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A Longitudinal Approach to the Analysis of Social Media Engagement: The Case of Anger-Driven Climate-Skeptic Message Propagation During the 2021 German Elections

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Abstract

Social media have become an important space for political agenda formation and mobilization, with user engagement playing a key role in spreading messages. Accordingly, prior research has extensively examined social media users' engagement and sharing behaviors. In this study, we examine the advantages of longitudinal modeling for analyzing social media engagement compared with cross-sectional approaches, focusing on the relationship between emotional reactions—particularly anger—and content propagation. Although cross-sectional approaches are commonly used to analyze social media data, engagement patterns are inherently temporal and therefore naturally call for a longitudinal, time-sensitive approach. We argue that longitudinal methods can be more effective than cross-sectional ones for analyzing time-evolving engagement dynamics. These methods indeed represent a middle ground between familiar cross-sectional approaches and sophisticated time-series techniques, avoiding some pitfalls of the former while relying on simpler assumptions than the latter. Longitudinal methods, in fact, reduce omitted variable bias, help account for time-varying factors—including algorithmic amplification and network propagation confounders—and accommodate irregular or sparse social media data. We empirically explore the differences between longitudinal and cross-sectional analysis by comparing estimates of the effect of anger on sharing using 1,137 environmentally themed Facebook posts by German political parties during the 2021 federal election, focusing on Alternative für Deutschland (AfD) and Die Grünen (The Greens), which represent opposite ends of the environmental policy spectrum. Cross-sectional estimates were derived using three sampling strategies: the last observation per post, the first post-election observation, and a randomly selected observation per post. Bayesian multilevel regression with a negative binomial specification was applied across both longitudinal and cross-sectional models. Our results indicate that longitudinal modeling yields more conservative and precise estimates, whereas cross-sectional methods tend to exaggerate effect sizes and interparty differences. All models suggest that anger is positively associated with sharing for AfD and negatively for Die Grünen, but longitudinal analysis provides greater inferential stability by controlling for time-invariant confounders and algorithmic amplification. Overall, the findings underscore the value of incorporating temporal dynamics into social media research, while also highlighting the challenges of applying longitudinal approaches to digital trace data, particularly with regard to data access.

Keywords

Social media engagement; Longitudinal analysis; Emotional communication; Bayesian multilevel modeling; Algorithmic amplification; Political communication

1 Introduction

Social media play a central role in shaping political agendas and driving political mobilization (Bennett & Segerberg, 2013; Gilardi et al., 2022), with user engagement serving as a primary mechanism for message propagation (boyd, 2010; Dijck & Poell, 2013). Because the spread of messages is central to political communication, researchers have examined the factors that shape social media users' engagement and sharing behavior (e.g., Eberl et al., 2020; Giglietto et al., 2019; Heidenreich et al., 2024; Trilling et al., 2022; Waldherr et al., 2025).

The propagation of social media content is a dynamic process that naturally calls for a longitudinal perspective. In contrast to cross-sectional approaches—still common in social media research due to their practicality, widespread familiarity, and ease of data collection—longitudinal methods are not limited to capturing a single snapshot in time. Instead, they analyze repeated observations from the same subjects, an important distinction with substantial methodological implications (Singer & Willett, 2003).

A key advantage of tracking the same subjects over time is that it reduces sensitivity to omitted-variable bias (Cochran & Chambers, 1965). By evaluating relationships within subjects, longitudinal methods control for characteristics that remain constant within individuals but vary across them (i.e., unobserved heterogeneity) (Petersen, 1993).

Another advantage of longitudinal methods is their ability to mitigate sampling bias (Jost et al., 2019). This is particularly relevant for social media events, where timing of observations matters: counting shares immediately after publication versus several hours or days later can yield very different insights, and inconsistent sampling may introduce bias.

A further challenge better addressed by longitudinal methods is algorithmic confusion (Salganik, 2019). For example, observed engagement in social media reflects not only user behavior but also network dynamics and algorithmic amplification (Dijck & Poell, 2013; Giglietto et al., 2019, 2020; Righetti & Balluff, 2025), which complicates analytic efforts to disentangle their respective effects. Longitudinal models can help separate human-driven from algorithm-driven dynamics by using lagged or autoregressive effects — for example, modeling how engaging content tends to attract further engagement.

In recent years, computational social science has emphasized the importance of temporal dynamics in social media data, advocating the use of time series methods (Wells et al., 2019). Time series analysis can effectively model communication processes, but its assumptions are often difficult to meet with social media data (Kirchgässner et al., 2012; Righetti, 2025b). Observations may be irregular, stationarity is frequently violated, and data are often sparse, zero-inflated, or count-based rather than continuous. These features violate the assumptions of standard techniques, often requiring transformations or complex models that complicate analysis and hinder interpretability.

This paper explores how longitudinal methods can bridge cross-sectional regression and time series modeling, combining their strengths while mitigating their limitations (Frees, 2004). Longitudinal methods integrate temporal modeling while maintaining reasonable assumptions within a familiar regression framework. While they necessitate more demanding data collection than cross-sectional approaches, they entail less stringent requirements than classic time series analysis. Their ability to account for unobserved confounders and capture time-evolving dynamics justifies the additional complexity, providing a stronger basis for inference (Singer & Willett, 2003).

We analyze the advantages of longitudinal methods through a case study on audience emotional reactions to photo posts, focusing on anger as a high-impact emotion that drives the spread of political content. The analysis centers on environmentally related messaging from political parties and candidates ahead of the 2021 German elections (Righetti et al., 2022). To maintain a manageable scope, we concentrate on two parties at the opposite ends of the environmental politics spectrum: Alternative für Deutschland (AfD) and the Green Party (Die Grünen). The central research question driving this study is as follows:

How do longitudinal estimates of the relationship between anger reactions and content propagation differ from cross-sectional estimates, in terms of coefficient sign, effect size, and statistical significance?

