Supplementary Appendix for “How to Stay Popular: Threat, Framing, and Conspiracy Theory Longevity”

Courtney Blackington and Frances Cayton

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Appendix A: Data Collection Procedure and Coding Rules

In January 2021, Twitter launched the Academic API. After providing details on the scientific study and project requiring Twitter data, it allowed researchers to stream up to millions of tweets without historic limits or rate-limitation problems (Twitter, n.d.). Until February 2023, Twitter's Academic API permissions provided free access to a limited number of tweets that due to rate-limiting and opaque sampling procedures could induce biased samples (Klašnja et al., 2017; Morstatter et al., 2013).

We use a keyword stream through Twitter's Academic API for our study. A keyword stream via the Academic API, when compared to the Firehose, has high keyword coverage. This coverage is near 100% for tweets streamed over the last 24 hours (Pfeffer et al., 2022). Our sampling strategy entailed scraping tweets every 24 hours over the three day period during which crash memorials occurred, suggesting we maintain a near-universal sample of CT-related tweets in this time period. One could obtain a non-random sample by streaming at the user-ID level and pre-selecting accounts to monitor. To avoid this, we streamed tweets via a constant list of hashtags, which we tested in June and July 2021. Instead of following a subset of users over the duration of the data collection, this approach allowed our sample to include anyone tweeting about the crash each month. As such, we could catch new voices in the CT discourse on social media.

We collected our sample using the following hashtags list: #Smoleńsk, #SmoleńskSabotage, #SmoleńskPamietamy, #KatastrofaSmoleńska, #10kwietnia, #miesiecznica, #10042010Fakty,#Pamietamy, #podkomisjasmoleńska, #Smolensk2010, #LechKaczyński, #LechaKaczyńskiego, and #96ofiar.

Translations of hashtags are offered in Table 4. These hashtags were selected based on a test stream of tweets in June and July 2021. After testing a broader list of hashtags, we found that this list of hashtags was commonly deployed in tweets about Smolensk, but also was rarely employed outside of the context of the Smoleńsk crash. As such, we have limited our streams to mostly relevant tweets. We did not place geographic limits on the tweets collected because some members of the Polish diaspora organize regular Smoleńsk commemorations abroad. Though hashtags were all in Polish, tweets were downloaded without a language restriction. We then filtered for only tweets in Polish or in an undetermined language. After reviewing this sample by-hand, we note that most tweets classified as using an undetermined language were in Polish but began with emojis. Thus, these tweets were retained in the sample. We also removed duplicate tweets. These are tweets with the same unique tweet ID which appeared twice within our sample; this often occurred due to a tweet having multiple keywords within its content. At the end of the streaming period, the authors compiled the full sample of tweets across months to create the dataset used in the analysis.

We independently hand coded all tweets. We coded any instance of invoking a conspiracy theory about Donald Tusk, the PO party, and CTs that PO and Russia jointly orchestrated the plane crash. We established general protocol for what counted to each type of CT using those tweets streamed in our June and July 2021 test streams. There, we independently identified patterns that served as guidelines for our coding.

For example, while CT entrepreneurs used many different strategies to invoke a CT, words like “assassination” (zamach) or photos that showed Tusk and Putin shaking hands were frequently used to invoke these CTs. Some photos showed blood dripping off of Tusk’s name or the PO party’s letters. We also identified tweets that did not invoke a CT when discussing the crash. Often, these tweets memorialized the crash victims, perhaps with a photo collage or a tribute to specific individuals who died in the crash. We also coded for religious symbols, such as photos of commemoration masses, crosses, votive candles, and praying. We went through each user and coded any PiS officials. We also coded for news coverage and local police/public safety details around memorials. After both authors coded the tweet corpus, we compared our codes and found that we matched with a 96.5 percent accuracy and Cohen’s Kappa of 0.76.

The authors coded tweets on a monthly basis. When our coding did not align, we pulled up the Tweet and discussed why we reached different conclusions before agreeing on the next steps. Usually this entailed revisiting the tweet, confirming the translation or imagery (whether there was a word, person, or location referenced that one of the authors did not realize), and then deciding jointly on the best coding.

Table 4: Hashtags Streamed

Polish Hashtag	English Translation
#Smoleńsk,	Smolensk
#SmoleńskSabotage	Smolensk Sabotage
#SmoleńskPamietamy	We Remember Smolensk
#KatastrofaSmoleńska	Smolensk Catastrophe
#10kwietnia	April 10th
#miesiecznica	Monthly commemoration
#10042010Fakty	April 10, 2010 Facts
#podkomisjasmoleńska	Smolensk Subcommittee
#Pamietamy	We Remember
#Smolensk2010	Smolensk 2010
#LechKaczyński	(President) Lech Kaczyński
#LechaKaczyńskiego	Lech Kaczyński (declination)
#96ofiar	96 victims

Appendix B: Descriptive Statistics for Tweets

The average number of tweets per account were 2.65 tweets, with a standard deviation of 5.76. The distribution of tweets by account is found in Figure 6. When subsetting the data to just those tweets engaging a CT, the mean tweets per account is 2.74 with a standard deviation of 5.39. This distribution is shown in Figure 7. Finally, we show the distribution of our outcome variable by month in Table 5.Per Twitter's regulations, we cannot share the data to reproduce Figures 6 and 7, nor Table 5 as it would make the user fully identifiable for each tweet. We do, however, provide the code to make these figures in our replication materials.

