Appendix: The Impact of Social Media on Political Elites

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Contents

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1 Additional Tables

Table A1: Population Covered by 3G and 4G

Year	Population covered by 3G + 4G	Share 3G + 4G
2009	638,787	0.04
2010	1,445,875	0.08
2011	3,154,995	0.18
2012	4,983,888	0.29
2013	6,366,120	0.36
2014	9,155,723	0.52
2015	10,283,244	0.57
2016	13,215,139	0.73
2017	16,322,988	0.88
2018	18,153,905	0.97
2019	18,464,155	0.97

Source: Subsecretaría Telecomunicacions Chile

Table A2: Daily Social Media Usage by Socio-demographic Variables 2011

Variables	Everyday use (%)	Total Sample (%)
Age range		
18-24	35.6	12
25-34	31.1	17.7
35-54	24.4	37.3
55+	8.9	33.1
Sex		
Male	68.9	40.3
Social class		
Upper	13.3	4.6
Middle	68.9	49.8
Lower	17.8	45.6
Education level		
High school or less	33.3	69.9
Incomplete College or Technical	37.8	18.4
College or more	28.9	11.7
Ideology		
Left	22.2	8,7
Right	8.9	11.4
Center	44.4	32.6
Independent + None	46.6	56.1

Source: Centro de Estudios Públicos

Table A3: Daily social Media Usage by Socio-demographic Variables 2020

Variables	Everyday use (%)	Total Sample (%)
Age range		
18-24	13,95	9,56
25-34	24,03	15,80
35-44	17,83	16,22
45-54	24,03	16,22
55-64	12,40	17,67
65+	7,75	24,53
Sex		
Male	52,71	37,21
Social class		
Upper	17,05	5,27
Middle	71,32	64,73
Lower	11,63	30,01
Education level		
High school or less	34,11	66,87
Incomplete College or Technical	27,13	20,24
College or more	37,21	11,78
Ideology		
Left	15,38	11,64
Right	12,40	9,22
Center	44,19	42,62
Independent + None	46,15	36,52

Source: Centro de Estudios Públicos

Table A4: Robustness Check of Effects 3G Coverage on Facebook Activity (Two Leads)

	(1)	(2)	(3)	(4)
Outcomes:	Page	Likes	Total	Shares
3G Share	0.447**	1.371**	1.414**	0.400
	(0.213)	(0.558)	(0.611)	(0.378)
3G Share (t+1)	-0.037	0.199	0.158	-0.209
	(0.122)	(0.602)	(0.663)	(0.466)
3G Share (t+2)	0.222	0.803	0.909	0.570
	(0.157)	(0.640)	(0.695)	(0.453)
Outcome mean	0.41	1.29	1.43	0.72
Outcome SD	0.49	1.75	1.9	1.16
N Clusters	60	60	60	60
Obs.	579	579	579	579
Controls	✓	✓	✓	✓
R^2	0.761	0.804	0.804	0.802

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district-year level. Adjusted models control for log of population, log of income, urban status, average age, and political coalition.

Table A5: Effects 3G Coverage on Facebook Activity (Two Lags)

	(1)	(2)	(3)	(4)
Outcomes:	Page	Likes	Total	Shares
3G Share	0.501**	0.507	0.615	-0.103
	(0.201)	(0.667)	(0.729)	(0.432)
3G Share (t-1)	0.080	0.905	0.976	0.753*
	(0.144)	(0.623)	(0.682)	(0.384)
3G Share (t-2)	0.162	1.443*	1.515	0.927
	(0.203)	(0.847)	(0.936)	(0.671)
Outcome mean	0.41	1.29	1.43	0.72
Outcome sd.	0.49	1.75	1.9	1.16
N Clusters	60	60	60	60
Obs.	462	462	462	462
Controls	✓	✓	✓	✓
R^2	0.801	0.807	0.808	0.809

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district-year level. Adjusted models control for log of population, log of income, urban status, average age, and political coalition.

Table A6: Effects of 4G Coverage on Facebook Activity

	(1)	(2)	(3)	(4)
Outcomes:	Likes	Likes	Likes	Likes
Share 4G	-0.320	-1.331	-1.324	-0.283
	(0.258)	(0.948)	(1.054)	(0.829)
Outcome mean	0.49	1.48	1.62	0.80
Outcome sd.	0.5	1.76	1.92	1.18
N of clusters	60	60	60	60
Obs.	466	466	466	466
Controls	✓	✓	✓	✓
R^2	0.797	0.815	0.814	0.822

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district-year level. The sample size for these regressions corresponds to politician*years in the 2013-2017 congressional session. Adjusted models control for 3G coverage, log of population, log of income, urban status, average age, and political coalition.

Table A7: Effects of 3G Coverage on Facebook Activity Among the Right

Outcomes:	(1) Pages	(2) Pages	(3) Likes	(4) Likes	(5) Total	(6) Total	(7) Shares	(8) Shares
Share 3G	0.307	0.231	1.222*	1.040	1.239	1.025	0.215	0.071
	(0.274)	(0.264)	(0.713)	(0.769)	(0.775)	(0.859)	(0.585)	(0.656)
Outcome mean	0.53	0.53	1.85	1.85	2.06	2.06	1.04	1.04
Outcome sd	0.50	0.50	1.95	1.95	2.17	2.17	1.32	2.32
N clusters	60	60	60	60	60	60	60	60
Obs.	329	323	329	323	329	323	329	323
Controls		✓		✓		✓		✓
R^2	0.780	0.793	0.790	0.800	0.788	0.799	0.737	0.749

Effects of 3G Coverage on Facebook Activity Among the Left

Outcomes:	Pages	Pages	Likes	Likes	Total	Total	Shares	Shares
Share 3G	0.679*	0.592*	0.878	0.714	1.210	0.876	0.550	0.276
	(0.341)	(0.336)	(1.023)	(0.957)	(1.119)	(1.010)	(0.665)	(0.571)
Outcome mean	0.57	0.57	2.03	2.03	2.35	2.35	1.54	1.54
Outcome sd	0.49	0.49	2.10	2.10	2.40	2.40	1.85	1.85
N clusters	60	60	60	60	60	60	60	60
Obs.	211	209	211	211	211	209	211	209
Controls		✓		✓		✓		✓
R^2	0.792	0.803	0.828	0.839	0.827	0.838	0.852	0.861

Effects of 3G Coverage on Facebook Activity Among the Center

Outcomes:	Pages	Pages	Likes	Likes	Total	Total	Shares	Shares
Share 3G	0.560	1.004	2.762	3.573**	2.849	3.700**	1.451	1.574**
	(0.711)	(0.603)	(1.799)	(1.391)	(1.917)	(1.538)	(0.900)	(0.699)
Mean outcome	0.47	0.47	1.44	1.44	1.62	1.62	0.84	0.84
Mean sd	0.50	0.50	1.76	1.76	1.98	1.98	1.21	1.21
N Clusters	60	60	60	60	60	60	60	60
Obs.	148	148	148	148	148	148	148	148
Controls		✓		✓		✓		✓
R^2	0.809	0.857	0.780	0.833	0.788	0.838	0.773	0.800

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. Controls include log of population, log of income, urban status, average age, vote share, and political coalition.

Table A8: Average Extremism by Year

Year	Average Extremism
2011	0.69
2012	0.74
2013	0.68
2014	0.79
2015	0.75
2016	0.66
2017	0.78
2018	0.65
2019	0.69
2020	0.67

Table A9: Bills 2011-2019

Issues	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
Science	5.7	0.2	7.6	2.1	0.9	1.1	1.1	0.9	0.4	1.8	1.9
Constitution	7.8	5.7	1.7	10.9	3.4	1.3	4.1	3.4	4.9	5.5	5.1
Defense	0.6	4.8	3.4	0.2	2.1	7.3	9.7	5.2	7.7	7.0	5.2
Economy	9.9	9.5	0.5	0.0	8.9	7.2	3.3	9.2	8.2	17.8	7.2
Education	1.9	4.6	2.7	28.5	21.2	10.9	28.4	9.8	3.3	5.4	11.6
Homeland	10.1	9.0	17.6	3.1	1.1	0.1	3.3	0.1	0.9	0.1	4.0
Fiscal policy	39.9	41.7	24.9	40.5	32.2	28.2	21.2	36.9	30.8	19.5	30.4
Infraestructure	0.0	1.1	0.3	0.0	13.1	12.5	4.2	18.8	15.0	23.3	9.5
Fishing	1.0	11.5	0.0	0.8	1.1	0.0	9.5	0.1	6.7	0.8	3.5
Health	5.7	3.7	6.8	0.0	3.3	4.1	2.5	3.7	0.7	0.6	3.0
Labor	2.7	1.5	0.9	0.4	2.0	5.5	1.8	3.0	4.0	6.1	3.6
Other	14.8	6.9	33.7	13.4	10.9	21.7	11.0	8.9	17.4	12.2	15.2
Total	100	100	100	100	100	100	100	100	100	100	100

Table A10: Effects of 3G on Extremeness

	(1)	(2)	(3)	(4)
Outcome:	Ideological Extremism			
3G Share	0.10	0.07	0.10	0.08
	(0.08)	(0.07)	(0.07)	(0.06)
3G Share (t+1)			0.07	0.03
			(0.09)	(0.07)
3G Share (t-1)			0.00	0.06
			(0.07)	(0.06)
Outcome mean	0.71	0.71	0.71	0.71
Outcome sd	0.21	0.21	0.21	0.21
N clusters	60	60	60	60
Obs.	826	814	523	521
Controls		✓		✓
R^2	0.726	0.774	0.735	0.788

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. The outcome for all regressions is the level of extremism in Congress. All models include politician*district and region*year fixed effects. Adjusted models control for 3G coverage, vote share, log of population, log of income, urban status, average age, and political coalition.

Table A11: Heterogeneous effects 3G vote share

	(1)	(2)
Outcome:	Ideological Extremism	
Share 3G	0.468**	0.464**
	(0.224)	(0.224)
Vote Share	-0.533	-0.515
	(0.331)	(0.334)
Share 3G*Vote Share	-0.777*	-0.799*
	(0.414)	(0.415)
		(0.005)
Outcome mean	0.69	0.69
Outcome sd	0.21	0.21
Adjusted	No	Yes
Obs.	1263	1263
N clusters	60	60
R^2	0.843	0.846

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district-year level. The sample size for these regressions correspond to politician*years in the 2013-2017 congressional session. Adjusted models control for 3G coverage, log of population, log of income, urban status, average age, and political coalition.

Table A12: Effects of Facebook Activity on Extremism

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	Ideological Extremism							
Page (t-1)	0.043	0.045*						
	(0.026)	(0.024)						
Likes (t-1)			0.029***	0.026***				
			(0.009)	(0.008)				
Total (t-1)					0.027***	0.024***		
					(0.008)	(0.007)		
Shares (t-1)							0.039***	0.032***
							(0.009)	(0.008)
Outcome mean	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69
Outcome sd	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
N Clusters	60	60	60	60	60	60	60	60
Obs.	1145	1137	1145	1137	1145	1137	1145	1137
Controls		✓		✓		✓		✓
R^2	0.820	0.849	0.819	0.852	0.825	0.853	0.825	0.851

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2020. The outcome for all regressions is the level of extremism in Congress. The models include politician*district and region*year fixed effects. Controls include log of population, log of income, urban status, average age, vote share, and political coalition.

Table A13: Effects Facebook Activity on Extremism Before 2014

	(1)	(2)	(3)	(4)
Outcome:	Ideological Extremism			
Page (t-1)	0.020			
	(0.025)			
Likes (t-1)		0.022*		
		(0.012)		
Total (t-1)			0.020*	
			(0.011)	
Shares (t-1)				0.061**
				(0.030)
Outcome mean	0.71	0.71	0.71	0.71
Outcome sd	0.18	0.18	0.18	0.18
N clusters	60	60	60	60
Obs.	417	417	417	417
Controls	✓	✓	✓	✓
R^2	0.804	0.807	0.807	0.807

Effects Facebook Activity on Extremism After 2014

	(1)	(2)	(3)	(4)
Outcome:	Ideological Extremism			
Page (t-1)	0.024			
	(0.022)			
Likes (t-1)		0.012*		
		(0.007)		
Total (t-1)			0.012**	
			(0.006)	
Shares (t-1)				0.017**
				(0.008)
Outcome mean	0.68	0.68	0.68	0.68
Outcome sd	0.23	0.23	0.23	0.23
Obs.	719	719	719	719
N clusters	60	60	60	60
Controls	✓	✓	✓	✓
R^2	0.941	0.941	0.941	0.941

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2020. The outcome for all regressions is level of extremism in Congress. The models include politician*district and region*year fixed effects. Controls include log of population, log of income, urban status, average age, vote share, and political coalition.

Table A14: Effects of Facebook (50th Percentile) Activity on Extremism

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Ideological Extremism					
Likes p50	0.03	0.03				
	(0.03)	(0.02)				
Total p50			0.03	0.02		
			(0.03)	(0.03)		
Shares p50					0.04	0.03
					(0.03)	(0.03)
Outcome mean	0.69	0.69	0.69	0.69	0.69	0.69
Outcome sd	0.21	0.21	0.21	0.21	0.21	0.21
N Clusters	60	60	60	60	60	60
Obs.	1145	1137	1145	1137	1145	1137
Controls		✓		✓		✓
R^2	0.819	0.848	0.819	0.848	0.819	0.848

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2020. The outcome for all regressions is the level of extremism in Congress. The models include politician*district and region*year fixed effects. Controls include log of population, log of income, urban status, average age, vote share, and political coalition.

