Ownership and Political Sorting on Platforms: Evidence from Twitter's Acquisition

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Abstract

How does a platform's political affiliation affect participation and the composition of its users? We study how Elon Musk's 2022 acquisition of Twitter affected platform participation and downstream political segregation in external news consumption. We use Comscore mobile usage panel data to implement both standard and synthetic difference-in-differences frameworks. We find that overall Twitter participation increases following the acquisition announcement, with the largest rise after the deal closes, suggesting that ownership changes can shift perceptions of a platform's political positioning even before formal changes in governance or design occur. The response is strongly asymmetric by user ideology, as measured by pre-acquisition news consumption: right-leaning users increase time spent substantially more than left-leaning users, who reduce their activity on the platform. We also find that the ownership change affects broader online news consumption among heavy users: right-leaning heavy users increase the share of right-leaning news in their consumption relative to lighter users, while left-leaning heavy users shift toward more left-leaning news. These results suggest that perceived shifts in platform political alignment following salient ownership changes can reshape participation on social platforms and also affect political segregation in information consumption beyond the platform.

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1 Introduction

Political affiliation shapes how individuals engage with firms and organizations, particularly in digital and platform settings. Users often sort into media environments they perceive as ideologically aligned (Gentzkow and Shapiro, 2010, 2011), and may participate differently depending on how they perceive a platform's values or alignment with their own views. Platforms are thus not neutral intermediaries: their governance choices, content moderation policies, and perceived orientation can influence who participates and how. Ownership changes can shift these perceptions even before any changes in governance or moderation policy occur, attracting some users while discouraging others.

But on social platforms, participation also depends on whom users expect to encounter there. A perceived rightward shift could raise engagement among right-leaning users and lower it among left-leaning users, but it could also reduce participation on either side if anticipated changes in the user mix make the platform less informative or less worth monitoring. Ideological sorting in media demand may not map one-for-one into participation on platforms, where attention, debate, and audience formation are central to user value.

This paper studies these forces in the context of Elon Musk's acquisition of Twitter, one of the most visible and contested ownership changes in the past decade. The acquisition unfolded through two distinct public moments: the announcement of Musk's offer in April 2022 and the closing of the deal in October 2022. We treat these events as salient shocks to Twitter's perceived political alignment and to users' expectations about the platform's future interaction environment. We ask two related research questions questions. First, how does a change in a platform's perceived political alignment affect participation and user composition? Second, does the change in ownership affected the downstream political segregation in news consumption?

We test these questions using panel data from Comscore covering approximately 41,000 U.S. users between October 2021 and March 2023. We classify users' political lean based on their pre-acquisition news consumption and track changes in Twitter engagement relative to a

synthetic control constructed from other large websites. Our empirical strategy uses synthetic difference-in-differences as the main platform-level design, with difference-in-differences and event-study specifications used to assess timing around announcement and implementation. To study ideological heterogeneity, we estimate effects separately by political group and complement those estimates with a triple-differences specification. To study downstream effects on external news consumption, we compare heavy vs. light pre-acquisition Twitter users and study changes in the share of right-leaning news in total news consumption.

We document three main findings. First, overall Twitter participation increases following the acquisition. The effects are strongest and most precisely estimated after implementation, but we also observe meaningful responses in the period between announcement and closing, consistent with users reacting to anticipated changes in platform's political alignment. This pattern suggests that expectations and signals about future platform decisions can affect user behavior even before formal policy changes are enacted.

Second, participation responses are strongly heterogeneous by political affiliation. Right-leaning users increase their engagement substantially, while left-leaning users show little change and, in some specifications, modest declines. The resulting gap between groups is economically meaningful and statistically significant, leading to a shift in the composition of the platform. This heterogeneity is consistent across specifications and robust to alternative estimation approaches and sample restrictions.

Third, these changes are accompanied by shifts in external news consumption among heavy Twitter users. Following the acquisition, right-leaning heavy users increase the share of right-leaning news in their consumption relative to lighter users. In contrast, left-leaning users increase their left-leaning news consumption. Together, these patterns suggest an increase in political segregation in online news consumption.

Overall, the results are consistent with users responding to a perceived change in Twitter's political alignment, and the timing of the responses, which begins around announcement and strengthens after closing, is in line with that interpretation. We caveat, however, that our

design does not separately identify between governance choices, moderation policy, or other algorithmic channels.