Figure 6: Descriptive Summary of Tweets Contributed by Account

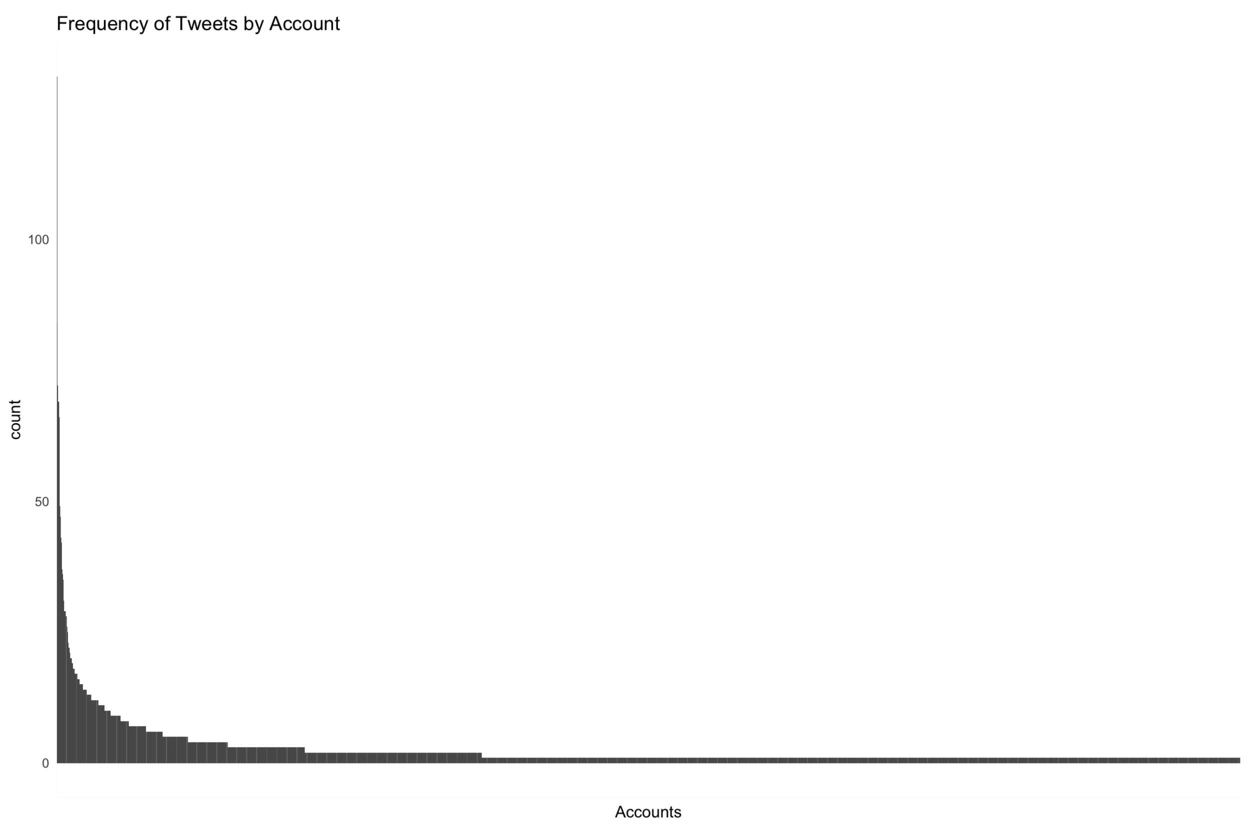


Figure 7: Descriptive Summary of CT Tweets Contributed by Account

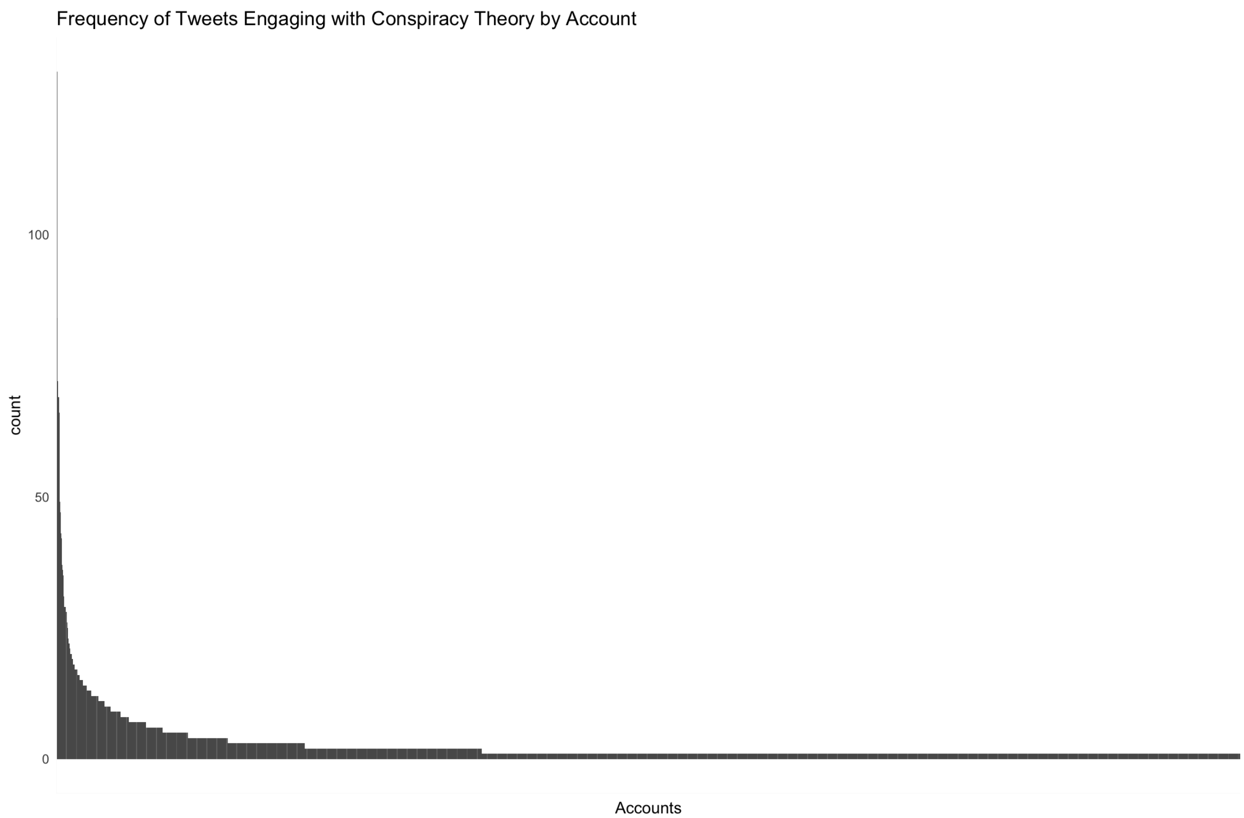


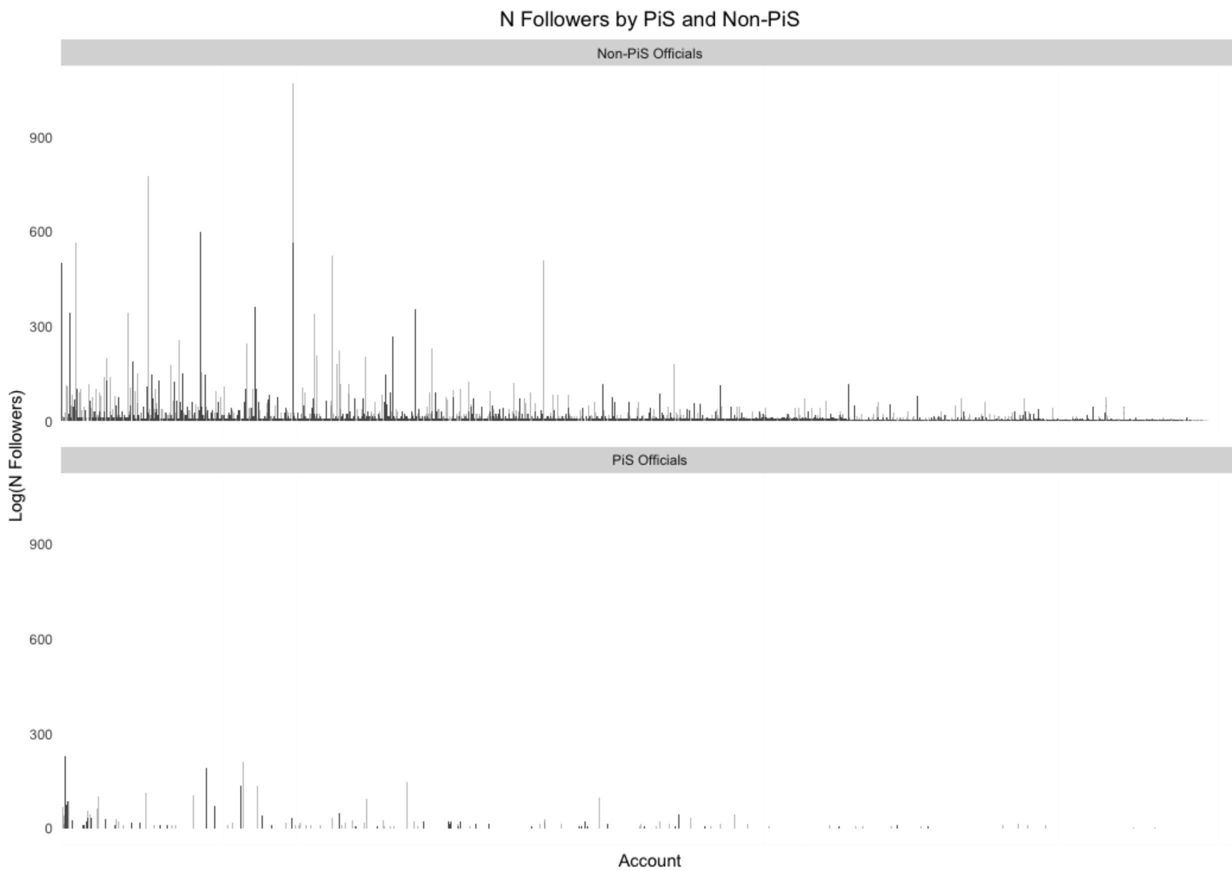
Table 5: Descriptive Statistics for Retweet and Like Outcome Variables

Month	Minimum, Retweet Count	Maximum, Retweet Count	Median, Retweet Count	Modal, Retweet Count	Minimum, Like Count	Maximum, Like Count	Median, Like Count	Modal, Like Count
Jan	0	186	1.00	0	0	809	3.00	0
Feb	0	88	1.00	0	0	518	3.00	0
Mar	0	344	1.00	0	0	947	3.00	0
Apr	0	781	1.00	0	0	1361	3.00	0
May	0	166	1.00	0	0	821	3.00	0
Jun	0	272	1.00	0	0	1362	3.00	0
Jul	0	211	1.00	0	0	1913	3.00	0
Aug	0	108	1.00	0	0	506	3.00	0
Sep	0	219	1.00	0	0	1063	3.00	0
Oct	0	171	1.00	0	0	844	3.00	0
Nov	0	117	1.00	0	0	525	3.00	0
Dec	0	198	1.00	0	0	1033	3.00	0

The average number of followers for non-PiS elites are 13,732; this figure is 40,561 for PiS elites. In our models we control for log(N Followers), with log-transforms of skewed variables— such as Twitter followers— standard in work with Twitter data (Hemsley, 2016; Kwak et al., 2010).

