

[37]Note that, even though we cannot reject the hypothesis that the coefficients for the VK founder and the younger cohorts are the same, this does not necessarily 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.

[38]We show that our baseline results are robust to using nonlinear models and present these results in Table A8 in the Supplemental Material. 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, in terms of both magnitudes and statistical significance.

[39]In the first comprehensive overview of the best practices of dealing with weak instruments in the presence of heteroscedasticity, Andrews, Stock, and Sun (2019) analyzed 230 specifications from publications in the *American Economic Review (AER)* in 2014–2018 and documented 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.

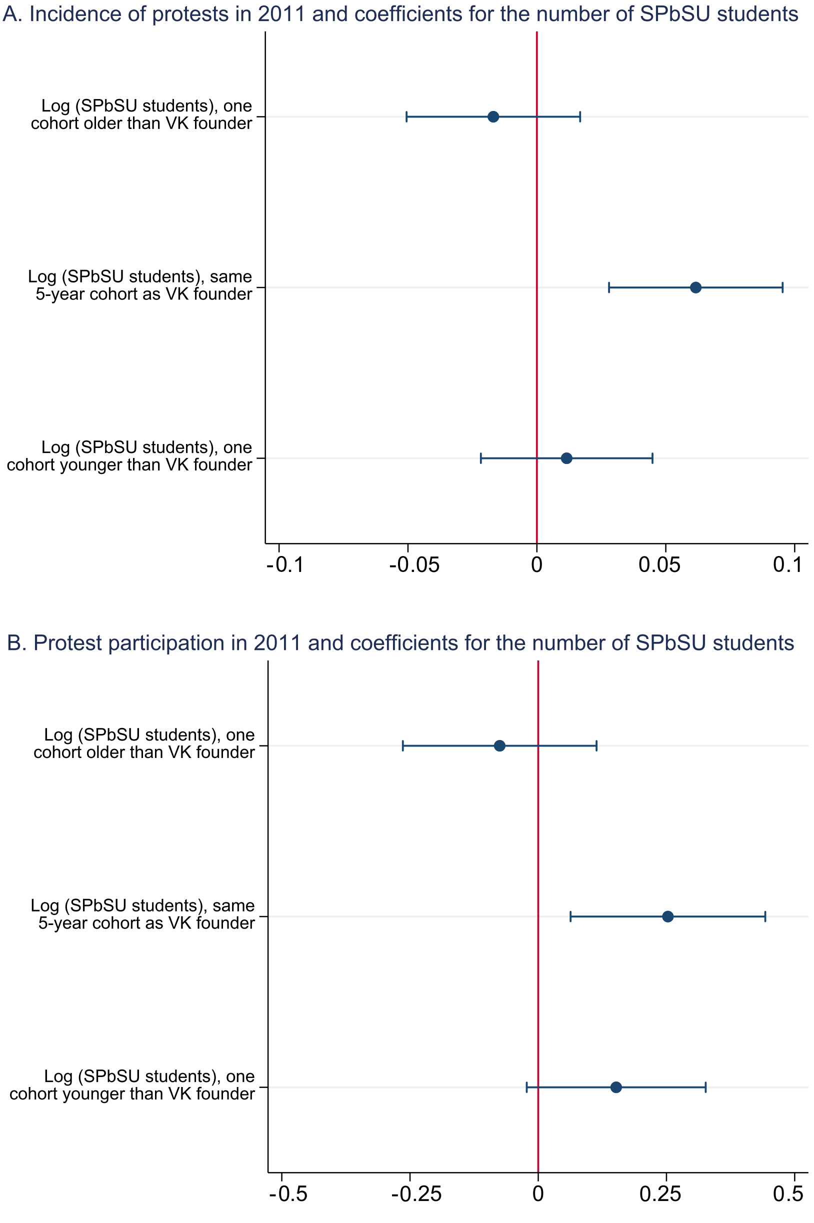

FIGURE 2.—VK penetration in 2011 and SPbSU student cohorts. *Notes*: Panel A and Panel B present the coefficients from columns (1) and (5) of Table SA.I, respectively. These reflect the association between the incidence of protests (Panel A) or the log of the number of protest participants (Panel B) 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 the 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 SA.I in the Appendix.