This paper contributes first to the economics of digital platforms and social media. Classic platform theory emphasizes that participation depends on platform design and on expectations about the other users or groups present on the platform, while recent work on social media highlights the roles of networks, curation, moderation, and substitution across platforms in shaping online activity and exposure (Rochet and Tirole, 2003; Armstrong, 2006; Rysman, 2009; Meeuwis, Parker, Schoar, and Simester, 2022; Aneja, Luca, and Reshef, 2023; Aridor et al, 2024.). We contribute to this literature by studying a different source of platform re-positioning: a salient ownership shock. In our setting, ownership changes are not just corporate events: they can change how users perceive a platform's political alignment and expectations about the platform's future interaction environment, which in turn change participation on the platform itself. We show that such a shock can lead to strongly asymmetric responses across ideological groups on a major platform.

The paper also contributes to the economics of media demand and political slant. A large literature shows that consumers prefer like-minded news, that media firms respond to those preferences in their positioning choices, and that slanted media can shape beliefs and polarization (Gentzkow and Shapiro, 2010, 2011; Martin and Yurukoglu, 2017; Bakshy, Messing, and Adamic, 2015; Allcott and Gentzkow, 2017; Levy, 2021.). Our contribution is to study a different margin: how a platform-level ownership shock affects user-side sorting and the ideological composition of news consumption outside the platform. Rather than focusing on editorial choice or persuasion within a news outlet, we show that changes in participation on a politically salient platform are associated with changes in the external news mix of its heavy users.

2 Background

Twitter was founded in 2006 as a public microblogging platform with an open follower network that enabled rapid information diffusion. Its structure allowed content to spread broadly across ideological and social lines, and the platform came to occupy an important role in public discourse, with heavy use by journalists, politicians, and other public figures. By the early 2020s, Twitter had become a central node in political communication. At the same time, it was widely perceived as politically left-leaning, in part due to its content moderation policies, which were frequently criticized by conservatives as restricting right-leaning speech.

In early 2022, Elon Musk, a highly visible user with tens of millions of followers and a history of politically charged posts, began signaling potential involvement in the platform. Unbeknownst to the public, he had accumulated a roughly 9% stake, making him Twitter's largest individual shareholder. On April 14, 2022, Musk made a formal offer to acquire Twitter, which was quickly accepted by the board. The subsequent months were marked by uncertainty and legal conflict, as Musk attempted to withdraw from the deal and Twitter sued to enforce it. The acquisition ultimately closed on October 27, 2022, when Musk took control of the company.

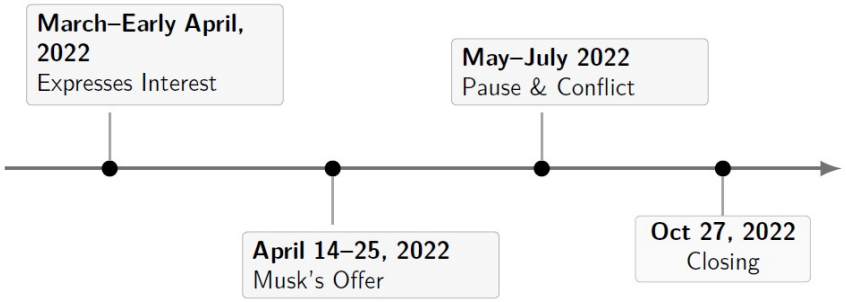


Figure 1: Twitter Acquisition Timeline

Following the acquisition, Musk implemented a series of high-profile changes to the platform. These included substantial reductions in the workforce, particularly in trust and safety teams, the reinstatement of previously banned accounts, changes to verification, and adjust-

ments to content moderation and recommendation systems. He also rebranded the platform as "X." Alongside these operational changes, Musk's increasingly visible political positioning contributed to perceptions of a shift in the platform's ideological orientation.

In this paper, we interpret the acquisition as a salient shock to perceived platform governance and political alignment. We do not attempt to separately identify the underlying channels, such as changes in moderation, algorithms, or branding. Instead, we treat the announcement and closing of the acquisition as two distinct moments when users received new information about the platform's likely direction, and examine how participation and behavior responded to each.