We plot these distributions of log(N followers) for both non-PiS elites and PiS elites in Figure 8. There, we see that non-PiS elites have higher log-follows than PiS elites. Regardless, controlling for log(N follows) in our regressions holds constant the effect of variable follows over retweets and likes.

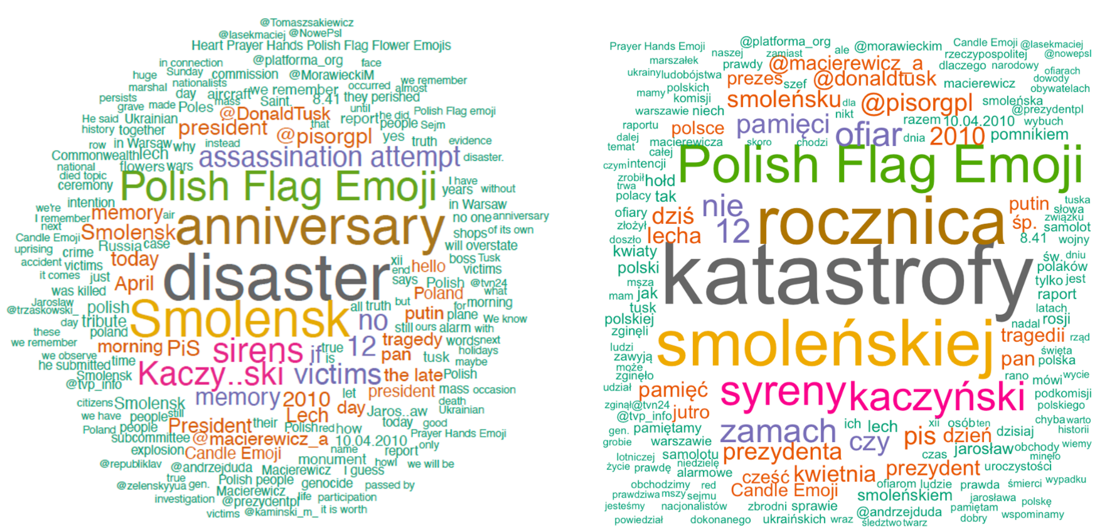
Figure 8: Log(N Followers) by PiS and Non-PiS Elites



Appendix C: Word Clouds

We create word clouds to visualize the discourse about Smoleńsk on Twitter on days that surround the monthly commemoration events. These offer an assumption-free way to assess the common themes within our corpus. We remove the hashtags used to scrape tweets from this analysis. The top words are shown in grey, brown, yellow, and pink. The most used word was "Smoleńsk," followed by "catastrophe, "we remember", and "assassination"-—a clear reference to the CT that Russian forces worked with PO to cause the Smoleńsk crash.
The most frequently used words also include Polish flag emojis, "April," "memory," "President," "Lech," and "Kaczyński." These phrases generally fall within those tweets memorializing the victims of the crash. However, considering the next most frequently used set of words, we see that CTs become common again. The purple and orange words reveal a trend toward politicization of tweets. References to Donald Tusk, monuments, and specific PiS officials like Macierewicz or PiS twitter accounts are quite common. In this manner, the word cloud suggests that as the tweets become more politicized, references to the CT also increase. We cannot share the data to reproduce Figure 9 as it would make the user fully identifiable for each tweet. We do, however, provide the code to make these figures in our replication materials.

Figure 9: Word Clouds



Appendix D: Regression Tables

Table 6: Tweet Content - Likes, Quasi Poisson Models

	Number of Likes		
	(1)	(2)	(3)
PO Consp.	0.042		
	(0.118)		
Tusk Consp.		-0.003	
		(0.139)	
Russia and PO Consp.			0.052
			(0.125)
Log(N Followers)	0.449***	0.449***	0.449***
	(0.025)	(0.025)	(0.025)
Log(N Friends)	0.136***	0.138***	0.136***
	(0.039)	(0.039)	(0.039)
Verified	-0.127	-0.131	-0.127
	(0.138)	(0.138)	(0.138)
Constant	-1.657***	-1.658***	-1.659***
	(0.354)	(0.353)	(0.353)
Observations	5,969	5,969	5,969

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 7: Tweet Content - Retweets, Quasi Poisson Models

	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	0.476***		
	(0.105)		
Tusk Consp.		0.380***	
		(0.122)	
Russia Consp.			0.521***
			(0.108)
Russia and PO Consp.	0.482***	0.481***	0.480***
	(0.027)	(0.027)	(0.027)
Log(N Followers)	0.165***	0.176***	0.170***
	(0.040)	(0.040)	(0.040)
Log(N Friends)	-0.421***	-0.441***	-0.426***
	(0.151)	(0.151)	(0.151)
Verified	-3.511***	-3.525***	-3.535***
	(0.375)	(0.376)	(0.373)
Observations	5,969	5,969	5,969

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 8: Tweet Content and PiS Officials - Likes Quasi-Poisson Models

	Number of Likes		
	(1)	(2)	(3)
PO Consp.	0.185		
	(0.125)		
Tusk Consp.		0.122	
		(0.146)	
Russia and PO Consp.			0.193
			(0.133)
PiS Officials	1.251***	1.214***	1.241***
	(0.124)	(0.123)	(0.124)
Log(N Followers)	0.474***	0.472***	0.473***
	(0.026)	(0.026)	(0.026)
Log(N Friends)	0.148***	0.151***	0.149***
	(0.040)	(0.040)	(0.040)
Verified	-0.220	-0.217	-0.220
	(0.137)	(0.136)	(0.137)
PO Consp.*PiS Official	-0.970		
	(0.891)		
Tusk Consp.*PiS Official		0.055	
		(0.983)	
PO and Russia Consp.*PiS Official			-0.750
			(0.816)
Constant	-1.581***	-1.567***	-1.566***
	(0.471)	(0.469)	(0.470)
Observations	5,969	5,969	5,969
Note:	Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).		

Table 9: Tweet Content and PiS Officials - Retweets, Quasi Poisson Models

	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	0.617***		
	(0.113)		
Tusk Consp.		0.494***	
		(0.130)	
Russia and PO Consp.			0.665***
			(0.116)
PiS Official	1.239***	1.168***	1.214***
	(0.135)	(0.133)	(0.134)
Log(N Followers)	0.502***	0.499***	0.500***
	(0.028)	(0.028)	(0.028)
Log(N Friends)	0.175***	0.188***	0.182***
	(0.042)	(0.042)	(0.042)
Verified	-0.476***	-0.488***	-0.476***
	(0.152)	(0.151)	(0.151)
PO Consp.*PiS Official	-1.281		
	(0.879)		
Tusk Consp.*PiS Official		-0.272	
		(0.974)	
Russia and PO Consp.*PiS Official			-1.047
			(0.788)
Constant	-3.408***	-3.413***	-3.369***
	(0.492)	(0.491)	(0.488)
Observations	5,969	5,969	5,969
Note:	Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).		