The next section reviews the literature on social media propagation to frame the paper's case study. It follows an outline of longitudinal analysis in contrast to cross-sectional and time-series approaches. The paper then introduces Bayesian hierarchical regression modeling as a method for conducting longitudinal analysis. This method is applied to a case study examining emotional reactions—specifically anger—and their relationship to the diffusion of environmental messages on social media during the 2021 German election. To address the research question, the results are compared with analyses of three cross-sections of the same dataset, each generated using a different sampling strategy. The final section discusses the findings and outlines limitations, data requirements, and directions for future research.

2 Social Media Engagement and Users' Emotions: Why It Matters and Why It's Hard to Study

A growing body of research has sought to identify which factors influence message propagation on social media. Early work has focused on message characteristics such as sentiment (Eberl et al., 2020), news value (Araujo & van der Meer, 2020; García-Perdomo et al., 2018; Trilling et al., 2017), and networked sharing (Giglietto et al., 2020). More recently, the role of emotions has received increasing attention, with particular emphasis on anger in relation to populist communication (Gerbaudo et al., 2023; Humprecht et al., 2024; Jost et al., 2020; Larsson, 2024), and visual communication (e.g., Doerr & Langa, 2025; Rossi et al., 2024).

Research has drawn attention to the mobilizing power of visual media and associated emotional responses (Doerr et al., 2013; Geise et al., 2025; Geise, Heck, et al., 2021; Geise, Panke, et al., 2021). Among these emotions, outrage and anger are particularly associated with heightened motivation to act (Jasper, 1997). On social media, anger-charged communication engages users with content signaling injustice or threat (Righetti, 2021a, 2025a; Righetti & Bertuzzi, 2020) and is consistently employed by populist parties (Humprecht et al., 2024). Overall, research suggests that emotions play a significant role in content propagation on social media, with anger being particularly effective in mobilizing audiences.

Social media users can convey their emotions through a variety of channels, including platform-specific affordances. Facebook, for example, has introduced "reactions" to allow users to easily express their emotional responses to content (Anwar & Giglietto, 2024). Facebook reactions include "Love," "Care," "Haha," "Wow," "Sad," and "Angry," with the "Angry" reaction being particularly relevant for studying online expressions of outrage. Recent research has leveraged users' reactions to examine patterns of ideological polarization (Rossi et al., 2024) and the anger-inducing communication of right-wing populists (Gerbaudo et al., 2023; Jost et al., 2020; Muraoka et al., 2021). These studies highlight key aspects of emotional engagement dynamics on social media and pave the way for further investigation.

Facebook reactions provide a convenient "natural laboratory" for approximating audience emotional responses. However, it is important to exercise caution when working with social media data (Salganik, 2019). For instance, not all users interact with social media posts, private activity can go unobserved, and accounts may be deleted (Righetti & Bertuzzi, 2024). Furthermore, algorithms contribute to influencing users' engagement behavior. Users' sharing of content amplifies messages among their contacts through networked connections and can trigger algorithmic amplification, further broadening their reach and increasing the likelihood of additional engagement (Giglietto et al., 2020; Righetti & Balluff, 2025). According to journalistic reports, Facebook algorithms favored posts generating higher emotional engagement, especially those eliciting anger (Merrill & Oremus, 2021). The interweaving of human behavior, technology-mediated networked dynamics, and algorithmic influence, generates "algorithmic confusion" in empirical data—a situation in which researchers cannot clearly determine whether, or to what extent, an outcome results from human choices or from a technological-algorithmic influence (Salganik, 2019). This is especially relevant when analyzing social media engagement, as failing to account for these effects can result in overestimating or underestimating the impact of specific message features.

Novel methodological approaches can be valuable to generate new insights from social media data without neglecting the inherent complexities. Longitudinal methods allow for stronger inferences than cross-sectional approaches by more effectively controlling for omitted variable bias (Petersen, 1993; Singer & Willett, 2003). They can mitigate algorithmic confusion by capturing temporal dynamics that can account for algorithmic amplification of post visibility and engagement—the so-called "rich-get-richer" effect (Dijck & Poell, 2013)—while separating this inertia from the structural effects of the studied factors.

In the next section, we provide a more thorough review of the potential advantages of longitudinal methods, contrasting them with cross-sectional approaches and distinguishing them from the closely related, partly overlapping techniques of classic time series analysis.

3 Advantages of Longitudinal Methods

Longitudinal and Cross-Sectional Methods

Longitudinal methods rely on repeated measurements from the same subjects to examine change and its predictors (Singer & Willett, 2003). Originating in the behavioral sciences, longitudinal designs have been used to study human development and life-course events (Sontag, 1971). Communication research has integrated longitudinal methodologies to study a variety of phenomena, including media use, exposure, and opinion dynamics (Kittel et al., 2020; Ohme et al., 2022; Thomas et al., 2021). Notably, longitudinal approaches seem to have been applied only occasionally in social media analysis (Theocharis & Jungherr, 2021).

Compared to cross-sectional approaches, longitudinal methods differentiate within-subject from between-subject variability, providing better control for stable confounders (Frees, 2004; Liu, 2015; Petersen, 1993; Singer & Willett, 2003). For example, a cross-sectional study might show that social media messages with more interactions—such as more likes or comments—tend to receive more shares. However, it can only estimate the average relationship between interactions and sharing across all posts. The observed correlations are susceptible to confounding by all message characteristics—such as topic, writing style, or media format—that are not accounted for.

