Analyzing Online Structures of Attention

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Wednesday, November 5, 2025

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About Me

2017: MIT B.S. in CS + Comparative Media Studies

2017 – 2019: Data Engineer, Kensho Technologies

2019 – 2021: Data Scientist, Kayak Software Corp.

2021 – present: PhD Student, Northeastern University Network Science Institute

2023– present: NSF GRFP Fellow in Social Sciences – Computationally Intensive Research

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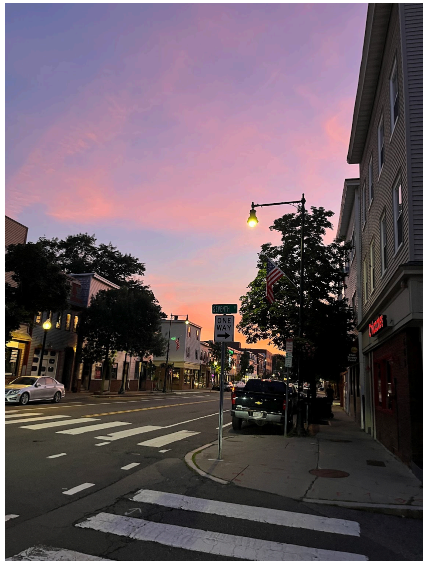

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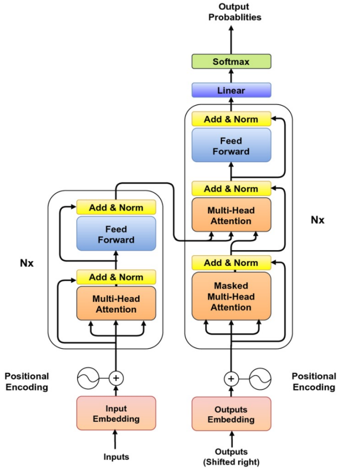
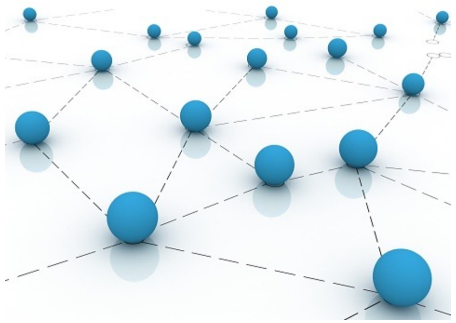
Python



NLP



Networks

R

MAXQDA

Semi-structured interviewing

Sysadmin work

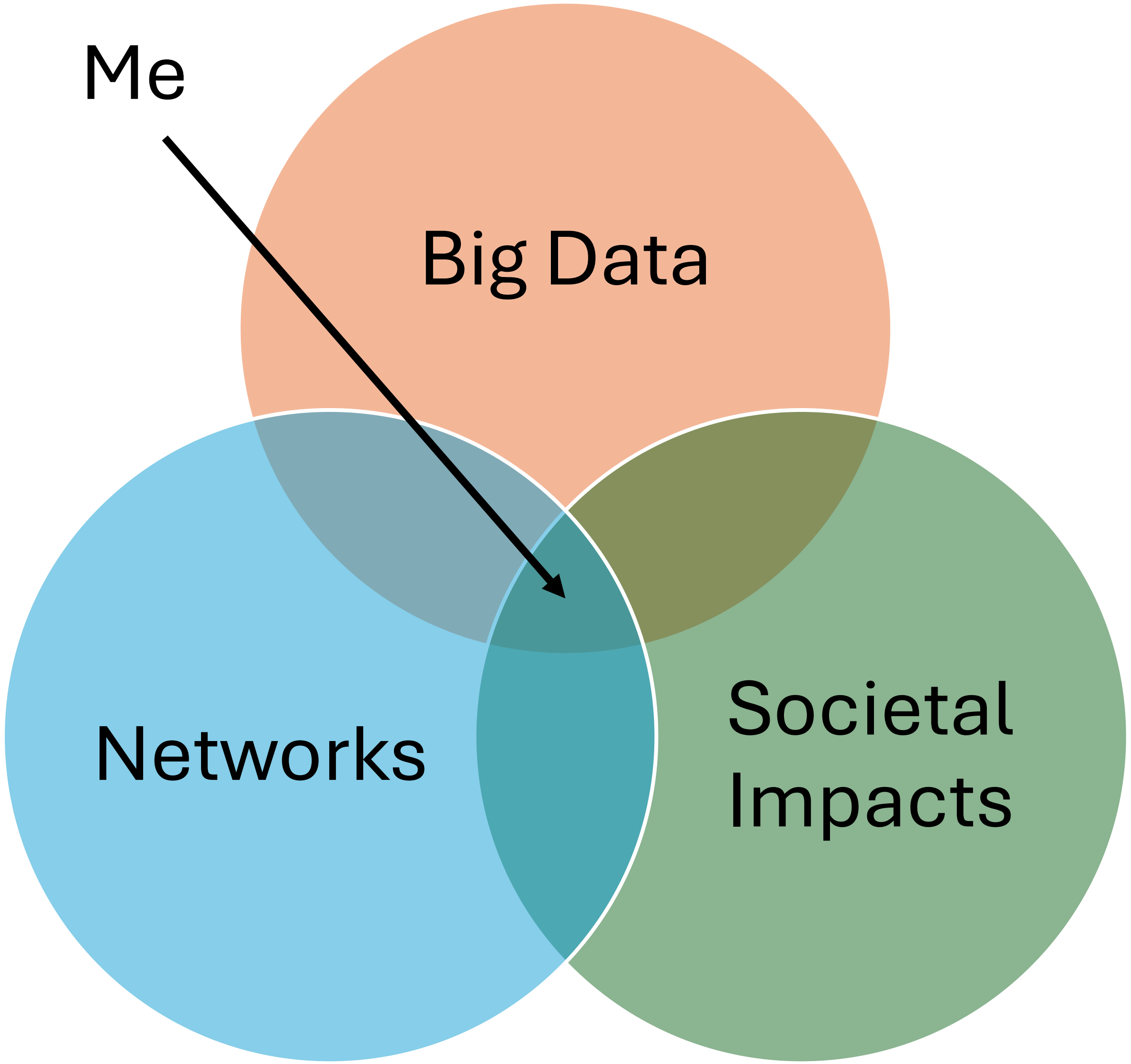
What do marginalized people’s experiences look like online?

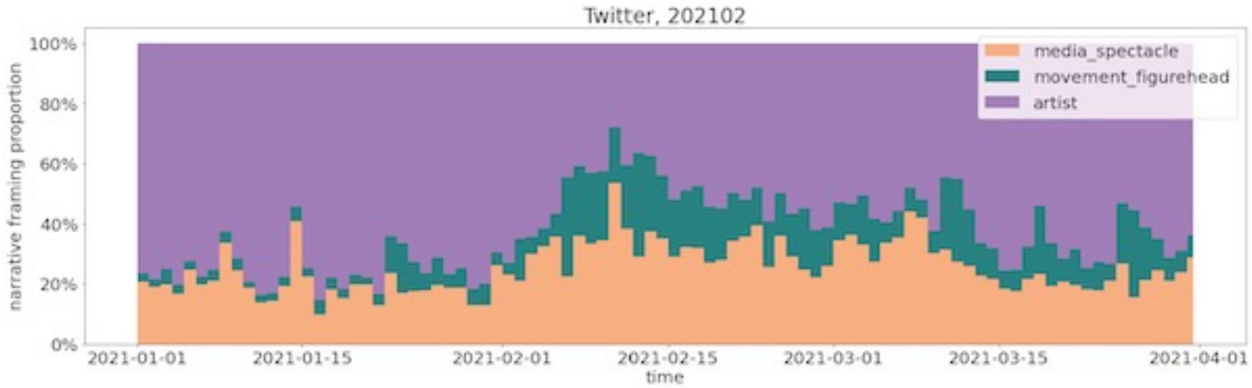
↓

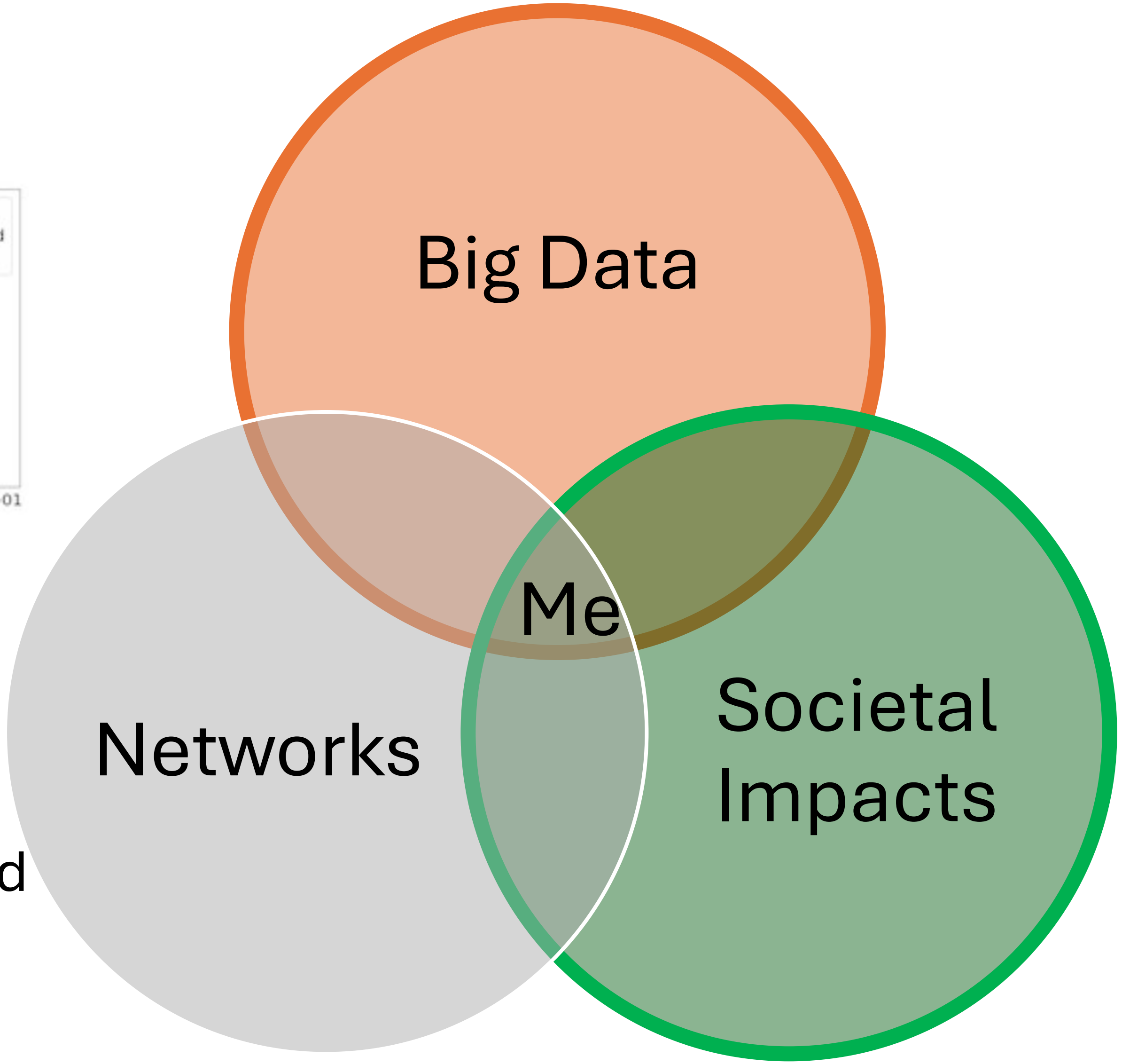
What kinds of systemic harms are happening online?

↓

How do we make online platforms more just, more safe, and more vibrant?





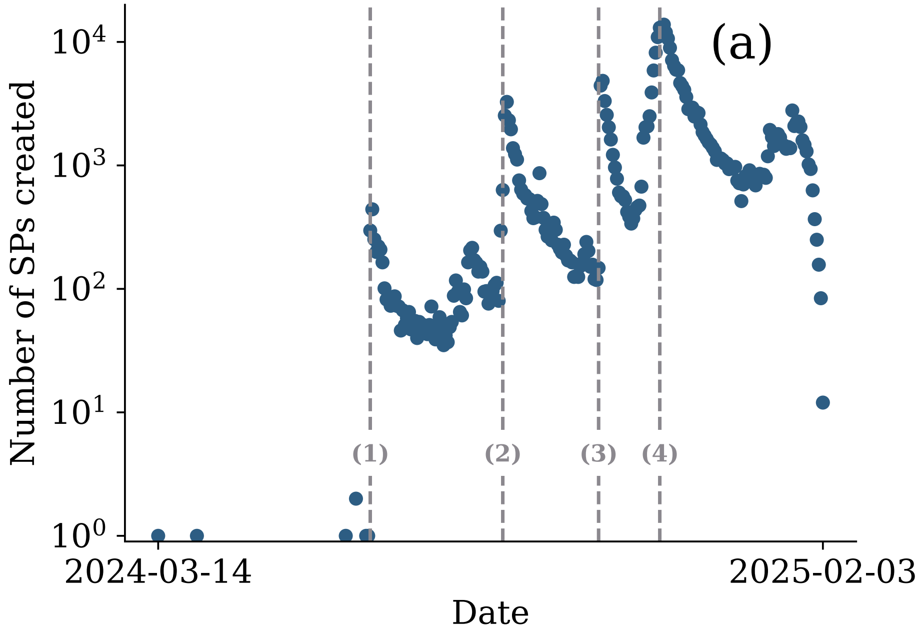


How did Wikipedia, TMZ, and Twitter talk about Britney Spears and #FreeBritney?