Table A15: Effects of Facebook (75th Percentile) Activity on Extremism

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Ideological Extremism					
Likes p75	0.05*	0.04**				
	(0.03)	(0.02)				
Total p75			0.07***	0.06***		
			(0.03)	(0.02)		
Shares p75					0.06**	0.06***
					(0.02)	(0.02)
Outcome mean	0.69	0.69	0.69	0.69	0.69	0.69
Outcome sd	0.21	0.21	0.21	0.21	0.21	0.21
N Clusters	60	60	60	60	60	60
Obs.	1145	1137	1145	1137	1145	1137
Controls		✓		✓		✓
R^2	0.820	0.848	0.821	0.849	0.820	0.849

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2020. The outcome for all regressions is the level of extremism in Congress. The models include politician*district and region*year fixed effects. Controls include log of population, log of income, urban status, average age, vote share, and political coalition.

Table A16: Effects of Facebook (90th Percentile) Activity on Extremism

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Ideological Extremism					
Likes p90	0.07**	0.05*				
	(0.03)	(0.02)				
Total p90			0.08*	0.05		
			(0.05)	(0.03)		
Shares p90					0.09**	0.07**
					(0.04)	(0.03)
Outcome mean	0.69	0.69	0.69	0.69	0.69	0.69
Outcome sd	0.21	0.21	0.21	0.21	0.21	0.21
N Clusters	60	60	60	60	60	60
Obs.	1145	1137	1145	1137	1145	1137
Controls		✓		✓		✓
R^2	0.820	0.848	0.820	0.848	0.820	0.849

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2020. The outcome for all regressions is the level of extremism in Congress. The models include politician*district and region*year fixed effects. Controls include log of population, log of income, urban status, average age, vote share, and political coalition.

Table A17: Effects of Internet Consumption on Democracy Best Government (Whole Sample)

Outcome:	(1) Support Dem.	(2) Support Dem.	(3) Conf. Elections	(4) Conf. Elections
Internet Consumption	-0.025	-0.079***	-0.027	-0.055***
	(0.017)	(0.021)	(0.017)	(0.020)
Outcome mean	0.45	0.45	0.29	0.29
Outcome sd	0.50	0.50	0.45	0.45
N clusters	71	71	71	71
Obs.	5516	4638	5710	4762
Controls		✓		✓
R^2	0.0767	0.101	0.0552	0.0706

Effects of Internet Consumption on Democracy Best Government (Before Facebook Page).

Outcome:	(1) Support Dem.	(2) Support Dem.	(3) Conf. Elections	(4) Conf. Elections
Internet Consumption	-0.029	-0.054	0.003	0.006
	(0.027)	(0.034)	(0.022)	(0.032)
Outcome mean	0.52	0.52	0.34	0.34
Outcome sd	0.49	0.49	0.47	0.47
N clusters	71	71	71	71
Obs.	1737	1450	1840	1504
Controls		✓		✓
R^2	0.189	0.218	0.147	0.176

Effects of Internet Consumption on Democracy Best Government (After Facebook Page).

Outcome:	(1) Support Dem.	(2) Support Dem.	(3) Conf. Elections	(4) Conf. Elections
Internet Consumption	-0.011	-0.079***	-0.064***	-0.109***
	(0.022)	(0.024)	(0.022)	(0.023)
Outcome mean	0.45	0.45	0.29	0.29
Outcome sd	0.50	0.50	0.45	0.45
N clusters	71	71	71	71
Obs.	3779	3188	3870	3258
Controls		✓		✓
R^2	0.0739	0.109	0.0579	0.0829

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the municipality level. Controls include income, education, urban status, and gender.

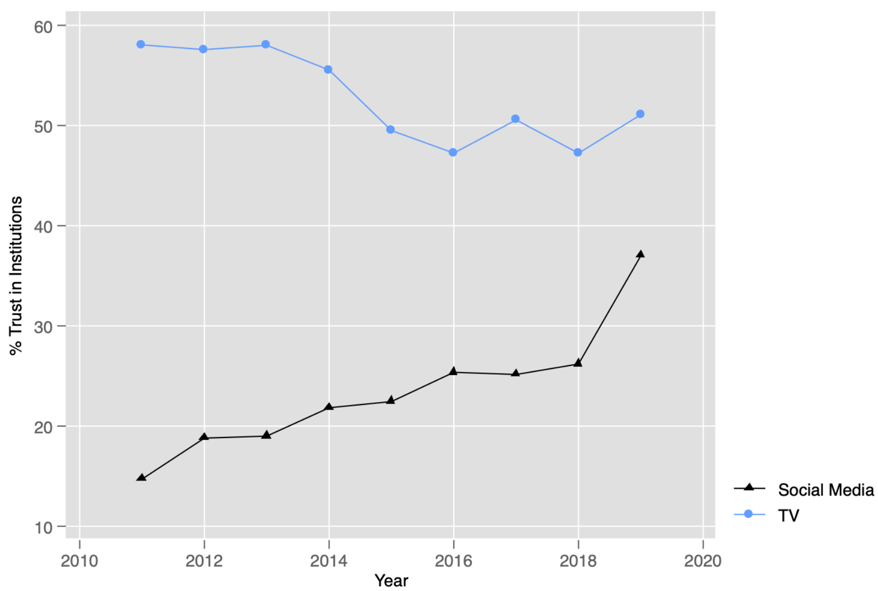
Table A18: Correlation Between Sentiments and Extremism

	(1)	(2)	(3)	(4)
Outcome:	Ideological Extremism			
Negative	0.023**			
	(0.010)			
Disgust		0.053*		
		(0.027)		
Positive			-0.005	
			(0.006)	
Happiness				-0.026
				(0.016)
Outcome mean	0.71	0.71	0.71	0.71
Outcome sd	0.21	0.21	0.21	0.21
N Clusters	56	56	56	56
Obs.	697	697	697	697
R^2	0.01	0.01	0.001	0.004

*p<.1; **p<.05; ***p<.01.

