Donetsk Don't Tell

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Online Appendix

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Contents

1. Survey Details

Representativeness

Our survey yields 903 respondents in Ukraine proper.[1] Representation is fairly even across voting-age groups -- the smallest category is 18-29 (18.1% of respondents), while the 30-44, 45-59, and 60+ categories, constitute 28.5%, 25.5%, and 28%, respectively. Just shy of 95% of respondents report an educational attainment of at least secondary school. Perhaps unsurprisingly given the substantial representation of older Ukrainians, only 44.9% of respondents are employed, while 27.1% are retired. Gender is fairly balanced, though favoring women (54.5%). While the survey favors urban areas, still ⅓ of respondents reside in rural locations. Moreover, as depicted in Figure 01, respondents are drawn fairly evenly from across the country's oblasts (provinces).

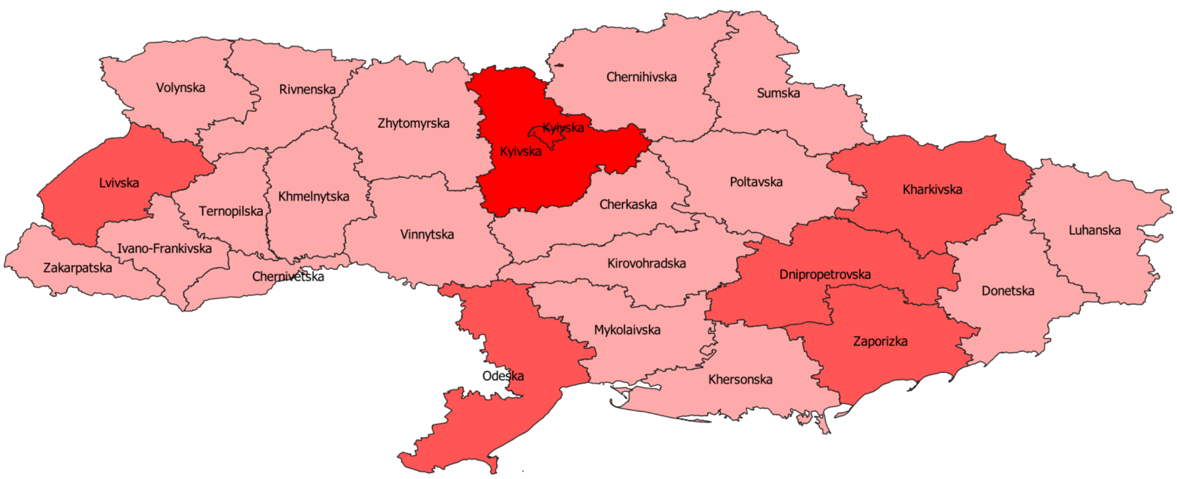

Figure 01: Survey representation by oblast

[1] A further 100 respondents were contacted in the Donbas region, but we drop them from the analysis due to concerns of selection bias.

Methods

To conduct the survey, we contracted the Kyiv International Institute for Sociology (KIIS) and its partner agency POLLSTER. KIIS is the premier institute for survey research of this kind in Ukraine and follows standard methodology and best practices, as outlined in more detail below.

Data collection method

The survey was conducted using anonymized computer-assisted telephone interviews (CATI).

Survey Procedure and Anonymity protection

According to a face-to-face survey conducted via random sample (by KIIS in February 2020), 96% of adults in Ukraine had personal mobile phones.

To conduct the survey at the initial stage, mobile phone numbers for all major mobile operators in Ukraine were generated completely randomly. The share of generated numbers per each mobile operator was approximately proportional to the share of total mobile numbers per each mobile operator (according to KIIS surveys). To remove non-existing numbers from the generated database, an "invisible" SMS message was sent to the generated numbers. The interviewers then called the generated numbers and invited the respondents who answered the call to take part in the survey.

Cases in the data file are stored with unique ID numbers. Names or other personal details are not recorded at any stage of the process. The file with contact phone numbers with the same ID is stored separately from the ID file. For a month after the completion of the project, this information is actively available to the core research group in case of inquiries from clients and respondents. After that, the file with phone numbers is deleted, and the data file is transferred to the archive on the server for 2 years.

During the field stage, 1003 interviews were collected. The survey included respondents from 146 settlements. Response rate – 14%.

Consent

Participation in the survey is voluntary, and participants can simply hang up the phone at any time to end the survey. Consent is recorded for each participant at the start of the interview. Sample text to be asked by the interviewer below [translated from Ukrainian]:

> "Hello! I am working at the research agency Pollster. We are carrying out a study of Ukrainian citizens to try to understand what people think about the media and how they feel about the important issues facing Ukraine today. Your phone number, like the 1,000 other phones in Ukraine, was randomly generated by a computer. All information obtained in the project will be used only in generalized form. No one, except the research team, will be able to connect

your answers with a certain phone number or your name. No one besides me and the organizers of the survey will know about our conversation. Participation in our research is completely voluntary and involves an interview that will take approximately 15 minutes. We very much want your answers to be candid. If you do not care to answer any question, tell me about that and we will move on to the next question. We thank you in advance for your help and cooperation."

Compensation

Participants are not compensated for their participation in this survey. The main reason is maintaining anonymity of participants, which are selected based on their phone numbers only—without linkage to any personal details (see above). Sending payment would necessitate linking phone numbers to names, thus forfeiting anonymity.

Ethics Review

We followed ethics guidelines of our host institutions when contracting POLLSTER. Moreover, the research methods used by the institute contracted for the survey, POLLSTER, have gone through review by its institutional review board headed by Dr. Natalia Kharchenko. Its researchers have all undergone at least eight hours of training to make sure they adhere to ethics standards and confidentiality rules.

The training program for this survey included special training (briefing) with:

- an explanation of the purpose of the survey;
- section-by-section review of the questionnaire in both Ukrainian and Russian,
- a clarification of peculiarities of the given survey procedure.
- trial interviews with other interviewers;
- a comprehensive discussion of directive and non-directive probing;
- human subjects protection.

Subsequent control interviews with researchers with instructors and supervisors ensure consistent adherence to ethics standards and research methodology.

Data Quality Control and Weighting

The *data quality control* included the next steps:

- 100% control of correctness and logic of questionnaires.
- Programming of logical checks and linkage between questions to prevent accidental mistakes during filling out.
- Additional data processing involves checking the completeness of the data file, controlling the outliers, checking / encoding text responses, and statistically weighing.

External control of a sample quality is carried out via comparison of received data with available statistics. To estimate possible shifts of the national sample (903 interviews), the raw results of the survey were compared with official statistics (in terms of type of location and gender-age population structure). The maximum discrepancy with statistics is less than 1%.