Table 10: Focusing Events - Likes, Quasi-Poisson Models

	Number of Likes		
	(1)	(2)	(3)
PO Consp.	-0.607*		
	(0.363)		
Tusk Consp.		-0.567	
		(0.392)	
Russia and PO Consp.			-0.310
			(0.428)
War	-0.377***	-0.348**	-0.325**
	(0.137)	(0.136)	(0.136)
Log(Followers)	0.452***	0.452***	0.452***
	(0.026)	(0.026)	(0.026)
Log(Friends)	0.135***	0.137***	0.134***
	(0.039)	(0.039)	(0.039)
Verified	-0.103	-0.111	-0.109
	(0.139)	(0.139)	(0.139)
PO Consp.*War	0.759**		
	(0.383)		
Tusk Consp.*War		0.674	
		(0.418)	
Russia and PO Consp.*War			0.424
			(0.447)
Constant	-1.237***	-1.265***	-1.269***
	(0.393)	(0.392)	(0.393)
Observations	5,969	5,969	5,969
Note:			Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 11: Tweet Characteristics and Frequency of Likes- Quasi-Poisson Models

	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	-0.078		
	(0.299)		
Tusk Consp.		-0.038	
		(0.320)	
Russia and PO Consp.			0.264
			(0.340)
War	-0.434***	-0.375***	-0.392***
	(0.142)	(0.139)	(0.138)
Log(N Followers)	0.486***	0.485***	0.484***
	(0.027)	(0.027)	(0.027)
Log(N Friends)	0.164***	0.175***	0.168***
	(0.041)	(0.041)	(0.041)
Verified	-0.391**	-0.418***	-0.402***
	(0.153)	(0.152)	(0.152)
PO Consp.*War	0.659**		
	(0.318)		
Tusk Consp.*War		0.508	
		(0.345)	
Russia & PO Consp.*War			0.317
			(0.358)
Constant	-3.041***	-3.111***	-3.070***
	(0.414)	(0.413)	(0.411)
Observations	5,969	5,969	5,969
Note:			Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 12: Focusing Events, Tweet Content, and PiS Officials - Likes, Quasi-Poisson Models

	Dependent variable:		
	Number of Likes		
	(1)	(2)	(3)
PO Consp.	-0.023		
	(0.365)		
Tusk Consp.		0.004	
		(0.391)	
Russia and PO Consp.			0.292
			(0.426)
War	0.145	0.165	0.188
	(0.337)	(0.335)	(0.335)
PiS Officials	1.664***	1.669***	1.695***
	(0.191)	(0.189)	(0.188)
Log(N Followers)	0.473***	0.471***	0.468***
	(0.025)	(0.025)	(0.025)
Log(N Friends)	0.117***	0.121***	0.113***
	(0.037)	(0.037)	(0.037)
Verified	-0.156	-0.160	-0.146
	(0.130)	(0.129)	(0.130)
PO Consp.*War	0.312		
	(0.385)		
PO Consp.*PiS Official	-2.367		
	(4.371)		
Tusk Consp.*War		0.226	
		(0.419)	
Tusk Consp.*PiS Official		-2.405	
		(4.368)	
Collusion Consp.*War			-0.084
			(0.446)
Collusion Consp.*PiS Official			-2.688
			(4.382)
War*PiS Official	-0.848***	-0.894***	-0.955***
	(0.233)	(0.230)	(0.231)
PO Consp.*War*Official	1.556		
	(4.387)		
Tusk Consp.*War*Official		1.668	
		(4.387)	
Collusion Consp.*War*Official			2.311
			(4.400)
Constant	-1.651***	-1.674***	-1.620***
	(0.446)	(0.445)	(0.444)
Observations	5,969	5,969	5,969
Note:	Standard Errors in parenthesis.		
	*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).		

Table 13: Focusing Events, Tweet Content, and PiS Officials - Retweets, Quasi Poisson Models

	Dependent variable:		
	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	0.389		
	(0.319)		
Tusk Consp.		0.410	
		(0.338)	
Russia and PO Consp.			0.745**
			(0.359)
War	-0.059	-0.031	-0.042
	(0.359)	(0.356)	(0.354)
PiS Officials	1.453***	1.446***	1.467***
	(0.210)	(0.207)	(0.205)
Log(N Followers)	0.503***	0.501***	0.498***
	(0.027)	(0.027)	(0.027)
Log(N Friends)	0.150***	0.163***	0.150***
	(0.041)	(0.040)	(0.040)
Verified	-0.423***	-0.445***	-0.421***
	(0.149)	(0.148)	(0.148)
PO Consp.*War	0.327		
	(0.340)		
PO Consp.*PiS Official	-3.073		
	(6.047)		
Tusk Consp.*War		0.178	
		(0.365)	
Tusk Consp.*PiS Official		-3.120	
		(6.038)	
Collusion Consp.*War			-0.063
			(0.378)
Collusion Consp.*PiS Official			-3.429
			(6.017)
War*PiS Official	-0.668**	-0.740***	-0.761***
	(0.259)	(0.255)	(0.254)
PO Consp.*War*Official	2.154		
	(6.057)		
Tusk Consp.*War*Official		2.304	
		(6.051)	
Collusion Consp.*War*Official			2.874
			(6.028)
Constant	-3.400***	-3.462***	-3.353***
	(0.484)	(0.483)	(0.478)
Observations	5,969	5,969	5,969
Note:	Standard Errors in parenthesis. *p $<$ 0.1; **p $<$ .05, ***p $<$ .01 (two-tailed tests).		

Appendix E: Robustness Check: Addressing Bots

In order to allay concerns that bots drive our results, we use Tweetbotornot in order to generate the probability that an account is a bot—where 0 is very unlikely and 1 is very likely to be a bot (Kearney 2018). The model underlying Tweetbotornot uses a supervised classifier, which generates the probability that each individual user is a bot based on user-level attributes, tweeting statistics, and patterns in tweet texts (Kearney 2018; Martini et al. 2021). Several different thresholds have been used to identify bots with this approach, from the conservative threshold of 0.3 (Luceri et al. 2019) to less conservative thresholds of 0.7 to 0.8 (Broniatowski et al. 2018; Keller and Klinger 2019; Woolley and Howard 2018). In our case, no observations fall between the conservative threshold of 0.3 and the less conservative threshold of 0.8, so we simply re-run the analysis we presented in the main text using the more conservative threshold. We show that our findings are robust when run on this subset of tweets in Figures 14 to 21. Thus, we do not believe that the presence of bots drives our findings.

Table 14: Tweet Content and Frequency of Likes Models with Bot 30 Data

	Number of Favorites		
	(1)	(2)	(3)
PO Consp.	0.047		
	(0.155)		
Tusk Consp.		0.105	
		(0.169)	
Russia-PO Consp.			0.198
			(0.161)
N(Followers)	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
N(Friends)	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)
Verified	1.108***	1.115***	1.136***
	(0.192)	(0.191)	(0.191)
Constant	3.241***	3.236***	3.236***
	(0.320)	(0.319)	(0.316)
Observations	3,132	3,132	3,132

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 15: Tweet Content and Frequency of Retweets Models with Bot 30 Data

	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	0.341**		
	(0.171)		
Tusk Consp.		0.368**	
		(0.187)	
Russia-PO Consp.			0.475***
			(0.177)
N(Followers)	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
N(Friends)	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)
Verified	0.855***	0.843***	0.881***
	(0.257)	(0.257)	(0.255)
Constant	1.934***	1.941***	1.956***
	(0.401)	(0.403)	(0.396)
Observations	3,132	3,132	3,132

Note: Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 16: Tweet Content, PiS Officials, and Frequency of Likes Models with Bot 30 Data

	Number of Favorites		
	(1)	(2)	(3)
PO Consp.	0.295*		
	(0.156)		
Tusk Consp.		0.358**	
		(0.171)	
Russia-PO Consp.			0.389**
			(0.162)
*PiS Official	1.232***	1.214***	1.167***
	(0.126)	(0.125)	(0.124)
N(Followers)	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
N(Friends)	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)
Verified	0.714***	0.722***	0.760***
	(0.181)	(0.181)	(0.181)
PO Consp.*PiS Official	-1.147***		
	(0.393)		
Tusk Consp.*PiS Official		-1.187***	
		(0.418)	
Russia-PO Consp.*PiS Official			-0.783*
			(0.411)
Constant	2.867***	2.874***	2.927***
	(0.300)	(0.300)	(0.297)
Observations	3,132	3,132	3,132

Note: Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 17: Tweet Content, PiS Officials, and Frequency of Retweets Models with Bot 30 Data

	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	0.524***		
	(0.185)		
Tusk Consp.		0.550***	
		(0.205)	
Russia-PO Consp.			0.613***
			(0.191)
PiS Official	1.011***	0.982***	0.948***
	(0.179)	(0.179)	(0.175)
N(Followers)	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
N(Friends)	0.0001***	0.0001***	0.0001***
	(0.00003)	(0.00003)	(0.00003)
Verified	0.523**	0.517*	0.566**
	(0.263)	(0.265)	(0.261)
PO Consp.*PiS Official	-0.948**		
	(0.480)		
Tusk Consp.*PiS Official		-0.962*	
		(0.515)	
Russia-PO Consp.*PiS Official			-0.627
			(0.502)
Constant	1.665***	1.686***	1.737***
	(0.406)	(0.411)	(0.401)
Observations	3,132	3,132	3,132
Note:			Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 18: Tweet Content, War, and Frequency of Likes Models with Bot 30 Data