3 Data

We use data from Comscore, a large panel of U.S. internet users that tracks complete mobile and desktop browsing and app behavior through opt-in monitoring software. The data provide detailed information on domains and apps visited, as well as time spent on each. We focus on mobile activity (iOS and Android), which captures the majority of platform usage. Our sample spans October 2021 through March 2023, providing six months of pre-announcement data and coverage through implementation and its aftermath. We aggregate the data to the monthly level at both the domain and user levels. April 2022 is coded as the announcement date and October 2022 as the implementation date.

Our platform sample consists of 165 large websites. We construct this sample by merging duplicate domains, excluding phone-specific applications, and restricting attention to the largest domains by total time spent. The sample includes major platforms such as Facebook, YouTube, TikTok, Amazon, and Netflix, as well as smaller but still widely used sites. Twitter (later X) is the treated unit, and the remaining 164 websites form the donor pool used to construct the synthetic control.

Our news sample includes approximately 200 websites. We begin with all news and social domains within the top 10,000 sites in Comscore and supplement this set with additional

politically salient outlets. We classify news sources by ideological slant using a combination of existing classifications and external sources. Our baseline ("moderate") classification includes a broad set of outlets on each side (e.g., Fox News, Breitbart, and Newsmax on the right; the New York Times, HuffPost, and Vox on the left). We also consider a narrower "strict" classification based only on Fox News and the New York Times, which serve as clear anchors for right- and left-leaning outlets, respectively, as well as an "expansive" classification and an alternative definition following Wojcieszak et al. (2023) in robustness checks. The full set of outlets included in each definition is reported in Appendix XX. (add)

Our user sample consists of approximately 41,500 individuals. We measure each user's political lean based on pre-acquisition news consumption (October 2021 to March 2022). Specifically, we define a user's lean as the difference between the share of time spent on right-leaning and left-leaning news among politically coded outlets. Users with a positive value are classified as right-leaning. Our main specifications use the moderate classification described above.

Table 1 reports summary statistics for the website and user samples. In the website sample, average monthly time per site is 7,007 hours. The most represented categories are Social Media and Communication (15.2%), News and Reading (13.9%), and Shopping and Delivery (12.7%). In the user sample, average monthly time across all sites is 29.3 hours, and users visit 42 distinct websites per month on average. Approximately 44.5% of users visit Twitter at least once in the pre-acquisition period; among these users, average monthly time on Twitter is 0.61 hours (2.64 hours conditional on visiting in a given month).

4 Empirical Strategy

Our main platform-level empirical approach is Synthetic Difference-in-Differences (SDiD) (Arkhangelsky et al., 2021). This choice is motivated by the fact that our setting features a single treated platform—Twitter. Relative to conventional DiD, SDiD combines synthetic-control-style reweighting of donor platforms with difference-in-differences adjustment for

Table 1: Descriptive Statistics

Variable	Median	Mean	Std. Dev.
Panel A: Websites (N = 165)			
Avg. monthly time (hours)	1,101	7,007	33,317
Avg. monthly visits (events)	92,105	694,075	3,241,004
Top categories (share of websites):			
Social Media & Communication	15.2%		
News & Reading	13.9%		
Shopping & Delivery	12.7%		
Panel B: Users (N = 41,547)			
Avg. monthly time (hours)	14.9	29.3	37.1
Avg. monthly visits (events)	791.8	2905.9	9793.1
Number of websites visited	41	42	26
Right-leaning (Strict)	0.000	0.009	0.148
Right-leaning (Moderate)	0.000	-0.011	0.261
Right-leaning (Expansive)	0.000	-0.035	0.312
Used Twitter, pre-purchase	0.000	0.445	0.497
Avg. monthly Twitter time, pre-purchase (hours)	0.00	0.27	2.64
conditional on using Twitter	0.02	0.61	3.94

common shocks. Intuitively, it places greater weight on donor units and pre-treatment periods that best match Twitter's pre-acquisition path, thereby reducing reliance on a single untreated average as the counterfactual.

We observe a domain-by-month panel and study outcomes such as total time spent and total usage events on platform i in month t, denoted by Y_{it}. For a given treatment date T_0, define

$$W_{it}(T_0) = \mathbf{1}\{i = \text{Twitter},\ t \geq T_0\}.$$

Our main SDiD specification estimates the average treatment effect on the treated, τ, from

$$(\hat{\tau}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg\min_{\tau,\mu,\alpha,\beta} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{\omega}_i \hat{\lambda}_t \left(Y_{it} - \mu - \alpha_i - \beta_t - \tau W_{it}(T_0)\right)^2, \tag{1}$$

where $\hat{\omega}_i$ and $\hat{\lambda}_t$ are the estimated unit and time weights. We estimate this specification separately using two treatment dates: April 2022, corresponding to the acquisition announcement, and October 2022, corresponding to implementation (deal closing). Throughout, our

primary platform-level results are based on this SDiD design.