Additionally, in the absence of a systematic sampling plan, engagement may be measured inconsistently across messages, capturing them at different stages of the engagement development. Engagement on social media unfolds over hours, days, or weeks, influenced by exposure patterns, platform algorithms, and external events. Depending on when data are collected, the observed engagement may not align with the end of the engagement lifecycle for a message, and comparing messages at different points can bias estimates of engagement levels (Jost et al., 2019).

In contrast, longitudinal models rely on multiple observations over time to analyze the covariation of time-evolving variables, such as emotional reactions and sharing. Thus, they provide a more robust basis for concluding about their relationship. Additionally, by mapping the engagement history through repeated observations, longitudinal methods are also less susceptible to time-related sampling bias.

Longitudinal approaches also offer methods to control for algorithmic bias. It is well established that social media recommendation algorithms boost the visibility of messages that attract engagement, thereby increasing their likelihood of getting more engagement (Dijck & Poell, 2013; Giglietto et al., 2019). As a result, widely shared posts may continue to spread partly because algorithms increase their visibility, rather than for any inherent characteristics, such as their emotional content or writing style. Cross-sectional designs cannot disentangle this confounding effect. By contrast, longitudinal approaches can model the influence of past values by incorporating lagged predictors or autoregressive error terms. While precisely modeling the effect of algorithmic amplification is challenging, these approaches offer a means of accounting for this phenomenon. Consequently, they provide a more robust framework for studying social media engagement processes.

Longitudinal and Time-Series Methods

Recent literature has emphasized the temporal dimension in computational communication science (Wells et al., 2019). Time series methods with roots in econometrics such as Vector Autoregression (VAR) (Sims, 1980) and Granger causality tests (Granger, 1969), have been applied to agenda-setting theory (Brosius & Kepplinger, 1990; Gilardi et al., 2022) and to digital communication processes analyzed as a system (Bastos et al., 2015; Kulichkina et al., 2024; Lukito, 2020; Righetti, 2021b).

While time-series and longitudinal methods share common features and techniques, and their distinctions may become blurred in advanced modeling approaches, they do not entirely overlap. In typical cases, classic time-series analysis differs from longitudinal methods in terms of disciplinary traditions, statistical assumptions, data requirements, and modeling objectives.

Time-series analysis is traditionally designed to examine one or a limited number of long series (e.g., GDP, stock prices), often requiring dozens of observations to reliably capture underlying temporal dependencies (Box & Jenkins, 1970; Hamilton, 1994). Even when extended to multiple series, such as in vector autoregression (VAR) (Sims, 1980), the focus remains on modeling interdependencies across time. Time is the primary reference in time series analysis, with observations indexed along this dimension. Because temporal relationships are central, time-series analysis typically requires synchronized and equally spaced observations, although modern methods have been developed to relax these constraints (Weerakody et al., 2021).

In contrast, longitudinal studies emphasize structural relationships between variables, using time primarily as a means to estimate them rather than as the central focus of the analysis. Within this framework, the units of analysis are generally treated as independent, with autocorrelation modeled as a nuisance to be considered rather than a fundamental object of inquiry. Also, longitudinal models more easily accommodate unequal spacing and durations of observations than time-series analysis. Longitudinal methods typically analyze a larger number of units, each with relatively few observations, rather than a few cases with numerous data points (Diggle, 2002; Singer & Willett, 2003). Panel data studies, for instance, may be effective with as few as two or three waves of measurement (Frees, 2004).

In summary, longitudinal methods occupy a middle ground between time-series and cross-sectional regression techniques (Frees, 2004). They retain some strengths of time-series approaches, but typically rely on simpler assumptions, avoid heavy transformations, and use a regression framework familiar to social scientists, yielding results that are easier to interpret. This makes them well-suited for analyzing structural relationships among social media variables, incorporating relevant temporal dimensions, and accounting for the multilevel organization inherent in such data.

Hierarchical Bayesian Regression as a Method for Longitudinal Approaches

From a methodological and technical perspective, hierarchical Bayesian regression provides a flexible framework for analyzing longitudinal data. It accommodates the nested structure inherent in repeated-measures designs, where observations are clustered within subjects or entities, and contributes additional strengths to the analysis (Gelman et al., 1995). Prior information can be incorporated in Bayesian models to leverage existing knowledge and regularize estimates, helping stabilize inferences in the presence of sparse or extreme social media engagement data. Additionally, the probabilistic nature of Bayesian inference provides full posterior distributions of parameters, offering a more nuanced interpretation of uncertainty and enabling probabilistic statements about the direction and magnitude of effects (Gelman & Hill, 2007). The *brms* package (Bürkner, 2017), built on the STAN software (Stan Development Team, 2025) and designed for the R statistical environment (R Core Team, 2024), provides a convenient framework for performing hierarchical Bayesian regression analysis.

In the following sections, we apply hierarchical Bayesian regression to examine how a longitudinal approach to social media engagement data compares with cross-sectional methods. The focus is on the emotional factors associated with the propagation of environmentally related images on Facebook during the 2021 German federal election.

4 Data and Methods

Starting in July 2021, we manually identified and collected the official Facebook accounts of Germany's seven main political parties and their candidates for the 2021 federal election (Righetti et al., 2022). Using CrowdTangle, an official META social media monitoring tool (CrowdTangle Team, 2020), we collected all public posts published by these accounts between August 16 and September 26, 2021. The resulting dataset includes 62,270 posts from 1,317 users.