→ Narratives fighting the status quo emerged on Twitter first, then spread somewhat

→ Cross-platform data infrastructure

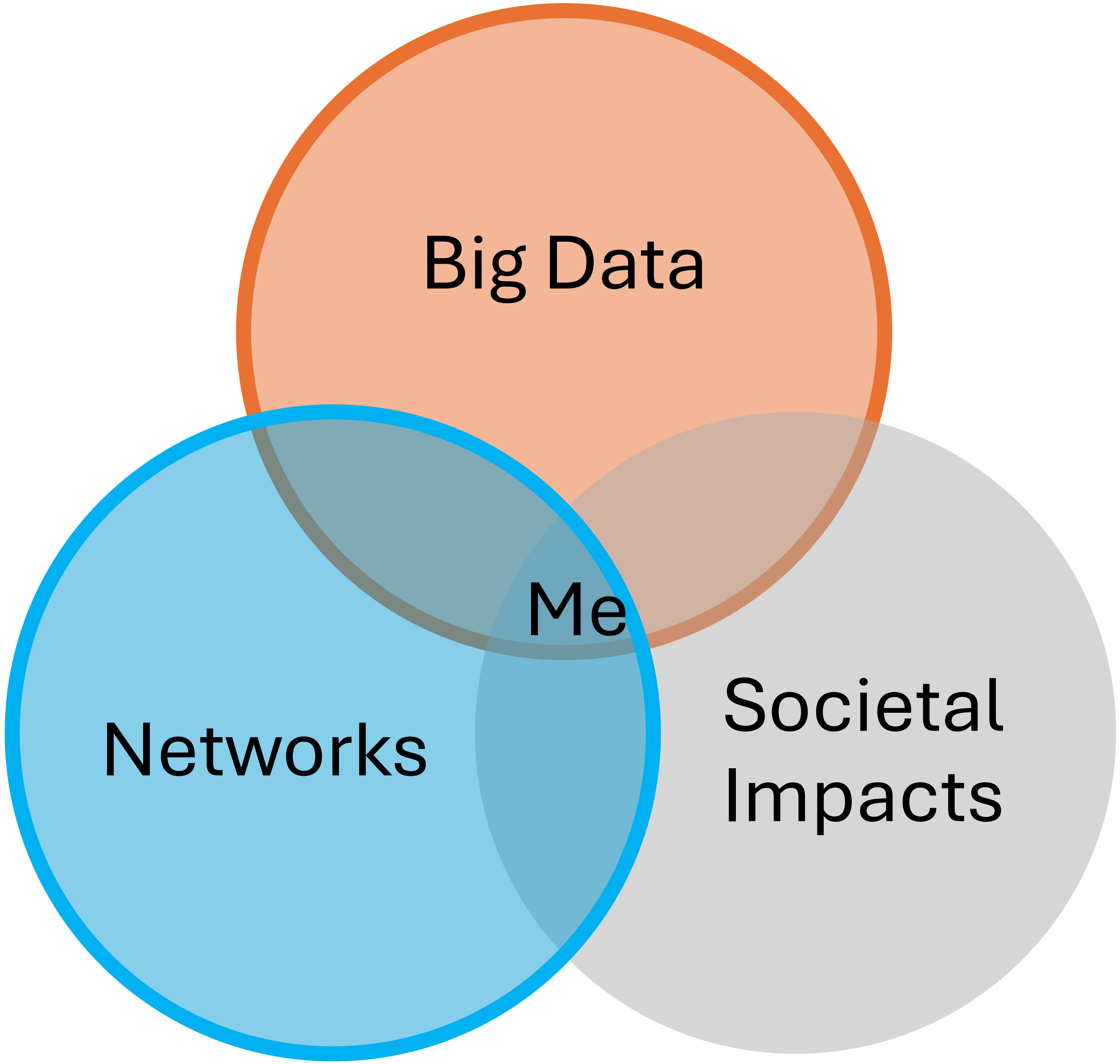
Smith, Alyssa Hasegawa, Adina Gitomer, and Brooke Foucault Welles. 2023. "You Want a Piece of Me: Britney Spears as a Case Study on the Prominence of Hegemonic Tales and Subversive Stories in Online Media." *First Monday*, ahead of print, December 7. https://doi.org/10.5210/fm.v28i12.13314.



What can we learn about network structure on Bluesky?

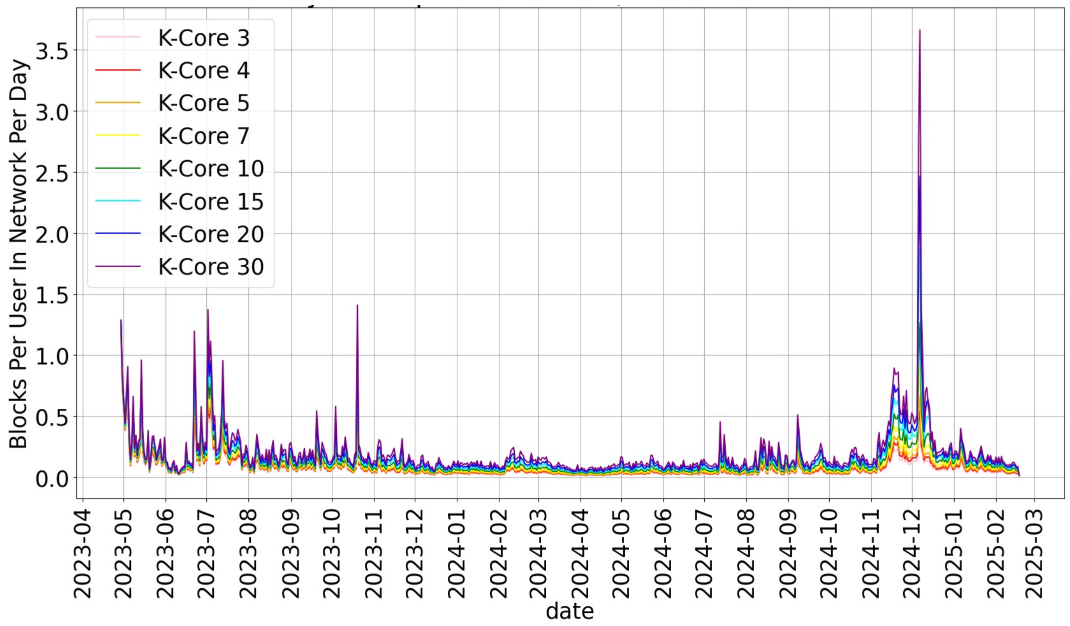
→ Open-source dataset that reflects platform features & off-platform events

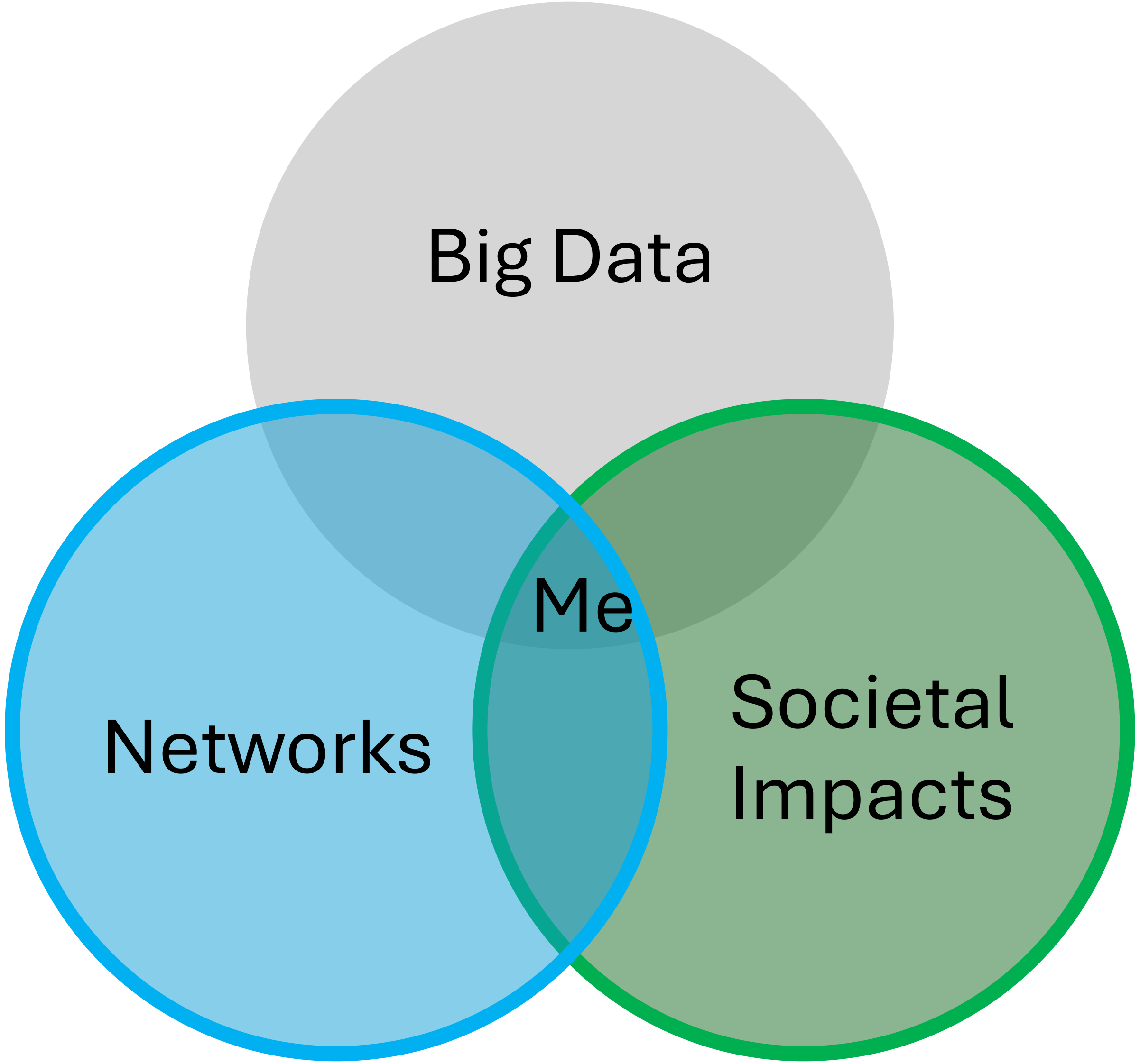
→ Large-scale network data



Smith, Alyssa, Ilya Amburg, Sagar Kumar, Brooke Foucault Welles, and Nicholas W. Landry. 2025. "A Blue Start: A Large-Scale Pairwise and Higher-Order Social Network Dataset." arXiv:2505.11608. Preprint, arXiv, May 16. https://doi.org/10.48550/arXiv.2505.11608.