TABLE II

VK PENETRATION AND PROTEST PARTICIPATION IN 2011[a]

Panel A. Probability of Protests

	Incidence of Protests, Dummy, Dec 2011							
	IV (1)	IV (2)	IV (3)	IV (4)	OLS (5)	OLS (6)	OLS (7)	OLS (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	*(0.18; 1.77)*	*(0.18; 1.56)*	*(0.18; 1.42)*	*(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-statistics	6.554	6.779	7.591	7.031				
Effective F-statistics (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 (1)	IV (2)	IV (3)	IV (4)	OLS (5)	OLS (6)	OLS (7)	OLS (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	*(0.24; 7.30)*	*(0.28; 6.56)*	*(0.30; 6.09)*	*(0.42; 6.47)*				
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-statistics	6.554	6.779	7.591	7.031				
Effective F-statistics (Montiel Olea and Pflueger (2013))	10.97	12.03	12.30	12.17				

[a]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" 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). Weak IV robust 95% confidence intervals are Anderson–Rubin confidence sets calculated using software in Finlay and Magnusson (2009), which accommodates heteroscedasticity.

calculated without the assumption of a strong instrument. As one can see, the intervals exclude zero in all of our specifications.[40]

For comparison, we display the OLS estimates for the same second-stage specifications in columns (5)–(8) of Panel A of Table II. The coefficients are still highly significant, but are much smaller in magnitude than the corresponding IV estimates. One explanation for the difference between OLS and IV is 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. Alternatively, the difference can be explained by the fact that our IV estimates reflect the local average treatment effects (LATE) and that the effect of VK on protests is higher in the cities in which the effect of the instrument on VK penetration was stronger.

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 (in our sample, the average VK penetration in 2011 was 15 percent), protest participants in absolute terms constituted only a tiny fraction of the population. Our data suggest that for cities that experienced protests, only 0.4% of the city population participated in these demonstrations. As the average city size in our sample was 117 thousand people, 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 II, assume a linear relationship between the number of VK users and political protests. To examine this association nonparametrically, 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 Supplemental Material).[41] 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 Supplemental Material). These results are consistent with Prediction 4 of our model and with the predictions of the threshold models of collective action (e.g., Granovetter (1978), Lohmann (1993, 1994)).

[40]These intervals are calculated as Anderson–Rubin intervals using an implementation by Finlay and Magnusson (2009). For the intervals calculated using other methods, such as Mikusheva and Poi (2006) and Chernozhukov and Hansen (2008), see Table A9 in the Supplemental Material. The results are nearly identical across these methods.

[41]We can also confirm the existence of a threshold level of VK penetration by estimating a nonlinear threshold model in which we allow the coefficient for the effect of VK penetration on protest activity to change at some point. The results of this estimation also indicate that 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 A10 in the Supplemental Material). The threshold is between 23,000 and 30,000 users or 23–25% as a share of a city's population.

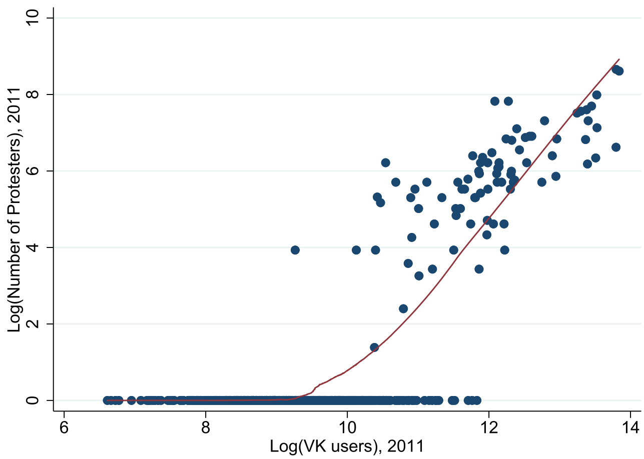

FIGURE 3.—Nonparametric relationship between VK penetration and number of protesters. *Notes*: This figure displays the association between the log of the number of protesters in each city during the first week of protests in December 2011 and the log of the number of VK users in these cities as of June 2011. Logarithm of any variable is calculated with 1 added inside. Blue dots illustrate the raw city-level data. The red line represents a nonparametric relationship between the two variables.