Survey Questions

1. Which party are you planning to vote for in the elections to oblast councils / [FOR KYIV] Kyiv city council on October 25, 2020?
   1.1 Servant of the People
   1.2 European Solidarity
   1.3 Opposition Platform for Life
   1.4 Batkivschyna
   1.5 Za Maibutnie (For the Future)
   1.6 Radical Party of Oleh Liashko
   1.7 Nash Krai
   1.8 UDAR of Vitali Klitschko
   1.9 Svoboda
   1.10 Party of Shariy
   1.11 Strength and Honor
   1.12 Proposition
   1.13 Holos
   1.14 Palchevsky Victory
   1.15 Another party (do not read out)
   1.16 I will not go to the ballot station (do not read out)
   1.17 I will spoil the ballot / I will cross out all the candidates
   1.18 It is hard to say, I have not decided yet (do not read out)
   1.19 Decline to answer (do not read out)

2. What is the single most important factor influencing your choice (please select only one)?

2.1 A desire for change	1
2.2 Saving democracy in Ukraine	2
2.3 A desire for continuity and stability	3
2.4 Economic policies (local budget, income tax reform)	4

2.5 Social Policies (pension reform)	5
2.6 Defense of Ukrainian identity	6
2.7 Local infrastructure improvements (roads, hospitals, playgrounds)	7
2.8 Local public housing policies	8
2.9 Ending the war in Eastern Ukraine	9
2.10 Government corruption	10
2.11 Maintain Ukrainian independence from Western influence	11
2.12 Maintain Ukrainian independence from Russian influence	12
2.13 International Relations with the EU	13
2.14 International Relations with Russia	14
2.15 Resolve the status of Crimea	15

3. Do you trust that the local elections in your district will be free of interference (electoral fraud)?
    3.1 Yes
    3.2 No
4. Do you trust that vote counting and results will be reliable?
    4.1 Yes
    4.2 No
5. How much do you trust the following institutions

	fully trust	trust somewhat	hard to say	somewhat distrust	do not trust at all

5.1 President of Ukraine	1	2	3	4	5
5.2 Verkhovna Rada of Ukraine	1	2	3	4	5
5.3 Government of Ukraine	1	2	3	4	5
5.4 Armed Forces of Ukraine	1	2	3	4	5
5.5 Security Service of Ukraine	1	2	3	4	5
5.6 National Police	1	2	3	4	5
5.7 Patrol police	1	2	3	4	5
5.8 Church	1	2	3	4	5
5.9 Ukrainian mass media	1	2	3	4	5
5.10 Russian mass media	1	2	3	4	5
5.11 Pro-European opposition	1	2	3	4	5
5.12 Pro-Russian opposition	1	2	3	4	5
5.13 Non-governmental organizations	1	2	3	4	5
5.14 Ordinary people in your settlement	1	2	3	4	5

6. What is your overall attitude towards the following countries and organizations?

	very good	mostly good	hard to say	mostl y bad	very bad
6.1 European Union	4	3	99	2	1
6.2 Russia	4	3	99	2	1

6.3 NATO	4	3	99	2	1
6.4 USA	4	3	99	2	1
6.5 International Monetary Fund	4	3	99	2	1

7. Which of these countries and organizations currently poses the greatest threat to Ukraine?
    7.1 USA
    7.2 Russia
    7.3 European Union
    7.4 International Monetary Fund

8. How much do you agree with the following statements on Ukraine's international relations?

	Strongly disagree	Disagree	Agree	Strongly agree
8.1 The Russian and Ukrainian people share a common heritage and history that is impossible to separate	1	2	3	4
8.2 Ukraine should pursue closer relations with the EU	1	2	3	4
8.3 Ukraine should pursue closer relations with Russia	1	2	3	4
8.4 Ukraine should pursue closer relations with the USA	1	2	3	4
8.5 Ukraine should join the European Union (EU)	1	2	3	4
8.6 Ukraine should become a member of NATO	1	2	3	4
8.7 Ukraine should join the Customs Union with Russia, Belarus, Kazakhstan, Armenia and Kyrgyzstan	1	2	3	4
8.8 Ukraine should remain strictly non-aligned and not	1	2	3	4

join either pro-Western or pro-Russian institutions				

9. How has Ukraine changed in your lifetime?

Over the course of my lifetime	Improved	Stayed the same	Declined
9.1 Life in Ukraine has ….	3	2	1
9.2 The strength of the community has ….	3	2	1
9.3 Ukraine's status on the world stage has …	3	2	1
9.4 Employment opportunities, jobs and the labour market in Ukraine have…	3	2	1

10. Demographic questions
    - 10.1 What year were you born?
    - 10.2 What is your gender?
        - 10.2.1 male
        - 10.2.2 female
        - 10.2.3 other
    - 10.3 What is your marital status?
        - 10.3.1 Never married
        - 10.3.2 married or civil union
        - 10.3.3 divorced
        - 10.3.4 separated
        - 10.3.5 widowed
        - 10.3.6 in a relationship
    - 10.4 What is the highest level of education you have completed?
        - 10.4.1 less than high school
        - 10.4.2 completed some high school
        - 10.4.3 high school graduate
        - 10.4.4 job-specific training program after high school
        - 10.4.5 Completed a Bachelor degree or equivalent
        - 10.4.6 Specialist
        - 10.4.7 Completed a Graduate Degree (Masters, PhD, or equivalent)
    - 10.5 What is your employment status?
        - 10.5.1 employed full time
        - 10.5.2 employed part time
        - 10.5.3 self-employed, entrepreneur

10.5.4 not employed, but looking for work
10.5.5 not employed and not looking for work
10.5.6 not employed, unable to work due to disability or illness
10.5.7 retired
10.5.8 student
10.5.9 homemaker

10.6 In 2019 the average household income in Ukraine was 12,118 UAH. Please rate your total household income compared to this average national income.

10.6.1 much lower
10.6.2 lower
10.6.3 average
10.6.4 higher
10.6.5 much higher

10.7 What languages do you speak at home and outside of home (at school (university)/work)? (you can select several options for each sub-question)

	At home	Outside of home, i.e. university or work
10.7.1 Ukrainian	1	1
10.7.2 Russian	2	2
10.7.3 Both, equally	3	3
10.7.4 Other (please specify)	4	4

11. How much do you trust the following news sources?

	Trust fully	Trust mostly	Hard to say	Somewhat distrust	Do not trust at all	Never heard of it
11.1 Ukrainian TV channel 1+1	4	3	2	1	0	99
11.2 Ukrainian TV channel: Україна	4	3	2	1	0	99
11.3 Ukrainian TV	4	3	2	1	0	99

channel: ICTV						
11.4 Ukrainian TV channel: СТБ	4	3	2	1	0	99
11.5 Ukrainian TV channel: Інтер	4	3	2	1	0	99
11.6 Ukrainian TV channel: 112 Україна	4	3	2	1	0	99
11.7 Ukrainian TV channel: NewsOne	4	3	2	1	0	99
11.8 Ukrainian TV: Прямий	4	3	2	1	0	99
11.9 Ukrainian TV: П’ятий канал	4	3	2	1	0	99
11.10 Ukrainian TV: Zik	4	3	2	1	0	99
11.11 Local TV channels	4	3	2	1	0	99
11.12 TV Channels from Russia	4	3	2	1	0	99
11.13 Western TV channels	4	3	2	1	0	99
11.14 Ukrainian Radio	4	3	2	1	0	99
11.15 Local radio	4	3	2	1	0	99

11.16 Local newspapers	4	3	2	1	0	99
11.17 News websites	4	3	2	1	0	99
11.18 Twitter	4	3	2	1	0	99
11.19 Facebook	4	3	2	1	0	99
11.20 VKontakte	4	3	2	1	0	99
11.21 WhatsApp	4	3	2	1	0	99
11.22 Telegram	4	3	2	1	0	99
11.23 Telegram Channel: Sorosiata	4	3	2	1	0	99
11.24 Telegram Channel: Tiomnyi Rytsar (DarkKnight)	4	3	2	1	0	99
11.25 Telegram Channel: Legitimnyi	4	3	2	1	0	99
11.26 Telegram Channel: Rezident	4	3	2	1	0	99
11.27 Telegram Channel: Joker	4	3	2	1	0	99
11.28 Other Telegram channel	4	3	2	1	0	99
11.29 Viber	4	3	2	1	0	99