The analysis centers on 8,897 posts related to environmental issues, identified using a comprehensive keyword list and validated by native German-speaking researchers[1].

Longitudinal dataset

From this set, we focused on photo posts, reflecting recent interest in visual communication and emotional responses to climate-related issues (e.g., Doerr & Langa, 2025; Rossi et al., 2024). To ensure sufficient data for longitudinal analysis, we selected photo posts with above-average total interactions (*M* = 99, *N* = 1,224)[2]. In March 2024, we queried the CrowdTangle "Historical Search" API to collect engagement observations for these posts over time (CrowdTangle Team, 2020). We successfully retrieved information for 1,137 posts (92.89% of the sample). Each post came with a median of 70 observations, spanning an average of 19 days. We aggregated data at the daily level, which is appropriate for the current inquiry and tempers correlation between consecutive data points (i.e., autocorrelation). All continuous predictors were standardized ($M = 0, SD = 1$). Variance inflation analysis showed no problematic multicollinearity (VIF: $[1.00, 1.22]$).

Cross-sectional datasets

From the longitudinal dataset, we derived three distinct cross-sectional datasets using different sampling strategies.

The first dataset retains the last available observation for each post, capturing engagement after it has had sufficient time to accumulate—on average, over a 19-day period. This represents a best-case scenario, in which posts have likely reached their diffusion peak. For example, in a study of the 2017 German federal election, held on 24 September 2017, engagement metrics for posts were collected in January 2018 (Jost et al., 2020). As the authors note, "Because the growth of new Reactions is typically saturated within few days (Jost et al., 2019) it is very likely that the number of Reactions did not change after the collection (…)."

The second dataset includes the first observation available on or after 27 September, simulating a situation in which a researcher collects data immediately following the election. In this case, posts published earlier in the data collection period are likely to have reached their maximum engagement, whereas those published closer to the election day may not yet have done so (Figure 1).

The third dataset randomly selects one observation per post, simulating a worst-case scenario in which engagement snapshots are collected in an unsystematic or opportunistic way.

[1] The full list of keywords is provided in the Appendix at the end of the paper.
[2] We acknowledge that, while this selection strategy reduces data sparsity and supports longitudinal modeling, it may also introduce selection bias. As a result, our findings primarily reflect the dynamics of highly engaging posts and may not generalize to all posts. A comparative analysis between below- and above-average posts could offer further insights into these differences (Waldherr et al., 2025).

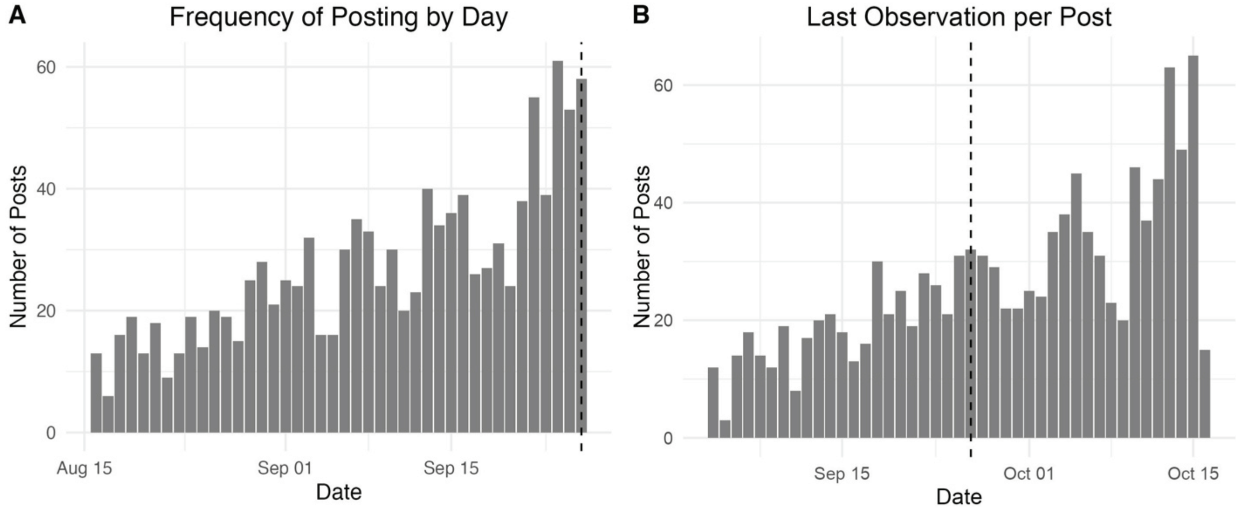

Figure 1. Daily posting frequency. Panel A (left) shows the distribution of the first (oldest) observation per message, while Panel B (right) shows the distribution of the last (most recent) observation. The dashed vertical line indicates the election day on 26 September 2021. Counts are aggregated by day.

Model Specifications

The models examine correlations between Angry reactions and numbers of Shares received by political parties' social media messages. We modeled the number of shares for each post using Bayesian regression with a Negative Binomial likelihood, suitable for over-dispersed count data, and standardized predictors so that coefficients reflect the effect of a one–standard-deviation change. To assess party-specific effects, we included an interaction between Angry reactions and party.

We fitted longitudinal and cross-sectional models, keeping the model structure consistent except for adjustments required by the data's temporal resolution. At their core, both categories of models predict the number of shares for each post based on Angry reactions, while allowing for party-specific effects and accounting for the total number of other reactions.