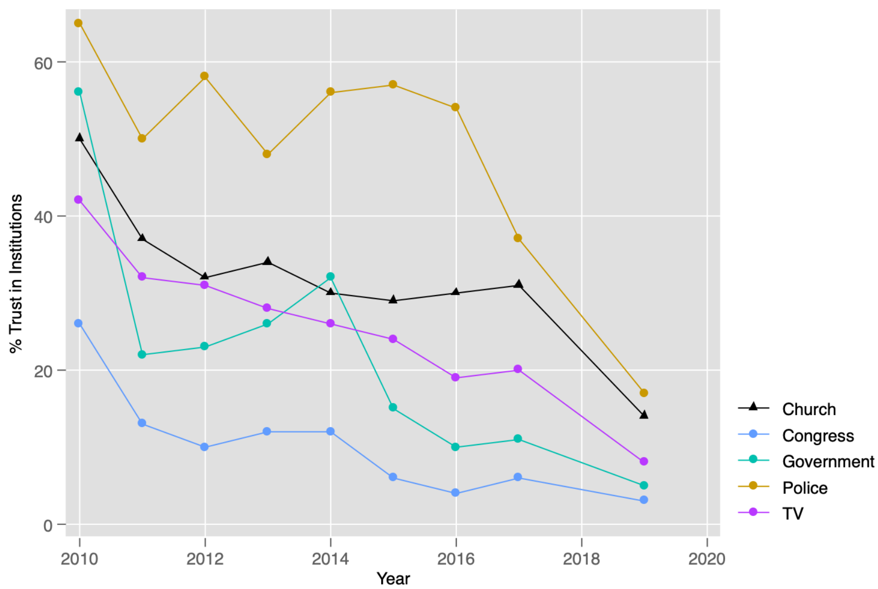
2 Additional Figures

Figure B1: Social Media and TV Consumption for Political News



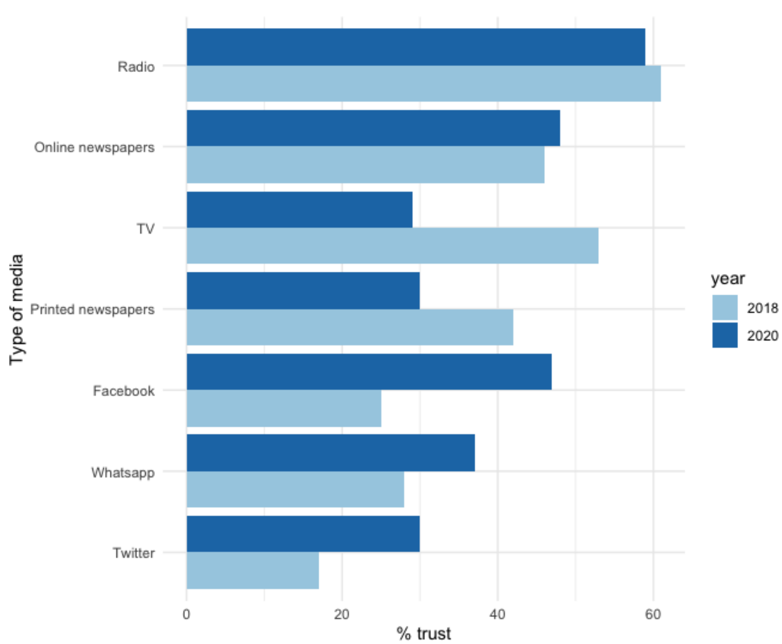
Source: Centro de Estudios Públicos

Figure B2: Trust in Institutions 2010-2020



Source: Centro de Estudios Públicos

Figure B3: Trust in the Media 2018-2020



Source: Cadem

Figure B4: Media Consumption in Chile 2018-2020

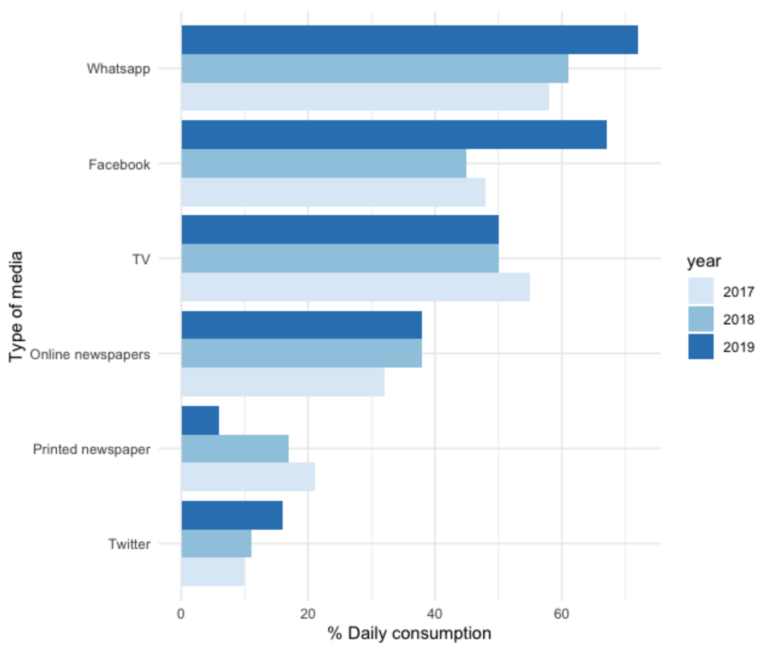


Figure B5: Increase in 3G coverage Metropolitan Area Chile 2011-2015

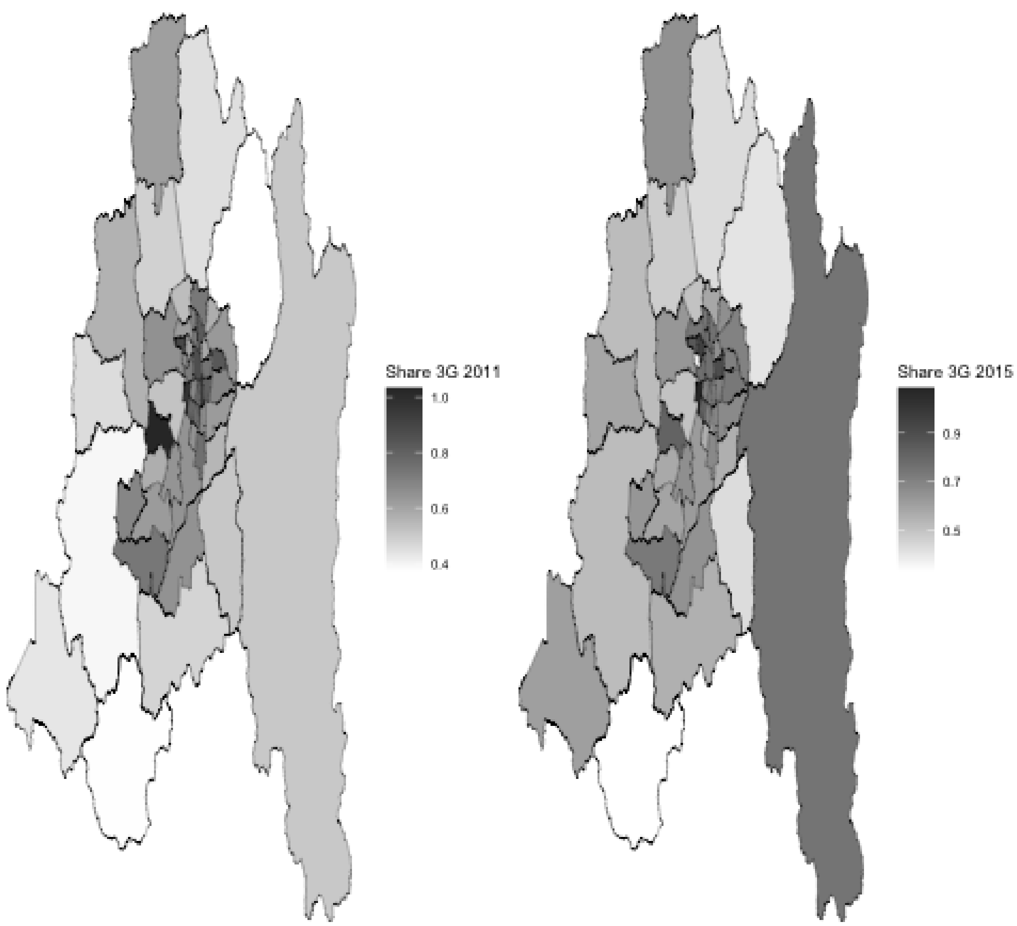


Figure B6: DW-Nominate Scores Over Time

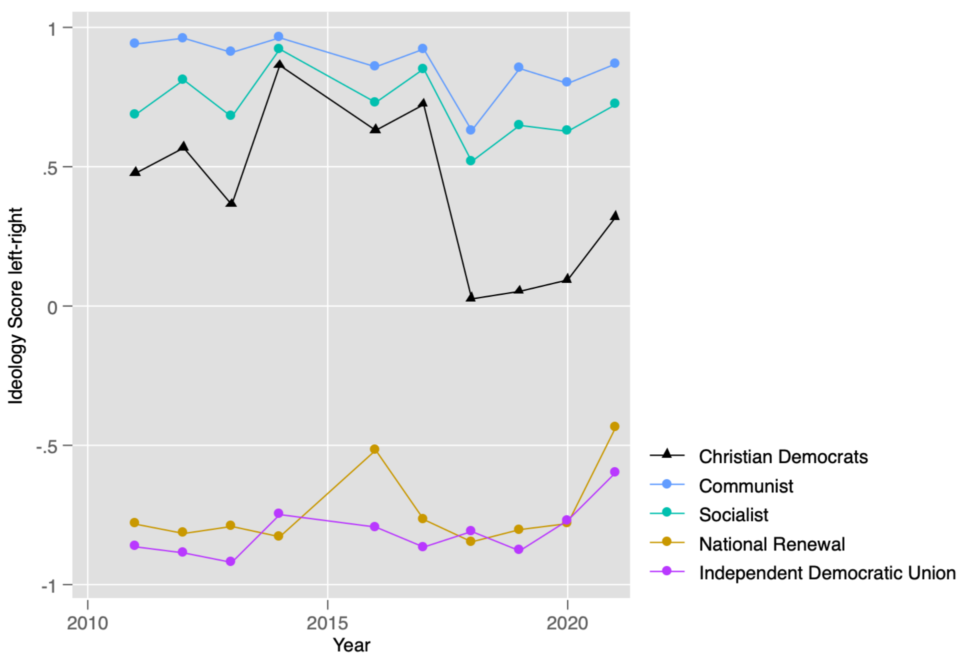


Figure B7: Heterogeneous Effects by Vote Share

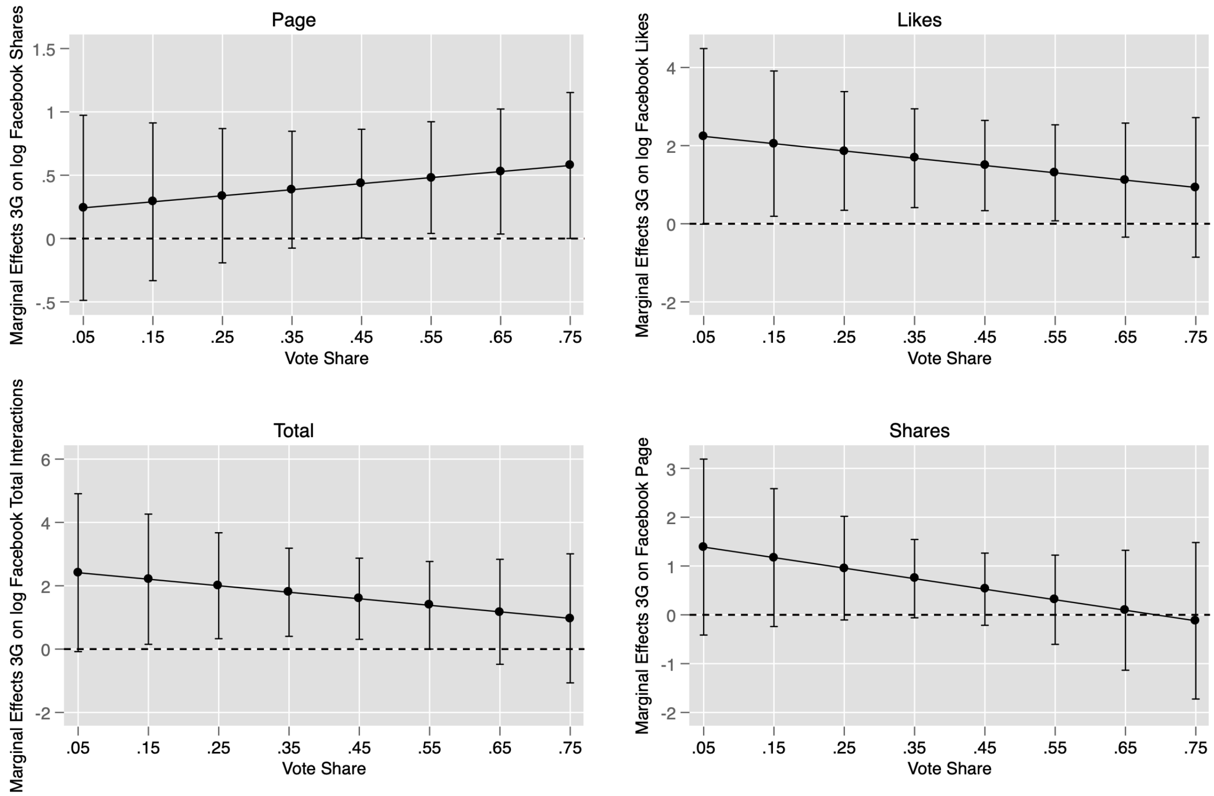


Figure B8: Heterogeneous Effects by Income

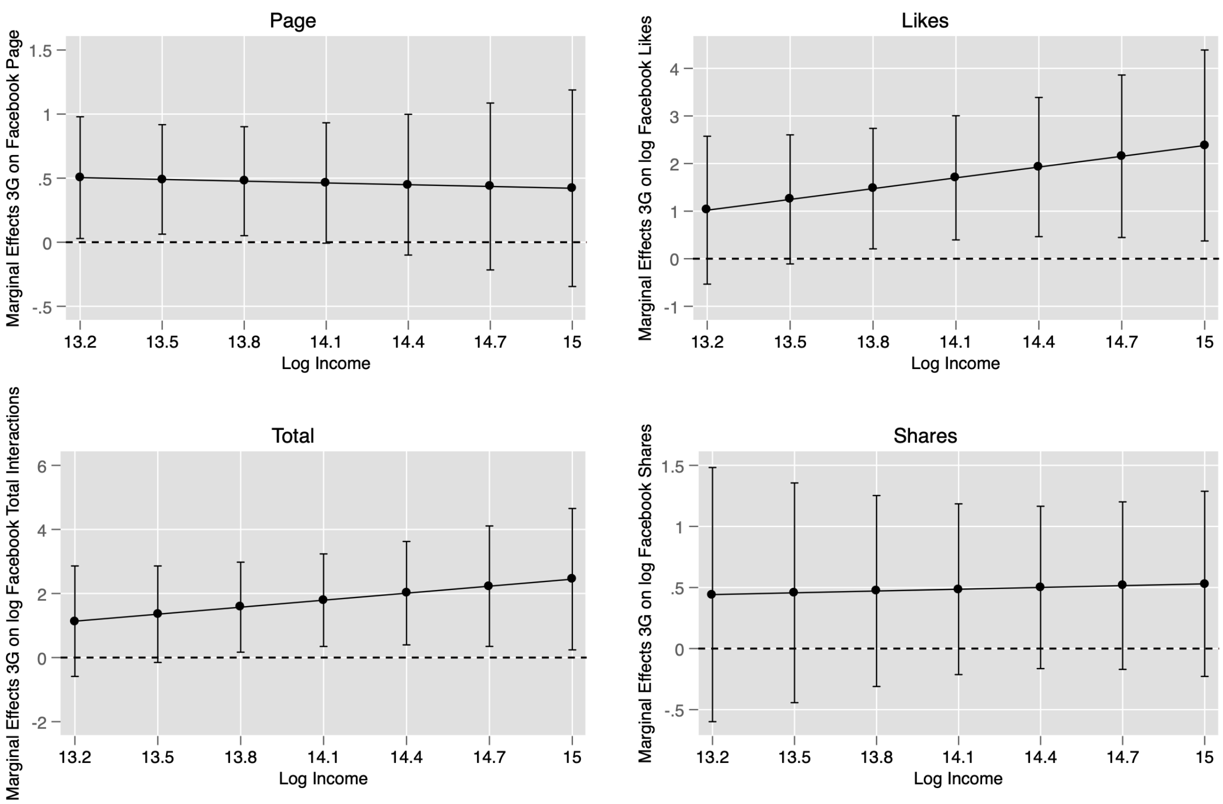