11.30 YouTube	4	3	2	1	0	99
11.31 YouTube Channel: Anatoliy and Olga Shariy	4	3	2	1	0	99
11.32 Youtube channel: Klymenko Time	4	3	2	1	0	99
11.33 Youtube channel: Strana.ua	4	3	2	1	0	99
11.34 Youtube channel: Vitaliy Portnikov	4	3	2	1	0	99
11.35 Youtube channel: Sergiy Ivanov	4	3	2	1	0	99
11.36 Youtube channel: Pavlo Kazarin	4	3	2	1	0	99

12. What sources do you most often use to get information about political events?

	daily	regularly	occasionally	rarely	never	Never heard of it
12.1 Ukrainian TV channel 1+1	4	3	2	1	0	99
12.2	4	3	2	1	0	99

Ukrainian TV channel: Україна						
12.3 Ukrainian TV channel: ICTV	4	3	2	1	0	99
12.4 Ukrainian TV channel: СТБ	4	3	2	1	0	99
12.5 Ukrainian TV channel: Інтер	4	3	2	1	0	99
12.6 Ukrainian TV channel: 112 Україна	4	3	2	1	0	99
12.7 Ukrainian TV channel: NewsOne	4	3	2	1	0	99
12.8 Ukrainian TV: Прямий	4	3	2	1	0	99
12.9 Ukrainian TV: П'ятий канал	4	3	2	1	0	99
12.10 Ukrainian TV: Zik	4	3	2	1	0	99
12.11 Local TV channels	4	3	2	1	0	99
12.12 TV Channels	4	3	2	1	0	99

from Russia						
12.13 Western TV channels	4	3	2	1	0	99
12.14 Ukrainian Radio	4	3	2	1	0	99
12.15 Local radio	4	3	2	1	0	99
12.16 Local newspapers	4	3	2	1	0	99
12.17 News websites	4	3	2	1	0	99
12.18 Twitter	4	3	2	1	0	99
12.19 Facebook	4	3	2	1	0	99
12.20 VKontakte	4	3	2	1	0	99
12.21 WhatsApp	4	3	2	1	0	99
12.22 Telegram	4	3	2	1	0	99
12.23 Telegram Channel: Sorosiata	4	3	2	1	0	99
12.24 Telegram Channel: Tiomnyi Rytsar (DarkKnight)	4	3	2	1	0	99
12.25 Telegram	4	3	2	1	0	99

Channel: Legitimnyi						
12.26 Telegram Channel: Rezident	4	3	2	1	0	99
12.27 Telegram Channel: Joker	4	3	2	1	0	99
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12.33 Youtube channel: Strana.ua	4	3	2	1	0	99
12.34 Youtube channel: Vitaliy Portnikov	4	3	2	1	0	99
12.35 Youtube channel:	4	3	2	1	0	99

Sergiy Ivanov						
12.36 Youtube channel: Pavlo Kazarin	4	3	2	1	0	99

13. How often do you encounter messages, speeches, texts, videos where the following ideas are sounded?

	I've never heard this	I encounter this from time to time	I encounter this frequently	I encounter this every time
13.1 Ukraine is now under external governance by Western curators, creditors and Sorosiata (Soros' followers)	1	2	3	4
13.2 Soros and International Monetary Fund want to exploit Ukrainian lands	1	2	3	4
13.3 The International Monetary Fund has enslaved Ukraine to obtain its natural resources	1	2	3	4
13.4 USA deployed a network of bio labs in Ukraine	1	2	3	4
13.5 The U.S. curates Ukrainian media, activists and politicians	1	2	3	4

13.6 The European Union uses Ukrainians for low-paid labor	1	2	3	4
13.7 Western actors are interfering with Ukraine's election on October 25, 2020	1	2	3	4
13.8 Russia is interfering with Ukraine's elections on October 25, 2020	1	2	3	4
13.9 The increase of gas prices is a genocide of Ukrainian people	1	2	3	4
13.10 Anti-corruption reforms in Ukraine are driven by Western capitalists who want to take over the Ukrainian economy	1	2	3	4
13.11 Land reforms in Ukraine are driven by the West because Western capitalists want to buy all Ukrainian land	1	2	3	4
13.12 The West is as corrupt as Ukraine or more	1	2	3	4
13.13 Zelenskiy only continues Poroshenko's policies because he is totally dependent on the West	1	2	3	4
13.14 Ukraine and Russia are equally responsible for the war in Donbas	1	2	3	4

13.15 EU integration brought no benefits to Ukraine	1	2	3	4
13.16 Far-right / nationalists are flourishing in Ukraine and are a real political threat	1	2	3	4
13.17 Medical reforms of Suprun are against the people	1	2	3	4

14. Do you agree with the following

	I do not agree at all, these are fabrications	Sounds dubious, but it may be something	I tend to agree, very much like the trust	I agree unequivocally, this is so
14.1 Ukraine is now under external governance by Western curators, creditors and Sorosiata (Soros' followers)	1	2	3	4
14.2 Soros and International Monetary Fund want to exploit Ukrainian lands	1	2	3	4
14.3 The International Monetary Fund has enslaved Ukraine to obtain its natural resources	1	2	3	4
14.4 USA deployed a network of bio labs in Ukraine	1	2	3	4

14.5 The U.S. curates Ukrainian media, activists and politicians	1	2	3	4
14.6 The European Union uses Ukrainians for low-paid labor	1	2	3	4
14.7 Western actors are interfering with Ukraine's election on October 25	1	2	3	4
14.8 Russia is interfering with Ukraine's elections on October 25	1	2	3	4
14.9 The increase of gas prices is a genocide of Ukrainian people	1	2	3	4
14.10 Anti-corruption reforms in Ukraine are driven by Western capitalists who want to take over the Ukrainian economic	1	2	3	4
14.11 Land reforms in Ukraine are driven by the West because Western capitalists want to buy all Ukrainian land	1	2	3	4
14.12 The West is as corrupt as Ukraine or more	1	2	3	4
14.13 Zelenskiy only continues	1	2	3	4

Poroshenko's policies because he is totally dependent on the West				
14.14 Ukraine and Russia are equally responsible for the war in Donbas	1	2	3	4
14.15 EU integration brought no benefits to Ukraine	1	2	3	4
14.16 Far-right / nationalists are flourishing in Ukraine and are a real political threat	1	2	3	4
14.17 Medical reforms of Suprun are against the people	1	2	3	4

15. Please evaluate the following statements, to what extent do you agree that...

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
15.1 'In reality, it is not the Government who is leading the country and we do not know who is pulling the strings in the background'	1	2	3	4	5
15.2 'Jews often act in secret,	1	2	3	4	5

behind the scenes.'					
15.3 'Things happen in the world, which the public is never informed about.'	1	2	3	4	5
15.4 'There are secret organizations that greatly influence political decisions.'	1	2	3	4	5

16. Are you proud to be Ukrainian?

16.1 I am very proud	1
16.2 I am somewhat proud	2
16.3 I am not very proud	3
16.4 I am not proud at all	4
16.5 I am not Ukrainian	5