6.2. *VK Penetration and Pro-Governmental Support*

We test whether an increase in VK penetration led to a change in electoral support for the pro-governmental candidates in the elections that took place after the creation of VK. Table III presents the results of the estimation of equation (1) 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.[42] 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, so that this OLS 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. At the same time, a reduction in the costs of collective action associated with higher VK penetration might have increased the probability that those supporting the opposition would go protest, and that the latter effect outweighed the former. Both patterns would be fully consistent with Predictions 1 and 2 of our theoretical framework.

An alternative explanation, however, is that the availability of VK increased political polarization, so that it increased both the number of pro-government supporters and the

[42]Note that, because the effect is present for the 2008 Presidential and the 2011 Parliamentary elections, it is highly unlikely that the positive impact of social media on pro-government vote was *caused* by the social media's effect on protests.

TABLE III

VK PENETRATION AND VOTING OUTCOMES[a]

	IV (1)	IV (2)	IV (3)	IV (4)	OLS (5)	OLS (6)	OLS (7)	OLS (8)
	Voting Share for United Russia, 2007							
Log (number of VK users), June 2011	0.055 [0.057]	0.048 [0.053]	0.064 [0.055]	0.022 [0.045]	−0.020 [0.013]	−0.025 [0.011]	−0.019 [0.012]	−0.030 [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 [0.008]	−0.005 [0.007]	−0.007 [0.008]	−0.007 [0.007]	−0.008 [0.008]	−0.004 [0.007]	−0.007 [0.007]	−0.007 [0.007]
Log (SPbSU students), one cohort older than VK founder	0.001 [0.009]	0.001 [0.008]	−0.001 [0.009]	−0.003 [0.007]	0.009 [0.007]	0.008 [0.006]	0.006 [0.007]	0.001 [0.005]
	Voting Share for Medvedev, 2008							
	IV	IV	IV	IV	OLS	OLS	OLS	OLS
Log (number of VK users), June 2011	0.143 [0.079]	0.140 [0.077]	0.156 [0.080]	0.118 [0.068]	−0.003 [0.011]	−0.009 [0.010]	−0.005 [0.011]	−0.014 [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 [0.010]	−0.004 [0.009]	−0.006 [0.010]	−0.005 [0.008]	−0.005 [0.007]	−0.003 [0.006]	−0.005 [0.007]	−0.004 [0.006]
Log (SPbSU students), one cohort older than VK founder	−0.002 [0.011]	−0.002 [0.010]	−0.005 [0.011]	−0.005 [0.010]	0.012 [0.007]	0.011 [0.006]	0.008 [0.007]	0.006 [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 [0.152]	0.217 [0.131]	0.259 [0.147]	0.198 [0.128]	−0.035 [0.018]	−0.039 [0.017]	−0.031 [0.017]	−0.045 [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 [0.015]	−0.000 [0.014]	−0.004 [0.016]	−0.003 [0.013]	−0.003 [0.012]	0.002 [0.010]	−0.003 [0.012]	−0.001 [0.011]
Log (SPbSU students), one cohort older than VK founder	−0.003 [0.020]	0.003 [0.017]	−0.003 [0.018]	−0.005 [0.016]	0.024 [0.012]	0.026 [0.011]	0.020 [0.011]	0.016 [0.011]
	Voting Share for Putin, 2012							
	IV	IV	IV	IV	OLS	OLS	OLS	OLS
Log (number of VK users), June 2011	0.152 [0.088]	0.144 [0.085]	0.155 [0.084]	0.114 [0.073]	−0.011 [0.011]	−0.013 [0.010]	−0.010 [0.011]	−0.020 [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 [0.010]	0.001 [0.009]	0.000 [0.010]	−0.001 [0.008]	0.000 [0.008]	0.002 [0.007]	0.001 [0.007]	0.000 [0.007]
Log (SPbSU students), one cohort older than VK founder	0.003 [0.013]	0.004 [0.012]	0.001 [0.012]	0.000 [0.010]	0.018 [0.007]	0.018 [0.007]	0.015 [0.007]	0.011 [0.006]