As a robustness check, we also estimate a conventional DiD specification that allows treatment effects to differ between the announcement and implementation periods:

$$Y_{it} = \beta_A\big(Twitter_i \times Announce_t\big) + \beta_I\big(Twitter_i \times Implement_t\big) + \alpha_i + \delta_t + \varepsilon_{it}, \qquad (2)$$

where $Twitter_i$ indicates the treated platform, $Announce_t$ equals one for months from April 2022 through September 2022, and $Implement_t$ equals one for months from October 2022 onward. The coefficients β_A and β_I therefore capture the announcement-period and implementation-period effects relative to the pre-announcement baseline. In these DiD specifications, we cluster standard errors at the domain level and report randomization-inference p-values (Conley and Taber, 2011; MacKinnon and Webb, 2020), which are appropriate in settings with a small number of treated units.

To study heterogeneity by political affiliation, we first estimate the SDiD specification separately for right- and left-leaning users, using ideology-specific domain-by-month panels. These estimates show how the platform-level response differs across ideological groups. As a formal test of asymmetry, we then estimate the following triple-differences specification at the user–platform–month level:

$$\begin{aligned} Y_{ipt} = {} & \beta_A\big(Twitter_p \times Announce_t\big) + \beta_I\big(Twitter_p \times Implement_t\big) \\ & + \gamma_A\big(Twitter_p \times Announce_t \times Right_i\big) + \gamma_I\big(Twitter_p \times Implement_t \times Right_i\big) \\ & + \alpha_{ip} + \delta_t + \varepsilon_{ipt}, \end{aligned} \qquad (3)$$

where $Right_i$ is an indicator for whether user i is right-leaning. The coefficients γ_A and γ_I capture the differential response of right-leaning relative to left-leaning users during the announcement and implementation periods, respectively.

For the news-consumption analysis, we use a related user-month DiD design that compares heavy pre-acquisition Twitter users to light or non-users. Heavy users are defined using

pre-treatment Twitter activity, so treatment intensity is predetermined with respect to the acquisition. Our main outcome is the share of right-leaning news in total news consumption in month t. We estimate specifications of the form

$$\begin{aligned} ShareRight_{it} = \beta_A\big(Heavy_i \times Announce_t\big) + \beta_I\big(Heavy_i \times Implement_t\big) \\ + \gamma_A\big(Heavy_i \times Announce_t \times Right_i\big) + \gamma_I\big(Heavy_i \times Implement_t \times Right_i\big) + \alpha_i + \delta_t + \varepsilon \end{aligned} \tag{4}$$

where $Heavy_i$ indicates whether user i was a heavy Twitter user before the acquisition. We include user and month fixed effects and cluster standard errors at the user level. Because treatment variation in this exercise is at the user level, rather than coming from a single treated platform, SDiD is not the appropriate design for this part of the analysis.

5 Results

We organize the results around three questions. First, did the acquisition change overall Twitter participation? Second, did the response differ by users' political affiliation? Third, were these participation changes accompanied by shifts in users' external news consumption?

5.1 Overall Effects on Twitter Participation

We begin by estimating the average effect of the acquisition on Twitter time spent, pooling across all users regardless of political lean. Table 2 reports SDiD estimates and Table 3 reports DiD estimates; Figures 3 and 4 present the corresponding time-series and event-study plots.

The SDiD results, reported in Table 2, show a positive effect of the acquisition on Twitter participation under both the announcement and implementation definitions of the post period. Panel A shows the effects using the announcement date (April 2022), and Panel B using the implementation date (October 2022). Across the board, the acquisition appears to have a positive effect on user participation, with the effect being more precisely estimated for the winsorized measure and after implementation. The effects are economically meaningful

and mostly marginally significant. For example, users spend 230 seconds more on average following the implementation.

The SDiD figures (Figure 3) show that Twitter's time-spent trajectory diverges visibly from the synthetic control beginning around the announcement date and accelerating after implementation (period 13).