Daily per capita block rate



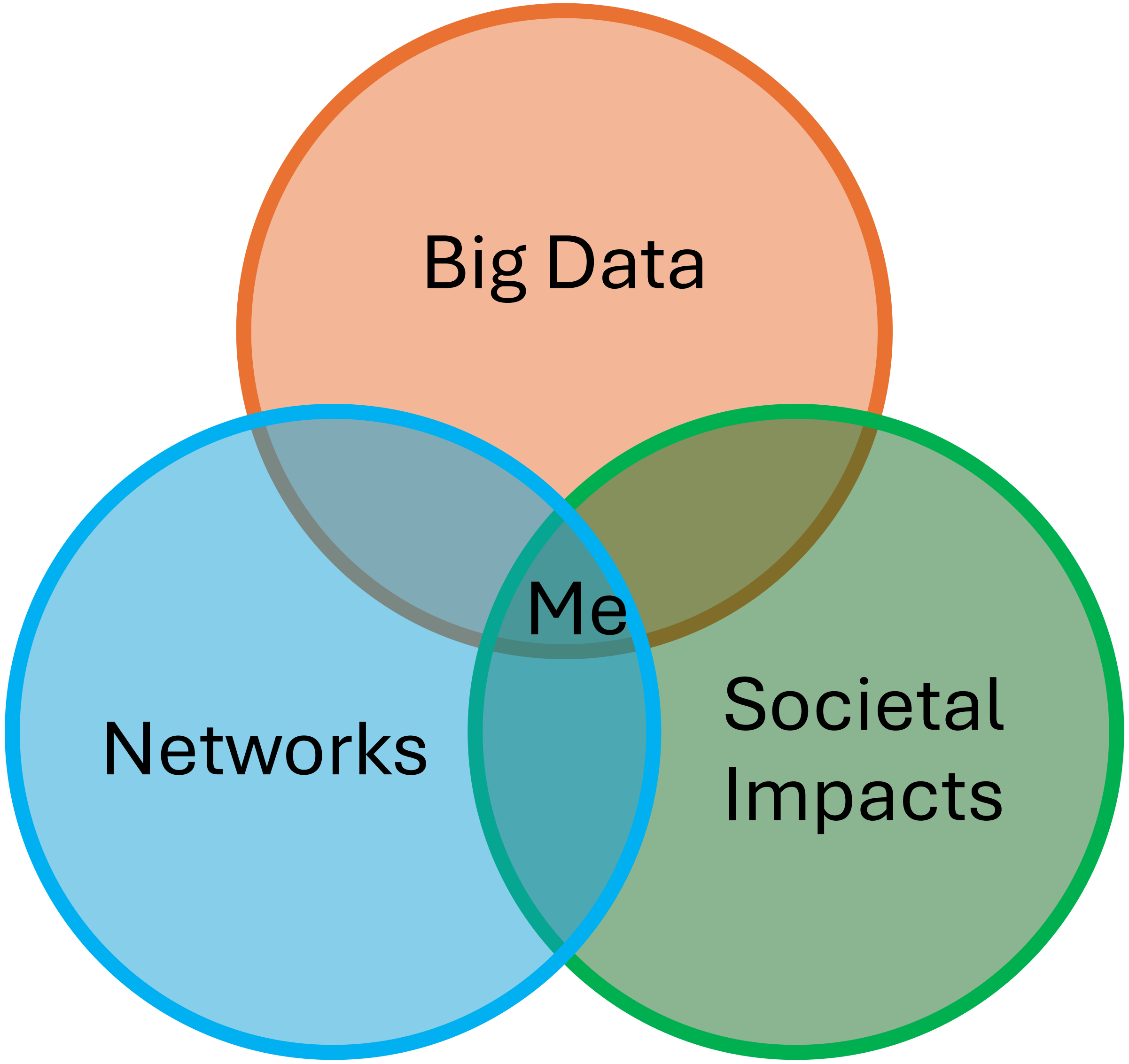


How are intracommunity attacks on Bluesky enabled by open platform data?

→ Story-making with data justifies attacks and enhances harmful narratives

→ Qualitative methods

Smith, Alyssa Hasegawa, Erika Melder, Michael Ann DeVito. 2025. “How Distributed, Consensus-Free Folklore Enables Transfeminine Disposability on Bluesky.” *Working Paper*.

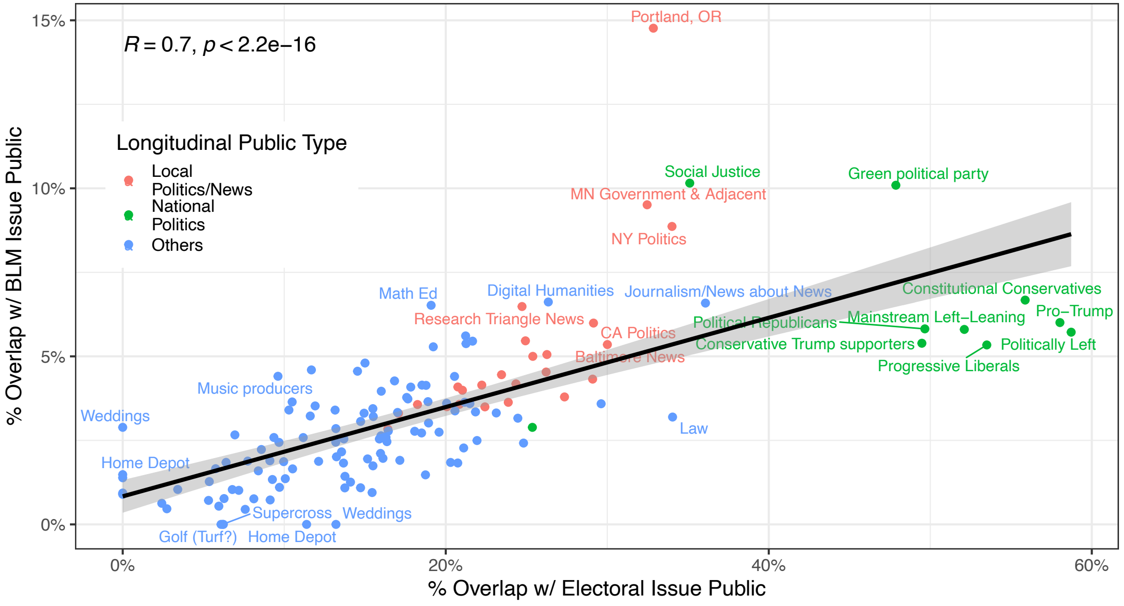


How does influence operate in U.S. news about trans people?

→ Influence flows in two steps from national to local media outlets

→ Natural language processing

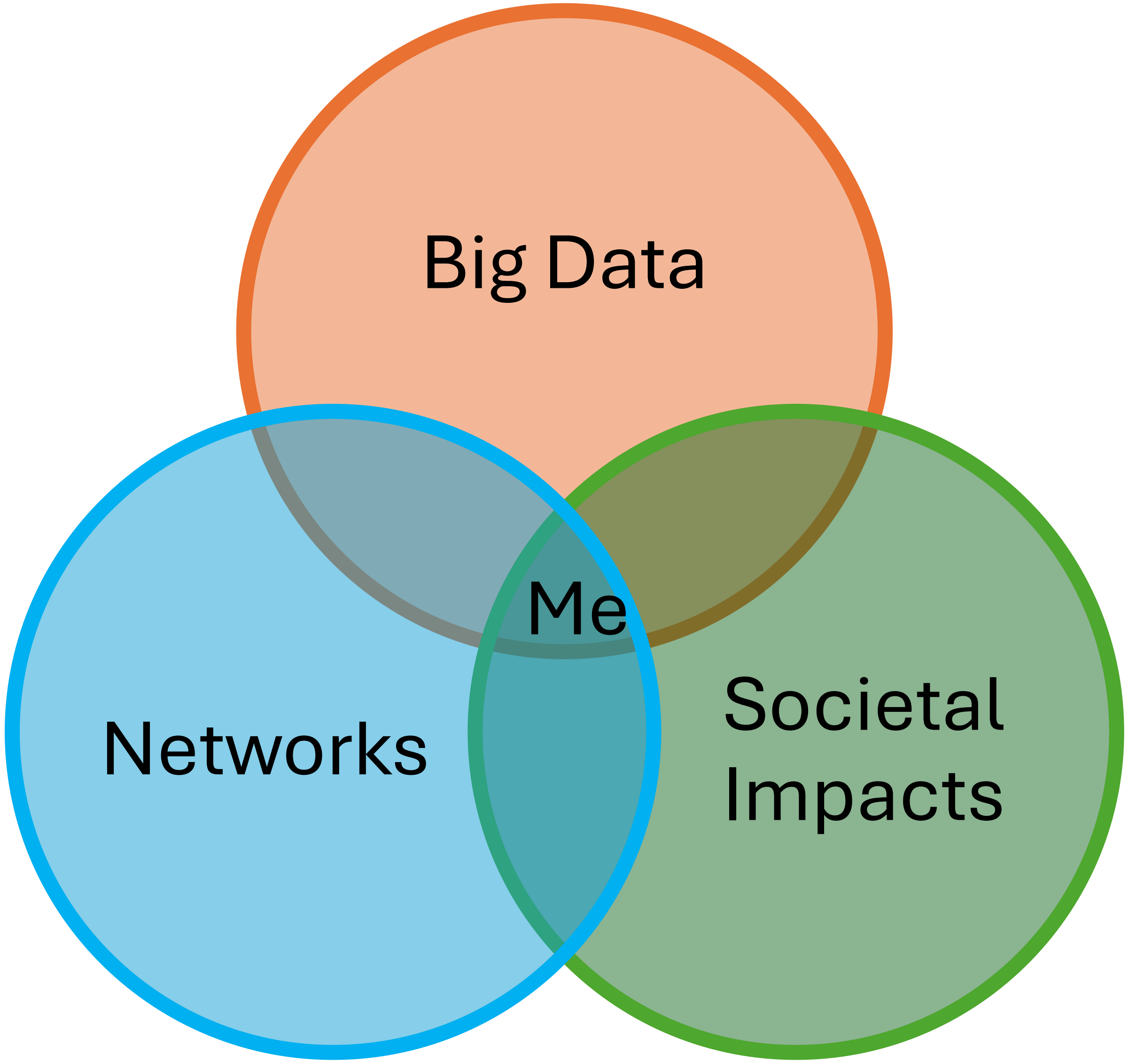
Smith, Alyssa Hasegawa, Sagar Kumar, Yukun Yang, and Pranav Goel. In Press 2025. “Locating the Asymmetry in Information Flow between Local and National Media on Transgender Discourses.” *Bulletin of Applied Transgender Studies*.



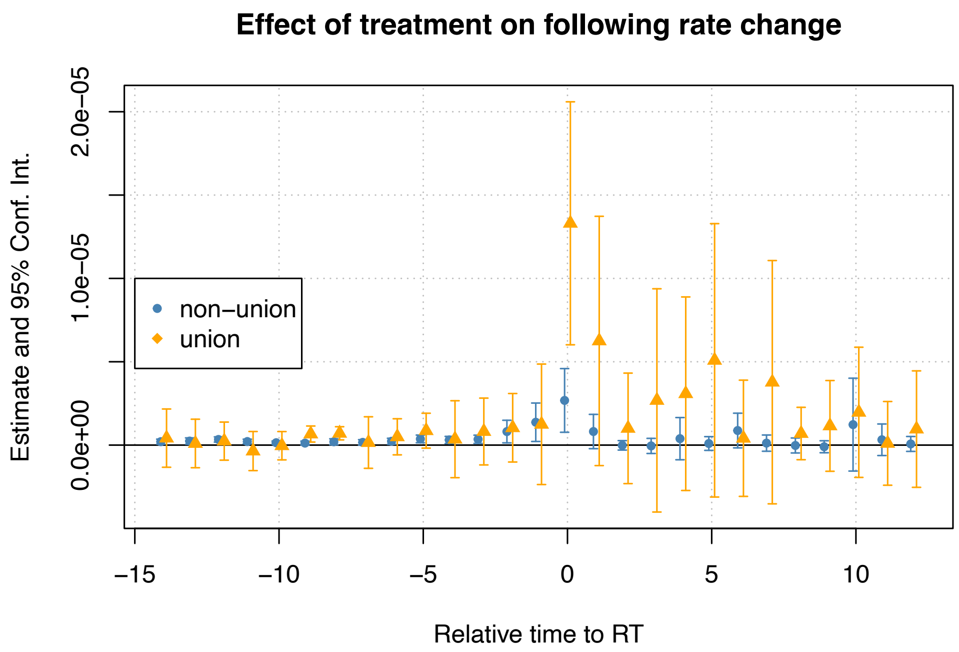
How do different kinds of public discourses intersect on Twitter?

→ Political discourse & social movements bleed into "ordinary" spaces online

→ Regression + network analyses

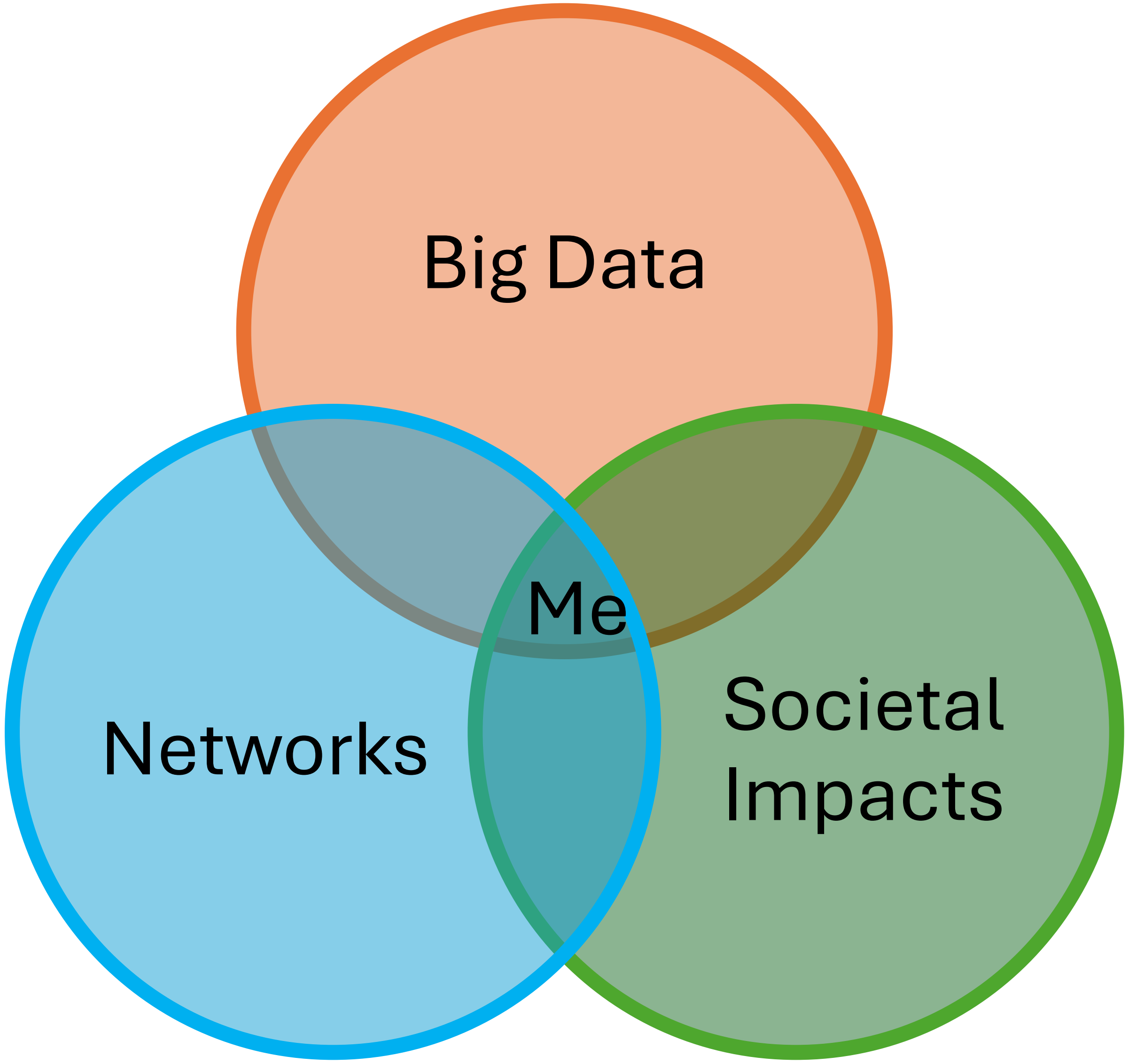


Smith, Alyssa Hasegawa, Ahana Bhattacharya, Holliday Sims, and Kenneth Joseph. 2025. "The Longitudinal Relational Public and its Intersection with Issue Publics." *Working Paper*.