(Continues)

number of people strongly opposed to the government.[43] 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 III could be explained by elec-

[43]This alternative explanation goes against the absence of a causal impact of social media on turnout (see Table A11 in the Supplemental Material), which also indicates that the results are unlikely to be driven by increased civic participation.

TABLE III—*Continued*

	Voting Share for United Russia, 2016							
	IV (1)	IV (2)	IV (3)	IV (4)	OLS (5)	OLS (6)	OLS (7)	OLS (8)
Log (number of VK users), June 2011	0.214 [0.108]	0.171 [0.098]	0.205 [0.097]	0.134 [0.072]	0.007 [0.019]	0.009 [0.017]	0.017 [0.018]	0.002 [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 [0.012]	0.004 [0.011]	0.000 [0.012]	0.001 [0.009]	0.000 [0.011]	0.006 [0.010]	0.001 [0.010]	0.001 [0.009]
Log (SPbSU students), one cohort older than VK founder	0.004 [0.016]	0.010 [0.015]	0.003 [0.015]	0.004 [0.011]	0.024 [0.011]	0.024 [0.011]	0.019 [0.010]	0.015 [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-statistics	6.554	6.779	7.591	7.031				
Effective F-statistics (Montiel Olea and Pflueger (2013))	10.97	12.03	12.30	12.17				

[a] 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. "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). Weak IV robust 95% confidence intervals are Anderson–Rubin confidence sets calculated using software in Finlay and Magnusson (2009), which accommodates heteroscedasticity.

toral fraud only if higher VK penetration was associated with a greater extent of electoral fraud, which does not seem 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 for President Dmitry Medvedev, Prime Minister Vladimir Putin, and for the government in general on a 6-point scale. They were also asked about their voting intentions in the upcoming parliamentary elections and their readiness to participate in a hypothetical protest demonstration.

The IV estimates for the effect of social media on the results of these polls are presented in Table IV. They turn out to be fully consistent with the effects on voting outcomes identified in Table III. Respondents in cities with 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.

TABLE IV

VK PENETRATION AND POLITICAL ATTITUDES[a]

	How Do You Assess the Work of President Dmitry Medvedev					
	Good and Getting Better (1)	Good and Remains the Same (2)	Good and Getting Worse (3)	Bad, but Getting Better (4)	Bad and Remains the Same (5)	Bad and Getting Worse (6)
Log (number of VK users), June 2011	0.234 [0.119]	−0.079 [0.130]	−0.052 [0.057]	−0.091 [0.059]	−0.016 [0.073]	0.031 [0.058]
Log (SPbSU students), one cohort younger than VK founder	−0.015 [0.015]	0.011 [0.009]	0.003 [0.007]	0.014 [0.005]	0.002 [0.010]	0.004 [0.008]
Log (SPbSU students), one cohort older than VK founder	−0.011 [0.017]	−0.016 [0.013]	−0.004 [0.010]	0.004 [0.007]	−0.011 [0.008]	−0.005 [0.007]
	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	0.185 [0.112]	−0.071 [0.119]	0.009 [0.045]	−0.060 [0.042]	−0.061 [0.071]	−0.008 [0.054]
Log (SPbSU students), one cohort younger than VK founder	−0.022 [0.016]	0.013 [0.009]	0.000 [0.006]	0.008 [0.004]	0.008 [0.008]	0.004 [0.007]
Log (SPbSU students), one cohort older than VK founder	−0.005 [0.016]	−0.022 [0.014]	−0.009 [0.007]	0.004 [0.005]	−0.003 [0.010]	−0.003 [0.006]
	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	0.292 [0.125]	0.102 [0.124]	−0.117 [0.073]	−0.078 [0.076]	−0.073 [0.100]	−0.019 [0.088]
Log (SPbSU students), one cohort younger than VK founder	−0.020 [0.018]	0.015 [0.013]	0.006 [0.008]	0.014 [0.007]	−0.001 [0.012]	−0.000 [0.009]
Log (SPbSU students), one cohort older than VK founder	−0.012 [0.018]	−0.026 [0.016]	0.004 [0.011]	0.004 [0.009]	−0.015 [0.010]	0.001 [0.010]