The DiD estimates, reported in Table 3, allow both the announcement and implementation indicators to enter simultaneously, providing a decomposition of the effect across the two periods. Panel A shows the effects using the raw time measure, and Panel B using the winsorized measure. Across specifications, the sustained participation increase is concentrated in the post-implementation period. The effects are large and highly significant after implementation: 395.2 seconds for raw time and 355.0 seconds for winsorized time, both significant at the 1% level with RI p-values of 0.054 and 0.050 respectively.

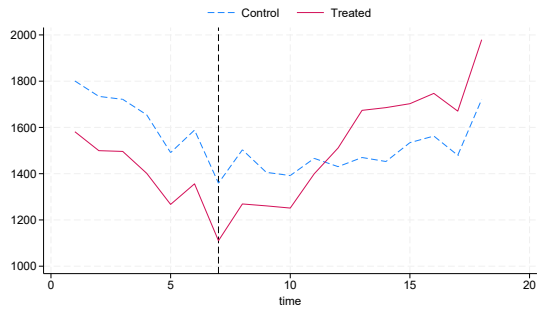
By contrast, the announcement coefficients are small or negative, suggesting that any initial response was modest before the deal closed. The event-study plots (Figure 4) confirm these patterns: pre-trend coefficients are close to zero, with a clear positive break emerging around August 2022, once the deal is finalized, and growing after the implementation date. Taken together, these results indicate that the acquisition led to a meaningful increase in Twitter participation, with the most robust effects emerging after the deal closed in October 2022. However, the overall average effect masks substantial heterogeneity by user type, which we explore next.

Taken together, the aggregate results point to a meaningful increase in Twitter participation following the acquisition, with the strongest effects in the post-implementation period. These average effects.

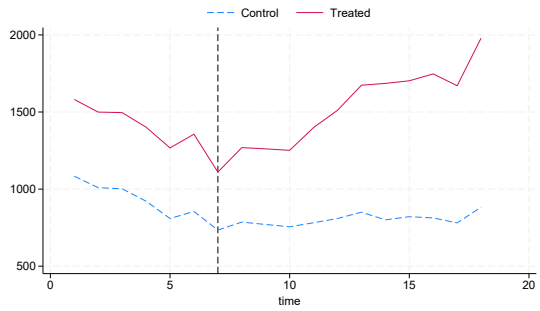
5.2 Heterogeneous Effects by Political Ideology

We next study whether participation responses differ by users' political affiliation. This is a natural margin of heterogeneity in our setting because the acquisition plausibly shifted Twitter's perceived political alignment. We classify users based on their pre-acquisition news

Figure 2: SDiD Time Series

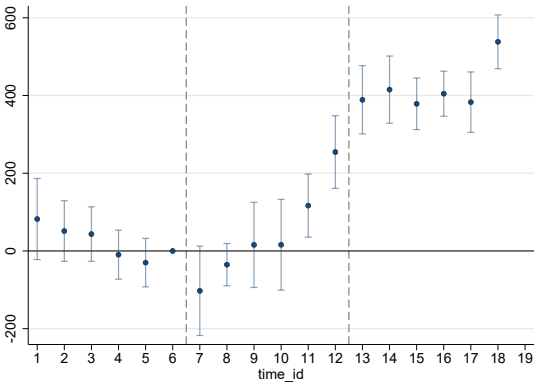


(a) Time Delta

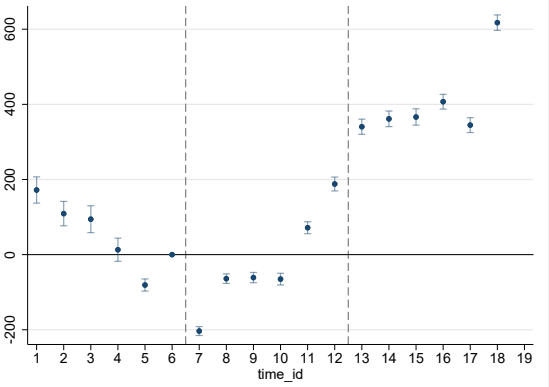


(b) Winsorized

Figure 3: DiD Event Study



(a) Time Delta



(b) Winsorized

Table 2: Synthetic Difference-in-Differences: Time Spent

	(1) Time	(2) Time (Winsor)
Panel A: Announcement Date		
Twitter × Announce	264.368	221.739*
	(312.281)	(133.462)
Observations	2,970	2,970
Panel B: Implementation Date		
Twitter × Implement	260.075*	230.586***
	(148.566)	(43.200)
Observations	2,970	2,970

Table 3: Difference-in-Differences Results: Time Spent

	(1) Time	(2) Time (Winsor)
Twitter × Announce	21.282	-73.609
	(56.333)	(16.908)***
	[0.960]	[0.220]
Twitter × Implement	395.198	354.973
	(35.690)***	(17.893)***
	[0.054]*	[0.050]**
Observations	2,970	2,970
R-squared	0.992	0.971

consumption and use the moderate political-lean definition as our main specification.