17. Which ethnicity do you personally identify with the most (pick only one)?

17.1 Armenian	1
17.2 Belorussian	2
17.3 Crimean Tatar	3
17.4 Hungarian	4
17.5 Romanian	5
17.6 Russian	6
17.7 Ukrainian	7
17.8 European	8
17.9 Jewish	9
17.10 Other, please specify	10

18. Would you rather live in a country that was more open to the world, or more secure

18.1 More open	1
18.2 More secure	2
18.3 Neither	3
18.4 Don't know	4

19. What values do you think are important to teach children?

19.1 It is important to raise a child to be ..	Respectful	Independent
19.2 It is important to raise a child to be ..	Obedient	Self sufficient
19.3 It is important to raise a child to be ..	Well behaved	Considerate
19.4 It is important to raise a child to be ..	Well mannered	Curious

2. Sample Regression Tables

Narrative Agreement and Foreign Policy Preferences (H1)

For the reader's convenience, we have printed the results for 1 of the 120 regressions below, where the dependent variable was agreement with the Russian narrative that the EU exploits Ukrainian labor, while the foreign policy preference was that the Ukraine should join NATO. Perhaps unsurprisingly, the regression results suggest a strong negative correlation: controlling for demographic and geographic variation, respondents who feel that Ukraine should join NATO tend to disagree that the EU exploits Ukrainian labor.

Dep. Variable:	agree_ukraine_should_join_nato	**R-squared:**	0.226
Model:	OLS	**Adj. R-squared:**	0.192
Method:	Least Squares	**F-statistic:**	nan
Date:	Wed, 05 Jan 2021	**Prob (F-statistic):**	nan
Time:	17:45:09	**Log-Likelihood:**	-520.75
No. Observations:	903	**AIC:**	1119.
Df Residuals:	864	**BIC:**	1307.
Df Model:	38		
Covariance Type:	HC1		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
eu_exploit_ukr_labor_6	-0.1202	0.031	-3.824	0.000	-0.182	-0.059
liberal_score	0.1914	0.056	3.432	0.001	0.082	0.301
age_gr_30-44	-0.0596	0.049	-1.214	0.225	-0.156	0.037
age_gr_45-59	0.0134	0.050	0.269	0.788	-0.084	0.111
age_gr_60+	0.0797	0.050	1.593	0.112	-0.019	0.178
dummy_Urban	0.0022	0.036	0.062	0.951	-0.068	0.072
gender_female	-0.0448	0.031	-1.443	0.149	-0.106	0.016
marital_status_married_or_dating	-0.0016	0.033	-0.048	0.962	-0.067	0.064
postsecondary_tech	-0.0326	0.039	-0.843	0.400	-0.109	0.043
postsecondary_academic	0.0177	0.050	0.353	0.724	-0.080	0.116
employed	-0.0051	0.034	-0.149	0.882	-0.072	0.062
household_econ_status_avg_or_above	0.1534	0.033	4.643	0.000	0.089	0.218
oblast_Cherkaska	0.5427	0.112	4.863	0.000	0.324	0.762
oblast_Chernihivska	0.4181	0.155	2.703	0.007	0.115	0.722
oblast_Chernivetska	0.4196	0.115	3.660	0.000	0.195	0.645
oblast_Dnipropetrovska	0.2093	0.103	2.023	0.043	0.006	0.412
oblast_Donetska [GCT]	0.1141	0.111	1.028	0.304	-0.104	0.332
oblast_Ivano-Frankivska	0.6001	0.109	5.520	0.000	0.387	0.813
oblast_Kharkivska	0.2577	0.098	2.621	0.009	0.065	0.451
oblast_Khersonska	0.2612	0.125	2.086	0.037	0.015	0.507
oblast_Khmelnytska	0.4865	0.119	4.091	0.000	0.253	0.720
oblast_Kirovohradska	0.4604	0.127	3.631	0.000	0.212	0.709
oblast_Kyiv City	0.5123	0.100	5.122	0.000	0.316	0.709
oblast_Kyivska	0.4705	0.101	4.669	0.000	0.273	0.668
oblast_Luhanska [GCT]	0.1998	0.131	1.522	0.128	-0.058	0.457
oblast_Lvivska	0.4893	0.100	4.902	0.000	0.293	0.685
oblast_Mykolayivska	0.3039	0.121	2.513	0.012	0.067	0.541
oblast_Odeska	0.0934	0.097	0.966	0.334	-0.096	0.283
oblast_Poltavska	0.6118	0.115	5.334	0.000	0.387	0.837
oblast_Rivnenska	0.6623	0.105	6.337	0.000	0.457	0.867
oblast_Sumska	0.4233	0.142	2.983	0.003	0.145	0.702
oblast_Ternopilska	0.5392	0.125	4.312	0.000	0.294	0.785
oblast_Vinnytska	0.4653	0.112	4.145	0.000	0.245	0.686
oblast_Volynska	0.5492	0.109	5.052	0.000	0.336	0.763
oblast_Zakarpatska	0.4474	0.117	3.816	0.000	0.217	0.678
oblast_Zaporizka	0.3517	0.103	3.421	0.001	0.150	0.554
oblast_Zhytomyrska	0.3681	0.119	3.092	0.002	0.134	0.602
identity_Ukrainian	0.1574	0.054	2.916	0.004	0.051	0.263
identity_Russian	-0.0983	0.073	-1.342	0.180	-0.242	0.045

Narrative Exposure and Agreement (H2)

To test H1, we run 15 (non-causal) regressions for each of the 15 Russian narratives, taking the following format:

$$agree_i = \beta_{exposed} \cdot exposed_i + oblast_i + \boldsymbol{\beta} \cdot \boldsymbol{X}_i + \varepsilon_i$$

Where the unit of observation i is a survey respondent; The dependent variable $agree_i$ is a binary indicator that takes the value 1 if respondent i expressed agreement with a given Russian narrative, 0 otherwise; the independent variable $exposed_i$ takes the value 1 if respondent i confirmed prior exposure to the Russian narrative, and 0 otherwise; $oblast_i$ is the intercept term for each oblast (province) in the study (see the map above); and $\mathbf{X}_i$ is an NxK matrix of demographic and geographic controls for respondent i (see Table 1 in this appendix for a complete list of these controls).

For the reader's convenience, we present below the results for one of these 15 regressions, corresponding to the Russian narrative that "EU integration brings no benefits to Ukraine".