How can individual users impact attention structures online?

→ I won't spoil this one just yet!
→ Custom data collection infrastructure



Smith, Alyssa Hasegawa, Jon Green, Brooke Foucault Welles, and David Lazer. 2025. "Emergent Structures of Attention on Social Media Are Driven by Amplification and Triad Transitivity." *PNAS Nexus*, April 1, pgaf106. https://doi.org/10.1093/pnasnexus/pgaf106.

Preview: What Shapes Attention?

I provide evidence that **being amplified on social media leads to follower accumulation.**

Raise your hand if you have...

- Followed an account on social media

...in the past week

Raise your hand if you have…

- Followed an account on social media
- Liked or commented on a post

…in the past week

Raise your hand if you have...

- Followed an account on social media
- Liked or commented on a post
- Viewed content on social media

...in the past week

Congratulations!

You have generated data with & about your attention!

Why Attention?

- Less curation by individual experts
- Curation delegated to users
  - Recommendation algorithms
  - Influencers
  - Engagement metrics
- Platform-level phenomenon

Who Is Moo Deng? The Viral Baby Hippo, Explained

Unlikely TikTok star “Moo Deng” has captured the attention of the internet—here’s how the adorable baby pygmy hippo won the hearts of millions of social media users.

By Dani Di Placido, Senior Contributor. ⓘ Dani Di Placido covers film, televisio...

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Published Sep 13, 2024, 01:43pm EDT, Updated Sep 17, 2024, 03:30pm EDT

'Demure' Is The Unlikely Gen Z Word Of The Moment — Here's Why

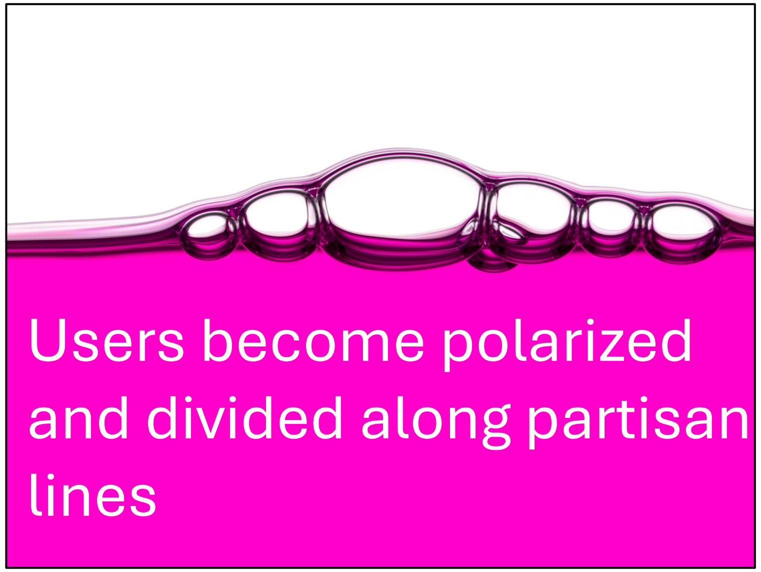
Very demure, very mindful.

By Amy Glover

14/08/2024 04:48pm BST

→ Dunivin et al. (2022); Wu (2017); Zhang et al. (2021)

Why Attention?



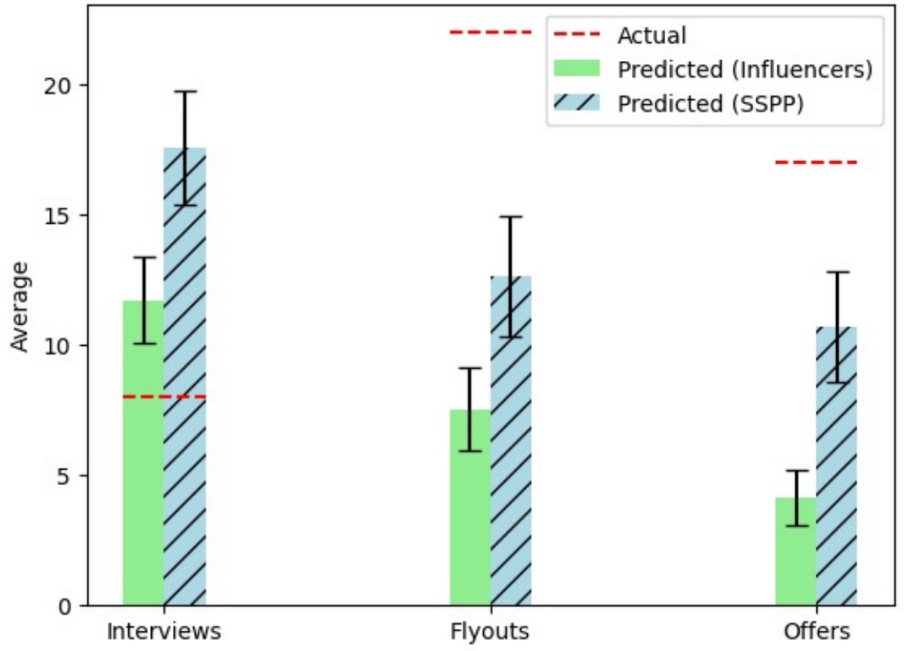
→ Cinelli et al. (2021); Green et al. (2025)

Why Attention?

Social Media and Job Market Success: A Field Experiment on Twitter

106 Pages • Posted: 20 May 2024 • Last revised: 23 Mar 2025

Figure 4: Predictions by Economist Influencers and SSPP Experts



- Amplification by influencers led to > 20% increase in job market outcome metrics
- Attention begets attention

→ Qiu et al. (2024)

Why Attention?

- Redirecting attention leads to offline consequences
- Particularly when coupled w/ misinformation

Bomb threats follow Libs of TikTok's campaign against Planet Fitness

Dozens of locations across the country have reported bomb threats since the gym began receiving viral attention

EXCLUSIVE

INTERNET

After Libs of TikTok posted, at least 21 bomb threats followed

The FBI and local law enforcement said bomb threats across the country have tied up government resources even when they turn out to be hoaxes.

EDUCATION, NEWS

After Libs of TikTok post, multiple bomb threats have been made at Waukesha middle school

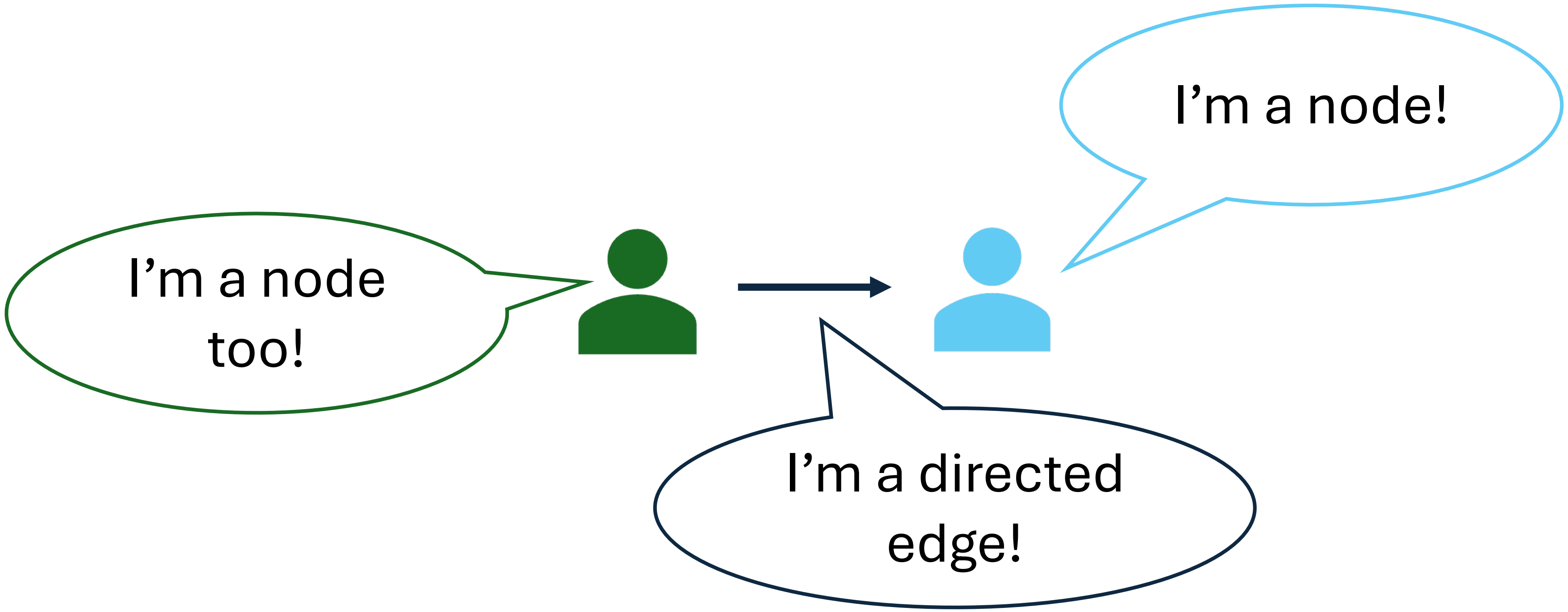
School district, Waukesha police say threats are not credible

BY CORRINNE HESS • MARCH 18, 2024 • UPDATED MARCH 18, 2024 at 4:33 PM

Overview

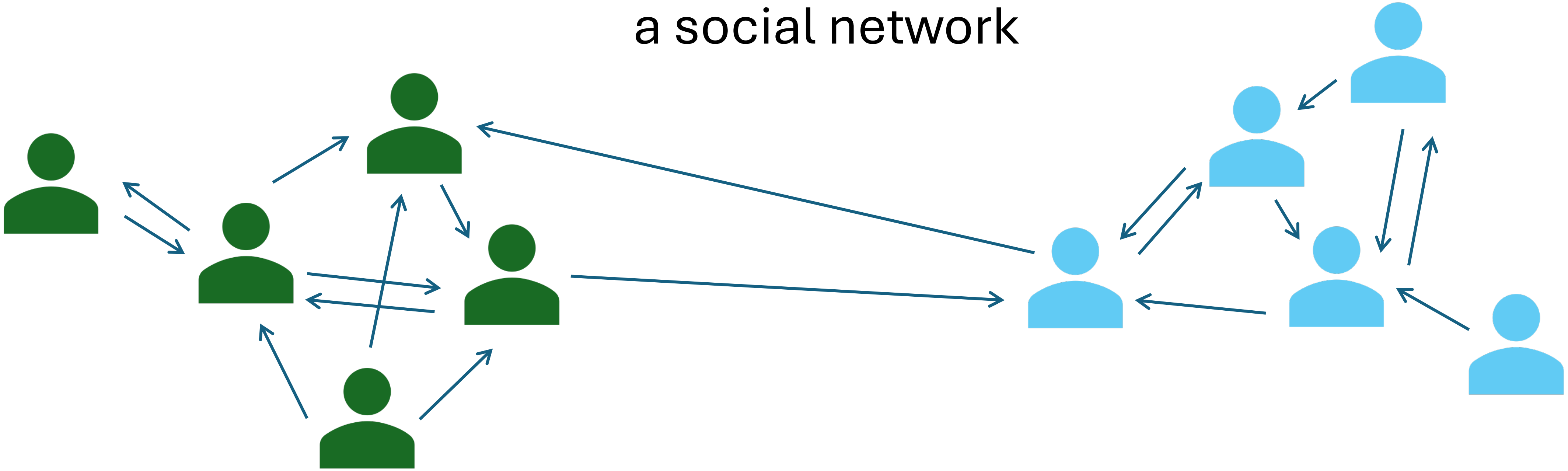
- A brief primer on networks
- Reshaping attention on Twitter/X
- Future work on online attention