To examine heterogeneity, we run separate SDiD estimates for right- and left-leaning user subsamples using the moderate political lean definition. In Table 4, the SDiD estimate for right-leaning users at the announcement date is approximately 677 seconds and statistically significant at 1% level, compared to a statistically insignificant, negative effect for left-leaning users. For the implementation date, the right-leaning estimate rises to approximately 781, while the left-leaning estimate remains near zero (–35 and statistically insignificant). Results using the strict definition are larger in magnitude for both groups: approximately 1,047 for right-leaning users at announcement (significant at 1%) and a reduction of 573 for left-leaning users (significant at 5%)), suggesting active disengagement among some left-leaning users.

The triple-differences specification in Table 5 confirms these patterns formally. The interaction $Post \times Twitter \times Right$ is positive and statistically significant for both announce-

ment and implementation periods under the moderate definition: approximately 465 at announcement and 1,096 at implementation, both statistically significant. The main effect of $Post \times Twitter$ is negative and significant, consistent with a baseline decrease among left-leaning users that is more than offset by a larger increase among right-leaning users. These patterns hold under the strict definition and are robust to controlling for pre-acquisition Twitter intensity.

Overall, the heterogeneous-effects analysis shows the paper's central empirical result: the acquisition did not raise participation uniformly. Instead, it generated a strongly asymmetric response by political affiliation, with large increases among right-leaning users and little comparable increase among left-leaning users.

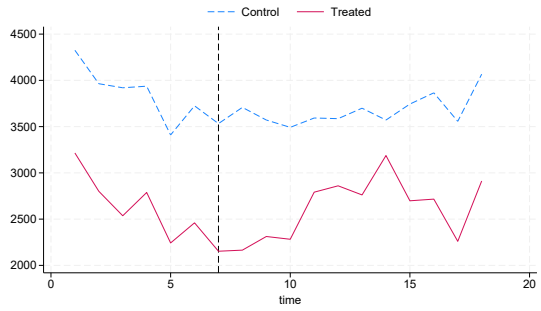
Table 4: Heterogeneous Effects by Political Ideology

	(1) Time	(2) Time (Winsor)	(3) Time	(4) Time (Winsor)
Panel A: Right Leaning Users				
Twitter × Announcement	691.196***	677.481***		
	(250.112)	(229.832)		
Twitter × Implementation			781.289***	896.687***
			(202.451)	(185.355)
Observations	2,970	2,970	2,970	2,970
Panel B: Left Leaning Users				
Twitter × Announcement	200.126	-19.867		
	(220.482)	(141.358)		
Twitter × Implementation			-34.781	-12.033
			(227.366)	(109.013)
Observations	2,970	2,970	2,970	2,970

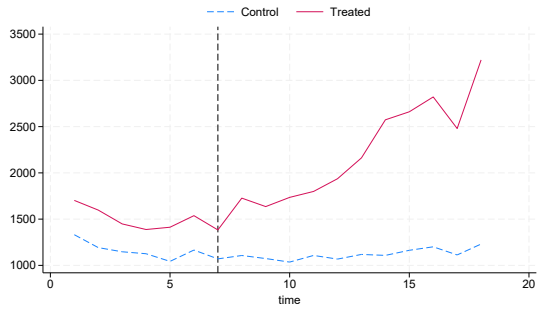
5.3 Effects on External News Consumption

We next examine whether the acquisition affected users downstream political engagement and news consumption. Our analysis uses a DiD design at the user-month level, in which we compare heavy pre-acquisition Twitter users to lighter or non-users. The intuition here is that heavy users are more exposed to the changes on the platform and thus are 'treated' by the shock, while non-users remain relatively unaffected. Since treatment in this set of