	Number of Likes		
	(1)	(2)	(3)
PO Consp.	-0.705		
	(0.430)		
Tusk Consp.		-0.687	
		(0.476)	
Russia-PO Consp.			-0.403
			(0.515)
War	-0.436***	-0.426***	-0.401***
	(0.139)	(0.137)	(0.137)
N(Followers)	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
N(Friends)	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)
Verified	1.128***	1.136***	1.151***
	(0.191)	(0.191)	(0.191)
PO Consp.*War	0.875*		
	(0.461)		
Tusk Consp.*War		0.925*	
		(0.509)	
Russia-PO Consp.*War			0.645
			(0.543)
Constant	3.104***	3.089***	3.058***
	(0.124)	(0.123)	(0.123)
Observations	3,132	3,132	3,132
Note:			Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 19: Tweet Content, War, and Frequency of Retweets Models with Bot 30 Data

	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	-0.142 (0.428)		
Tusk Consp.		-0.109 (0.471)	
Russia-PO Consp.			0.175 (0.499)
War	-0.293* (0.175)	-0.270 (0.173)	-0.267 (0.171)
N(Followers)	0.00000*** (0.00000)	0.00000*** (0.00000)	0.00000** (0.00000)
N(Friends)	0.0001*** (0.00002)	0.0001*** (0.00002)	0.0001*** (0.00002)
Verified	0.864*** (0.252)	0.852*** (0.253)	0.881*** (0.251)
PO Consp.*War	0.566 (0.465)		
Tusk Consp.*War		0.560 (0.511)	
Russia-PO Consp.*War			0.319 (0.532)
Constant	1.778*** (0.156)	1.774*** (0.155)	1.746*** (0.153)
Observations	3,132	3,132	3,132

Note: Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Appendix F: Parallel Trends and Placebo Tests for Difference-in-Differences Models

As noted, a central assumption of the difference-in-differences model is that the pre-treatment trends between the treatment (CT) and control (non-CT) groups are the same. If this assumption were violated, we would not be able to identify the true effect of a focusing event on CT discourse. Fortunately, we are able to test for this assumption. We first offer visual confirmation of the trend in Figures 10 to 12.

We also test this assumption using a placebo test on the full range of models with a series of randomly generated dates as placebo 'starts of the war.' If a parallel trends assumption holds, we would not expect to see a significant effect on these dates. We note that, indeed, the placebo dates do not show an effect of the war on CT tweets. These results for the likes models are found in Tables 22, 23, 24. For retweets, placebo results are in Tables 25 through 27.

While considering the limitations of our difference-in-differences approach we also note that as the war started on 24 February, and still continues, this test does not fall within the subset of differences-in-differences test occurring over multiple treatment periods or with variation in treatment timing (Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021).

Table 20: Tweet Characteristics and Frequency of Likes- Quasi-Poisson Bot 30 Models

	Dependent variable:		
	Number of Favorites		
	(1)	(2)	(3)
PO Consp.	0.085		
	(0.405)		
Tusk Consp.		0.087	
		(0.444)	
Russia and PO Consp.			0.393
			(0.478)
War	0.176	0.183	0.215
	(0.393)	(0.391)	(0.390)
PiS Officials	2.090***	2.088***	2.113***
	(0.202)	(0.200)	(0.199)
Verified	0.938***	0.945***	0.976***
	(0.180)	(0.179)	(0.179)
N(Followers)	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
N(Friends)	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)
PO Consp.*War	0.235		
	(0.437)		
PO Consp.*PiS Official	-2.950		
	(4.232)		
Tusk Consp.*War		0.319	
		(0.480)	
Tusk Consp.*PiS Official		-2.951	
		(4.236)	
Collusion Consp.*War			-0.069
			(0.507)
Collusion Consp.*PiS Official			-3.245
			(4.247)
War*PiS Official	-1.458***	-1.468***	-1.575***
	(0.266)	(0.262)	(0.261)
PO Consp.*War*Official	2.283		
	(4.251)		
Tusk Consp.*War*Official		2.217	
		(4.256)	
Collusion Consp.*War*Official			3.052
			(4.268)
Constant	2.449***	2.450***	2.443***
	(0.315)	(0.314)	(0.312)
Observations	3,132	3,132	3,132

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 21: Tweet Characteristics and Frequency of Retweets- Quasi-Poisson Bot 30 Models

	Dependent variable:		
	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	0.479		
	(0.455)		
Tusk Consp.		0.487	
		(0.495)	
Russia and PO Consp.			0.791
			(0.518)
War	0.185	0.198	0.182
	(0.527)	(0.530)	(0.519)
PiS Officials	1.831^{***}	1.816^{***}	1.831^{***}
	(0.282)	(0.281)	(0.274)
Verified	0.719^{***}	0.709^{***}	0.748^{***}
	(0.260)	(0.261)	(0.258)
N(Followers)	0.00000^{***}	0.00000^{***}	0.00000^{***}
	(0.00000)	(0.00000)	(0.00000)
N(Friends)	0.0001^{***}	0.0001^{***}	0.0001^{***}
	(0.00003)	(0.00003)	(0.00003)
PO Consp.*War	0.042		
	(0.496)		
PO Consp.*PiS Official	-3.492		
	(7.585)		
Tusk Consp.*War		0.072	
		(0.541)	
Tusk Consp.*PiS Official		-3.500	
		(7.670)	
Collusion Consp.*War			-0.253
			(0.556)
Collusion Consp.*PiS Official			-3.784
			(7.558)
War*PiS Official	-1.377^{***}	-1.381^{***}	-1.452^{***}
	(0.372)	(0.370)	(0.362)
PO Consp.*War*Official	3.031		
	(7.601)		
Tusk Consp.*War*Official		3.005	
		(7.688)	
Collusion Consp.*War*Official			3.719
			(7.576)
Constant	1.314^{***}	1.330^{***}	1.338^{***}
	(0.425)	(0.427)	(0.417)
Observations	3,132	3,132	3,132

Note: Standard Errors in parenthesis.
$^{*}p < 0.1$; $^{**}p < .05$, $^{***}p < .01$ (two-tailed tests).