Dep. Variable:	eu_intgr_no_benefits_15_agree	**R-squared:**	0.201
Model:	OLS	**Adj. R-squared:**	0.165
Method:	Least Squares	**F-statistic:**	nan
Date:	Wed, 05 Jan 2021	**Prob (F-statistic):**	nan
Time:	17:16:03	**Log-Likelihood:**	-524.30
No. Observations:	903	**AIC:**	1127.
Df Residuals:	864	**BIC:**	1314.
Df Model:	38		
Covariance Type:	HC1		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
eu_intgr_no_benefits_15_exposed	0.3501	0.040	8.664	0.000	0.271	0.429
liberal_score	-0.1143	0.052	-2.181	0.029	-0.217	-0.011
age_gr_30-44	-0.0534	0.047	-1.140	0.255	-0.145	0.039
age_gr_45-59	-0.0236	0.048	-0.493	0.622	-0.118	0.070
age_gr_60+	0.0511	0.050	1.031	0.303	-0.046	0.148
dummy_Urban	-0.0369	0.035	-1.041	0.298	-0.106	0.033
gender_female	0.0033	0.031	0.107	0.915	-0.057	0.064
marital_status_married_or_dating	-0.0227	0.033	-0.689	0.491	-0.088	0.042
postsecondary_tech	0.0036	0.038	0.094	0.925	-0.071	0.079
postsecondary_academic	-0.0094	0.049	-0.190	0.849	-0.106	0.088
employed	-0.0222	0.033	-0.665	0.506	-0.088	0.043
household_econ_status_avg_or_above	-0.0625	0.033	-1.913	0.056	-0.127	0.002
oblast_Cherkaska	0.5224	0.112	4.650	0.000	0.302	0.743
oblast_Chernihivska	0.5113	0.158	3.227	0.001	0.200	0.822
oblast_Chernivetska	0.3384	0.113	2.987	0.003	0.116	0.561
oblast_Dnipropetrovska	0.5280	0.098	5.413	0.000	0.337	0.720
oblast_Donetska [GCT]	0.5565	0.110	5.056	0.000	0.341	0.773
oblast_Ivano-Frankivska	0.4224	0.107	3.933	0.000	0.212	0.633
oblast_Kharkivska	0.5183	0.095	5.453	0.000	0.332	0.705
oblast_Khersonska	0.7332	0.120	6.097	0.000	0.497	0.969
oblast_Khmelnytska	0.3878	0.106	3.645	0.000	0.179	0.597
oblast_Kirovohradska	0.2671	0.107	2.487	0.013	0.056	0.478
oblast_Kyiv City	0.4409	0.096	4.575	0.000	0.252	0.630
oblast_Kyivska	0.4088	0.103	3.968	0.000	0.207	0.611
oblast_Luhanska [GCT]	0.6166	0.127	4.858	0.000	0.367	0.866
oblast_Lvivska	0.2093	0.084	2.481	0.013	0.044	0.375
oblast_Mykolayivska	0.4902	0.114	4.299	0.000	0.266	0.714
oblast_Odeska	0.5229	0.096	5.462	0.000	0.335	0.711
oblast_Poltavska	0.3282	0.116	2.836	0.005	0.101	0.555
oblast_Rivnenska	0.2584	0.112	2.314	0.021	0.039	0.478
oblast_Sumska	0.3725	0.133	2.804	0.005	0.112	0.633
oblast_Ternopilska	0.4211	0.109	3.861	0.000	0.207	0.635
oblast_Vinnytska	0.4114	0.114	3.603	0.000	0.187	0.635
oblast_Volynska	0.3590	0.106	3.401	0.001	0.152	0.566
oblast_Zakarpatska	0.6373	0.113	5.651	0.000	0.416	0.859
oblast_Zaporizka	0.4351	0.101	4.303	0.000	0.237	0.634
oblast_Zhytomyrska	0.5328	0.116	4.575	0.000	0.304	0.761
identity_Ukrainian	-0.0054	0.054	-0.099	0.921	-0.112	0.101
identity_Russian	0.1485	0.074	1.996	0.046	0.002	0.295

Agreement, Exposure and Media Consumption

To test H3, we run the following regressions for each of the 15 Russian narratives:

$$agree_i = \beta_{media} \cdot media\_consumption_i + oblast_i + \boldsymbol{\beta} \cdot \boldsymbol{X}_i + \varepsilon_i$$

$$exposed_i = \beta_{media} \cdot media\_consumption_i + oblast_i + \boldsymbol{\beta} \cdot \boldsymbol{X}_i + \varepsilon_i$$

As before, the unit of observation is the survey respondent *i*. Dependent variables $agree_i$ and $exposure_i$, and independent variables $oblast_i$ and $\mathbf{X}_i$, are defined the same way as above. The independent variable of interest, $media\_consumption_i$, takes the value 1 if respondent *i* consumes at least 1 of the 36 media types mentioned in the survey, and 0 otherwise. For the reader's convenience, we print below the results of one of the 30 regressions, corresponding to agreement with the narrative "the West is as corrupt as the Ukraine or more".

Dep. Variable:	west_just_as_corrupt_12	**R-squared:**	0.089
Model:	OLS	**Adj. R-squared:**	0.049
Method:	Least Squares	**F-statistic:**	nan
Date:	Wed, 05 Jan 2021	**Prob (F-statistic):**	nan
Time:	17:22:12	**Log-Likelihood:**	-578.91
No. Observations:	903	**AIC:**	1236.
Df Residuals:	864	**BIC:**	1423.
Df Model:	38		
Covariance Type:	HC1		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
media_consumption	-0.0583	0.044	-1.315	0.189	-0.145	0.029
liberal_score	-0.0294	0.058	-0.505	0.613	-0.144	0.085
age_gr_30-44	0.0581	0.049	1.180	0.238	-0.039	0.155
age_gr_45-59	0.0215	0.049	0.438	0.661	-0.075	0.118
age_gr_60+	0.0875	0.051	1.709	0.088	-0.013	0.188
dummy_Urban	-0.0166	0.038	-0.441	0.659	-0.090	0.057
gender_female	0.0065	0.033	0.200	0.842	-0.058	0.071
marital_status_married_or_dating	-0.0695	0.035	-2.002	0.046	-0.138	-0.001
postsecondary_tech	0.0924	0.040	2.323	0.020	0.014	0.171
postsecondary_academic	0.0094	0.052	0.183	0.855	-0.092	0.111
employed	-0.0401	0.036	-1.124	0.261	-0.110	0.030
household_econ_status_avg_or_above	-0.0656	0.035	-1.888	0.059	-0.134	0.003
oblast_Cherkaska	0.5009	0.121	4.152	0.000	0.264	0.738
oblast_Chernihivska	0.4996	0.165	3.025	0.003	0.175	0.824
oblast_Chernivetska	0.4410	0.122	3.601	0.000	0.201	0.681
oblast_Dnipropetrovska	0.4696	0.105	4.470	0.000	0.263	0.676
oblast_Donetska [GCT]	0.6029	0.121	5.000	0.000	0.366	0.840
oblast_Ivano-Frankivska	0.4875	0.119	4.095	0.000	0.254	0.721
oblast_Kharkivska	0.5260	0.105	4.991	0.000	0.319	0.733
oblast_Khersonska	0.6308	0.133	4.747	0.000	0.370	0.892
oblast_Khmelnytska	0.5637	0.119	4.731	0.000	0.330	0.798
oblast_Kirovohradska	0.4976	0.133	3.741	0.000	0.236	0.759
oblast_Kyiv City	0.5075	0.108	4.682	0.000	0.295	0.720
oblast_Kyivska	0.5810	0.107	5.417	0.000	0.371	0.792
oblast_Luhanska [GCT]	0.5776	0.145	3.983	0.000	0.293	0.862
oblast_Lvivska	0.4492	0.103	4.364	0.000	0.247	0.651
oblast_Mykolayivska	0.6493	0.125	5.196	0.000	0.404	0.895
oblast_Odeska	0.4437	0.102	4.356	0.000	0.244	0.644
oblast_Poltavska	0.4979	0.126	3.955	0.000	0.251	0.745
oblast_Rivnenska	0.3728	0.123	3.025	0.003	0.131	0.615
oblast_Sumska	0.2954	0.124	2.388	0.017	0.053	0.538
oblast_Ternopilska	0.3803	0.125	3.044	0.002	0.135	0.626
oblast_Vinnytska	0.4864	0.119	4.103	0.000	0.254	0.719
oblast_Volynska	0.4931	0.122	4.044	0.000	0.254	0.732
oblast_Zakarpatska	0.8125	0.119	6.802	0.000	0.578	1.047
oblast_Zaporizka	0.4806	0.110	4.387	0.000	0.266	0.696
oblast_Zhytomyrska	0.5125	0.121	4.221	0.000	0.274	0.751
identity_Ukrainian	-0.1113	0.058	-1.926	0.054	-0.225	0.002
identity_Russian	0.1780	0.084	2.114	0.035	0.013	0.343