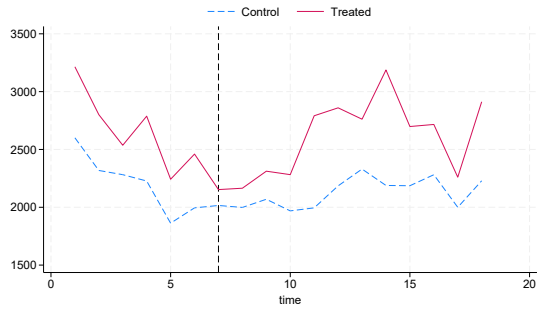
Figure 4: SDiD by Political Affiliation (Moderate Definition)



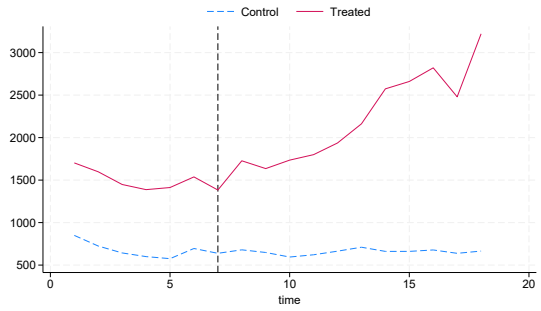
(a) Left Leaning Users, Time Delta



(b) Right Leaning Users, Time Delta



(c) Left Leaning Users, Winsorized



(d) Right Leaning Users, Winsorized

specifications is assigned at the user-level, we conduct a simple DiD analysis, clustering standard errors at the user-level and without any p-value corrections. The outcome is the share of right-leaning news in total news consumption in a given month. Finally, we allow for heterogeneous effects on news consumption by users' political lean.

Table 6 reports the results. Among left-leaning users, being a heavy Twitter user is associated with a small, statistically significant decrease in right-leaning news share after the announcement (approximately –0.018 to –0.019 percentage points depending on specification, $p < 0.05$). Among right-leaning users, heavy Twitter users show an increase in right-leaning news share of approximately 0.031 to 0.038 percentage points ($p < 0.01$). The differential effect—captured by the triple interaction of Heavy User × Post × Right—is approximately 0.051 to 0.057 percentage points ($p < 0.01$) under the moderate definition. These results are robust across alternative definitions of political lean, unwinsorized outcomes, and subsamples

Table 5: Effect By Political Affiliation: Time Spent

	Moderate Definition		Strict Definition	
	(1)	(2)	(3)	(4)
	Time	Time (Winsor)	Time	Time (Winsor)
Twitter × Announce × Right	465.182	439.774	1361.755	1265.818
	(23.100)***	(13.486)***	(60.097)***	(18.265)***
	[0.052]*	[0.032]**	[0.034]**	[0.014]**
Twitter × Implement × Right	1095.761	1056.773	2052.315	1957.898
	(35.578)***	(18.167)***	(76.900)***	(26.374)***
	[0.024]**	[0.012]**	[0.030]**	[0.010]***
Twitter × Announce	-185.960	-220.799	-763.900	-747.309
	(30.877)***	(11.602)***	(21.788)***	(17.636)***
	[0.122]	[0.090]*	[0.046]**	[0.042]**
Twitter × Implement	73.646	84.630	-597.652	-535.493
	(22.236)***	(14.623)***	(58.992)***	(23.807)***
	[0.394]	[0.332]	[0.108]	[0.098]*
Observations	5940	5940	5940	5940
R-squared	0.977	0.908	0.977	0.842

with positive total news consumption.

These results suggest that the acquisition not only shifted who uses Twitter, but also shaped the information environment. Ownership pushes users in opposite direction, each increasing news consumption of channels affiliated with their own political lean, essentially increase polarization in new consumption. This finding is consistent with the growth of echo-chambers, leading users to further segregate on opinions and information consumption (Cinelli et al., 2021; Di Tella et al., 2025).