(Continues)

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).[44] 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. In line with Prediction 1 of our theoretical framework, these results suggest that reductions in the costs of collective action are the primary channel through which social media affects political protests, despite the fact that the information mechanism pulls in the opposite direction.[45]

[44]This result is supported by the negative effect of VK penetration on the share of invalid ballots in 2011 and 2012 elections (see Table A11 in the Supplemental Material). At the time of these elections, submitting invalid ballots was a common strategy of voicing discontent toward the government, and was promoted by a number of opposition leaders.

[45]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

TABLE IV—*Continued*

	Which Party Are You Planning to Vote for in December Elections					
	United Russia (1)	Just Russia (2)	LDPR (3)	KPRF (4)	Patriots of Russia (5)	Yabloko (6)
Log (number of VK users), June 2011	0.249	0.043	−0.051	−0.032	−0.002	−0.007
	[0.148]	[0.053]	[0.050]	[0.062]	[0.008]	[0.013]
Log (SPbSU students), one cohort younger than VK founder	−0.007	−0.001	0.007	0.004	0.001	0.002
	[0.015]	[0.005]	[0.005]	[0.005]	[0.001]	[0.002]
Log (SPbSU students), one cohort older than VK founder	−0.038	−0.003	0.003	0.001	0.000	−0.002
	[0.020]	[0.007]	[0.008]	[0.007]	[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	−0.270	0.096	0.182			
	[0.156]	[0.173]	[0.140]			
Log (SPbSU students), one cohort younger than VK founder	0.001	−0.003	0.001			
	[0.014]	[0.016]	[0.012]			
Log (SPbSU students), one cohort older than VK founder	0.022	−0.023	−0.001			
	[0.019]	[0.023]	[0.021]			

[a] Robust standard errors in brackets are adjusted by clusters within regions. Unit of observation is an individual respondent. Survey weights are applied. Logarithm of any variable is calculated with 1 added inside. The table presents results of 27 separate IV regressions. 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).

6.3. *Identifying Assumptions Checks*

6.3.1. *Placebo Results for Earlier Protests*

Table SA.II in the Appendix presents the results of the placebo regressions in which we estimate the same IV specifications as in columns (1)–(4) of Table II, 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 almost 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 SA.II because of large standard errors. However, in Panel A, we can reject this hypothesis for pro-democracy protests in 1987–1992 and the labor protests in 1997–2002.

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.

6.3.2. *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 III using various pre-VK electoral outcomes as dependent variables. These voting outcomes capture pre-existing political preferences, and the results in Table II suggest that they are collectively important for predicting the protest activity of 2011. Table SA.III in the Appendix 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 III, 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 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 Tables II and III).

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 address this possibility, we collect data on 62 other Russian universities of comparable quality.[46] Next, we replicate our baseline first-stage regression for each of these 62 universities. We then compare the resulting coefficients with those of the corresponding SPbSU cohorts. Figure SA.1 in the Appendix shows the empirical cumulative distribution functions of the coefficients for Durov's cohort (Figure SA.1(A)), the younger cohort (Figure SA.1(B)), and the older cohort (Figure SA.1(C)).[47] We highlight other universities in Saint Petersburg as they could have experienced spillovers because of their proximity to SPbSU, that is, their students could have also been more likely to join VK earlier.

Figure SA.1(A) indicates that the coefficient for Durov's cohort at SPbSU lies at the top end of the distribution and that, 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 SA.1(B) and SA.1(C). Thus, the results in Figure SA.1 indicate that out of all the cohorts in SPbSU, only Durov's cohort looks special for predicting 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 for student cohorts and instead rely on the information from the profiles of Odnoklass-

[46]See Section 4 for a discussion of how these universities were selected.