Agreement, Exposure and Media Type

The regressions for Table 4 are almost identical to the regressions for Table 3 (see above), except that two new independent variables are added:

$$agree_i = \beta_{media} \cdot media\_consumption_i + \beta_{TV} \cdot TV\_consumption_i + \beta_{SM} \cdot SM\_consumption_i + oblast_i + \boldsymbol{\beta} \cdot \boldsymbol{X}_i + \varepsilon_i$$

$$exposed_i = \beta_{media} \cdot media\_consumption_i + \beta_{TV} \cdot TV\_consumption_i + \beta_{SM} \cdot SM\_consumption_i + oblast_i + \boldsymbol{\beta} \cdot \boldsymbol{X}_i + \varepsilon_i$$

The first of the new independent variables is $TV\_consumption_i$, which takes the value 1 if respondent *i* regularly consumes at least one of the TV channels mentioned in the survey, and 0 otherwise. The other variable, $SM\_consumption_i$, takes the value 1 if respondent *i* regularly consumes at least one of the social media channels mentioned in the survey, and 0 otherwise.

For the reader's convenience, we print below the results of one of the 30 regressions, corresponding to exposure to the narrative "Medical reforms of Suprun are against the people".

Dep. Variable:	medical_suprun_bad_17	**R-squared:**	0.136
Model:	OLS	**Adj. R-squared:**	0.096
Method:	Least Squares	**F-statistic:**	nan
Date:	Wed, 05 Jan 2021	**Prob (F-statistic):**	nan
Time:	17:24:42	**Log-Likelihood:**	-564.58
No. Observations:	903	**AIC:**	1211.
Df Residuals:	862	**BIC:**	1408.
Df Model:	40		
Covariance Type:	HC1		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
media_consumption	0.0950	0.057	1.680	0.093	-0.016	0.206
SM_consumption	0.0600	0.039	1.542	0.124	-0.016	0.136
TV_consumption	0.0511	0.040	1.292	0.197	-0.027	0.129
liberal_score	0.0184	0.057	0.322	0.747	-0.094	0.130
age_gr_30-44	0.1145	0.045	2.542	0.011	0.026	0.203
age_gr_45-59	0.1440	0.048	3.001	0.003	0.050	0.238
age_gr_60+	0.2366	0.052	4.524	0.000	0.134	0.339
dummy_Urban	0.0763	0.037	2.054	0.040	0.003	0.149
gender_female	0.0716	0.033	2.185	0.029	0.007	0.136
marital_status_married_or_dating	-0.0141	0.034	-0.413	0.680	-0.081	0.053
postsecondary_tech	-0.0084	0.039	-0.214	0.830	-0.086	0.069
postsecondary_academic	-0.0365	0.051	-0.709	0.478	-0.138	0.065
employed	-0.0265	0.036	-0.744	0.457	-0.097	0.043
household_econ_status_avg_or_above	-0.0346	0.034	-1.004	0.316	-0.102	0.033
oblast_Cherkaska	-0.0834	0.111	-0.754	0.451	-0.300	0.134
oblast_Chernihivska	0.0256	0.164	0.156	0.876	-0.297	0.348
oblast_Chernivetska	-0.2192	0.104	-2.112	0.035	-0.423	-0.016
oblast_Dnipropetrovska	0.0457	0.103	0.441	0.659	-0.157	0.249
oblast_Donetska [GCT]	0.1132	0.117	0.969	0.333	-0.116	0.343
oblast_Ivano-Frankivska	-0.0312	0.112	-0.280	0.780	-0.250	0.188
oblast_Kharkivska	0.0142	0.101	0.140	0.888	-0.185	0.213
oblast_Khersonska	0.1899	0.132	1.440	0.150	-0.069	0.449
oblast_Khmelnytska	0.1013	0.123	0.824	0.410	-0.140	0.343
oblast_Kirovohradska	0.1084	0.133	0.817	0.414	-0.152	0.369
oblast_Kyiv City	-0.0008	0.107	-0.007	0.994	-0.210	0.208
oblast_Kyivska	0.0141	0.108	0.131	0.896	-0.197	0.225
oblast_Luhanska [GCT]	-0.1101	0.127	-0.864	0.388	-0.360	0.140
oblast_Lvivska	-0.1562	0.096	-1.623	0.105	-0.345	0.033
oblast_Mykolayivska	0.0876	0.119	0.736	0.462	-0.146	0.321
oblast_Odeska	-0.0302	0.095	-0.318	0.751	-0.217	0.156
oblast_Poltavska	-0.1573	0.120	-1.307	0.192	-0.393	0.079
oblast_Rivnenska	0.0105	0.129	0.081	0.935	-0.242	0.263
oblast_Sumska	-0.0246	0.126	-0.195	0.845	-0.272	0.223
oblast_Ternopilska	0.0791	0.139	0.567	0.571	-0.195	0.353
oblast_Vinnytska	0.1079	0.114	0.949	0.343	-0.115	0.331
oblast_Volynska	-0.1311	0.106	-1.234	0.218	-0.340	0.077
oblast_Zakarpatska	0.2375	0.131	1.817	0.070	-0.019	0.494
oblast_Zaporizka	0.0991	0.105	0.947	0.344	-0.106	0.304
oblast_Zhytomyrska	0.2046	0.122	1.680	0.093	-0.034	0.444
identity_Ukrainian	0.0290	0.054	0.538	0.590	-0.077	0.135
identity_Russian	0.2548	0.076	3.353	0.001	0.106	0.404

Agreement, Exposure and Partisan Media Type (H2 & H3)

The regressions for Table 5 expand upon the regressions for Table 4 (see above) by adding a few extra independent variables:

$$agree_i = \beta_{media} \cdot media\_consumption_i + \beta_{TV} \cdot TV\_consumption_i + \beta_{SM} \cdot SM\_consumption_i + \beta_{medvechuk} \cdot medvechuk\_consumption_i + \beta_{telegram} \cdot telegram\_consumption_i + \beta_{telegram\_partisan} \cdot telegram\_partisan\_consumption_i + \beta_{youtube} \cdot youtube\_consumption_i + \beta_{youtube\_partisan} \cdot youtube\_partisan\_consumption_i + oblast_i + \boldsymbol{\beta} \cdot \boldsymbol{X}_i + \varepsilon_i$$

$$exposed_i = \beta_{media} \cdot media\_consumption_i + \beta_{TV} \cdot TV\_consumption_i + \beta_{SM} \cdot SM\_consumption_i + \beta_{medvechuk} \cdot medvechuk\_consumption_i + \beta_{telegram} \cdot telegram\_consumption_i + \beta_{telegram\_partisan} \cdot telegram\_partisan\_consumption_i + \beta_{youtube} \cdot youtube\_consumption_i + \beta_{youtube\_partisan} \cdot youtube\_partisan\_consumption_i + oblast_i + \boldsymbol{\beta} \cdot \boldsymbol{X}_i + \varepsilon_i$$

For the reader's convenience, we print below the results of one of the 30 regressions, corresponding to exposure to the narrative "Gas prices are a genocide of the Ukrainian people".