5.4 Robustness

The main findings are robust to a range of alternative specifications and sample restrictions. For platform participation, the SDiD results are robust to implementation details of the estimator, to using individual-level rather than domain-level data, to estimating on a balanced panel of users observed throughout the sample period, and to using usage events rather than time spent as the outcome. For ideological heterogeneity, the main asymmetry is robust to alternative political-lean definitions, including strict, expansive, and alternative classification schemes. For external news consumption, the results are robust to alternative

Table 6: Effects on External News Consumption (Announcement)

	(1) Narrow Def.	(2) Moderate Def.	(3) Expansive Def.	(4) Alternative Def.
Panel A: Left-Wing Users				
Heavy User Announce	-0.032	-0.018**	-0.019***	-0.019*
	(0.021)	(0.007)	(0.006)	(0.011)
Observations	3094	19131	31181	9027
R-Squared	0.416	0.420	0.385	0.477
Panel B: Right-Wing Users				
Heavy User Announce	0.026*	0.031***	0.038***	0.029**
	(0.014)	(0.012)	(0.012)	(0.012)
Observations	7484	13020	14294	13262
R-Squared	0.587	0.493	0.468	0.578
Panel C: Differential Effect				
Heavy User Announce	-0.037*	-0.018**	-0.019***	-0.019*
	(0.021)	(0.007)	(0.006)	(0.011)
Heavy User Announce × Right	0.064***	0.051***	0.057***	0.049***
	(0.025)	(0.014)	(0.014)	(0.016)
Observations	10578	32151	45475	22289
R-Squared	0.767	0.724	0.679	0.696
Right Users Effect	0.027	0.032	0.038	0.029
P-value	0.050	0.007	0.001	0.013

ideology definitions and to restricting the sample to users with nontrivial news consumption.

Across these checks, two patterns remain stable. First, the aggregate increase in Twitter participation is strongest after implementation rather than immediately at announcement. Second, the acquisition generates a markedly stronger response among right-leaning users than among left-leaning users, both on-platform and in the composition of heavy users' external news consumption. Detailed robustness results are reported in the Online Appendix.

6 Interpretation and Limitations

Our results are consistent with users responding to a perceived shift in platform political alignment. The key patterns—positive announcement effects for right-leaning users, negative or null effects for left-leaning users, and downstream news shifts concentrated among heavy Twitter users—are jointly consistent with a model in which users sort into or out of a platform

based on its perceived ideological identity.

The announcement effects, which begin before the deal formally closed, indicate that perceived alignment rather than actual governance or algorithmic changes drove the early response. This is consistent with Hotelling-style reasoning: platforms, like products, can attract or repel consumers based on their perceived ideological position, and users may react to signals about future positioning even before changes are implemented. The pattern is also consistent with the idea noted by Elfenbein and others that even the anticipation of a political shift in a platform's identity can reallocate consumers across competing products.

Several channels could mediate these effects: changes in platform governance (e.g., reduced content moderation), changes in brand identity (e.g., association with Musk's political persona), network effects (e.g., arrival of right-leaning peers makes the platform more attractive to other right-leaning users), and algorithmic changes (Gauthier et al., 2026). Our design does not allow us to separately identify these channels, and we are careful not to attribute the effects to any single mechanism.

We find suggestive evidence against a pure algorithmic channel for the news consumption results: there is no change in Twitter's role as a news gateway, as measured by outbound traffic to news websites following a Twitter visit, and no systematic change in the direction of outbound traffic. This is consistent with the news consumption effects operating through compositional changes in who is using Twitter—and thus what political content users encounter—rather than through changes in what Twitter algorithmically recommends.

Our study has important limitations. First, we cannot separately identify the governance, moderation, brand, and algorithmic channels. Second, we do not observe direct belief changes or sentiment, so we cannot confirm that the participation shifts are driven by changes in subjective platform perceptions rather than, say, changes in platform quality. Third, we cannot fully rule out that network effects generate anticipatory participation responses that are attributed to the announcement even if users are ultimately responding to expected compositional changes rather than the ownership signal per se.

7 Conclusion

We document that Musk's acquisition of Twitter—a salient ownership shock with clear political valence—reshaped platform participation and downstream information consumption. Overall Twitter participation increased following the acquisition, with right-leaning users responding much more strongly than left-leaning users. The differential participation response is large, robust, and already visible following the announcement, before the deal formally closed.

Among heavy Twitter users, the ownership shock also shifted news consumption toward more right-leaning outlets for right-leaning users, and marginally in the opposite direction for left-leaning users.

These findings have broader implications for the economics of platform markets and political economy. Platform ownership can shape not just platform size but platform composition, and these compositional changes can propagate into users' broader information environments. Ownership changes at politically salient platforms may re-sort participants along ideological lines even before formal implementation, suggesting that the ownership signal itself can be an important determinant of user behavior. As high-profile platform ownership changes become more common—and as platforms become increasingly central to political information consumption—understanding how ownership signals shape participation and composition is of growing empirical and policy relevance.

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