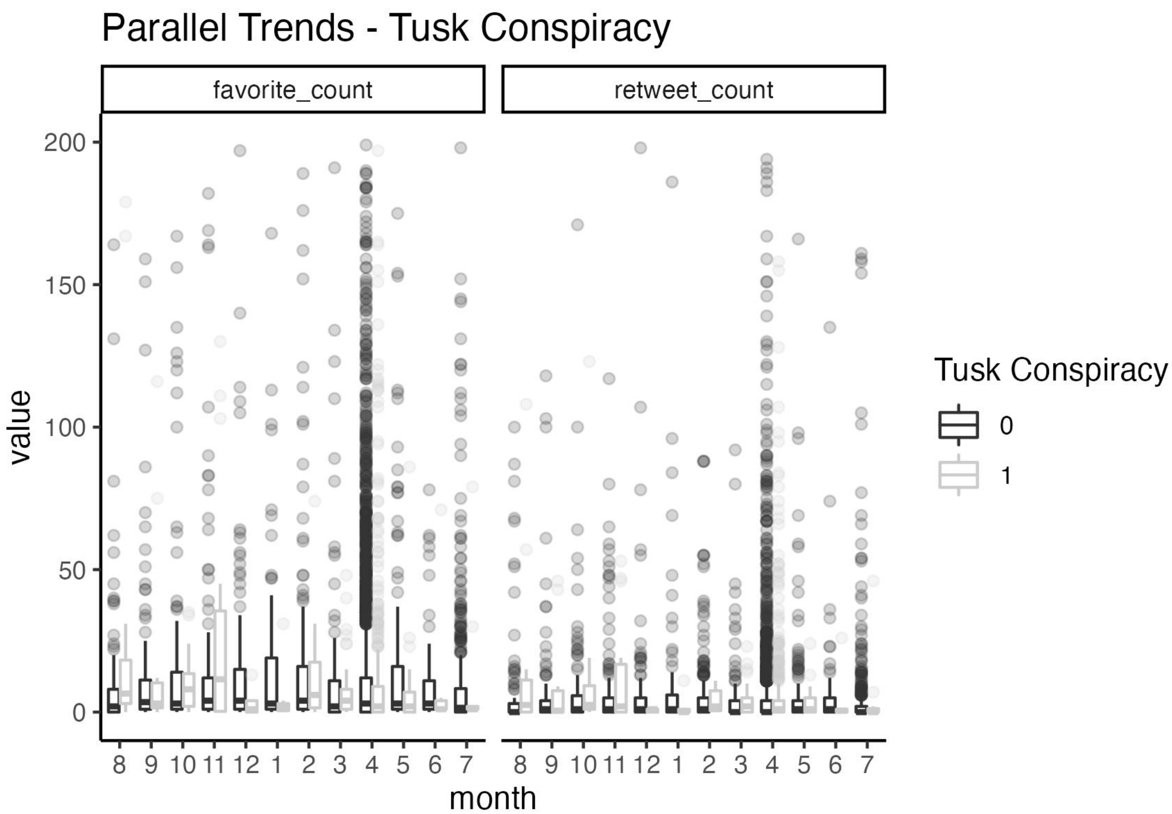


Figure 10: Parallel Trends - Tusk

Parallel trends for those tweets with and without the Tusk CT prior to February 2022 (”2” on each axis). Graph capped at 200 for visibility, though outliers gain up the thousands in retweets and likes.

Table 22: Likes, Tusk Placebo

Term	Estimate	P-value
Intercept	-1.6086	0.0358
Tusk CT	-0.4792	0.1618
Tusk CT*Placebo	-0.5813	0.6101
Log(N Followers)	0.5627	0
Log(N Friends)	0.0933	0.176
Placebo	-0.3309	0.7079
Verified	-0.8366	0.0217

Results from 100 simulations of Placebo treatment dates. Includes month fixed effects.

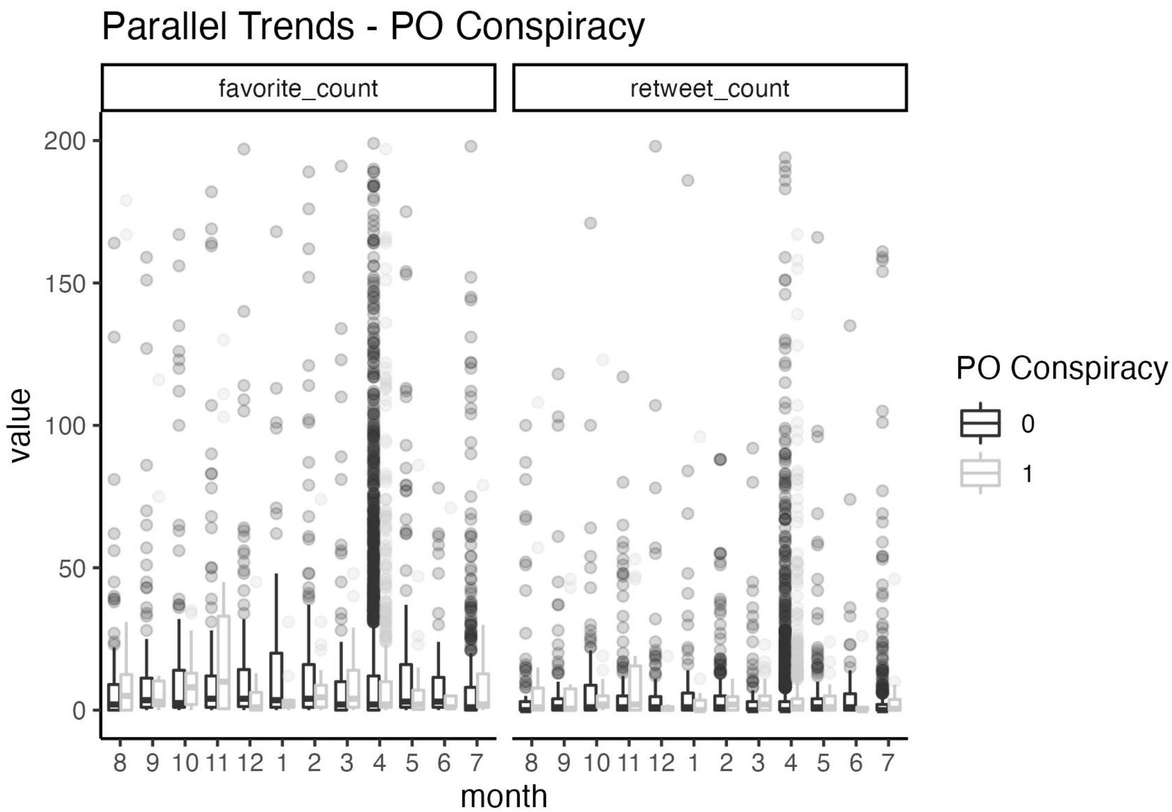


Figure 11: Parallel Trends - PO

Parallel trends for those tweets with and without the PO CT prior to February 2022 (”2” on each axis). Graph capped at 200 for visibility, though outliers gain up the thousands in retweets and likes.

Table 23: Likes, PO Placebo

Term	Estimate	P-value
(Intercept)	-1.6015	0.0355
Placebo	-0.0257	0.5069
PO CT	-0.5677	0.0791
PO CT*Placebo	-0.2648	0.7167
log_follow	0.5599	0
log_friends	0.0986	0.1514
Verified	-0.839	0.0207

Results from 100 simulations of Placebo treatment dates. Includes month fixed effects.

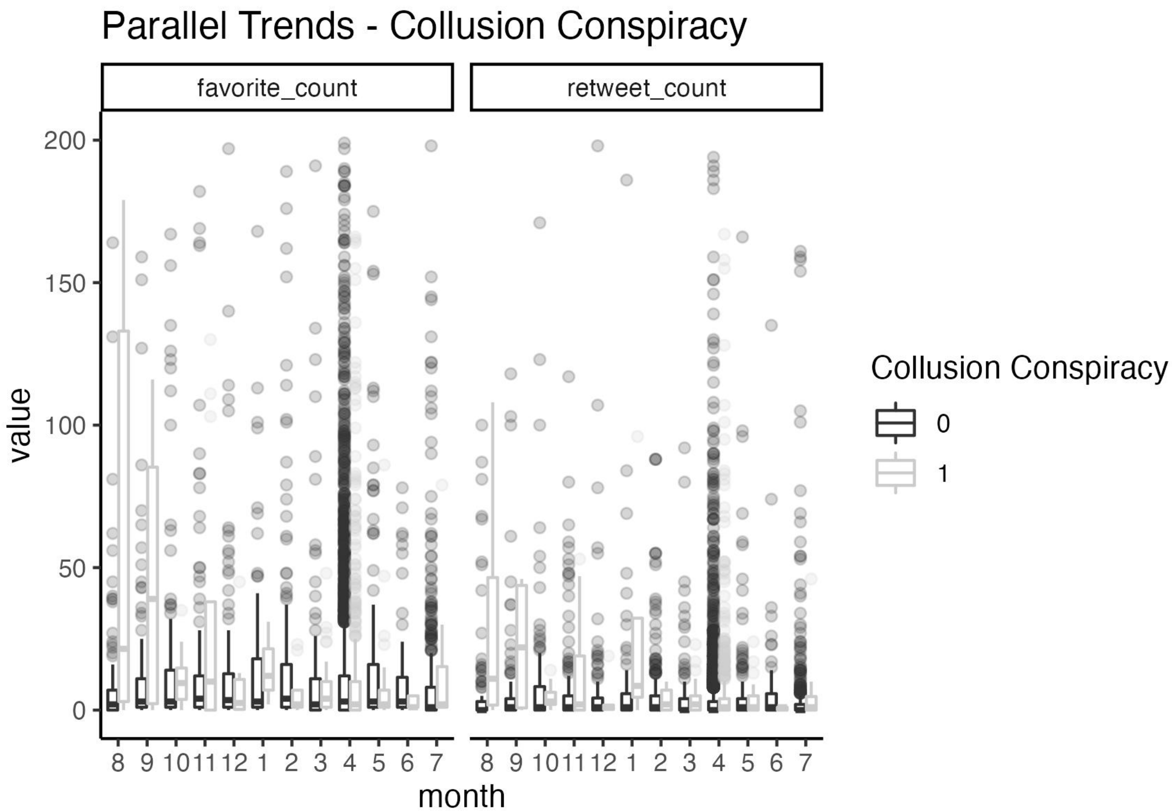


Figure 12: Parallel Trends - Collusion

Parallel trends for those tweets with and without the Collusion CT prior to February 2022 (”2” on each axis). Graph capped at 200 for visibility, though outliers gain up the thousands in retweets and likes.