Dep. Variable:	gas_price_genoicde_9	**R-squared:**	0.126
Model:	OLS	**Adj. R-squared:**	0.080
Method:	Least Squares	**F-statistic:**	nan
Date:	Wed, 05 Jan 2021	**Prob (F-statistic):**	nan
Time:	17:26:52	**Log-Likelihood:**	-558.30
No. Observations:	903	**AIC:**	1209.
Df Residuals:	857	**BIC:**	1430.
Df Model:	45		
Covariance Type:	HC1		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
media_consumption	0.1602	0.058	2.763	0.006	0.046	0.274
SM_consumption	-0.0568	0.051	-1.105	0.269	-0.158	0.044
TV_consumption	-0.0242	0.043	-0.560	0.576	-0.109	0.061
medvechuk_consumption	0.1086	0.047	2.299	0.022	0.016	0.201
telegram_consumption	-0.1016	0.051	-2.004	0.045	-0.201	-0.002
telegram_partisan_consumption	-0.0466	0.127	-0.367	0.713	-0.296	0.202
youtube_consumption	0.0279	0.049	0.575	0.565	-0.067	0.123
youtube_partisan_consumption	0.0790	0.063	1.264	0.207	-0.044	0.202
liberal_score	-0.0207	0.057	-0.365	0.715	-0.132	0.090
age_gr_30-44	0.0208	0.047	0.447	0.655	-0.071	0.112
age_gr_45-59	0.0787	0.049	1.605	0.109	-0.018	0.175
age_gr_60+	0.1327	0.053	2.481	0.013	0.028	0.238
dummy_Urban	0.0602	0.038	1.571	0.116	-0.015	0.135
gender_female	-0.0294	0.033	-0.901	0.368	-0.093	0.035
marital_status_married_or_dating	-0.0205	0.034	-0.603	0.547	-0.087	0.046
postsecondary_tech	-0.0030	0.040	-0.074	0.941	-0.082	0.076
postsecondary_academic	-0.0138	0.053	-0.262	0.793	-0.117	0.090
employed	-0.0276	0.036	-0.759	0.448	-0.099	0.044
household_econ_status_avg_or_above	-0.0892	0.034	-2.637	0.009	-0.156	-0.023
oblast_Cherkaska	0.4112	0.126	3.272	0.001	0.165	0.658
oblast_Chernihivska	0.4218	0.163	2.587	0.010	0.102	0.742
oblast_Chernivetska	0.3370	0.126	2.664	0.008	0.089	0.585
oblast_Dnipropetrovska	0.3726	0.106	3.506	0.000	0.164	0.581
oblast_Donetska [GCT]	0.2198	0.114	1.930	0.054	-0.004	0.443
oblast_Ivano-Frankivska	0.4619	0.119	3.875	0.000	0.228	0.696
oblast_Kharkivska	0.2925	0.105	2.782	0.006	0.086	0.499
oblast_Khersonska	0.3711	0.134	2.760	0.006	0.107	0.635
oblast_Khmelnytska	0.2403	0.118	2.037	0.042	0.009	0.472
oblast_Kirovohradska	0.3965	0.136	2.915	0.004	0.130	0.663
oblast_Kyiv City	0.2633	0.105	2.508	0.012	0.057	0.469
oblast_Kyivska	0.2697	0.106	2.549	0.011	0.062	0.477
oblast_Luhanska [GCT]	0.3260	0.131	2.492	0.013	0.069	0.583
oblast_Lvivska	0.1351	0.095	1.422	0.155	-0.051	0.322
oblast_Mykolayivska	0.4154	0.123	3.372	0.001	0.174	0.657
oblast_Odeska	0.1963	0.097	2.028	0.043	0.006	0.386
oblast_Poltavska	0.2746	0.132	2.086	0.037	0.016	0.533
oblast_Rivnenska	0.3120	0.131	2.390	0.017	0.056	0.568
oblast_Sumska	0.1331	0.132	1.006	0.315	-0.126	0.393
oblast_Ternopilska	0.5095	0.141	3.610	0.000	0.232	0.786
oblast_Vinnytska	0.1729	0.106	1.629	0.104	-0.035	0.381
oblast_Volynska	0.3213	0.121	2.657	0.008	0.084	0.559
oblast_Zakarpatska	0.5462	0.142	3.848	0.000	0.268	0.825
oblast_Zaporizka	0.3286	0.109	3.019	0.003	0.115	0.542
oblast_Zhytomyrska	0.3234	0.117	2.776	0.006	0.095	0.552
identity_Ukrainian	-0.0765	0.056	-1.363	0.173	-0.187	0.034
identity_Russian	-0.0085	0.081	-0.105	0.917	-0.167	0.150

3. Twitter: Evidence of American Influence?

We also conducted a content analysis on Twitter because prior research and reporting has highlighted its importance as a platform for disinformation dissemination (Karina Shyrokykh 2020), and for the pragmatic reason that—in contrast to the other social media platforms—it allows automated ingestion of data. Our twitter dataset consists of all tweets mentioning any of over 2000 possible spellings of 46 Ukrainian word-pairs corresponding to the 15 narratives we track. Our sample period is September 13th to December 22nd, 2020, chosen to include the 2020 local elections in Ukraine where targeted Russian meddling could be expected. We collapse the 46 word-pairs into 9 samples of data corresponding to the narratives tracked. We then scour the samples for account birthdate anomalies, a tried-and-true method for detecting coordinated campaigns (Abrahams and Leber 2021; Jones 2019). Using the birth anomaly detection method, we find little evidence of coordinated Russian manipulation, but instead intriguing overlap with American right-wing narratives related to the 2020 presidential elections.

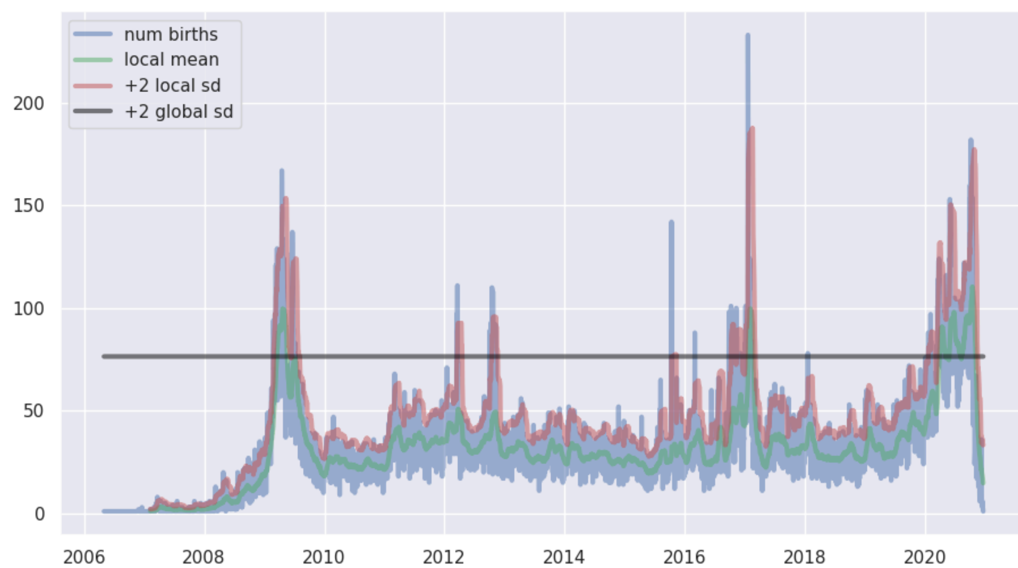

Figure 2: Birth date anomaly detection for tweets related to two corruption-related narratives. Anomalous birth spikes are visible wherever the blue curve rises two standard deviations above the global mean (horizontal black line) and two standard deviations above the rolling mean (red curve).