A Brief Primer on Networks



A Brief Primer on Networks

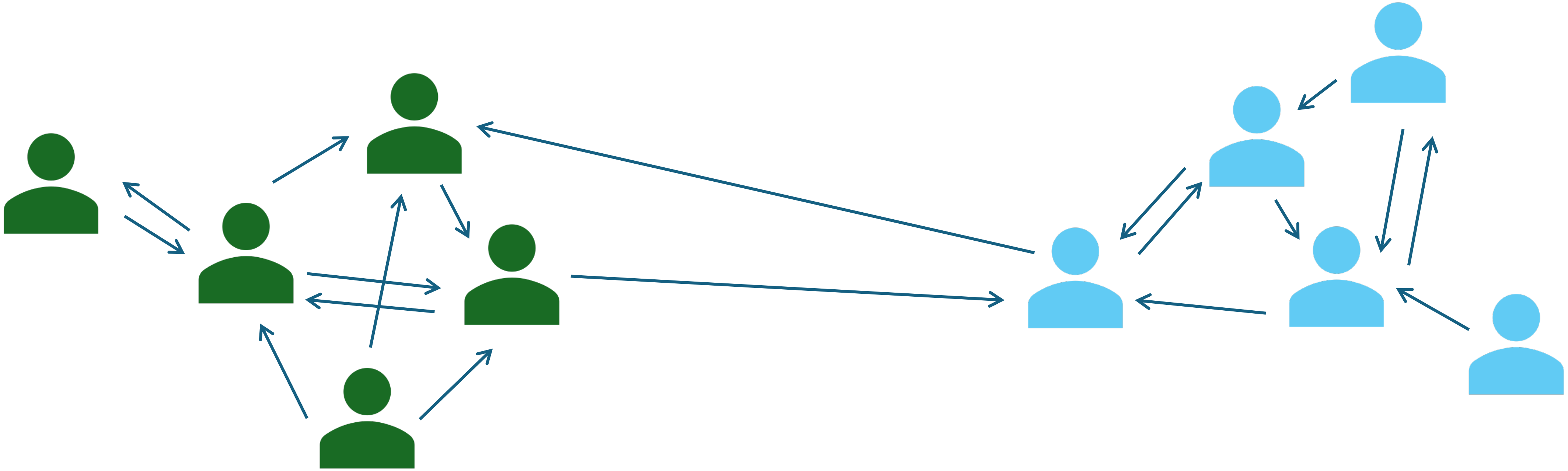
This is an example of a social network



Communities

Networks usually have community structure:

- Dense ties **within** a community
- Fewer ties **between** communities

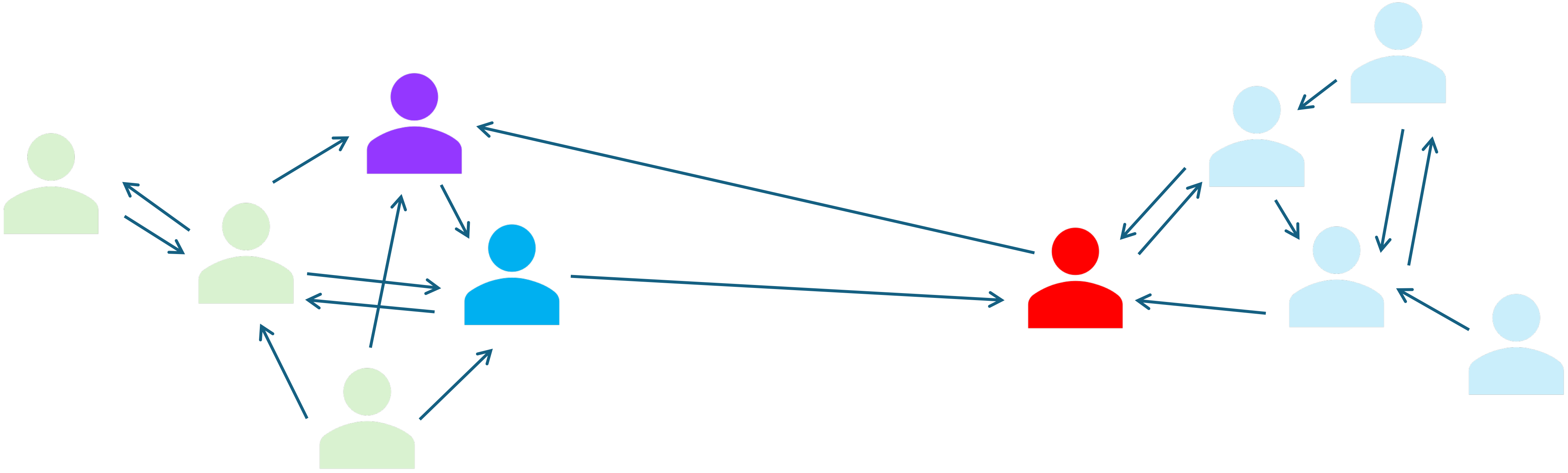


→ Girvan and Newman (2004)

Bridges & Brokers

Some nodes connect multiple communities. They have...

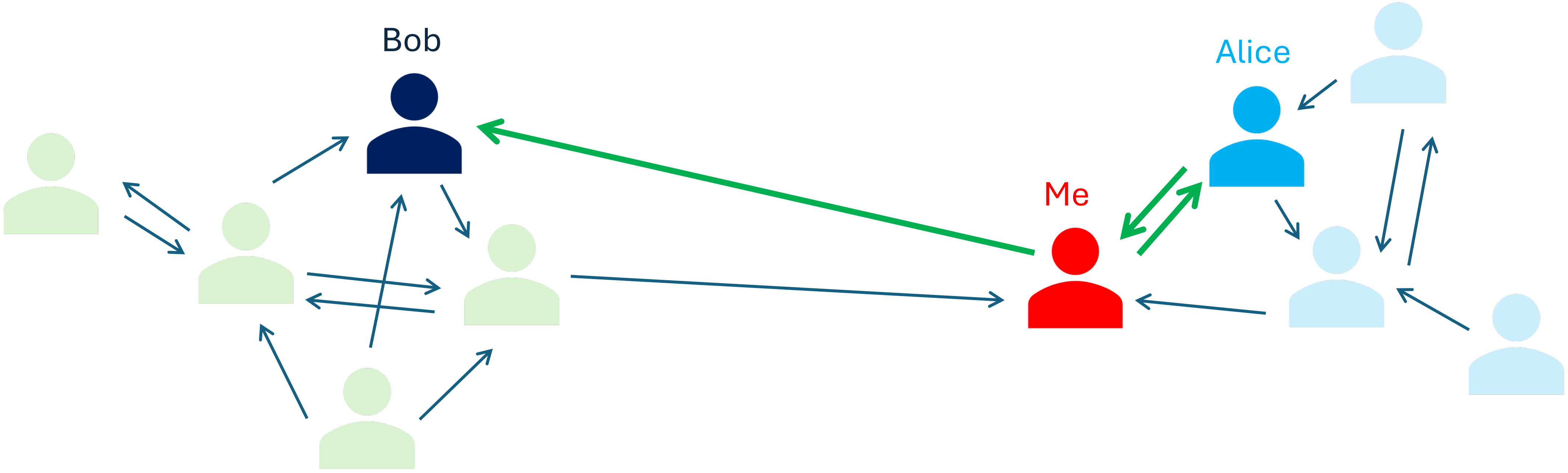
- Access to novel information → unique insights
- The ability to connect people across communities



→ Granovetter (1973); Burt (2004)

The *“Third who Joins”*

- Helps create links as a mutual tie
- Provides novel information & joins communities



→ Obstfeld (2005)

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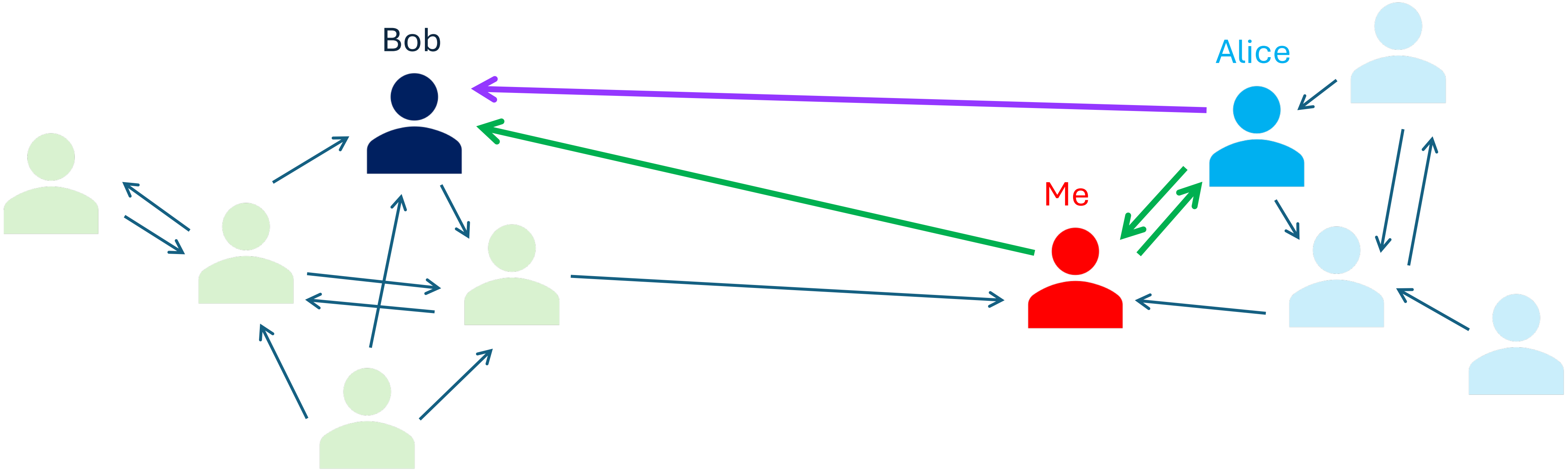


→ Obstfeld (2005)

Emergent structures of attention on social media are driven by amplification and triad transitivity

<u>Alyssa Smith</u>, Jonathan Green, Brooke Foucault Welles, David Lazer

With thanks to Hana Chalmers, Samantha Furey, Sasheen Joseph, and Alexandra Madaras.

→ Smith et al. (2025) in *PNAS Nexus*

Big Ideas

Attention brokers are influential users who frequently amplify content.

They create new ties in their network by exposing their followers to novel content.

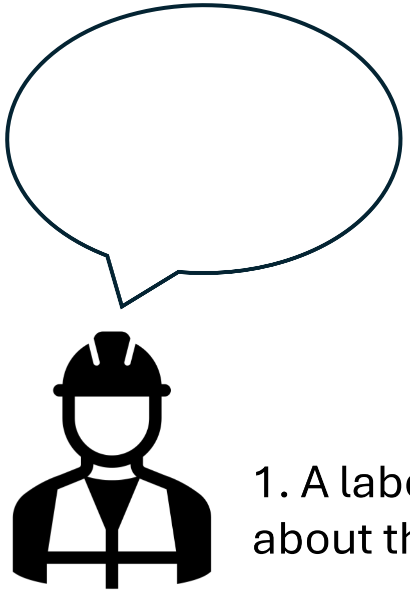
Individual users can shape attention patterns.

An Illustrated Example

- Introducing Jorts the Cat:
  - Viral /r/amitheasshole post
  - Twitter account
  - Labor activism
- Jorts is one of two case studies.