Figure B9: Heterogeneous Effects by Population

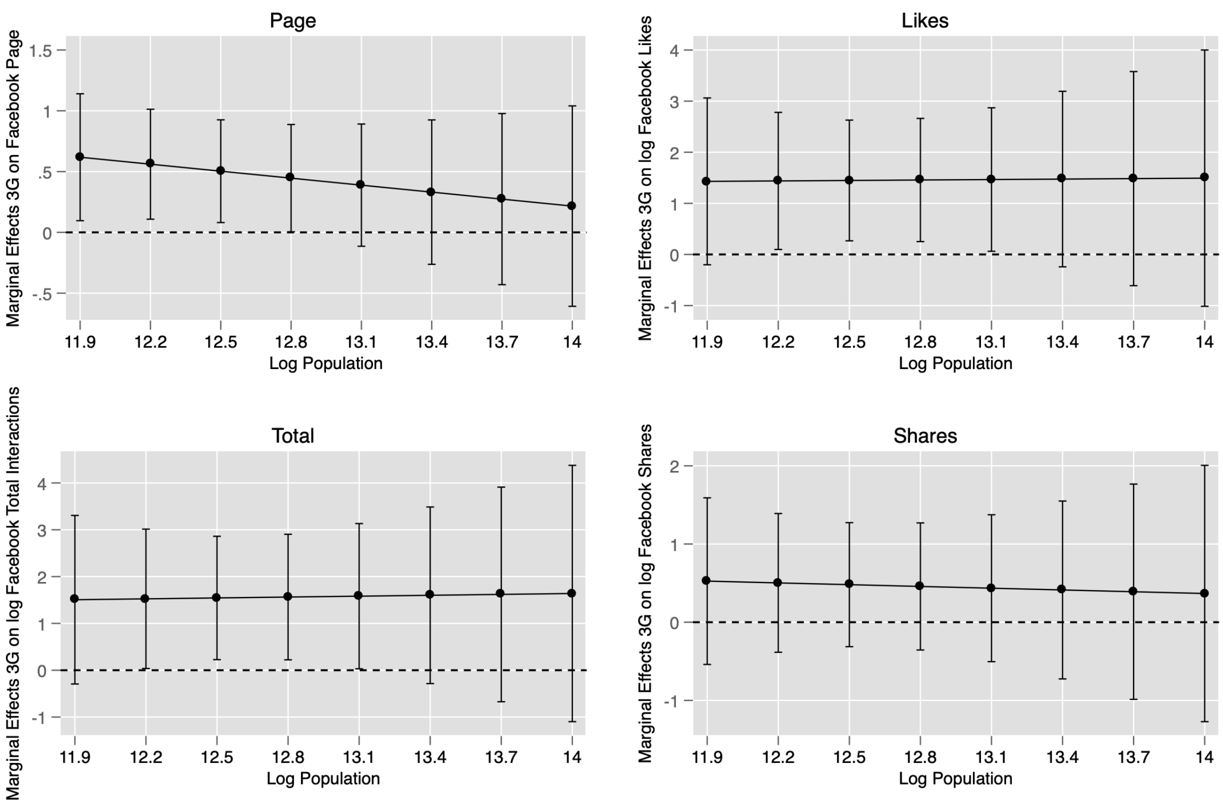


Figure B10: Heterogeneous Effects by Average Age

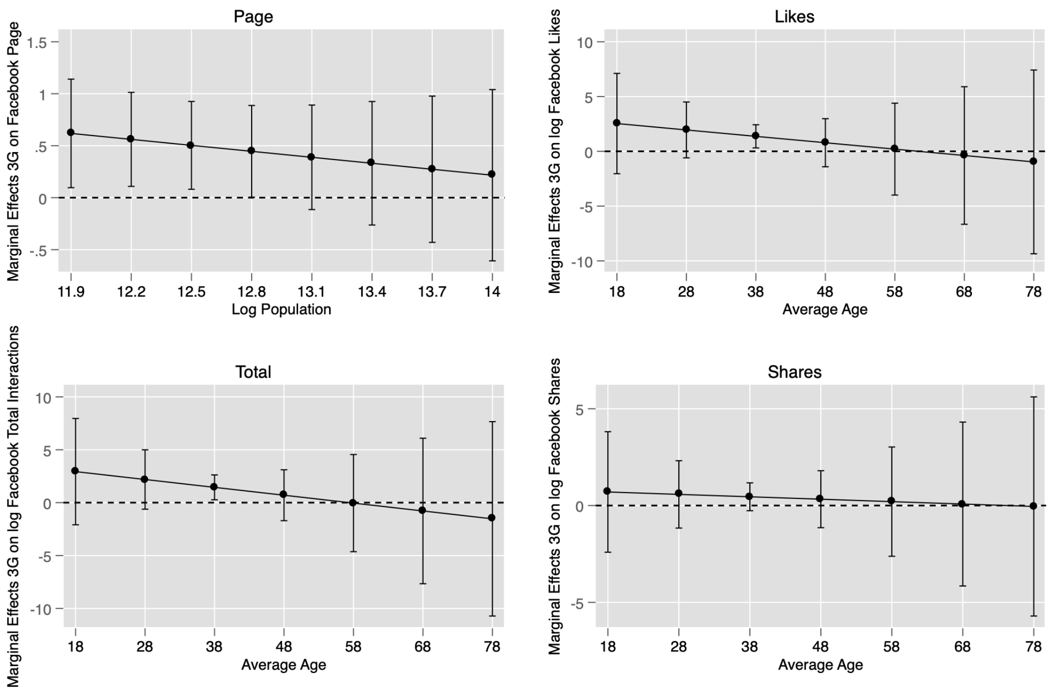


Figure B11: Heterogeneous Effects by Percentage of Urban Population

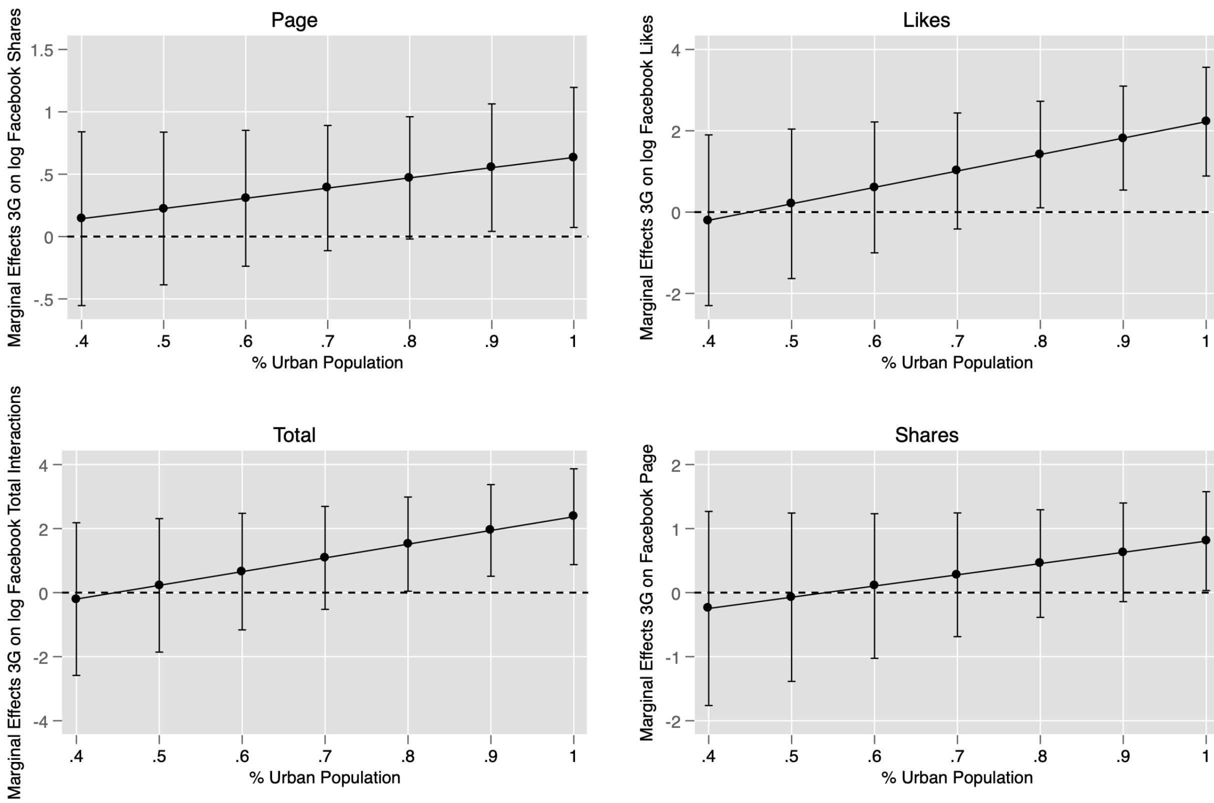
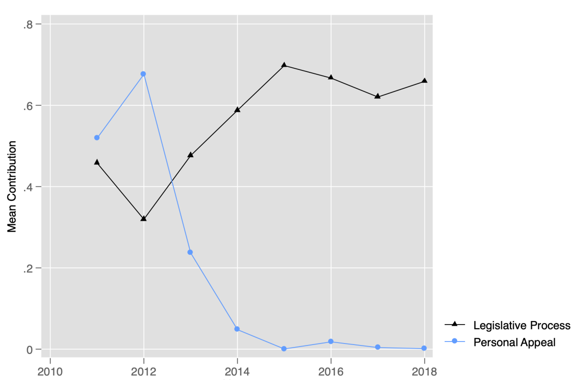
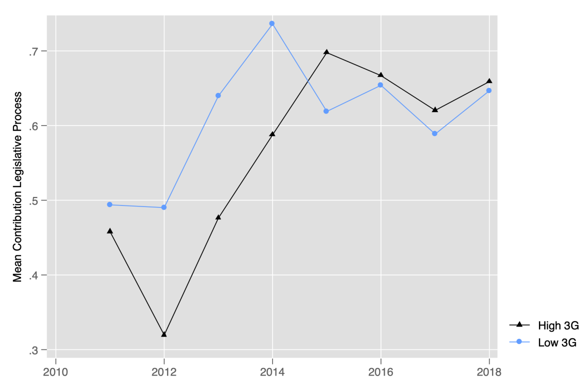


Figure B12: Mean Contribution Topics Facebook Posts



(a) High 3G



(b) By 3G Status

Figure B13: Histograms Extremism Measure by Year

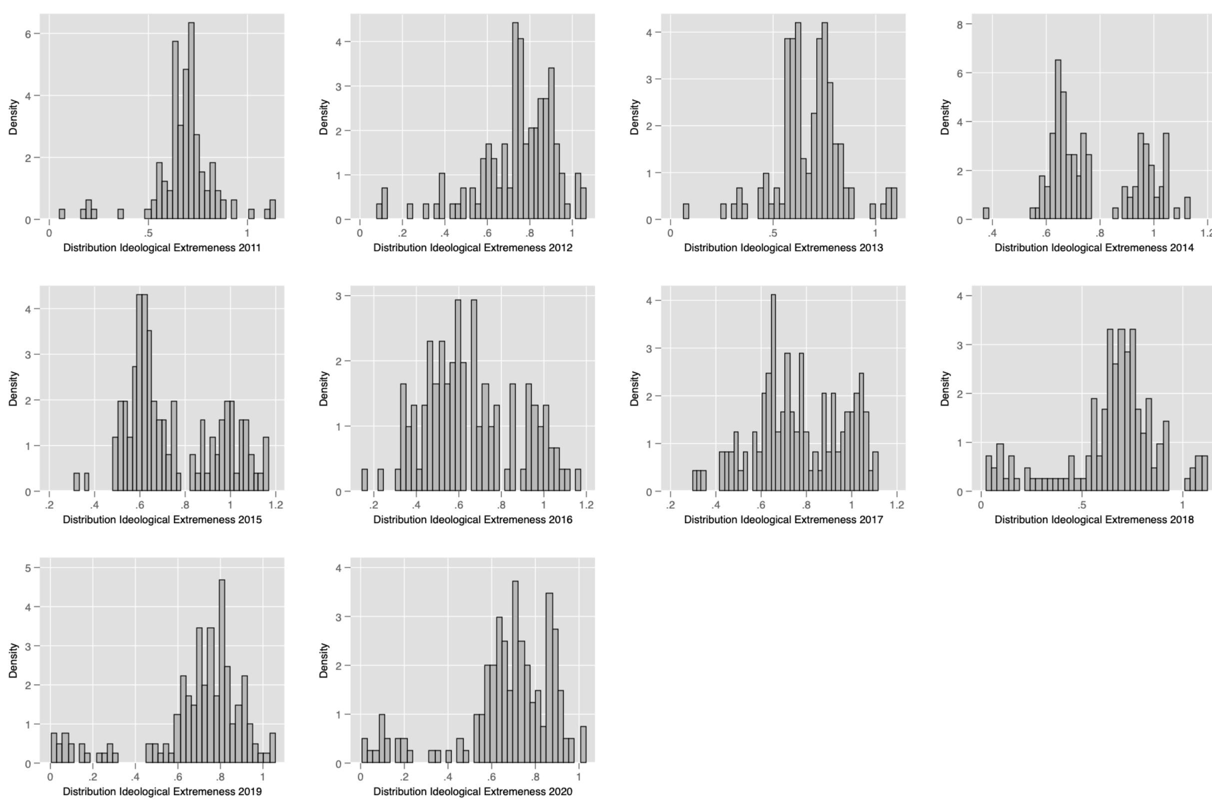
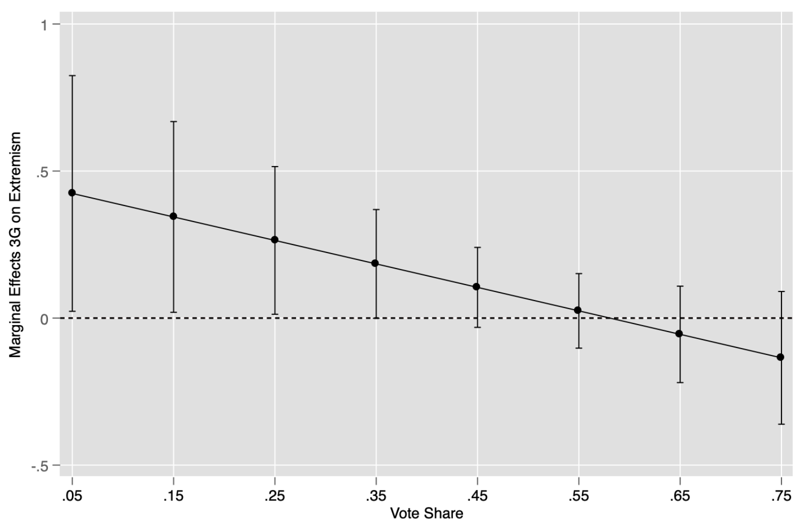
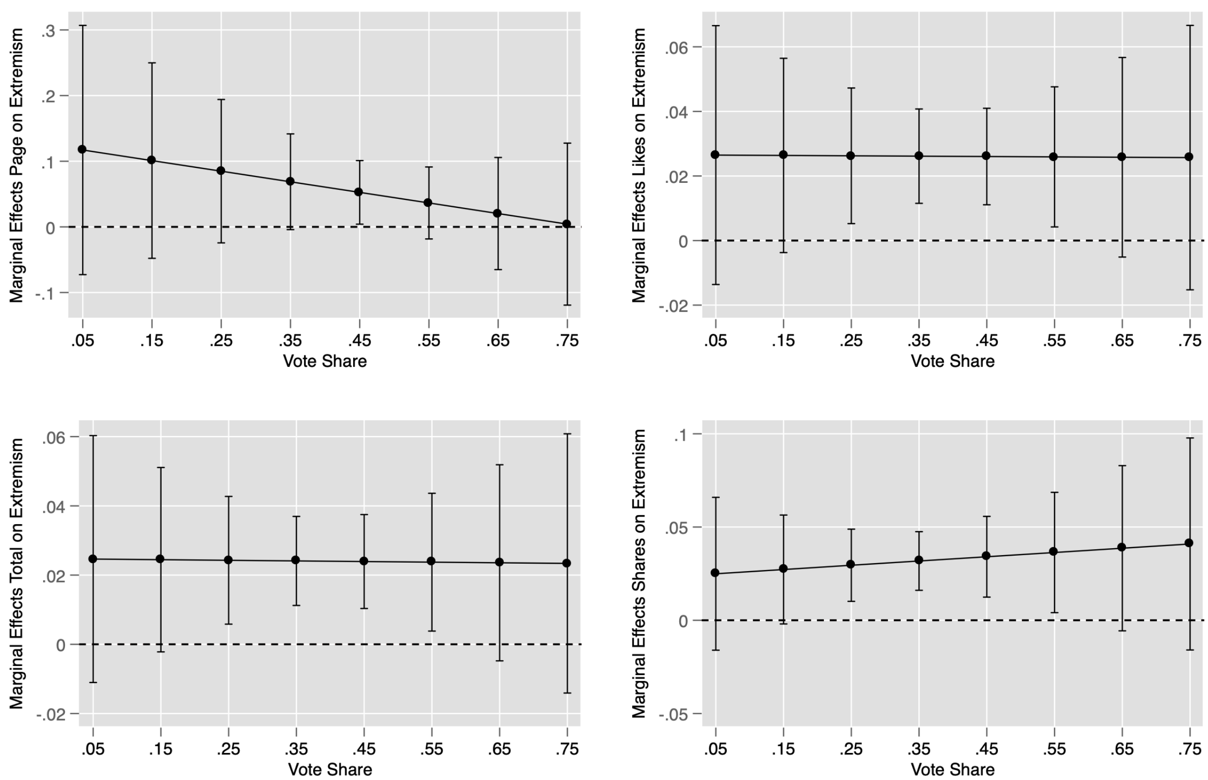


Figure B14: Coefficient Plot Effect of 3G on Extremism by Vote Share



The circle represents the point estimate, and the line the 95% confidence interval.