[47]Figure A7 in the Supplemental Material provides the corresponding graphs for the reduced form regressions.

niki users to infer the number of students in each university at each point in time. As was noted in Section 4, this concern is partially mitigated by the fact that 80% of adults in Russia active on social media were using Odnoklassniki at the time our data collection took place. This proportion was most likely 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 to this particular age cohort, to SPbSU, or to Saint Petersburg—the founder of Odnoklassniki, Albert Popkov, was born in Yuzno-Sakhalinsk on Sakhalin island, studied in Moscow at a technical college in the early 1990s, 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 address 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 A12 in the Supplemental Material 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 in smaller cities as the probability of a non-reporting error should be substantially smaller for bigger cities. However, as documented in Section 6.4.3 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.

6.3.6. *Alternative Definitions of Cohorts*

We perform several additional robustness checks to ensure that our results are not driven by our definition of cohorts. 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 A13 in the Supplemental Material for these robustness results).[48] Note that, independent of the width of the cohort window, the main IV coefficient for protest participation is quite 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 thus 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 cohort, 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 the cohorts.[49]

6.4. *Additional Evidence on Mechanisms*

6.4.1. *Political Content on VK*

The nature of political content on social media (parameter s_ω) plays an important role in our theoretical framework. If it is, on average, anti-regime, then we should expect an unambiguous positive effect of social media penetration on protests. If it is pro-regime, then the impact of social media on protests depends on the relative strength of the information and coordination channels. In Section 6.2, we documented that VK penetration has had a positive impact on the support for the Russian government, which suggests that VK content was likely pro-regime or, at least, neutral. However, it is still a question if it is true in the data.

We analyzed the content of all posts on VK before the 2011 elections, and confirm that VK content was not predominantly anti-regime. Specifically, our results suggest that Putin, Medvedev, and the ruling party were mentioned much more often in blog posts than the opposition candidates (see Figure A8 in the Supplemental Material). According to the standard content analysis measures, most of these posts were neutral, with the majority of posts consisting of jokes and funny stories, and sometimes even poems about the ruling candidates (see Figure A9 in the Supplemental Material). Very few posts were negative toward the government. Overall, our content analysis suggests that, at least on average, the information on social media preceding the elections was either neutral or positive toward the regime.

6.4.2. *Protest Participation and Online Protest Communities*

We also 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

[48]We believe that creating Durov's exact 1-year cohort is not an optimal approach for constructing the instrument because 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 even when 1-year cohorts are used, the results become noisier yet still point in the same direction.

[49]See Table A14 in the Supplemental Material for the baseline results calculated for the cohorts defined based on the years of study. Note that fewer people report their years of study on Odnoklassniki than their year of birth. Specifically, out of the 22,500 people we use to construct our instrument based on the year of birth, 3700 (16.4%) did not report their starting year of education and 4700 (20.8%) did not report their 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.

events. These communities were accessible to all VK users and were used for informing and coordinating offline protests. To provide evidence that the availability of such communities was systematically related to offline protests, Table A15 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 as 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.

6.4.3. *Effect of City Size*

According to Prediction 3 of 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. Additionally, the effect caused by the information channel is not expected to be stronger in larger cities, meaning that the impact of social media on voting in favor of the regime should not increase with city size.

Figures 4 and SA.2 in the Appendix present evidence supporting these predictions. In order to generate these figures, in the baseline IV specification we interact both the instrument and the endogenous variable with the indicator for whether a city's population exceeds a certain threshold.[50] We then display the coefficients on the interaction between the VK penetration and the population indicator, varying the population threshold.

Figure 4 shows that the IV coefficients for the effect of VK penetration on both the incidence of protests and the number of participants tend to be larger in larger cities. In particular, the additional effect on the incidence of protests increases from 0.02 to 0.05–0.07 and becomes more statistically significant with increases in city size threshold from 25,000 to 100,000. After reaching the threshold of about 100,000, the additional effect plateaus. However, the interaction coefficients for 25,000 and 150,000 city size thresholds are still statistically different from each other at the 10% significance level (p-value = 0.093).