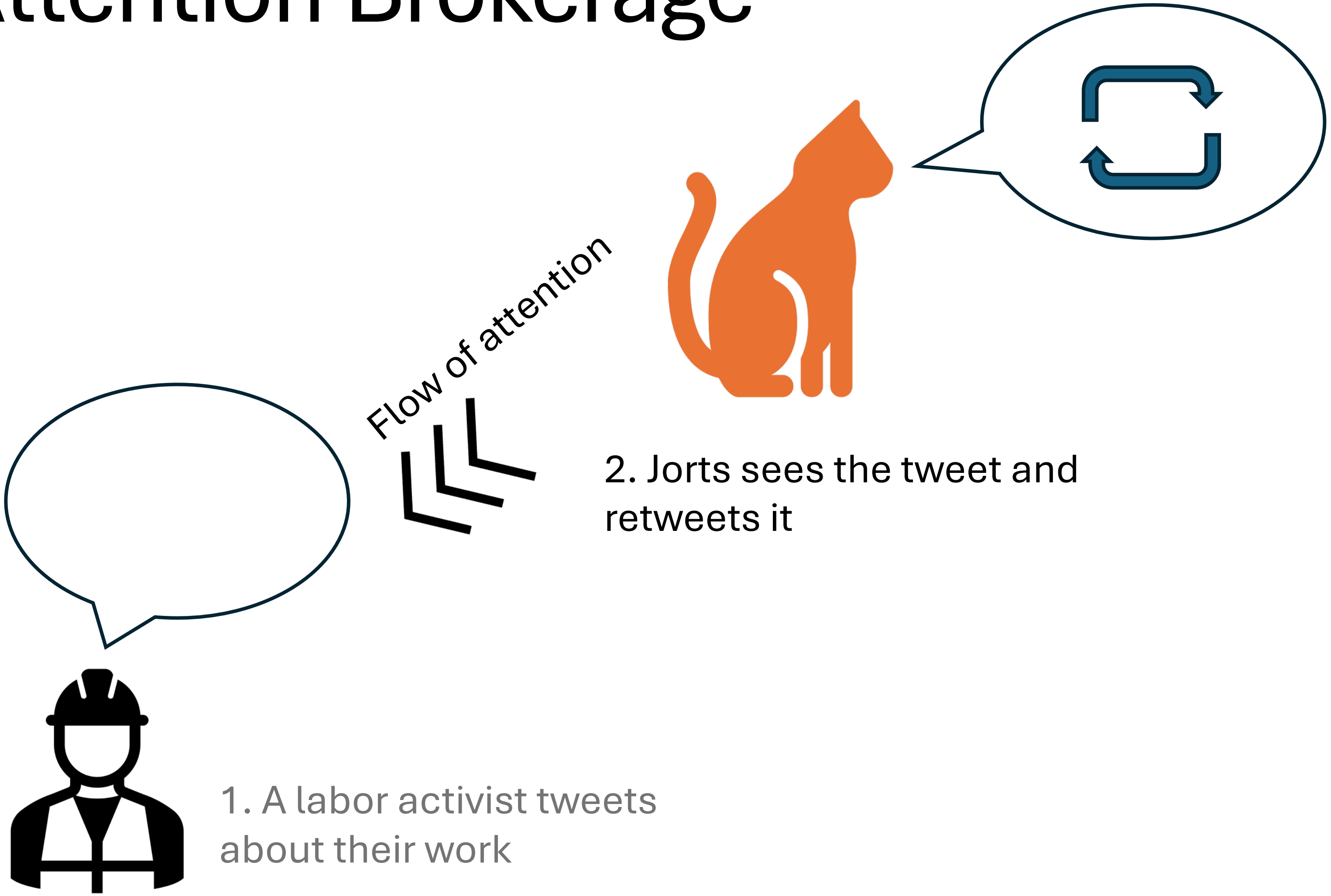
Image via jortsthecat.bsky.social (link)