Figure B15: Coefficient Plot Effects Facebook Activity on Extremism by Vote Share



The circle represents the point estimate, and the line the 95% confidence interval.

Figure B16: Effects of 3G on Elite Extremism by Demographic Covariates

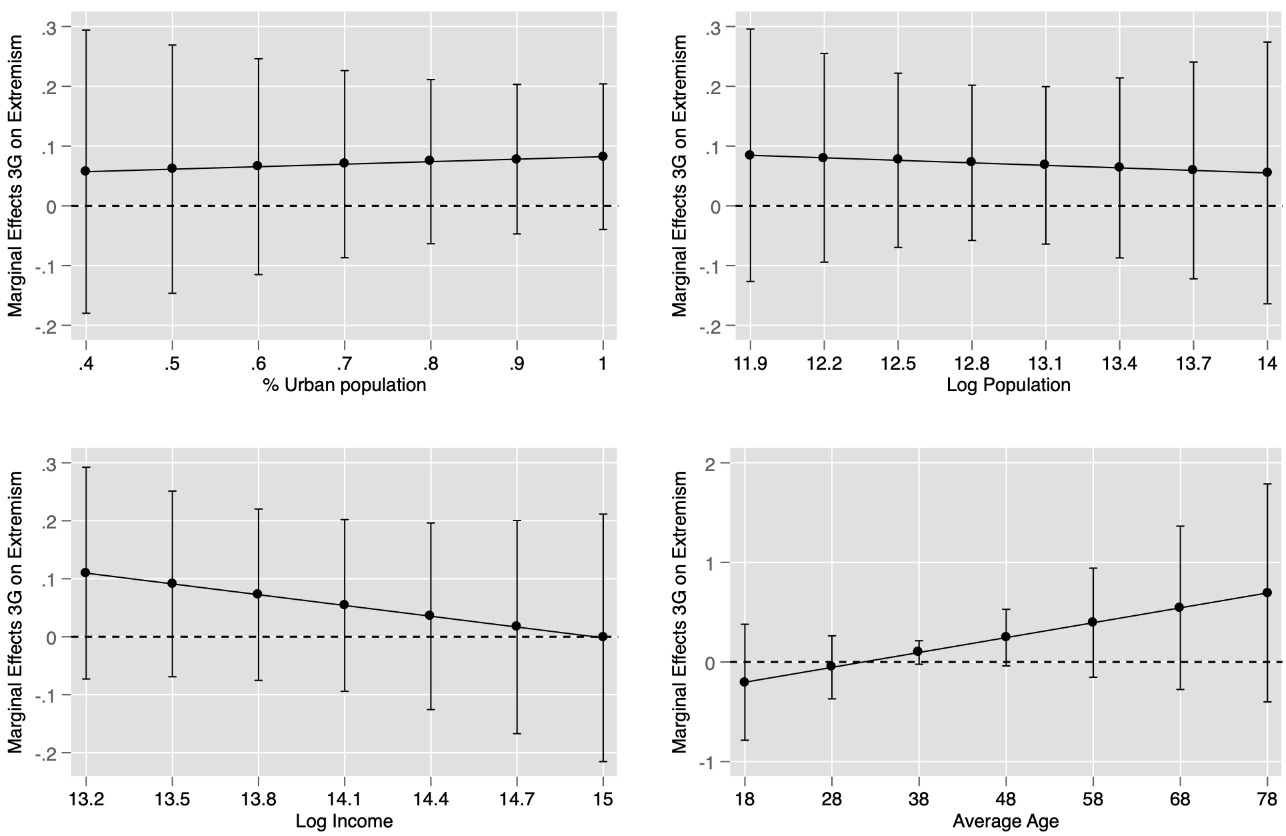


Figure B17: Effect of Facebook Page on Elite Extremism by Demographic Covariates

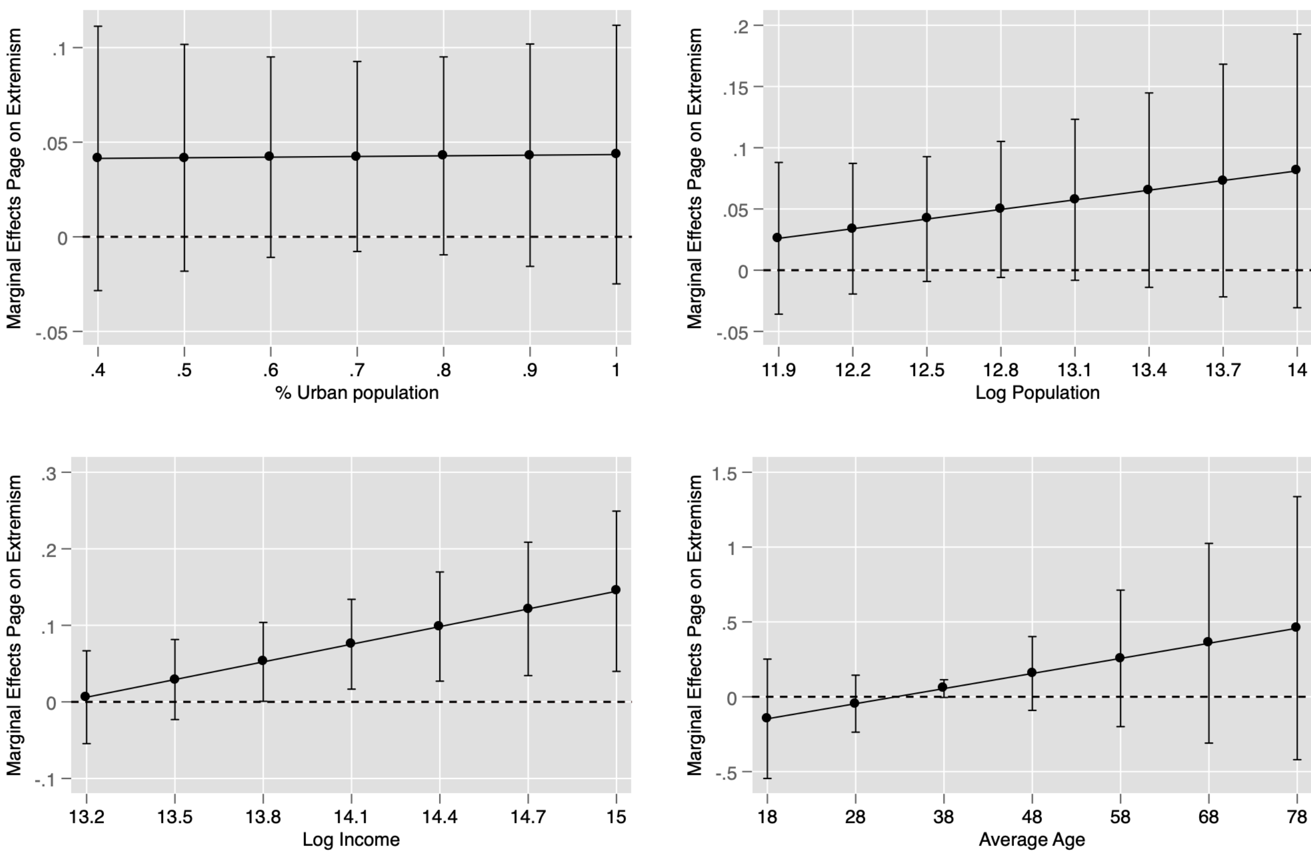


Figure B18: Effect of Facebook Likes on Elite Extremism by Demographic Covariates

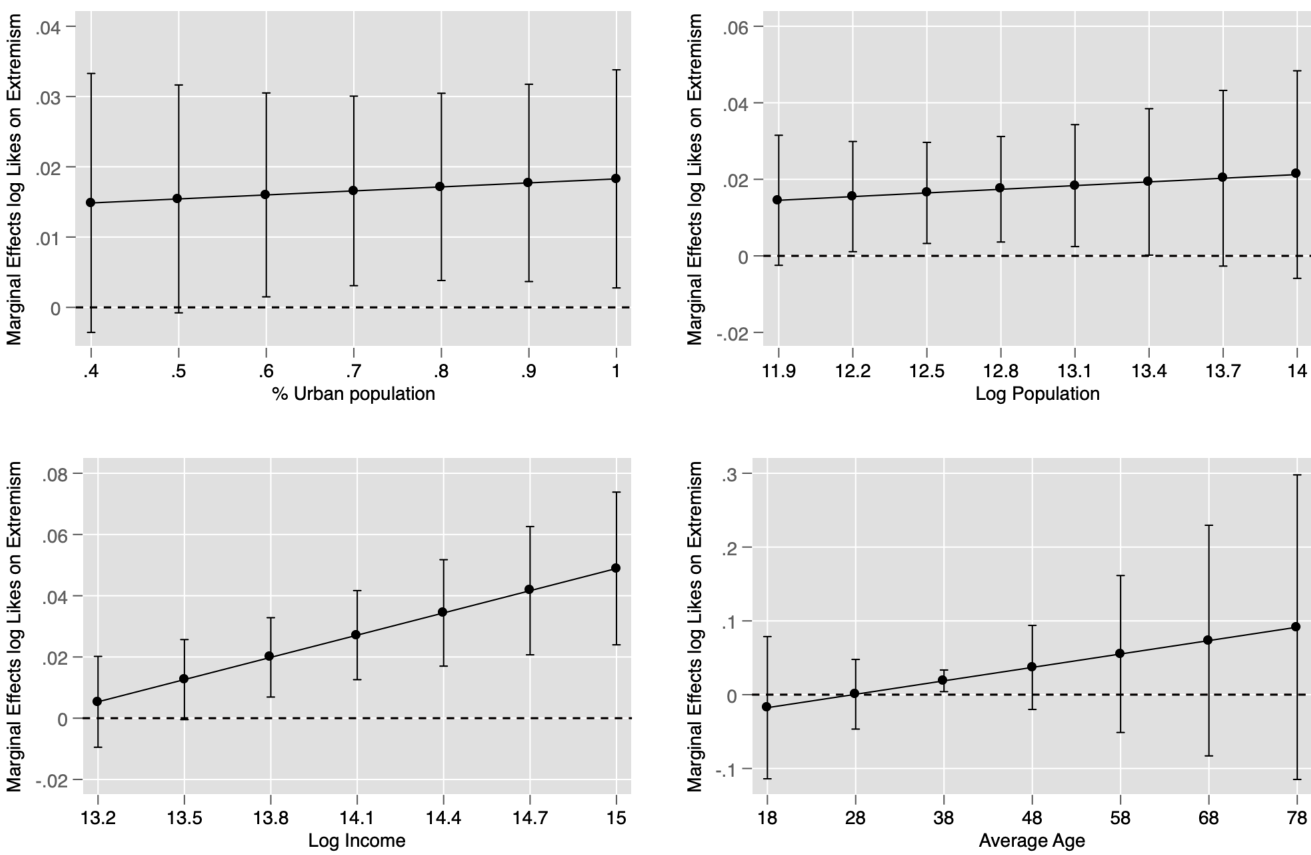


Figure B19: Effect of Facebook Total Interactions on Elite Extremism by Demographic Covariates

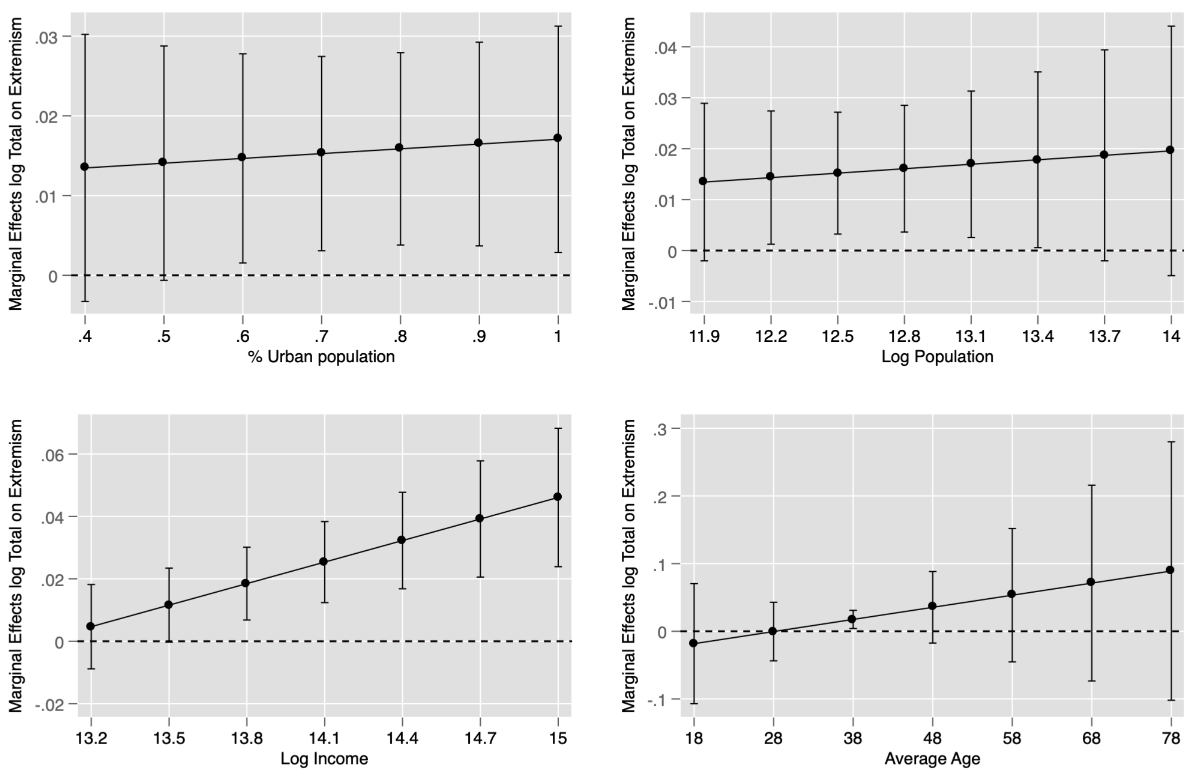


Figure B20: Effect of Facebook Shares on Elite Extremism by Demographic Covariates