At the same time, the effect of social media on the vote share of United Russia in 2011 and of Putin in 2012 does not exhibit any particular pattern of heterogeneity in city size (Figure SA.2). This further supports the idea that the positive impact of social media on protest participation is not driven by the information channel.[51]

[50]See Figure A10 in the Supplemental Material for the distribution of city sizes. Despite a large number of smaller cities, our results are robust to weighting the observations by city population (see Table A16 in the Supplemental Material).

[51]We can also investigate the heterogeneity of the results with respect to the other city characteristics, and not just city size. Table A17 reports our baseline IV results for various subsamples. We find that the effect comes mostly from 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 decreased effective F-statistics, which could lead to an overrejection problem (Andrews, Stock, and Sun (2019)).

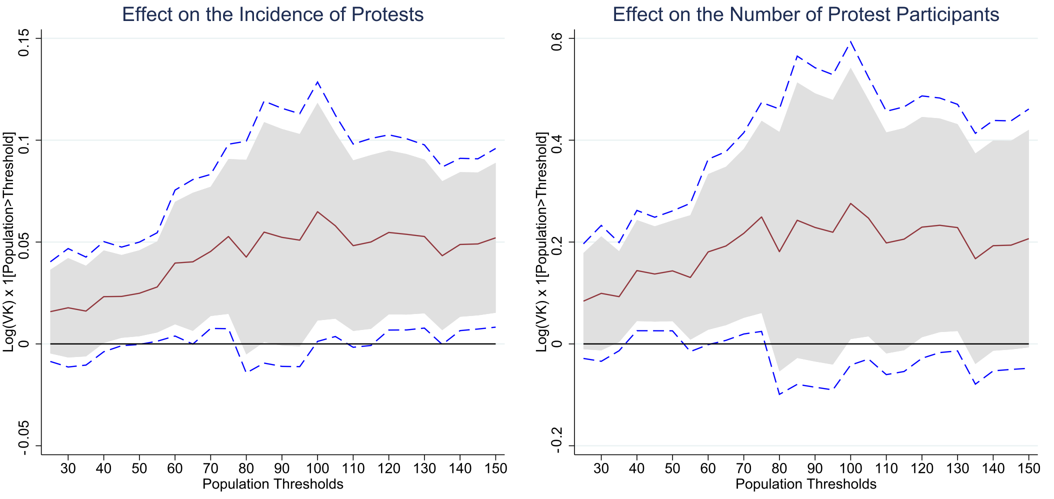

FIGURE 4.—Effect of social media on protest participation as a function of population threshold. *Notes*: The graphs display the additional effect of VK penetration on protest incidence and the logarithm of the number of protesters in December 2011 in larger cities. Specifically, in the baseline IV specification, both the instrument and the endogenous variable are interacted with the indicator for whether city population exceeds a certain threshold, in addition to including the instrument and the endogenous variable on their own. The figures show the resulting coefficients on the interaction between VK penetration and the population indicator, varying the population threshold on the x-axis (in thousands). Gray areas and dashed lines show the 90% and 95% confidence intervals, respectively.

6.4.4. *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.[52] In particular, we compute a fractionalization index, that is, the probability that two randomly picked social media users in a city belong to the same network. In the simplest case of non-overlapping audiences, 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 social media users in city i. Because we do not have information on the overlap of the audiences between 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 a partial overlap between the users from different networks.[53]

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 an OLS framework.[54] The information effect depends on the total

[52]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.

[53]See the derivations in Section A.2 of the Supplemental Material and the results in Table A18 in the Supplemental Material.