Attention Brokerage

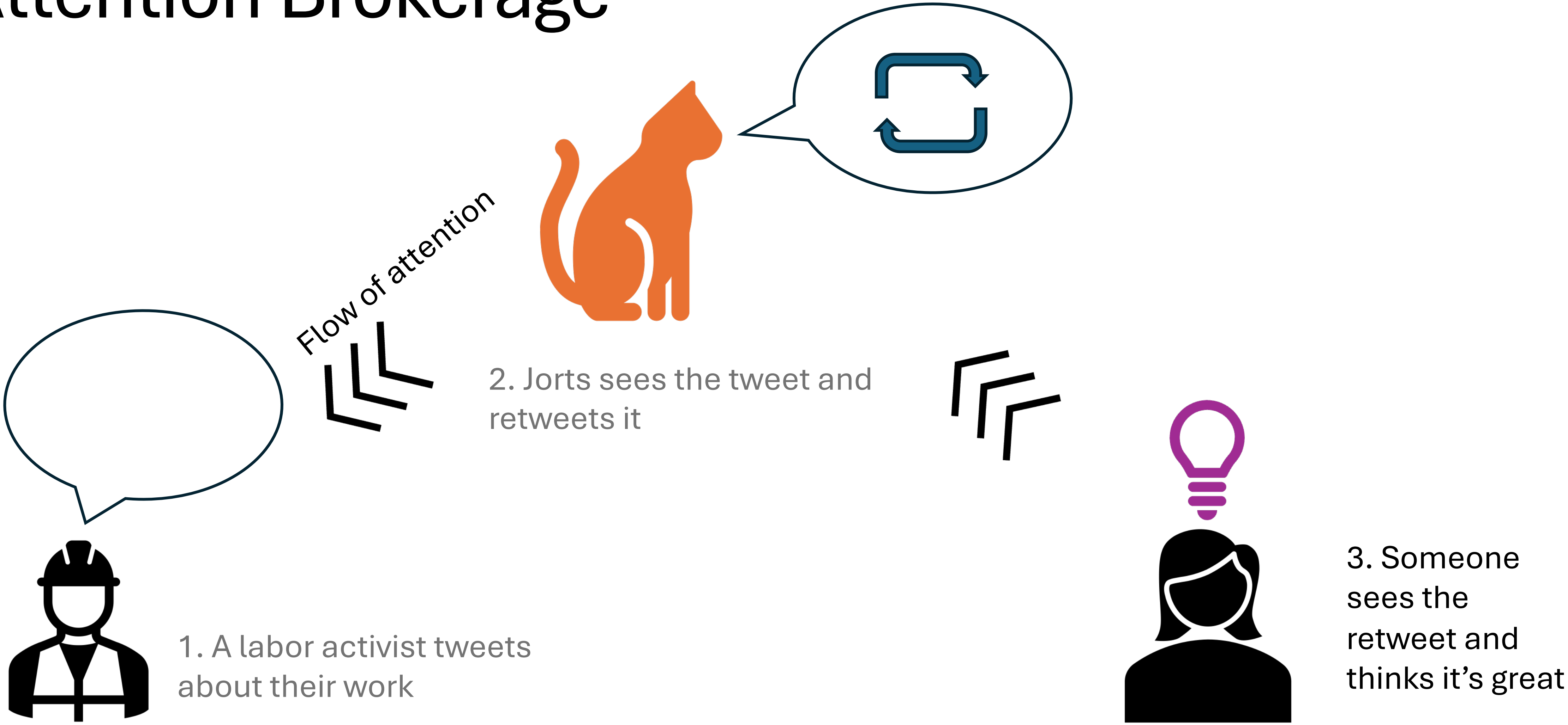


1. A labor activist tweets about their work

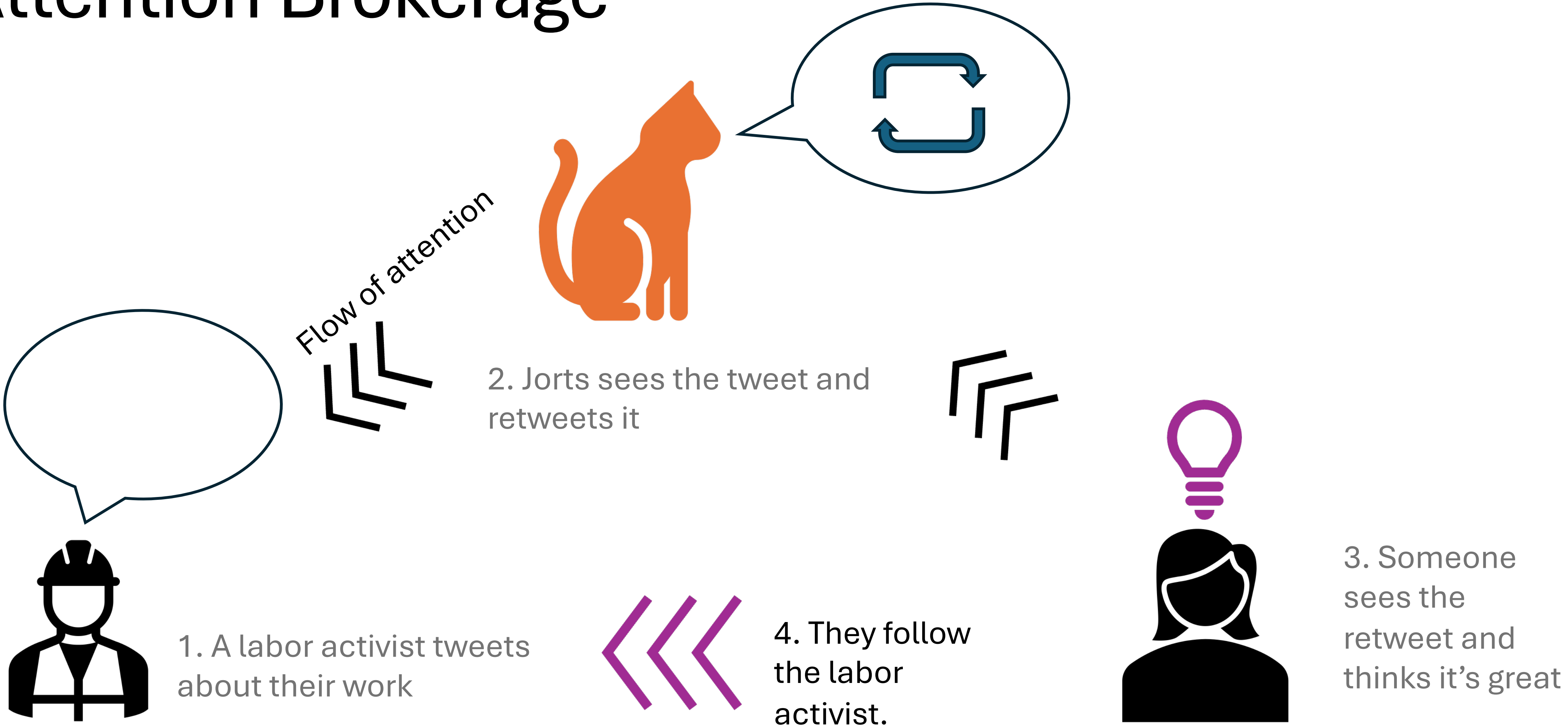
Attention Brokerage



Attention Brokerage

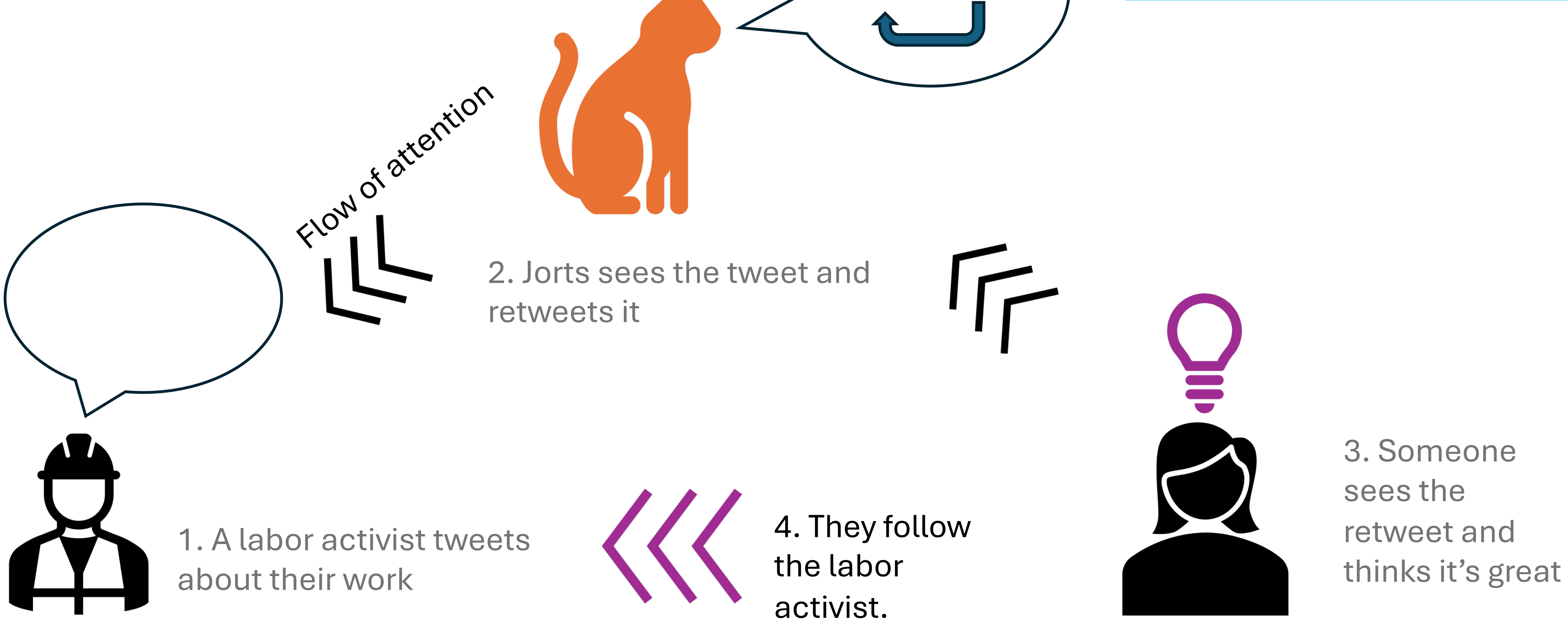


Attention Brokerage



Attention Brokerage

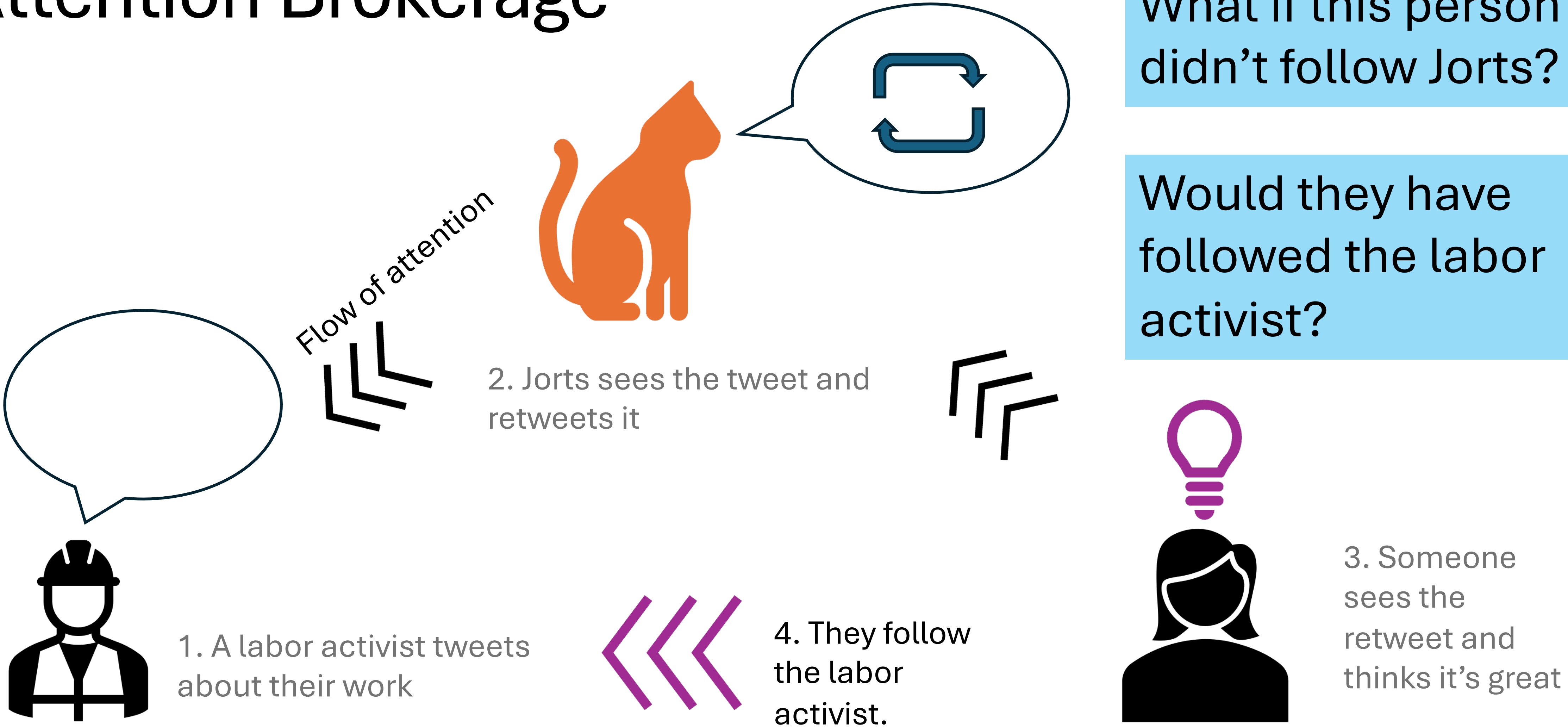
What if this person didn’t follow Jorts?



Attention Brokerage

What if this person didn't follow Jorts?

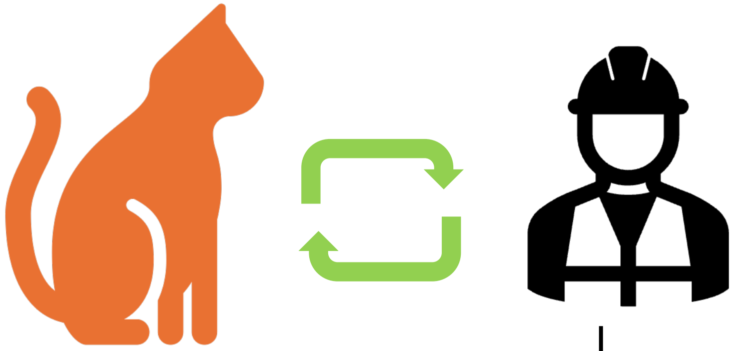
Would they have followed the labor activist?



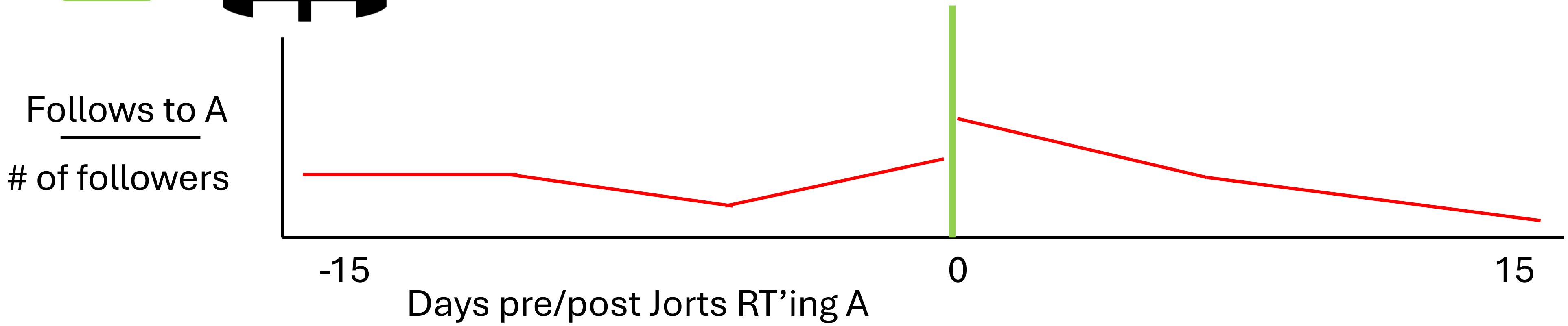
What We’re Measuring

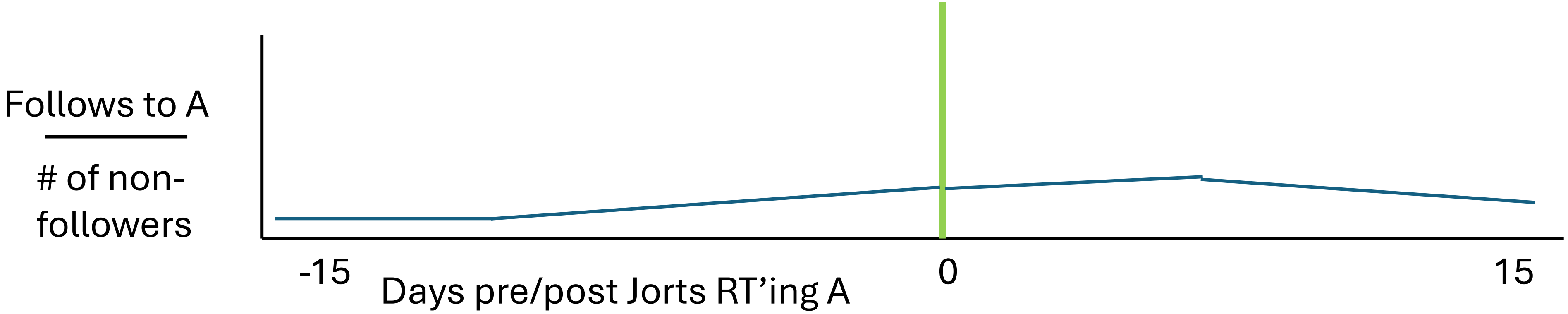
1. Estimate population for:
   a) Jorts’ active followers
   b) Active non-followers
2. For each account Jorts retweets:
   a. Label (labor-related Y/N)
   b. Time-bounded follows within +/- 2 weeks of RT
   c. Interpolate daily follows
   d. Daily per-capita follow rate

What We're Measuring

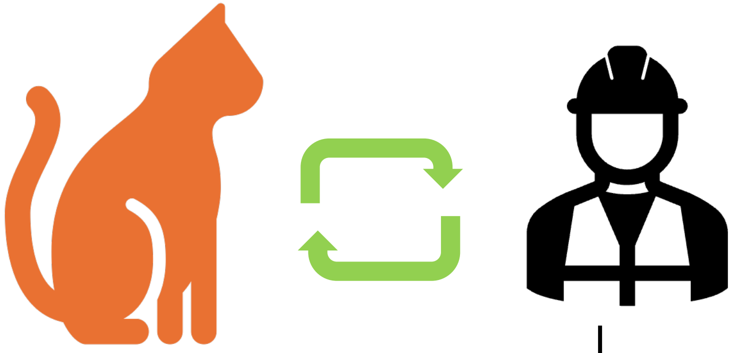


For every account A retweeted by Jorts, we compute...

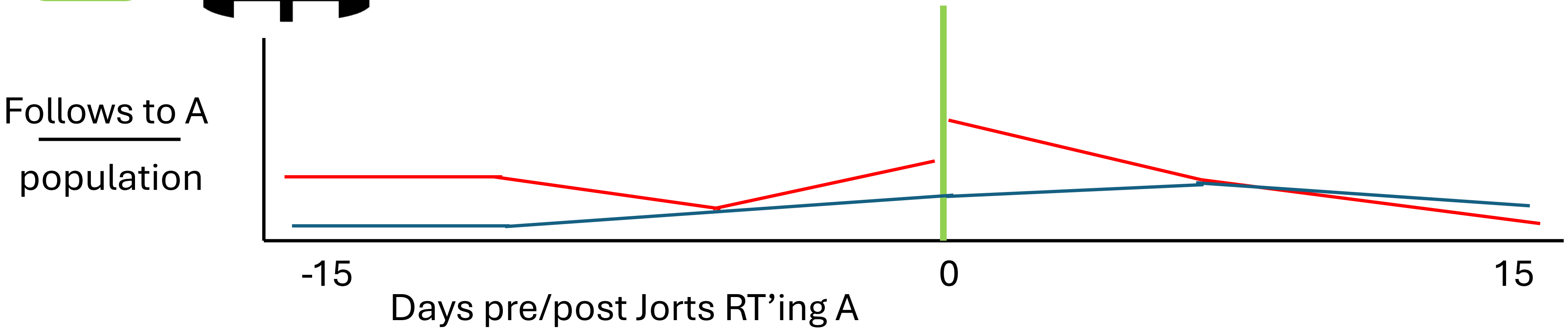




What We're Measuring



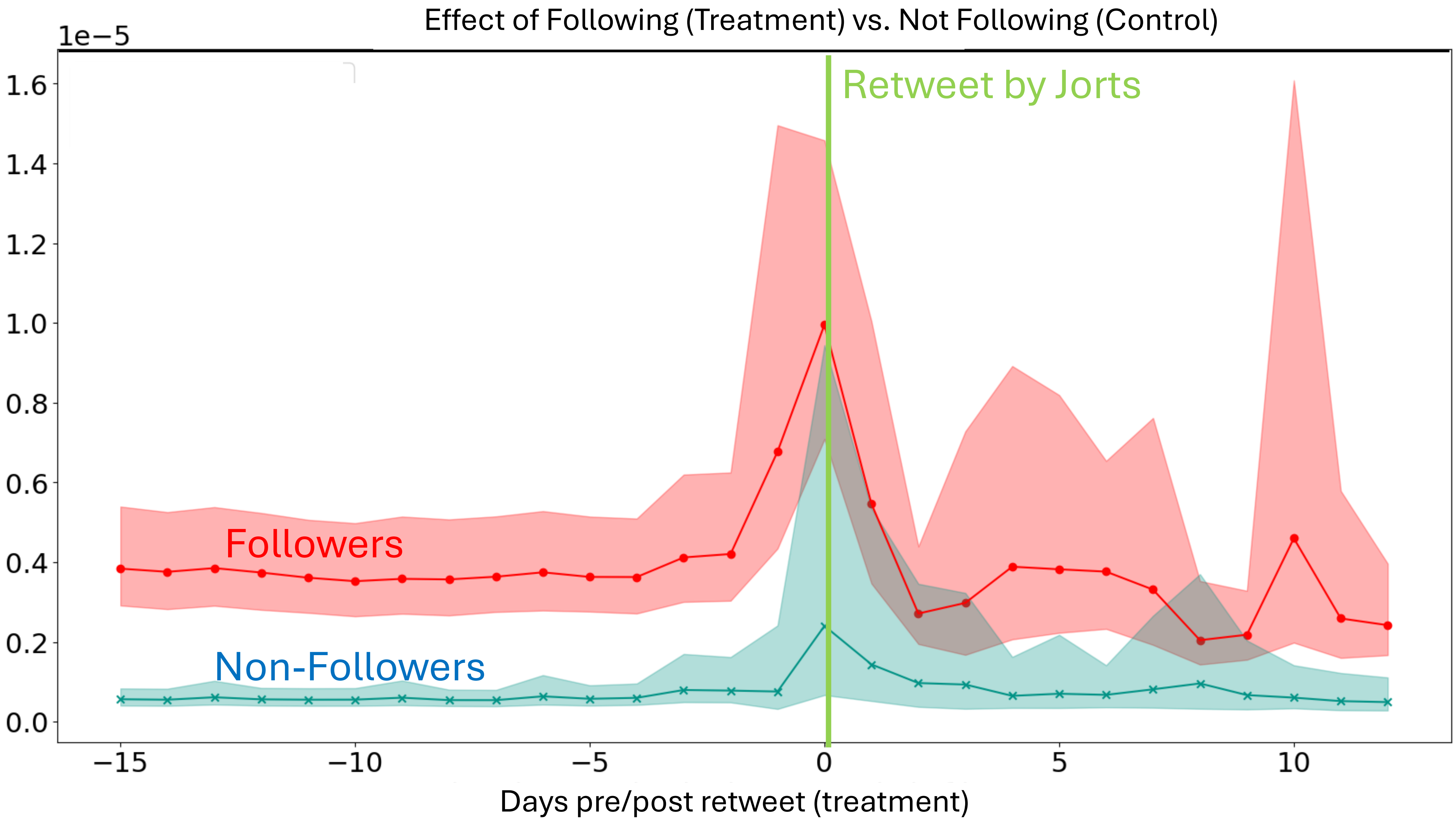
This is one account of ~700



We aggregate & figure out what **effect** Jorts has on average over many accounts