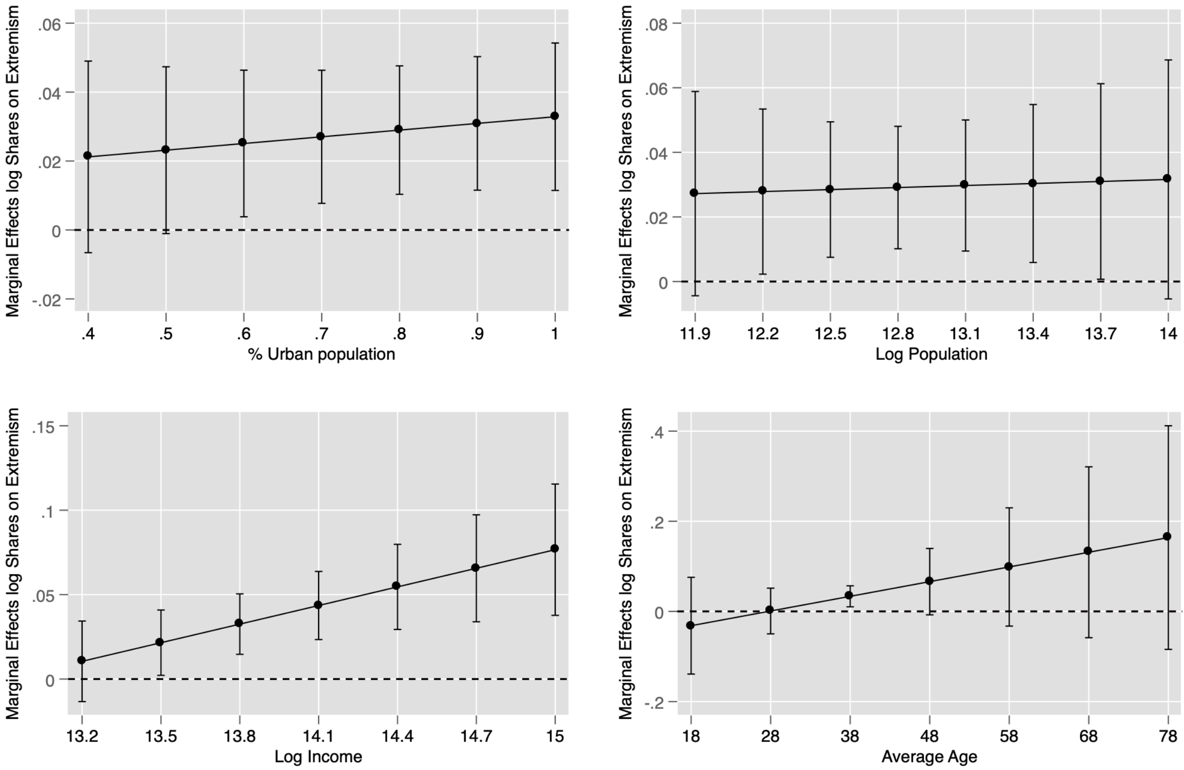


Figure B21: Distribution of Extremism by Policy Area

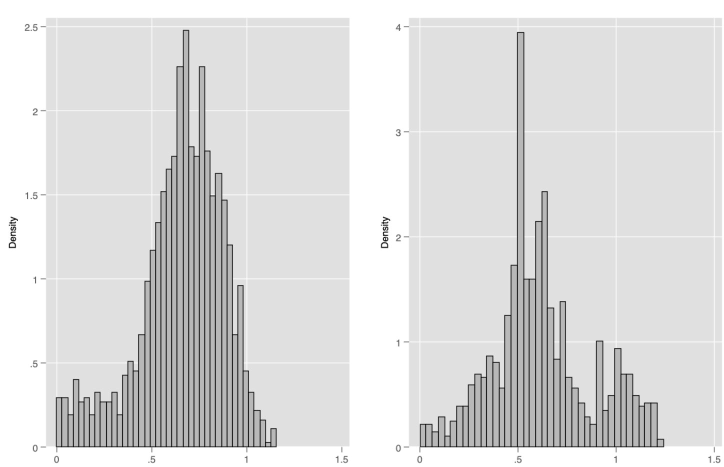
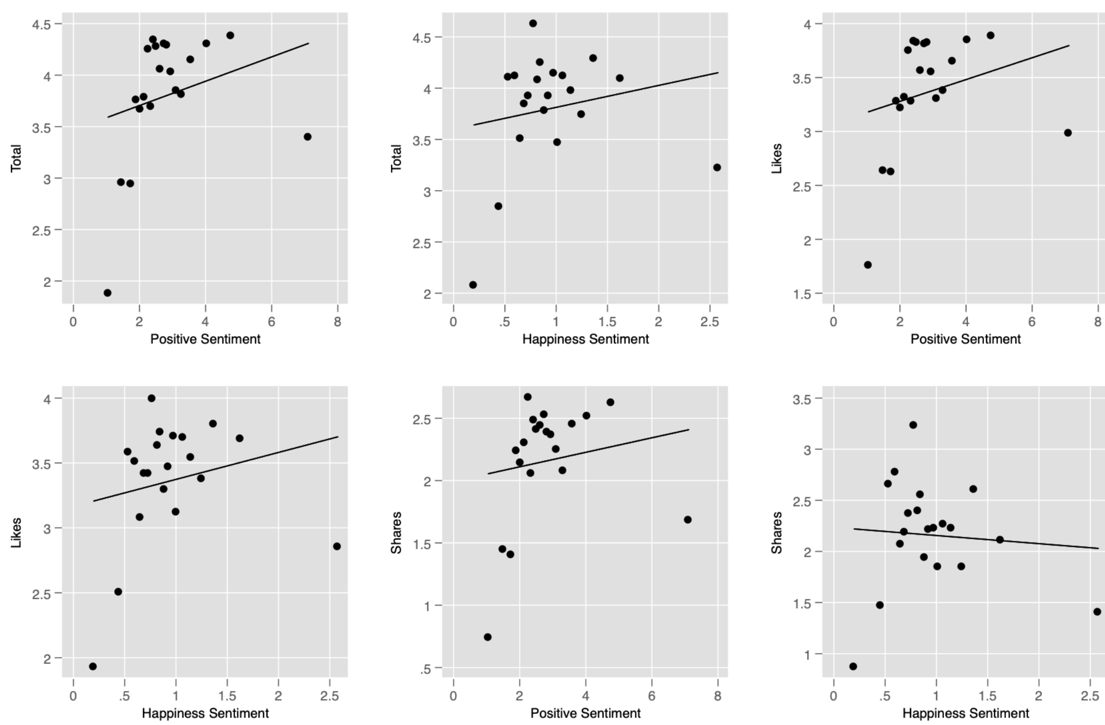


Figure B22: Correlation Between Positive Sentiments and Facebook Interactions



3 Measures

3.1 Internet Access

To construct this measure, I obtained shape files of access to 3G Mobile Internet from the company Collin's Bartholomew Mobile Coverage Explorer. This data consists of 1*1 grid cells indicating the presence or absence of 3G coverage at such level. I combined this data with a proxy of population density obtained from the Socioeconomic Data and Applications Center, a data center owned by NASA's earth observing center. Then, I multiplied the data indicating the presence or absence of 3G coverage by the population density in a 1*1 grid cell in all the Chilean territory.[1]

The resulting data shows how many people are covered by 3G in Chile in a given unit, either a district or a municipality. Then, I sum up the number of people covered by 3G; and finally, I divide the number of people covered by the population, resulting in the share of Chileans covered by 3G in the corresponding administrative unit. This procedure has been conducted by Guriev et al. (2021), and it is described in their replication materials.

Even if access to 3G mobile internet appears to be an adequate proxy of internet consumption in the included period, it is important to corroborate whether the share of citizens covered by 3G at some aggregate unit correlates to internet consumption at the individual level. To this end, I validate the measure using polling data. In particular, I merged the 3G data with the Latin American Public Opinion Project (LAPOP) at the municipality level, in order to check for a positive correlation between access to 3G mobile internet and individual internet consumption.

Here, I used the following survey question: "How frequently do you use the internet?". I considered frequent users to be respondents using the internet either every day or some times per week and non-frequent to people who responded either sometimes per month, rarely, or never. Then, I regressed this indicator of Internet consumption on the Share 3G variable, using 2011,

[1]For the 2010-2014 period, I used the population density of 2010 according to the NASA dataset; for the years beyond 2015, I used the density of 2015.

2012, 2014, and 2017 waves.[2]

Table A19: Correlation Between 3G Mobile Internet and Individual Consumption

	(1)	(2)	(3)	(4)
Outcome:	Frequent Internet Consumption			
Share 3G	0.259***	0.207***	0.089**	0.052
	(0.053)	(0.037)	(0.038)	(0.053)
Year	2011	2012	2014	2017
Outcome mean	0.38	0.40	0.46	0.68
Outcome sd	0.48	0.49	0.50	0.47
R^2	0.0148	0.0214	0.00389	0.000628
Obs.	1621	1415	1415	1500

*p<.1; **p<.05; ***p<.01.

In Table A19, we see the results of this validation exercise, with some insightful results. In general, there is a positive correlation between internet consumption and access to 3G mobile internet, corroborating the validity of the 3G measure. For instance, in 2011, a one percentage point increase in the share of people covered by 3G increases individual internet consumption by 26 probability points. Tellingly, the correlation decreases over time, partly because frequent internet consumers also augmented by a large amount, so municipality-level access became less important. Still, given that my data started in 2011, access to 3G is a good predictor of consumption, at least among the municipalities included in the LAPOP survey.

3.2 Attention and Reactions

It is important to discuss whether these are adequate measures to capture the construct of interest, namely, Facebook attention. Having a Facebook page is a clear behavioral measure that completely depends on the politician and indicates the desire to at least participate in Facebook. In the case of the other indicators —likes, shares, and total reactions—, they are generated through

[2] The main limitation of this exercise is that the LAPOP survey does not include all the Chilean municipalities. In fact, it includes observations from 120 municipalities in the included years, about one-third of the total number of municipalities. Moreover, most of the included localities are urban —which is common in public opinion polls—, so rural observations may be underrepresented.

the interaction between politicians and the public, in the sense that they not only depend on the politicians themselves. Certainly, a higher number of Facebook likes implies that a politician is active on this platform, either because he/she posts lots of messages, pays to have a broader audience, or because he/she is very popular offline. Thus, it is not controversial to affirm that reactions are a basic proxy of attention and activity. Nonetheless, I want to highlight an aspect of the reaction measure that is relevant to the analysis relating to Facebook's attention and ideological extremism. In addition to a proxy of activity, the number of reactions implies that Facebook users approve or disapprove of certain messages. In this sense, as politicians monitor these reactions, they can learn which types of messages are more successful, which ultimately could affect different outcomes.

3.3 DW-Nominate

I want to discuss the merits of this variable. DW nominate scores are typically used as a measure of latent ideology in American politics. Indeed, scholars have used it to show the increasing levels of polarization between Democrats and Republicans (e.g. Ladewig, 2021) and for analyzing the impact of close elections on ideological positioning (e.g. Lee et al., 2004), among other topics. I use this variable mainly because it incorporates the whole set of non-unanimous roll-call votes without cherry-picking any particular vote that we may think reveals extremism.

The other option would have been exactly that: Pick a few votes of important bills per year, decide ex-ante which option indicates an extreme position, and use it as the outcome. I decided against this option precisely because there are several arbitrary decisions involved. For instance, there might be votes that we can consider extreme, such as the attempt to impeach the president of Chile in 2019. However, the impeachment was practically split along party lines, as the opposition took it as a display of strength. So the definition of being "extreme" would apply to all deputies on one side of the political spectrum. Therefore, by using latent ideology in all roll-call votes, I relied on a measure that includes most of the bills per year, avoiding such arbitrary decisions —choosing bills and defining ad-hoc what is extreme.

It is worth discussing whether the left-right scale is adequate to measure extremism in the

Chilean context. Within Latin America, Chile has one of the most stable party systems. There are historical parties that represent clear ideological stances, such as the Socialists and the Communists on the left and National Renewal and Independent Democratic Union on the right. Previous research has shown that legislators' congressional behavior aligns with party ideology in the left-right dimension (Argote and Navia, 2018). Thus, this is the most meaningful construct differentiating parties, and deviations from this scale are an adequate way to measure extremism. Indeed, Figure B6 shows the average DW-nominate score for each of the main Chilean parties in the included period. In general, we see that the scores are predictable: the Communist Party appears on the extreme left, the Socialist Party in the Center-left, Christian Democrats in the center, National Renewal in the Center Right, and Independent Democratic Union on the far right. The only radical shift concerns the Christian Democrats from 2017 to 2018, mostly explained by a change of government. From 2014 to 2017, the Christian Democrats were part of the government coalition, together with the Socialists and the Communists. Thus, they converged to the positions of these two parties because, as part of the government coalition, they had to support the executive. In 2017, a right-wing coalition won the presidential election; thus, the Christian Democrats returned to their more "natural" position in the middle ground.