Table 24: Likes, Collusion Placebo

Term	Estimate	P-value
Intercept	-1.5389	0.042
Collusion CT	-0.2694	0.4905
Collusion CT*Placebo	-0.3404	0.7261
Log(N Followers)	0.5656	0
Log(N Friends)	0.0772	0.2626
Placebo	-0.0346	0.5305
Verified	-0.8352	0.0235

Results from 100 simulations of Placebo treatment dates. Includes month fixed effects.

Table 25: Retweets, Tusk Placebo

Term	Estimate	P-value
Intercept	-2.985	0.0007
Tusk CT	0.1282	0.596
Tusk CT*Placebo	-1.0658	0.2152
Log(N Followers)	0.5397	0
Log(N Friends)	0.114	0.0731
Placebo	0.0679	0.3133
Verified	-0.664	0.0447

Results from 100 simulations of Placebo treatment dates. Includes month fixed effects.

Table 26: Retweets, PO Placebo

Term	Estimate	P-value
Intercept	-2.9849	0.0008
PO CT	0.0195	0.8722
PO CT*Placebo	-0.5361	0.3806
Log(N Followers)	0.5389	0
Log(N Friends)	0.1172	0.0673
Placebo	0.0476	0.3796
Verified	-0.6627	0.0458

Results from 100 simulations of Placebo treatment dates. Includes month fixed effects.

Table 27: Retweets, Collusion Placebo

Term	Estimate	P-value
Intercept	-2.9224	0.001
Collusion CT	0.3256	0.238
Collusion CT*Placebo	-0.3303	0.6672
Log(N Followers)	0.541	0
Log(N Friends)	0.1024	0.1042
Placebo	0.0212	0.3859
Verified	-0.6469	0.0511

Results from 100 simulations of Placebo treatment dates. Includes month fixed effects.

Appendix G: International Investigation Reports

In this section, we describe the two official investigations launched into the Smoleńsk plane crash, one led by Russia and the other by Poland. We also detail an ongoing investigation by the PiS government in Poland.

In accordance with the Chicago Convention on International Civil Aviation, the Russian prosecutor's office started an investigation via Russia's Interstate Aviation Committee (IAC) in order to identify what caused the crash (Koczanowicz, 2012; Żukiewicz & Zimny, 2015). A Polish military prosecutor office also launched an investigation into the crash causes, which was led by the Minister of Internal Affairs (Koczanowicz, 2012; Żukiewicz & Zimny, 2015).

The Russian official report placed fault for the crash on the pilots and also suggested that the deceased President Lech Kaczyński pressured the pilots to land in Smolensk (Koczanowicz, 2012). The Polish official report split the blame between the Polish pilots and the Russian air traffic controllers (Koczanowicz, 2012). One key area of friction centered on the behavior of the Russian air traffic controller. Though both investigations found that the Russian dispatcher informed the Polish pilots about the poor weather conditions for landing and gave the Polish pilots information about other airports they could land at, the Russian dispatcher did not order the plane to turn around (Khalitova et al., 2020). The Polish investigators indicated that the Russian dispatcher should have ordered the plane to turn around, whereas the Russian investigators stated that the Russian civil dispatcher lacked the authority to issue order to the Polish Air Force plane (Khalitova et al., 2020).

The Russian report indicated that General Andrzej Blasik, then-head of the Polish air force, "pressured" the pilots to land the plane despite the fog and lack of visibility with alcohol in his blood (Metzel, 2011). The Russian investigation also stated that the Polish crew's decision to not switch to a different airfield despite warnings of poor weather conditions at the airport in Smolensk caused the plane crash (BBC, 2011). "Psychological pressure from the high-ranking passengers" to try to land at the airport in Smolensk was also cited in the Interstate Aviation Committee's final report as a cause of the crash (Khalitova et al., 2020).

According to the head of the Polish investigation committee, Jerzy Miller, “an accumulation of causes led to the crash” (Metzel, 2011). First, the pilots lacked sufficient training to fly a TU-154 plane and incorrectly positioned the plane during landing (Metzel, 2011). Second, the plane’s crew also did not cooperate efficiently (Metzel, 2011). Third, the plane’s crew was slow to respond to warnings from the automatic terrain warning system that the plane was too low (Metzel, 2011). Fourth, the airport control tower sent incorrect information about where the plane was positioned, which kept the crew from identifying their mistakes (Metzel, 2011). Fifth, the Russian air traffic controllers informed the pilots that the plane was descending on-course, which was not accurate (Metzel, 2011). Sixth, the airport lacked enough lighting to provide visibility on the approach (Khalitova et al., 2020; Metzel, 2011).

In 2015 Reuters reported that transcripts from the cockpit’s black box show that the pilots warned against landing in the weather but were pressured to land by senior officials onboard (Reuters, 2015).

In April 2022, PiS released a report led by former Minister of Defense and PiS official Antoni Macierewicz, which challenged the existing international reports and blamed Russia (Kublik & Wójcik, 2022). An investigative report lead by TVN24 in Poland found that the Macierewicz report misrepresented findings commissioned from the U.S. National Institute for Aviation Research and manipulated the plane’s black box recordings in order to support the CTs that PiS spreads (Ptak, 2022). In turn, Macierewciz claimed TVN’s investigation is false (Ptak, 2022).

Most recently, Poland’s Supreme Audit Office could not identify the purpose of nine contracts worth 602,600 złoty (about 140,000 USD) associated with the Macierewicz investigations (Dobrosz-Oracz, 2023).

Appendix H: Regression Tables for Poisson Models

We evaluate all models with the standard Poisson model. As expected when comparing quasi-Poisson and Poisson models, the point estimates remain the same. Under the Poisson models our standard errors change and many of our results gain further significance. This is due to the quasi-Poisson's more conservative assessment of standard errors, which we discuss in the Analysis section of the main paper.

Table 28: Tweet Content - Likes, Poisson Models

	Number of Likes		
	(1)	(2)	(3)
PO Consp.	0.042***		
	(0.007)		
Tusk Consp.		-0.003	
		(0.008)	
Russia and PO Consp.			0.052***
			(0.008)
Log(N Followers)	0.449***	0.449***	0.449***
	(0.002)	(0.002)	(0.002)
Log(N Friends)	0.136***	0.138***	0.136***
	(0.002)	(0.002)	(0.002)
Verified	-0.127***	-0.131***	-0.127***
	(0.008)	(0.008)	(0.008)
Constant	-1.657***	-1.658***	-1.659***
	(0.022)	(0.022)	(0.022)
Observations	5,969	5,969	5,969
Log Likelihood	-220,860.300	-220,877.400	-220,854.600
Akaike Inf. Crit.	441,732.700	441,766.800	441,721.200

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 29: Tweet Content - Retweets, Poisson Models

	Number of Retweets		
	retweet_count		
	(1)	(2)	(3)
PO Consp.	0.476***		
	(0.012)		
Tusk Consp.		0.380***	
		(0.014)	
Russia and PO Consp.			0.521***
			(0.013)
Log(N Followers)	0.482***	0.481***	0.480***
	(0.003)	(0.003)	(0.003)
Log(N Friends)	0.165***	0.176***	0.170***
	(0.005)	(0.005)	(0.005)
Verified	-0.421***	-0.441***	-0.426***
	(0.018)	(0.018)	(0.018)
Constant	-3.511***	-3.525***	-3.535***
	(0.044)	(0.044)	(0.044)
Observations	5,969	5,969	5,969
Log Likelihood	-61,759.780	-62,119.610	-61,690.560
Akaike Inf. Crit.	123,531.600	124,251.200	123,393.100

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 30: Tweet Content and PiS Officials - Likes, Poisson Models