Figure 2 presents a birth anomaly detection chart for all Twitter accounts that tweeted tweets containing word pairs related to Russian narratives around Ukrainian corruption.[2] Birth spikes transcending two standard deviations above the global and local means are visible as tall blue spikes.

[2] In particular, these are narratives 10 and 12 from the survey, alleging that Western capitalists are behind calls for anti-corruption reforms in the Ukraine, and that the West is as corrupt or more corrupt than the Ukraine.

Across our 9 samples, an average of just 4.54% of Twitter users were born during anomalous birth spikes. Only two samples yielded a substantial number of tweets (more than 50 thousand each), namely, the sample of tweets mentioning both "Ukraine/ian(s)" and "corrupt(ion)" in English, Ukrainian, or Russian (narratives 13 and 14); and the sample of tweets corresponding to the Donbas war (narrative 7). For narratives 13/14 and 7, anomalously born users comprised merely 4% and 3.1% of all users, respectively. However, these users showed superior follower numbers than normal Twitter users. On average, anomalous users tweeting content corresponding to narratives 13 and 14 had roughly 22,000 followers, for example, compared to 6000 average users for normal accounts. Did we thus uncover a coordinated Russian social media influence campaign showing a highly effective use of inauthentic users reaching a large audience—thus disconfirming H4?

A closer look at the data produces a surprise, underlining the challenge of attributing social media campaigns and their transnational linkages. The biggest, most anomalous spikes in both datasets tended to occur on the days immediately following Donald Trump's inauguration as president of the United States (January 2017). How did these accounts end up in our data? The answer lies in the temporal overlap between the American 2020 presidential elections, which proceeded in November 2020, less than two weeks after the Ukrainian elections. To discredit Democratic candidate Joseph Biden, right-wing American influencers and media played up a corruption scandal involving Biden's son, Hunter, his laptop, and Ukrainian prime minister Zelenskiy. Evidently, a sizeable group of anomalous accounts with high average follower numbers amplified this content—yet the "cover" of these suspicious accounts suggests the target audience was American, rather than Ukrainian. Users born on those days overwhelmingly chose English names (Kathy Floyd, Jeff Teismann, Jennifer Astin, etc) and described themselves in English -- "proud mom", "Exodus 23:1", "Combat vet. Pilot. Christian.", and so forth, repeating the themes of Christianity, conservatism, and veteran status.

The fact that these account births pre-date the Ukrainian elections by almost four years, and maintained English-language bios referencing American politics during the September-December 2020 sample period, suggests that they were not created with the primary intent of interfering with Ukraine's October 2020 elections. More suspicious are several more birth spikes from October 2020 itself (2nd, 6th, and 7th), but again they turn out to be English-language accounts largely referencing American politics, suggesting they were created with an eye to commenting on the American 2020 presidential elections rather than the Ukrainian elections.
Ordering all of the Twitter accounts in our sample from most retweeted to least, we find that the most amplified accounts are John Solomon, Donald Trump, James Woods, and Representative Matt Gaetz, all of whom are major figures in the American right-wing media ecosystem. Zooming out to a network view of retweet patterns, we can clearly see two islands of conversation. On the one hand, there is the 'American' conversation, in which the aforementioned influencers are prominent nodes. On the other hand, there is a smaller conversation (depicted in green) centered on ZelenskyyUa, the widely followed Ukrainian-language Twitter account of Ukraine's president, Volodymyr Zelensky.

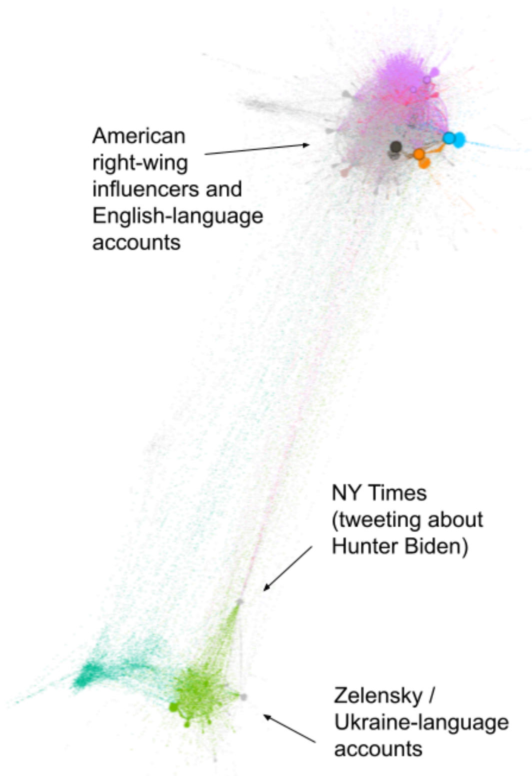

Figure 03: Retweet network of tweets mentioning both 'Ukraine' and 'corruption', in English or Ukrainian, Sept 13, 2020 - Dec 22, 2020. Communities near the top (purple/grey) are led by right-wing American influencers such as Donald Trump, Matt Gaetz, John Solomon and James Woods. Communities near the bottom (green) center on Ukrainian president Zelensky. The two clusters are connected primarily because they both retweet the NY Times' tweet about the Hunter Biden / Ukraine corruption allegations.

What connects these two disparate communities and conversations? Notably, the graph reveals the New York Times' official Twitter handle, @nytimes, as a critical bridge between the American and Ukrainian conversations. Looking more closely, it turns out the Times tweeted just once about Ukraine and corruption, referencing their own news article from the 23rd of September, 2020, in which Hunter Biden, son of then presidential hopeful Joe Biden, was reportedly cleared of suspicion of corruption with regard to Ukraine.[3] This topic of Hunter Biden, then, turns out to be the primary connective tissue between the American and Ukrainian threads of conversation. Far from offering evidence of a Russian influence operation targeting the Ukraine, the data seem if anything to suggest that American right-wing influencers, amplified by coordinated English-language accounts, played up the topic of corruption and the Ukraine in an effort to discredit Joe Biden ahead of the American presidential elections (with possible side effects on Ukraine). Indeed, just a few months later, Twitter purged many of these same right-wing American accounts for terms of service violations.

[3] https://www.nytimes.com/2020/09/23/us/politics/biden-inquiry-republicans-johnson.html

Thus, if anything, the Twitter discourse on Ukraine's elections seems to have been accidentally 'polluted' by an overlapping American domestic discourse (advanced by right-wing American influencers, and amplified by the anomalously born accounts). This finding explains why Twitter usage of our Ukrainian respondents did not show correlation to narrative exposure or agreement—they were not the target audience. Who was behind these anomalous accounts? We do not know, and these findings underline the challenge of attributing social media influence operations, in line with H5.