The longitudinal model uses daily observations to capture how sharing activity evolves over time. An offset term adjusts for the exact duration of observation within each day. Because posts with more shares reach larger audiences in subsequent periods due to algorithmic effects and social network dynamics, serial correlation may occur. This is addressed by including a lagged Shares variable ($Shares_{t-1}$). Weekday indicators are also included to capture weekly seasonality, another source of autocorrelation. Random intercepts for party, account within party, and posted message within account capture baseline differences across hierarchical levels.

The cross-sectional models capture the same relationships as the longitudinal model but in a static context, where each post is treated as independent. Similar to the longitudinal model, the cross-sectional models include Angry reactions and their interaction with party, and other reactions. As these models lack temporal information, neither lagged shares nor day-of-week effects are included. Instead, the number of followers is included to control for differences in accounts' audience size[3].

Since the offset term is not consistently included in cross-sectional models, we estimated versions with and without it to assess sensitivity to this specification. The offset term can help control for unequal observation durations, as often occurs in cross-sectional data—for example, when a post engagement is observed shortly after publication versus several weeks later.

All models were estimated in a Bayesian framework using the *brms* package (Bürkner, 2017) in the R environment (R Core Team, 2024) with the *cmdstanr* backend (Gabry et al., 2024)[4]. The formal model specifications are reported in the Appendix.

In the next section, we present the results of the longitudinal analysis, followed by a comparison with cross-sectional models that vary in sampling strategy and in the inclusion of the offset term.

5 Results

Results from the longitudinal Bayesian model indicate that Angry reactions are positively correlated with daily Shares for AfD ($\beta = 0.08\ [0.07, 0.09]$). The effect for Die Grünen is credibly lower than AfD by 0.16 units ($\beta = -0.16\ [-0.19, -0.13]$), which corresponds to a negative effect for Die Grünen as shown in the posterior distribution (Figure 2).

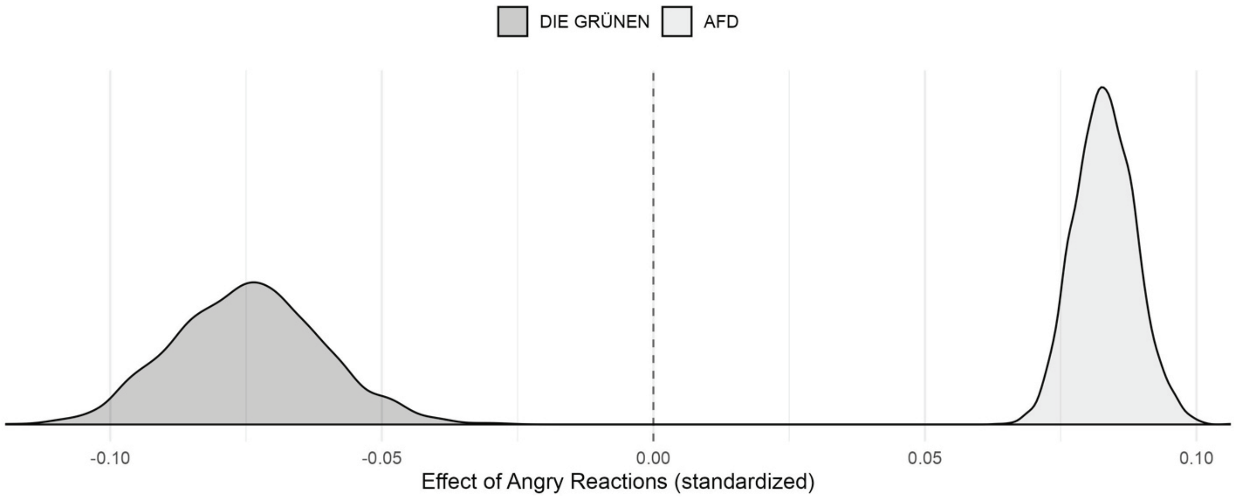

Figure 2. Posterior distributions of the effect of standardized Angry reactions on daily share counts from the longitudinal negative binomial model. AfD shows a small positive effect, while Die Grünen show a negative effect. Dashed vertical line indicates a null effect (0).

[3] While not strictly necessary, given the model's ability to control for relatively stable factors, the number of followers is also included in the longitudinal model to maintain a consistent structure.
[4] The *cmdstanr* backend is an interface to *CmdStan*, the command-line version of *Stan*, which provides fast and efficient Bayesian sampling. The model used the standard *brms* setup of four chains with 2,000 iterations each, including 1,000 warm-up iterations per chain. Markov chains are sequences of samples used to approximate the posterior distribution of model parameters. Iterations are individual samples within each chain, and the warm-up (or burn-in) period allows the sampler to stabilize before collecting samples for inference.

For AfD, a one-standard-deviation increase in Angry reactions—corresponding to approximately 19 reactions based on the pooled SD across parties—is associated with an 8% increase in expected shares. Because AfD posts typically receive many Angry reactions and show high variability, including extreme cases ($M = 4.34, SD = 34.2$ at the party level), this correlation reflects a notable association in practice. In contrast, Die Grünen posts typically receive fewer Angry reactions ($M = 1.18, SD = 10.4$; party-level descriptives), and the corresponding association with shares is comparatively smaller. For illustrative purposes, Figure 3 presents the AfD posts in our dataset that received the highest number of Angry reactions.

It is noteworthy that the coefficient of the lagged dependent variable—incorporated to address autocorrelation arising from networked and algorithmic propagation—is both substantial and statistically robust ($\beta = 0.25\ [0.24, 0.26]$).