[54]Note that we are forced to use OLS for this specification as we do not have a good instrument for fractionalization. One could argue that, conditional on the total number of users and other controls, the split among different platforms was idiosyncratic and path-dependent, and because of this the OLS identifying assumption may actually hold in this case. However, we still caution the readers that the obtained estimates may not be causal and refrain from using the causal language throughout the section.

number of users in both networks and not on their sorting into the two networks because 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 because both coordination and social pressure work within the same network (regardless of which one). Thus, the more divided the users are between the networks, the harder it is for the collective action channel to operate.

Table SA.IV in the Appendix displays the results. These estimates imply that fractionalization is negatively associated with both protest participation and the incidence of the protests. Consistent with Prediction 3 of our theoretical framework, the negative effect of social media fractionalization on protest participation increases in magnitude with city size such that the negative effect is statistically significant only for large cities, for example, for a subsample of cities with a population over 100,000. Specifically, the results in column (5) indicate that, in larger cities, a one-standard-deviation increase in network fractionalization, which is about 0.13 points, is associated with a 37% lower protest participation and a 7.5 percentage point lower probability of protests occurring (see Figure 5 for additional information on how this effect depends on city size).[55] This pattern points toward the importance of the coordination function of social media in its effect on protest participation. Moreover, we find no association between social media fractionalization and voting outcomes (see Table A20 in the Supplemental Material), further suggesting that the link between fractionalization and protests is due to the coordination channel.

6.5. *Consequences for 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 primarily to the federal government, meaning 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.[56] Table A21 in the Supplemental Material presents the results. Overall, they 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. We refer the reader to Section A.3 of the Supplemental Material for a more detailed discussion of these results.

[55]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 A19 in the Supplemental Material. 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 A19, our results remain robust to this exercise.

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

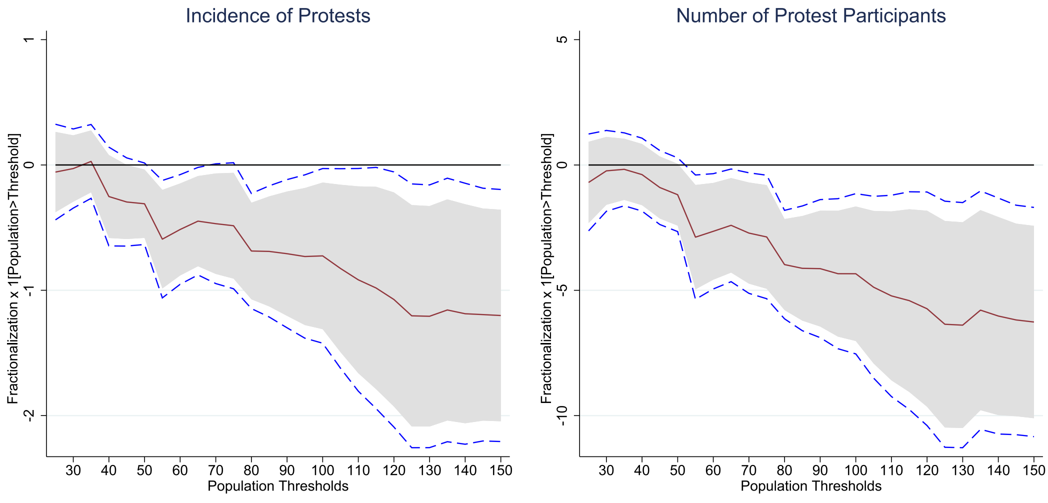

FIGURE 5.—Social media fractionalization and protests as a function of population. *Notes*: The graphs display the additional association of social media fractionalization and protest participation in larger cities. Specifically, in the OLS specification, fractionalization is interacted with the indicator for whether the city population exceeds a certain threshold, in addition to including the fractionalization variable on its own. The figures show the resulting coefficients on the interaction between VK penetration and the population indicator, varying the population threshold on the x-axis (in thousands). Gray areas show the 90% confidence intervals. Dashed lines display the 95% confidence intervals.

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 for 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 one's ability to overcome the collective action problem.

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, Pan, and Roberts (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, for environmental activism, and for hate crimes (see Bursztyn, Egorov, Enikolopov, and Petrova (2019) on the latter). We expect social media to reduce the costs of collective action in all of these circumstances, so 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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