3.4 Extremism

The extremism measure described in the manuscript has, in general, a normal distribution. Figure B13 displays histograms of this variable on a yearly basis, showing that the distribution approaches normality, although there are some years where it is more skewed (2012 and 2020). As this variable is measured in absolute deviations from the average per year, it implies that most legislators moderately deviate from the yearly average, as they represent different political parties. However, just a few legislators could be classified as extremists since it is unusual to exceed the threshold of one.

Instead of calculating the absolute deviation from the mean per year, I could have calculated the deviation from the average of the whole period. I decided against this option because, in measuring extremeness, it is important to adjust for the composition of Congress in a particular year. For instance, if Congress is especially leftist, legislators would have to adopt even more radical positions than the average to be considered an extremist. A right-wing deputy who has not changed positions would also be considered more extremist than before in this new left-wing congress, which makes sense because now the median legislator is more to the left. Thus, yearly adjusting for the position of the average legislator captures more adequately the level of extremism. That being said, the overtime average of this measure is very stable —always in the range of 0.65-0.78 (see table A8)— meaning that there are no dramatic changes in the average legislator.

I obtained the data on roll-call voting of Chilean legislators for 2010-2020 through an official request to the Chamber of Deputies. By the law of transparency, they have to answer these requests within a period. I collapsed the ideology score at the politician-year level and merged it into the master data.

3.5 Why Facebook and not Twitter?

Another relevant discussion that merits a longer explanation is why I decided to focus on Facebook and not on other social media platforms for the most part of the analysis.[3] Two main reasons led me to this decision. First, Facebook is, by far, the most popular social media platform in Chile today and in the past ten years. According to a recent poll conducted in November 2021,[4] about 50% of adults report using Facebook on a daily basis, 35 percentage points more than Twitter (see table A20).

Other media reports corroborate this basic trend. For instance, when analyzing the percentage of web traffic that comes from social media sites, we see that 66% comes from Facebook, 4.3% comes from Youtube, and only 3.5% comes from Twitter. In this sense, Facebook is also a platform that directs people to other news sites.

The second reason concerns the nature of the interactions between politicians and the pub-

[3] I only use Twitter data in a short subsection in Chapter 5.

[4] This data is from a poll conducted by Netquest, a renowned survey firm in the Americas. It was commissioned by me for another research project.

Table A20: Social Media Daily Use

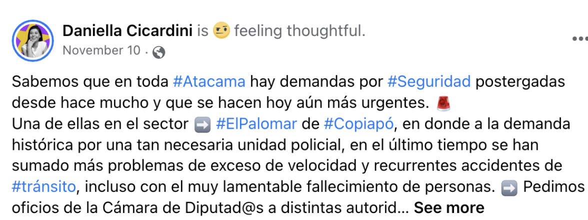
Media	Everyday use (%)
Facebook	49.4
Twitter	15.5
Instagram	37.1
Online Newspapers	25.0
TV	51.0
Whatsapp	49.3
Newspapers	3.9
Radios	24.3

Source: Netquest

lic. Given that Twitter is used by a small share of Chileans —the most politicized and interested in public affairs—, it is usually a platform to discuss national politics. Indeed, the nature of the platform is to highlight "trending topics," which usually affect the whole country, such as elections, televised debates, legislative discussions, and so on. Instead, Facebook is a platform where politicians are more eager to communicate about local affairs.[5] A quick glance into legislators' Facebook pages corroborates this idea. Figure B23 shows a good example of this characteristic for two legislators. For instance, we see a Facebook message mentioning some very specific initiatives in public safety matters for their respective constituencies. We hardly see these types of messages on a platform like Twitter.

Figure B23: Example of How Politicians Use Facebook

(a) Legislator Renzo Trisotti Facebook Page



(b) Legislator Daniella Cicardini Facebook Page

[5]In Chapter 5, I present evidence derived from quantitative text analysis sustaining this claim.

3.6 Sentiment

The NRC VAD dictionary, used to conduct the sentiment analysis, was specially designed to analyze the sentiments and emotions of short sentences, such as Facebook messages or tweets (Kiritchenko et al., 2014). Moreover, it has been used in several research articles, covering issues from hashtags analysis (Mohammad and Kiritchenko, 2015) to movie dialogues (Hipson and Mohammad, 2021). To provide an example from my dataset, this is a Spanish sentence associated with a negative sentiment:

> "Se han perdido 30 mil puestos de empleo en lecherías y esta decisión de la comision antidistorsiones es una verdadera falta de respeto a nuestros productores lecheros"

In English, this sentence reveals a legislator complaining about the loss of employment in the milk-producing sector. Meanwhile, this is a sentence associated with joy:

> "Un gran saludo y abrazo para tod@s que las energías del universo reinen en sus hogares y llege el amor, la paz y las esperanzas de un buen año nuevo 2020 de grandes desafíos para el pais, la región y en especial para nuestro querido puerto de Coquimbo, Bendiciones para ustedes y sus familias."

This is basically a message about love and peace in the context of the new year.

4 Additional Data Sources

4.1 Covariates

In some of the regression models, I use covariates, either to control for district-level characteristics or to estimate heterogenous effects. The demographic covariates were obtained from the CASEN survey, a periodic, nationally representative survey including more than 200,000 observations, which is used to register socioeconomic information of Chilean families. I used the CASEN survey versions 2011, 2013, 2015, and 2017; for each year, I computed the average population, income, urban population, and average age and collapsed at the district level. The data is available at http://observatorio.ministeriodesarrollosocial.gob.cl. Then, I merged it with the master data. To obtain the vote share, I used data from the Chilean Electoral Services, which computes the vote share for each legislator in their respective district. Data is available at https://www.servel.cl/

4.2 Public Opinion

To provide evidence of one of the hypothesized mechanisms, I use data from the LAPOP survey, a nationally representative public opinion poll of several Latin American countries. In this case, I use the observations of Chile for the 2012, 2014, 2017, and 2019 waves. As with any public opinion poll, the LAPOP survey is not representative at the municipality level, so there could be a threat to the external validity of this analysis. However, as I use multiple waves, there is a decent number of observations per municipality —110 individuals on average. Still, I caution that the sample most likely over-represents urban places, as many rural locations are not typically reached by these types of polls. I merged this data with the 3G share variable at the municipal level over time, resulting in a repeated cross-sectional dataset covering 119 of the 345 Chilean municipalities. Given that the 3G data covers until 2018, I merged the 2018 3G data with the 2019 LAPOP survey.

5 Challenges for Causal Identification

As I advanced in the introduction, a necessary component of my research design is to have variation in access to the internet; hence, I use data on 3G mobile internet rollout across the Chilean territory. However, 3G rollout in Chile was certainly not randomly assigned, as more covered places are likely more populated and urban compared to less covered ones. In this sense, the mere comparison among localities will, most likely, yield biased results. To address this potential endogeneity problem, I applied several statistical techniques for observational data, with the purpose of approaching causal identification as best as possible. This discussion is valid for all the empirical chapters of this manuscript —Chapter 5 and Chapter 6.

First, I remind the reader that the two-way fixed effects model adjusts for politician heterogeneity and region-specific time trends. This implies that differences across politicians and events affecting particular regions are already accounted for, as the source of the variation is within-politician over time. In this sense, any potential effect implies that a given politician changed their behavior concurrently with increases in 3G access.

Second, I estimate all the models with and without time-variant demographic and political controls. If the hypothesized effects are robust, I expect that the coefficients will not change dramatically after the inclusion of such controls; if the coefficient goes to zero in an adjusted model, it would mean that the independent variable of interest —for example, 3G internet— was capturing the effect of one of the included covariates.

Third, I included lead versions of the independent variable of interest in all the relevant models in cases where I have enough observations and statistical power. If an effect exists, then the coefficient of the lead variables —that is, the same independent variable in future time— should be zero.

Finally, for the main hypothesis of the book —the one relating Facebook interactions with ideological extremism (see Chapter 6)—, I conducted different types of analysis, each of them with different assumptions. For instance, in addition to the two-way fixed effects models, I implemented an instrumental variable specification with the hope of providing additional empirical evidence.

None of these strategies by itself would completely assure the validity of the causal estimates because there is always the possibility of an omitted confounder. However, if we find the same result in different specifications, it is more likely than not that these results are credible. In other words, in the absence of a field experiment or of a clean natural experiment, I follow the logic of a detective solving a crime: finding all the necessary set of facts that points towards a conclusion, even if such a conclusion is not 100% irrefutable.

6 Robustness Check Topic Modeling

Topic modeling enables the characterization of the primary subjects within a collection of documents through the recognition of word patterns contained within them. Within the framework of panel data, this examination elucidates how specific subjects gain increasing significance as time progresses. In particular, topic modeling detects the *k* number of topics for a given document. For each *k* topic, there is a distribution of words. In this sense, document *i* can be characterized by a distribution of topics *k*, and, in turn, topic *k* includes a set of words in different proportions. The share of each document for each topic is also denominated the "mean contribution." I use a Latent Dirichet Allocation (LDA) topic modeling, which utilizes a prior distribution called Dirichet for the per-document topics and the per-topic words.

Table A21: Top 20 Words Policy Topic among High 3G

Policy			
5 Topics	**10 Topics**	**15 Topics**	**20 Topics**
Proyecto	Proyecto	Proyecto	Proyecto
Vecinos	Vecinos	Vecinos	Vecino
Gobierno	Gobierno	Gobierno	Gobierno
Trabajo	Comuna	Comuna	Comuna
Comuna	Trabajo	Trabajo	Trabajo
Pais	País	País	País
Años	Años	Años	Años
Nacional	Nacional	Nacional	Nacional
Ley	Región	Región	Región
Región	Ley	Ley	Ley
Educación	Educación	Educación	Cámara
Salud	Cámara	Cámara	Educación
Cámara	Salud	Sector	Sector
Reunión	Sector	Salud	Presidente
Nueva	Presidente	Reunión	Salud
Comisión	Reunión	Equipo	Nueva
Diputados	Nueva	Presidente	Reunión
Nuevo	Equipo	Nueva	Equipo
Parte	Diputados	Diputados	Vida
Sector	Nuevo	Nuevo	Diputados

In the paper, I included the analysis with 8 topics. As a robustness check, I ran the topic model algorithm with a different number of topics: 20, 15, 10, and 5. In each of the iterations, the results are very similar to the ones presented in the results section: Among the high 3G group, two different topics predominate in the period, which are distinguishable from each other. Table A21 shows the top 20 words of the Policy topic with varying numbers of k among the high 3G group in the original language. Meanwhile, Table A22 shows the top 20 words of the Appeal topic in the high 3G group. Both tables confirm that the themes are clearly identified regardless of the total number of topics defined previously.

Table A22: Top 20 Words Appeal Topic among High 3G

Appeal			
5 Topics	**10 Topics**	**15 Topics**	**20 Topics**
Mejor	Mejor	Mejor	Mejor
Gobierno	Esfuerzo	Esfuerzo	Esfuerzo
Esfuerzo	Siempre	Siempre	Siempre
Ayudar	Ver	Ver	Ayudar
Siempre	Gente	Ayudar	Ver
Concepción	Ayudar	Gente	Piensas
Haré	Piensas	Piensas	Contáctame
Piensas	Contáctame	Contáctame	Haré
Contáctame	Haré	Haré	Apoyarte
Ver	Apoyarte	Apoyarte	Concepción
Atentamente	Concepción	Concepción	Sur
Apoyarte	Gobierno	Online	Gobierno
Gente	Online	Gobierno	Atentamente
Apoyo	Bío-Bío	Bío-Bío	Bío-Bío
Chiguayante	Atentamente	Atentamente	Online
Bío-Bío	Ley	Ley	Ley
Revisar	Chiguayante	Chiguayante	Chiguayante
Diputados	Sandra	Sandra	Dipuatdos
Online	Hermann	Hermann	Sandra
Ley	Diputados	Vida	Hermann

The subsequent Tables shows the two main predominant topics among the low 3G group. The first topic is related to policy, whose top 20 words are displayed in table A23.

Finally, Table A24 shows the second most relevant topic according to the model, for the low 3G group. As explained in the previous section, this is difficult to identify, although most of their

Table A23: Top 20 Words Policy Topic among Low 3G

Policy			
5 Topics	**10 Topics**	**15 Topics**	**20 Topics**
Proyecto	Proyecto	Proyecto	Proyecto
Gobierno	Gobierno	Gobierno	Gobierno
Vecinos	Vecinos	Ley	Ley
Región	Ley	Vecinos	Vecinos
Ley	Región	Región	Región
Comuna	País	Comuna	Comuna
Años	Años	Años	Años
Ahora	Comuna	País	Trabajo
País	Ahora	Ahora	País
Trabajo	Trabajo	Trabajo	Ahora
Nacional	Educación	Nacional	Nacional
Educación	Nacional	Educación	Educación
Diputados	Diputados	Diputados	Diputados
Salud	Salud	Salud	Salud
Personas	Personas	Vida	Personas
Parte	Vida	Personas	Vida
Nuevo	Alcalde	Regional	Parte
Vida	Nuevo	Parte	Regional
Años	Regional	Nuevo	Nuevo
Todas	Parte	Alcalde	Alcalde

keywords relate to policy, such as "ley" and "proyecto". In this sense, among the low 3G group, it seems that the only one relevant topic, shown in Table A23.