Figure 3. The four AfD Facebook images that received the highest number of Angry reactions. (1) Frames the Green Party's mobility transition as an attack on drivers, claiming it will cost them €48 billion. (2) Accuses CDU's Armin Laschet of tolerating the arrival of Afghan criminals and mocks his reaction to flood victims, combining anti-immigration and anti-elite messaging. (3) Warns of a 40-cent fuel price increase, featuring AfD candidate Tino Chrupalla in a serious pose. (4) Claims climate policies will raise fuel prices by 70 cents, ridiculing Olaf Scholz as indifferent to citizens' costs and rebranding him as a "chancellor for citizen rip-offs". It is worth noting that 3 out of 4 pictures have the same topic: costs associated with driving a car.

Comparing Longitudinal with Cross-Sectional Models

We compared the longitudinal model with three cross-sectional ("CS") approaches reflecting common design choices: the last observation per post, on average 19 days after publication ("CS Last"); the first observation after the election, on or just after 27 September ("CS Sep-27"); and a single random observation per post ("CS Random").

Table 1 reports the estimated coefficients for Angry reactions for both AfD and Die Grünen. In all models, AfD serves as the reference category, and the coefficient for Die Grünen represents the interaction term Angry × Party, which should be interpreted relative to the baseline coefficient of AfD within each model.

Table 1. Standardized coefficients (with 95% confidence intervals) for AfD (reference) and Die Grünen (interaction with Angry × Party) across longitudinal and cross-sectional models. Die Grünen coefficients should be interpreted relative to AfD.

Model	Party	Estimate	l-95% CI	u-95% CI
Longitudinal	AfD	0.08	0.07	0.09
	Die Grünen	-0.16	-0.19	-0.13
CS Sep-27	AfD	0.30	0.12	0.49
	Die Grünen	-1.19	-1.62	-0.67
CS Last	AfD	0.57	0.43	0.72
	Die Grünen	-0.75	-1.14	-0.30
CS Random	AfD	0.23	0.10	0.38
	Die Grünen	-2.32	-3.16	-1.34
CS Sep-27 (no offset)	AfD	0.57	0.42	0.73
	Die Grünen	-0.77	-1.17	-0.32
CS Last (no offset)	AfD	0.57	0.43	0.72
	Die Grünen	-0.75	-1.14	-0.29
CS Random (no offset)	AfD	0.36	0.28	0.45
	Die Grünen	-0.41	-0.97	0.26

Clear differences emerge in effect size and the precision of estimates between the longitudinal and cross-sectional specifications. In particular, cross-sectional models tend to produce more extreme coefficients and larger differences between parties.

In the longitudinal model, AfD has a baseline coefficient of $\beta = 0.08\ [0.07, 0.09]$. In the cross-sectional models, baseline coefficients range from $\beta = 0.23\ [0.10, 0.38]$ in the “random” model, to $\beta = 0.57\ [0.43, 0.72]$ in the “Last” model, with the intermediate “CS Sep-27” cross-section estimated at $\beta = 0.30\ [0.12, 0.49]$.

The interaction term for Die Grünen (Angry × Party) is $\beta = -0.16\ [-0.19, -0.13]$ in the longitudinal model. This relative difference becomes more pronounced in cross-sectional models: in CS Sep-27, Die Grünen posts show a larger negative effect ($\beta = -1.19\ [-1.62, -0.67]$), and in CS Random, the negative difference is even stronger ($\beta = -2.32\ [-3.16, -1.34]$). The cross-sectional “Last” model shows an intermediate effect, but it remains larger than that of the longitudinal model ($\beta = -0.75\ [-1.14, -0.30]$).

Comparing models without offsets to their offset-included counterparts also reveals differences. For Die Grünen, the interaction coefficients remain negative but vary in magnitude and uncertainty, with the larger difference notable for the Random model (no offset: $\beta = -0.41\ [-0.97, 0.26]$ vs. offset: $\beta = -2.32\ [-3.16, -1.34]$) and the Sep-27 model (no offset: $\beta = -0.77\ [-1.17, -0.32]$ vs. offset: $\beta = -1.19\ [-1.62, -0.67]$). Instead, the Last model is robust to the exclusion of the offset specification (no offset: $\beta = -0.75\ [-1.14, -0.29]$ vs. offset: $\beta = -0.75\ [-1.14, -0.30]$). The same holds for AfD. The September 27 cross-sectional model without the offset produces estimates that closely align with those of the “Last” model, both with and without the offset.

5 Discussion

This study explored the advantages of longitudinal approaches to social media engagement. We discussed longitudinal methods in comparison with cross-sectional and time series analysis, situating longitudinal models as their middle ground. We compared longitudinal against cross-sectional regressions by using the empirical case of environmental-related visual content propagation and angry public reactions during the 2021 German election.

In our analysis, the longitudinal model returned more precise estimates than the cross-sectional models, with narrower confidence intervals. Cross-sectional coefficients were more uncertain and extreme, accentuating differences between parties. We interpret these differences as reflecting the ability of longitudinal multilevel approaches to account for stable, time-invariant characteristics at both the account and party levels, as well as to control for temporal autocorrelation arising from networked diffusion and algorithmic amplification (Frees, 2004; Singer & Willett, 2003). In contrast, cross-sectional estimates are inflated by unaccounted confounding factors, which can exaggerate observed differences. These limitations carry important theoretical implications, as they may affect the accuracy and precision of conclusions regarding party dynamics and differences between parties.

Still, in this specific case, the broader conclusions remain consistent across all models. The findings highlight the prevalence of anger in the far-right community and its correlation with the spread of climate-skeptic messages. In contrast, the green community sees a considerably lower prevalence of this emotion and a negative correlation with the spread of environmentalist messages. These findings are consistent with recent research on social media and emotions (Gerbaudo et al., 2023; Jost et al., 2020; Muraoka et al., 2021), corroborating their results through additional and robust methodological choices, and further advance the literature on emotions in environmental communication (Doerr & Langa, 2025; Rossi et al., 2024).