	Number of Likes		
	(1)	(2)	(3)
PO Consp.	0.246***		
	(0.008)		
Tusk Consp.		0.187***	
		(0.009)	
Russia and PO Consp.			0.217***
			(0.008)
PiS Officials	1.127***	1.089***	1.074***
	(0.007)	(0.006)	(0.006)
Log(N Followers)	0.485***	0.483***	0.482***
	(0.002)	(0.002)	(0.002)
Log(N Friends)	0.102***	0.106***	0.096***
	(0.002)	(0.002)	(0.002)
Verified	-0.256***	-0.258***	-0.248***
	(0.008)	(0.008)	(0.008)
PO Consp.*PiS Official	-1.074***		
	(0.023)		
Tusk Consp.*PiS Official		-0.998***	
		(0.025)	
PO and Russia Consp.*PiS Official			-0.730***
			(0.024)
Constant	-1.841***	-1.837***	-1.772***
	(0.022)	(0.022)	(0.022)
Observations	5,969	5,969	5,969
Log Likelihood	-208,451.700	-208,934.400	-209,244.000
Akaike Inf. Crit.	416,919.400	417,884.900	418,504.100

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 31: Tweet Content and PiS Officials - Retweets, Poisson Models

	Number of Retweets		
	retweet_count		
	(1)	(2)	(3)
PO Consp.	0.672***		
	(0.013)		
Tusk Consp.		0.561***	
		(0.015)	
Russia and PO Consp.			0.685***
			(0.014)
PiS Official	1.056***	0.982***	0.996***
	(0.014)	(0.013)	(0.013)
Log(N Followers)	0.511***	0.508***	0.506***
	(0.003)	(0.003)	(0.003)
Log(N Friends)	0.139***	0.153***	0.137***
	(0.005)	(0.005)	(0.005)
Verified	-0.515***	-0.530***	-0.512***
	(0.017)	(0.017)	(0.017)
PO Consp.*PiS Official	-1.163***		
	(0.040)		
Tusk Consp.*PiS Official		-1.069***	
		(0.044)	
Russia and PO Consp.*PiS Official			-0.873***
			(0.042)
Constant	-3.690***	-3.692***	-3.634***
	(0.045)	(0.046)	(0.045)
Observations	5,969	5,969	5,969
Log Likelihood	-59,262.150	-59,855.850	-59,408.150
Akaike Inf. Crit.	118,540.300	119,727.700	118,832.300

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 32: Focusing Events and Likes- Poisson Models

	Number of Likes		
	(1)	(2)	(3)
PO Consp.	-0.607***		
	(0.022)		
Tusk Consp.		-0.567***	
		(0.024)	
Russia and PO Consp.			-0.310***
			(0.026)
War	-0.377***	-0.348***	-0.325***
	(0.008)	(0.008)	(0.008)
Log(Followers)	0.452***	0.452***	0.452***
	(0.002)	(0.002)	(0.002)
Log(Friends)	0.135***	0.137***	0.134***
	(0.002)	(0.002)	(0.002)
Verified	-0.103***	-0.111***	-0.109***
	(0.008)	(0.008)	(0.008)
PO Consp.*War	0.759***		
	(0.023)		
Tusk Consp.*War		0.674***	
		(0.025)	
Russia and PO Consp.*War			0.424***
			(0.027)
Constant	-1.237***	-1.265***	-1.269***
	(0.024)	(0.024)	(0.024)
Observations	5,969	5,969	5,969
Log Likelihood	-219,602.400	-219,850.300	-220,080.700
Akaike Inf. Crit.	439,220.700	439,716.500	440,177.400

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 33: Focusing Events and Retweets- Poisson Models

	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	-0.078**		
	(0.035)		
Tusk Consp.		-0.038	
		(0.037)	
Russia and PO Consp.			0.264***
			(0.040)
War	-0.434***	-0.375***	-0.392***
	(0.016)	(0.016)	(0.016)
Log(N Followers)	0.486***	0.485***	0.484***
	(0.003)	(0.003)	(0.003)
Log(N Friends)	0.164***	0.175***	0.168***
	(0.005)	(0.005)	(0.005)
Verified	-0.391***	-0.418***	-0.402***
	(0.018)	(0.018)	(0.018)
PO Consp.*War	0.659***		
	(0.037)		
Tusk Consp.*War		0.508***	
		(0.040)	
Russia & PO Consp.*War			0.317***
			(0.042)
Constant	-3.041***	-3.111***	-3.070***
	(0.048)	(0.048)	(0.048)
Observations	5,969	5,969	5,969
Log Likelihood	-61,380.790	-61,845.200	-61,417.490
Akaike Inf. Crit.	122,777.600	123,706.400	122,851.000

Note: Standard Errors in parenthesis.
*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 34: Focusing Events, Tweet Content, and PiS Officials- Likes, Poisson Models

	Dependent variable:		
	Number of Likes		
	(1)	(2)	(3)
PO Consp.	0.003		
	(0.023)		
Tusk Consp.		0.032	
		(0.025)	
Russia and PO Consp.			0.292***
			(0.027)
War	0.101***	0.127***	0.144***
	(0.011)	(0.011)	(0.011)
PiS Officials	1.677***	1.681***	1.705***
	(0.012)	(0.012)	(0.012)
Log(N Followers)	0.471***	0.469***	0.467***
	(0.002)	(0.002)	(0.002)
Log(N Friends)	0.114***	0.118***	0.111***
	(0.002)	(0.002)	(0.002)
Verified	-0.168***	-0.171***	-0.159***
	(0.008)	(0.008)	(0.008)
PO Consp.*War	0.268***		
	(0.024)		
PO Consp.*PiS Official	-2.623***		
	(0.278)		
Tusk Consp.*War		0.181***	
		(0.026)	
Tusk Consp.*PiS Official		-2.656***	
		(0.279)	
Collusion Consp.*War			-0.102***
			(0.028)
Collusion Consp.*PiS Official			-2.905***
			(0.279)
War*PiS Official	-0.839***	-0.885***	-0.941***
	(0.015)	(0.015)	(0.015)
PO Consp.*War*Official	1.796***		
	(0.279)		
Tusk Consp.*War*Official		1.909***	
		(0.280)	
Collusion Consp.*War*Official			2.497***
			(0.280)
Constant	-1.834***	-1.851***	-1.796***
	(0.025)	(0.025)	(0.025)
Observations	5,969	5,969	5,969
Log Likelihood	-206,236.300	-206,623.100	-206,793.600
Akaike Inf. Crit.	412,496.500	413,270.200	413,611.100
Note:			Standard Errors in parenthesis. *p < 0.1; **p < .05, ***p < .01 (two-tailed tests).

Table 35: Focusing Events, Tweet Content, and PiS Officials- Retweets, Poisson Models

	Dependent variable:		
	Number of Retweets		
	(1)	(2)	(3)
PO Consp.	0.424***		
	(0.037)		
Tusk Consp.		0.450***	
		(0.039)	
Russia and PO Consp.			0.756***
			(0.041)
War	-0.057***	0.002	-0.029
	(0.021)	(0.020)	(0.020)
PiS Officials	1.457***	1.450***	1.469***
	(0.024)	(0.024)	(0.024)
Log(N Followers)	0.501***	0.499***	0.496***
	(0.003)	(0.003)	(0.003)
Log(N Friends)	0.149***	0.163***	0.149***
	(0.005)	(0.005)	(0.005)
Verified	-0.440***	-0.460***	-0.438***
	(0.017)	(0.017)	(0.017)
PO Consp.*War	0.280***		
	(0.039)		
PO Consp.*PiS Official	-3.407***		
	(0.708)		
Tusk Consp.*War		0.129***	
		(0.042)	
Tusk Consp.*PiS Official		-3.443***	
		(0.708)	
Collusion Consp.*War			-0.088**
			(0.044)
Collusion Consp.*PiS Official			-3.730***
			(0.709)
War*PiS Official	-0.651***	-0.724***	-0.740***
	(0.030)	(0.030)	(0.030)
PO Consp.*War*Official	2.471***		
	(0.710)		
Tusk Consp.*War*Official		2.615***	
		(0.710)	
Collusion Consp.*War*Official			3.150***
			(0.710)
Constant	-3.549***	-3.601***	-3.493***
	(0.051)	(0.051)	(0.050)
Observations	5,969	5,969	5,969
Log Likelihood	-58,833.080	-59,421.480	-58,940.360
Akaike Inf. Crit.	117,690.200	118,867.000	117,904.700
Note:	Standard Errors in parenthesis.		
	*p < 0.1; **p < .05, ***p < .01 (two-tailed tests).		

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