Table A24: Top 20 Words Second Most Relevant Topic among Low 3G

Undistinguishable			
5 Topics	**10 Topics**	**15 Topics**	**20 Topics**
Ley	Ley	Ley	Ley
Proyecto	Proyecto	Serena	Serena
Comisión	Serena	Proyecto	Proyecto
UDI	Reunión	Reunión	Reunión
Reforma	Rumbo	Rumbo	Rumbo
Serena	Modifica	Comisión	Coquimbo
Reunión	Comisión	Coquimbo	Comisión
Arica	Adultos	Constitución	Adultos
Nuñez	Sala	Adultos	Vicuña
Cámara	Votar	Modifica	Constitución
Linares	JJVV	Vicuña	Modifica
Rumbo	Constitución	Sala	Sala
Concejal	Club	Club	JJVV
Coquimbo	Establece	JJVV	Club
Maule	Actividades	Objeto	Votar
Gutierrez	Distrital	Votar	Siguientes
Candidatos	Vicuña	Siguientes	Objeto
Sala	Coquimbo	Establece	Establece
Entrevista	Vecinos	Proyectos	Actividades
Bachelet	Objeto	Actividades	Discutir

7 Extremism in the Chilean Context

What does extremism mean in the context of Chile during this period? What is the role of the institutional factors? Before stating the Chapter's main conclusions, it is important to answer these questions to have a better understanding of the results. The first thing to notice is that when legislators belong to the government coalition, they tend to be more disciplined in supporting the government (Argote and Navia, 2018). This implies that parties with divergent ideologies tend to converge when they are in government —as it is the case between Socialists and Christian Democrats (see Figure A7).

Indeed, a glance at the most extreme legislator each year confirms this argument. Table A25 shows that from 2011 to 2013, the most extreme legislators were from the Communist Party, which is not surprising given their history and their current positions: Support of the Maduro regime in Venezuela, embracing of the Soviet Union in the past, among other positions along these lines. However, between 2014 and 2017, the most extreme legislators belonged to the right, typically to the Independent Democratic Union, the party that emerged from the Pinochet dictatorship. In the 2018-2020 period, the extremist legislators were, again, from left-wing parties which formed a coalition with the communists. It is worth noting that the most extreme politicians always belong to the opposition —when the right governs, they are from the left and vice versa. This is likely because being in government creates incentives for aligning with the executive.

Table A25: Most Extreme Legislators by Year

Most extreme legislator	Party	Year	Who governed?
Hugo Gutierrez	Communist	2011	Right
Lautaro Carmona	Communist	2012	Right
Hugo Gutierrez	Communist	2013	Right
German Becker	National Renewal	2014	Center-Left
Gustavo Hasbún	Independent Democratic Union	2015	Center-Left
Gustavo Hasbún	Independent Democratic Union	2016	Center-Left
Jorge Ulloa	Independent Democratic Union	2017	Center-Left
Claudia Mix	Comunes	2018	Right
Florcita Alarcón	Humanist	2019	Right
Pamela Jiles	Humanist	2020	Right

In addition, in the Chilean presidential regime, all the initiatives in bills that involve the allocation of fiscal resources, must come from the executive. In other words, legislators are not allowed to propose bills involving fiscal resources. In this sense, the executive, as co-legislator, controls the timing and the priorities of the legislative agenda.

Likewise, Chile changed its electoral system in the 2017 parliamentary election, decreasing the number of districts and increasing the number of seats allocated per district. This reform allowed parties to gain legislative seats with a very small vote share, allowing for the inclusion of more extreme parties in congress in 2017, and especially in 2021. Thus, there was a higher number of players in congress that could find it beneficial to move to oppose the government.

These three factors —the difference in legislative behavior when in government versus opposition, the preeminence of the executive as co-legislator, and the proliferation of parties away from the center ground— implies that moving to the extreme means, to a large extent, opposing the government. Indeed, when a government becomes unpopular (as is usually the case), being against the government may entail more visibility in the media, among other benefits.

8 Extremism by Policy Area

Table A26: Effects of Facebook Activity on Extremism on the Economy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	Ideological Extremism							
Page (t-1)	0.038	0.042						
	(0.027)	(0.026)						
Likes (t-1)			0.024**	0.022**				
			(0.010)	(0.009)				
Total (t-1)					0.022**	0.020**		
					(0.008)	(0.008)		
Shares (t-1)							0.034***	0.029***
							(0.011)	(0.011)
Outcome mean	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66
Outcome sd	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22
N Clusters	60	60	60	60	60	60	60	60
Obs.	1145	1137	1145	1137	1145	1137	1145	1137
Controls		✓		✓		✓		✓
R^2	0.761	0.779	0.763	0.780	0.764	0.780	0.764	0.780

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2020. The outcome for all regressions is level of extremism in congress. The models include politician*district and region*year fixed effects. Controls include log of population, log of income, urban status, average age, vote share, and political coalition.

In the paper, I documented the existence of an effect of Facebook activity on elite extremism. Extremism was calculated using all roll-call votes of Chilean Deputies from 2011 to 2020. However, it is important to differentiate between different types of roll-call votes, to analyze whether the effect of Facebook activity on extremism applies to a specific area.

To this end, I classified roll-call votes into two large policy areas: The economy and public services.[6] In the economy, I included votes related to agriculture, fishing, the labor market, productivity, and fiscal policy. Meanwhile, public services include health care, education, and housing. Figure B21 shows that the distribution of these variables approaches normality, similar to the extreme variables that include all roll-call votes.

[6] The DW-nominate algorithm needs a minimum number of votes to operate. Thus, I could not use more policy areas, as there were not enough votes per year. Indeed, I tried running the package with votes related to foreign affairs and institutional reforms, among other areas, but it was not possible.

Table A27: Effects of Facebook Activity on Extremism on Public Services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	Ideological Extremism							
Page (t-1)	-0.016	-0.007						
	(0.032)	(0.03)						
Like (t-1)			0.012	0.012				
			(0.011)	(0.010)				
Total (t-1)					0.011	0.011		
					(0.010)	(0.009)		
Shares (t-1)							0.030*	0.027**
							(0.017)	(0.013)
Outcome mean	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62
Outcome sd	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
N Clusters	60	60	60	60	60	60	60	60
Obs.	1145	1137	1145	1137	1145	1137	1145	1137
Controls		✓		✓		✓		✓
R^2	0.581	0.617	0.582	0.618	0.582	0.618	0.584	0.619

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2020. The outcome for all regressions is level of extremism in congress. The models include politician*district and region*year fixed effects. Controls include log of population, log of income, urban status, average age, vote share, and political coalition.

Table A26 shows the results of the two-way fixed effect model when using the extremism indicator only for roll-call votes that apply to the economy. In general, we see that the effect is very similar to the one estimated with all the votes, although with somewhat more uncertainty. We can corroborate this when looking at the coefficient plot displayed in Figure B24.

Table A28: Effects of Facebook Activity on Extremism on Public Services

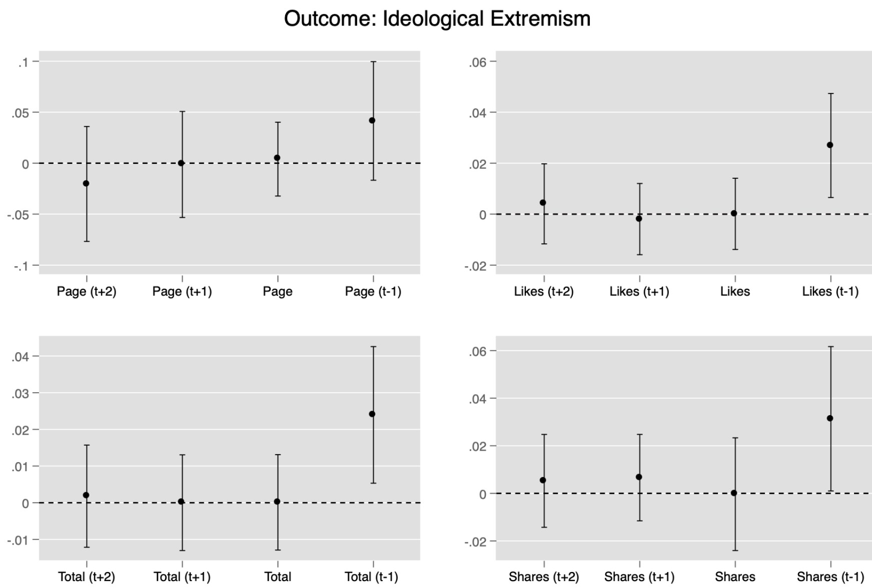
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:				Ideological Extremism				
Page (t-1)	-0.016	-0.007						
	(0.032)	(0.03)						
Like (t-1)			0.012	0.012				
			(0.011)	(0.010)				
Total (t-1)					0.011	0.011		
					(0.010)	(0.009)		
Shares (t-1)							0.030*	0.027**
							(0.017)	(0.013)
Outcome mean	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62
Outcome sd	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
N Clusters	60	60	60	60	60	60	60	60
Obs.	1145	1137	1145	1137	1145	1137	1145	1137
Controls		✓		✓		✓		✓
R^2	0.581	0.617	0.582	0.618	0.582	0.618	0.584	0.619

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2020. The outcome for all regressions is level of extremism in congress. The models include politician*district and region*year fixed effects. Controls include log of population, log of income, urban status, average age, vote share, and political coalition.

However, regarding public services, the effects are considerably smaller and, most of the time, not statistically significant (see Figure B25 for the respective coefficient plot).

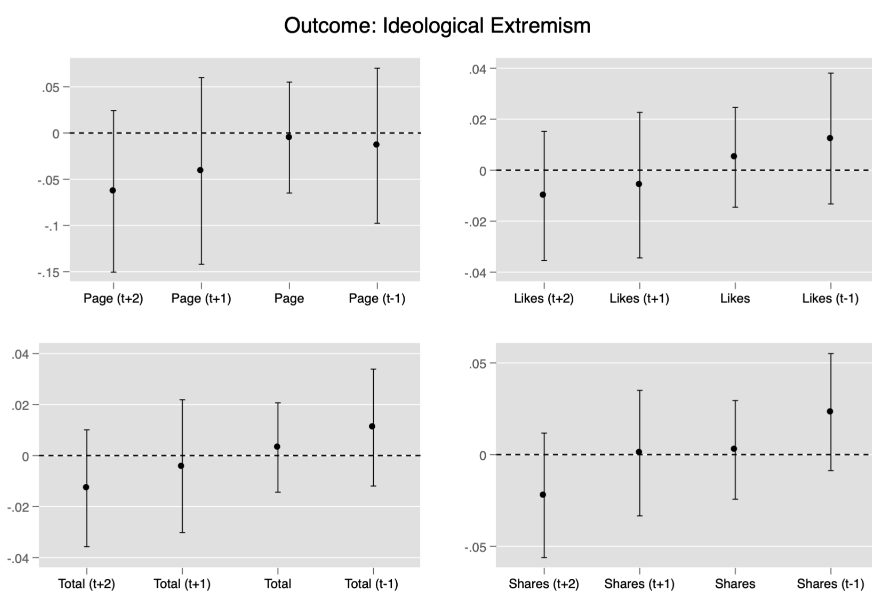
This suggests that legislators are moving more to the extreme in areas that are at the core of their ideological stances, such as the economy, and to a lesser extent, in the provision of public services.

Figure B24: Coefficient Plot Effects Facebook Activity on Extremism on the Economy



The circle represents the point estimate, and the line is the 95% confidence interval.

Figure B25: Coefficient Plot Effects Facebook Activity on Extremism on Public Services



The circle represents the point estimate, and the line is the 95% confidence interval.

9 Background on Internet Expansion in Chile

It is important to add more background information about internet expansion. There was a significant expansion of smartphones in Chile at the beginning of the 2010s decade. Even if the expansion occurred in rural and urban households, it was driven mainly by the former, as these have lower baseline access to broadband internet coverage. Indeed, a survey conducted by the Chilean Ministerio de Transportes y Comunicaciones shows that by 2016, among rural households, 69% had mobile internet in their cellphones, whereas only 26% had fixed broadband; in urban households, the percentages are quite different: 55% had mobile internet, while 68% has fixed broadband (Subsecretaría de Telecomunicaciones de Chile, 2017). In this sense, to a large extent, 3G internet coverage expanded internet coverage among rural households, as urban places already had relatively high internet access.

During these years, Chileans have increased their consumption of politics through social media, although TV remains the main source of political information. Polling data show that the percentage of people who consume political news through Facebook and Twitter either frequently or sometimes increased in the 2010-2020 period, whereas there is some decrease in TV consumption for this purpose.

References

Argote, P. and P. Navia (2018, April). Do Voters Affect Policies? Within-Coalition Competition in the Chilean Electoral System. *Journal of Politics in Latin America 10*(1), 3–28.

Guriev, S., N. Melnikov, and E. Zhuravskaya (2021, November). 3G Internet and Confidence in Government*. *The Quarterly Journal of Economics 136*(4), 2533–2613.

Hipson, W. E. and S. M. Mohammad (2021, September). Emotion dynamics in movie dialogues. *PLOS ONE 16*(9), e0256153. Publisher: Public Library of Science.

Kiritchenko, S., X. Zhu, and S. M. Mohammad (2014, August). Sentiment Analysis of Short Informal Texts. *Journal of Artificial Intelligence Research 50*, 723–762.

Ladewig, J. W. (2021, September). Income Inequality and Ideological Positions in the U.S. Congress. *Political Research Quarterly 74*(3), 599–614. Publisher: SAGE Publications Inc.

Lee, D. S., E. Moretti, and M. J. Butler (2004, August). Do Voters Affect or Elect Policies? Evidence from the U. S. House. *The Quarterly Journal of Economics 119*(3), 807–859.

Mohammad, S. M. and S. Kiritchenko (2015). Using Hashtags to Capture Fine Emotion Categories from Tweets. *Computational Intelligence 31*(2), 301–326. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/coin.12024.

Subsecretaría de Telecomunicaciones de Chile (2017, December). IX Encuesta de Acceso y Usos de Internet.