At the same time, they challenge techno-deterministic interpretations of algorithmic power (Bruns, 2019b). While algorithms can be designed to amplify emotional content to keep users engaged on a platform (Merrill & Oremus, 2021), the observed between-party differences suggest that algorithms alone do not necessarily drive anger or polarization. Heterogeneous levels of anger across parties, along with varying relationships between angry reactions and shares, suggest that political communication culture and audience attitudes condition which content performs best on social media. Rage and polarization are not inevitable consequences of algorithms. Rather, social media environments are structured by the interplay between audience and creator cultures, in interaction with algorithmic and technological affordances (Bennett & Segerberg, 2013; Dijck & Poell, 2013; Kakavand, 2024; Righetti & Kakavand, 2025). From these concomitant causes emerge a varied, emotionally and symbolically charged landscape where content circulates along differentiated paths and at varying paces.

Sensitivity analyses regarding the inclusion of offset terms provide important guidance for best methodological practices in social media research. Among cross-sectional designs, the “Last” cross-section—which uses the final observation available for each post—emerges as the most robust. In contrast, cross-sectional models based on alternative sampling strategies, such as the first observation after the election or a randomly selected observation per post, exhibited greater variation in coefficient magnitude and uncertainty when the offset was excluded. This pattern arises because the “Last” model captures each post after sufficient time has passed for engagement to saturate, effectively observing it at the conclusion of its engagement lifecycle. These findings reinforce previous analyses highlighting the importance of timing in social media data collection (Jost et al., 2019, 2020).

These findings also have practical implications for social media data collection. Even when longitudinal data collection is not feasible, accuracy can be partially improved by timing cross-sectional sampling to coincide with periods of near-saturated engagement or by including an offset term in the regression model to account for differences in exposure time. In our dataset, engagement stabilized roughly 19 days after publication, making the use of an offset unnecessary for the “Last” model. However, our analysis is limited to Facebook, while other social media may show different temporal dynamics (Waldherr et al., 2025). We also observed that the September 27 cross-sectional model without the offset closely approximates the Last model. However, this similarity is somewhat coincidental, as many posts published close to the election day had not yet reached full engagement. Including the offset for this model substantially adjusts for these exposure differences, producing coefficients that differ from both the no-offset Sep-27 model and the Last model. In contrast, the Last model is robust to the inclusion of the offset because engagement had largely stabilized by that point. Overall, these analyses provide insights into the dynamics of engagement on social media and underscore the importance of carefully considering both timing and exposure when designing observational studies.

Turning to the longitudinal model, the credibly high coefficient for the lagged Shares variable highlights the influence of past engagement on current sharing. This underscores the importance of accounting for sources of “algorithmic confusion” (Salganik, 2019) and positions longitudinal methods as a promising approach to examining algorithmic influence and amplification dynamics in social media communication.

While longitudinal modeling offers substantial advantages over cross-sectional approaches, several methodological considerations warrant discussion. First, they come with the major limitation of requiring more complex data collection than cross-sectional methods, as repeated measurements are needed for each subject. In our study, we relied on CrowdTangle historical data (CrowdTangle Team, 2020). However, this tool is no longer available, along with the convenient data collection it enabled. To ensure proper data collection in the absence of similar platform-provided tools, researchers must develop a technological infrastructure capable of regularly monitoring new social media messages of interest to capture them in a timely manner. This process typically involves querying the social media platform's Application Programming Interface (API)—a set of protocols that allows programs to access and retrieve data automatically. Each query, or “API call,” retrieves specific information for the content of interest, such as post content, engagement levels or other time-varying attributes. An example of such infrastructure is provided in a study on online media coverage in the run-up to the 2018 Italian general election, where automated agents were employed to collect news stories and record engagement every two hours for an entire week, starting from the date and time each story was published (Giglietto et al., 2018, pp. 81–82). While feasible, we should recognize that this creates a practical burden for researchers and remains constrained even for those able to set up such infrastructure, due to platform-imposed restrictions on API calls. Overall, this underscores that high-quality research depends on broader and unrestricted access to social media data (Bruns, 2019a).

We also acknowledge the limitations inherent in our modeling choices. For cross-sectional models, the use of the offset method assumes that the underlying rate of events is proportional to the exposure, and is therefore most appropriate when the event rate is relatively homogeneous across the observation period—a condition that is only a rough approximation in the case of social media dynamics. For the longitudinal model, our decision to aggregate observations at the daily level was driven by practical necessity: finer temporal resolutions exhibited persistent and severe autocorrelation that could not be adequately controlled through lagged dependent variables or autoregressive terms of higher orders. This daily aggregation successfully reduced autocorrelation to manageable levels, allowing for stable parameter estimation. However, it limits the ability to observe the precise within-day causal ordering between reactions and shares. This trade-off was necessary to achieve model stability, and the resulting estimates remain more reliable than cross-sectional alternatives. However, this imposes the limitation that the analysis remains correlational. Drawing causal conclusions about the effect of Angry reactions on shares would require more sophisticated methods and finer-grained data. Still, longitudinal methods provide a framework for causal estimation under appropriate assumptions and modeling choices—an approach we plan to explore in future work.

In conclusion, our study underscores important methodological implications for study design in computational social science. Cross-sectional approaches, while simpler and widely used, ignore temporal dynamics and can exaggerate effect sizes, introducing bias—particularly for non-stationary processes such as social media engagement or when careful sampling designs and exposure controls are lacking. Longitudinal modeling, although requiring more complex data collection, mitigates these limitations by leveraging repeated measures to disentangle within-post variation from between-post differences, providing more reliable inference. Substantively, our case study offers important insights into the differentiated role of anger across party communities and the complex emotional and symbolic landscape of social media, highlighting how political culture and its interplay with algorithms shape these dynamics. Overall, these findings underscore the importance of longitudinal research design and analytical approaches in advancing theoretical development.

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7 Methodological appendix

- *Longitudinal Modeling*

We modeled the number of shares for post i by account j in party k on day t using a Bayesian multilevel Negative Binomial regression. The model accounts for party-specific effects of Angry reactions, lagged shares, day-of-week effects, and varying exposure times. Random intercepts are included for party, account within party, and platform within account.

The model can be formally expressed as:

$$Y_{ijt} \sim \textit{NegBinomial}(\mu_{ijt}, \phi)$$

$$\begin{aligned}
log(\mu_{ijt}) = \quad & \beta_0 \\
& + \beta_1\, z_other_reactions_{ijt} \\
& + \beta_2\, (z_diff_angry_{ijt} \times \textit{party}_k) \\
& + \beta_3\, \textit{lag_shares}_{ijt} \\
& + \beta_4\, \textit{followers}_{ijt} \\
& + \boldsymbol{\gamma}\, \textit{day_of_week}_t \\
& + log\left(\textit{exposure}_{ijt}\right) \\
& + u_k + u_{jk} + u_{ijk}
\end{aligned}$$

Where:

- Y_{ijt}: Number of shares for post i, account j, party k, day t
- μ_{ijt}: Expected number of shares
- ϕ: Negative Binomial shape parameter
- $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$: Fixed-effect coefficients
- $z\_other\_reactions_{ijt}$: Standardized total reactions other than Angry
- $z\_diff\_angry_{ijt}$: Standardized Angry reactions
- $party_k$: Political party of the account
- lag_shares_{ijt}: Number of shares in the previous time interval (lagged dependent variable)
- $\gamma\, day\_of\_week_t$: Day-of-week effects
- $log\left(exposure_{ijt}\right)$: Offset for exposure time, allowing the model to estimate rates rather than raw counts
- u_k, u_{jk}, u_{ijk}: Random intercepts for party, account within party, and platform within account

This structure captures the hierarchical nature of the data, party-specific effects, temporal dependencies, and varying exposure times.

For the regression coefficients, we used

$$\beta_k \sim Normal(0, 0.2^2),$$

reflecting the expectation that standardized covariate effects are likely modest on the log scale while allowing sufficient flexibility for moderate associations.

For the group-level standard deviations, we specified a weakly informative Student-t prior:

$$\sigma \sim Student\_t(3,0,0.1),$$

and for the dispersion parameter, we used

$$\phi \sim Gamma(2,0.1),$$

favoring plausible overdispersion values while avoiding extremes that could hinder sampling efficiency.

- *Cross-sectional models*

The cross-sectional models can be formally expressed as:

$$Y_i \sim \textit{NegBinomial}(\mu_i, \phi)$$

$$\begin{aligned} log(\mu_i) = \quad & \beta_0 \\ & +\beta_1\, z\_other\_reactions\_total_i \\ & +\beta_2\, z\_actual.angryCount_i \\ & +\beta_3\, (\textit{party}_i \times z\_actual.angryCount_i) \\ & +\beta_4\, z\_followers_i \\ & +log(\textit{exposure}_i) \end{aligned}$$

Where:

- Y_i: Observed number of shares for post i
- μ_i: Expected number of shares for post i
- ϕ: Negative Binomial dispersion (shape) parameter
- $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$: Fixed-effect coefficients
- $z\_other\_reactions\_total_i$: Standardized count of other (non-angry) reactions
- $z\_actual.angryCount_i$: Standardized count of Angry reactions
- $\textit{party}_i$: Political party indicator (used in interaction with Angry reactions)
- $z\_followers_i$: Standardized follower count of the account
- $log(\textit{exposure}_i)$: Offset term accounting for exposure time (so the model estimates rates rather than raw counts)

Environmental-related keywords

antiatom, atomausstieg, atomenergie, klimaschutz, klimawandel, ökosteuer, umweltpolitik, Klima, globale Erwärmung, Treibhausgase, CO2-Fußabdruck, nachhaltige Entwicklung, erneuerbare Energien, fossile Brennstoffe, CO2-Emissionen, CO2-Kompensation, Entwaldung, Aufforstung, Biodiversität, Ökosystemdienstleistungen, Pariser Abkommen, Kyoto-Protokoll, IPCC, Nachhaltigkeit, Energieeffizienz, Solarenergie, Windenergie, Bioenergie, CO2-Steuer, Emissionshandel, Klimaanpassung, Meeresspiegelanstieg, Versauerung der Ozeane, extreme Wetterereignisse, Naturschutz, Wasserknappheit, Luftverschmutzung, Umweltgerechtigkeit, grüne Technologie, grünes Bauen, Stadtgrün, nachhaltige Landwirtschaft, saubere Energie, Kreislaufwirtschaft, Klimafinanzierung, Klimaresilienz, Umweltaktivismus, Fridays for Future, Greenpeace, Letzte Generation, CO2, Treibhausgasemissionen, Klimapolitik, Klimakommunikation, Umweltbewusstsein, Klimakrise, Klimaerhitzung, E-Autos, EAutos, Klimaregierung, Klimastreik, 1,5°C-Plan, 15CPlan