Differences-in-Differences

Follow rate to RT'ed account (Outcome Variable)



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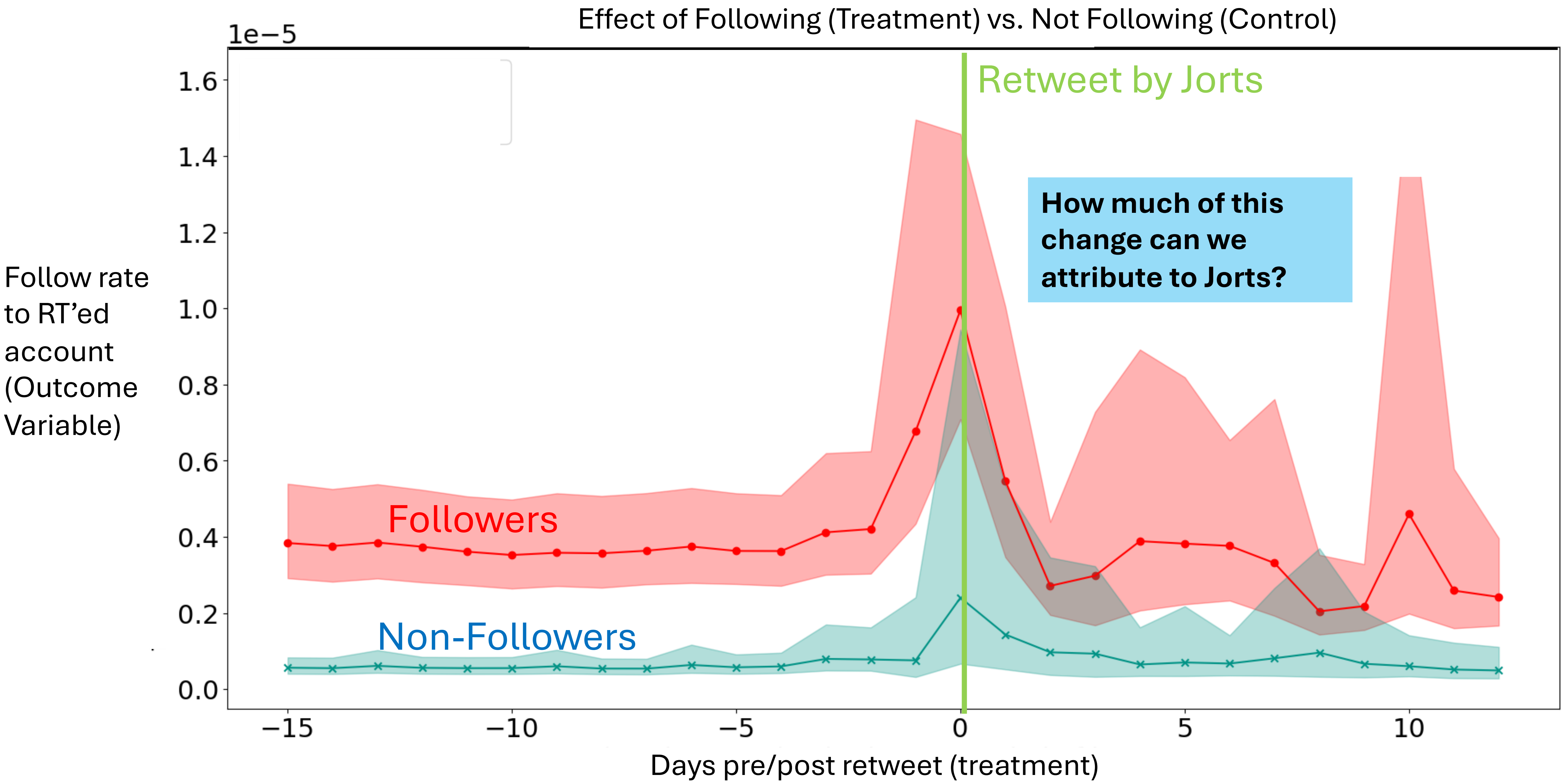

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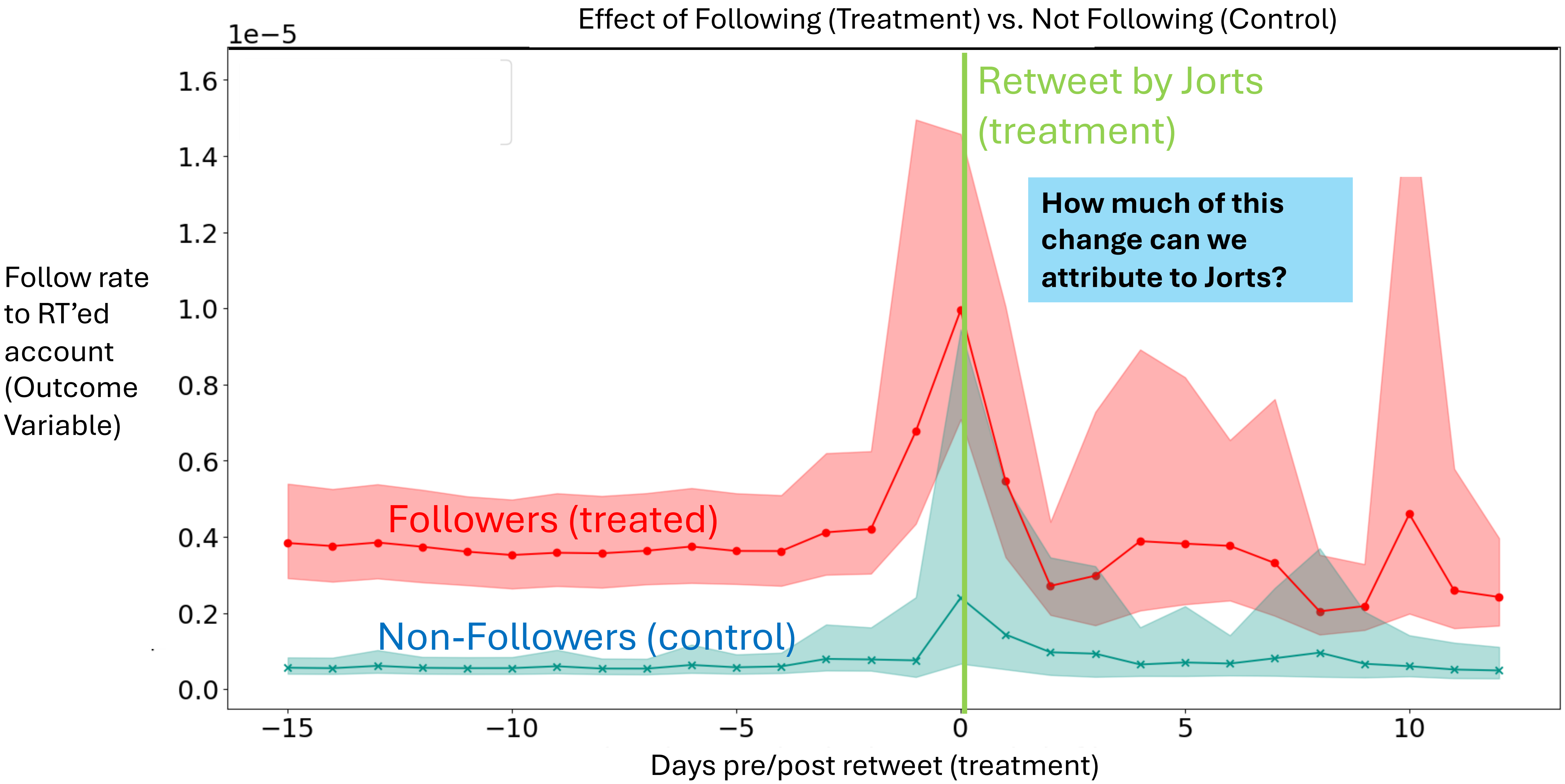

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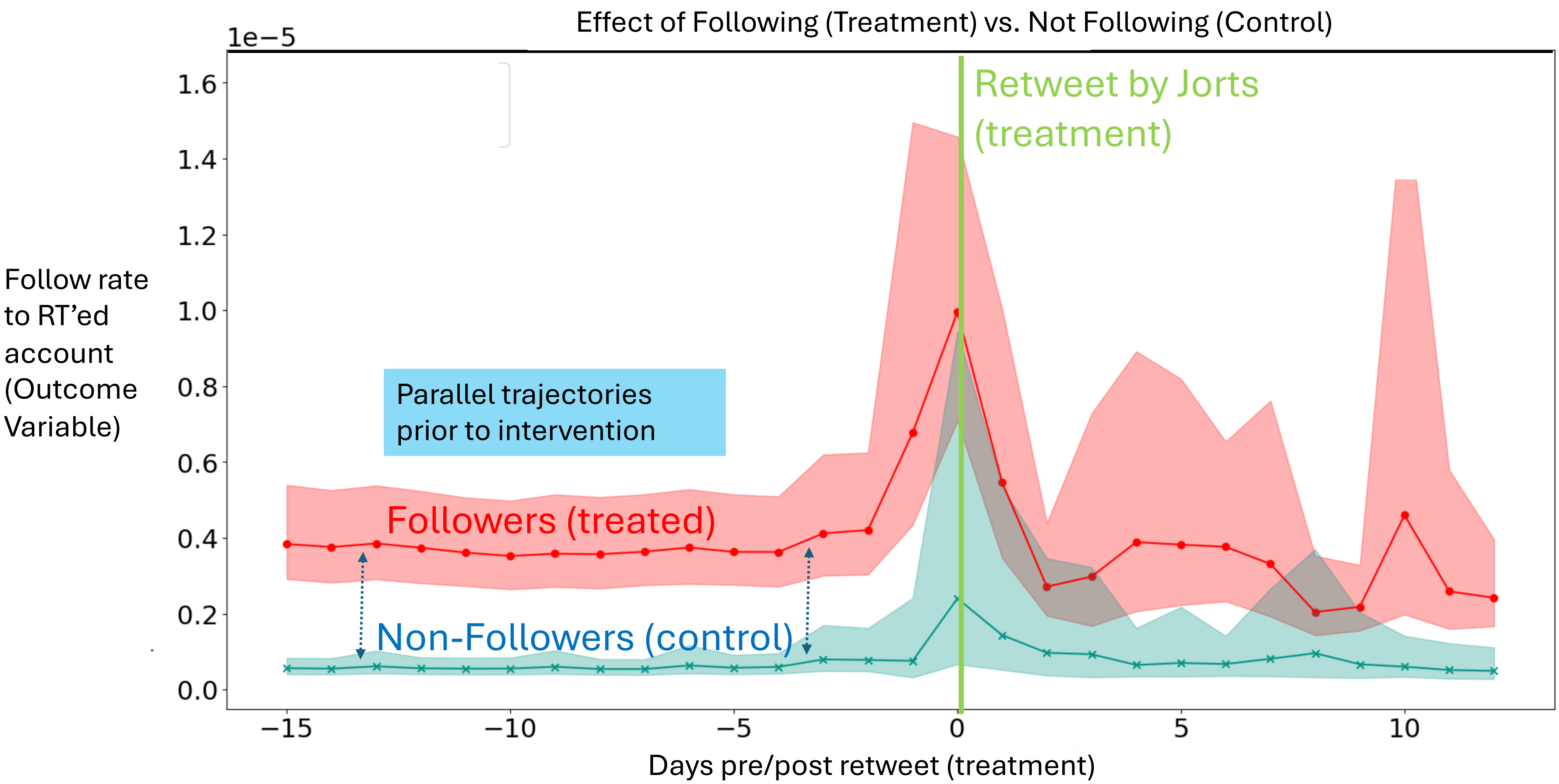

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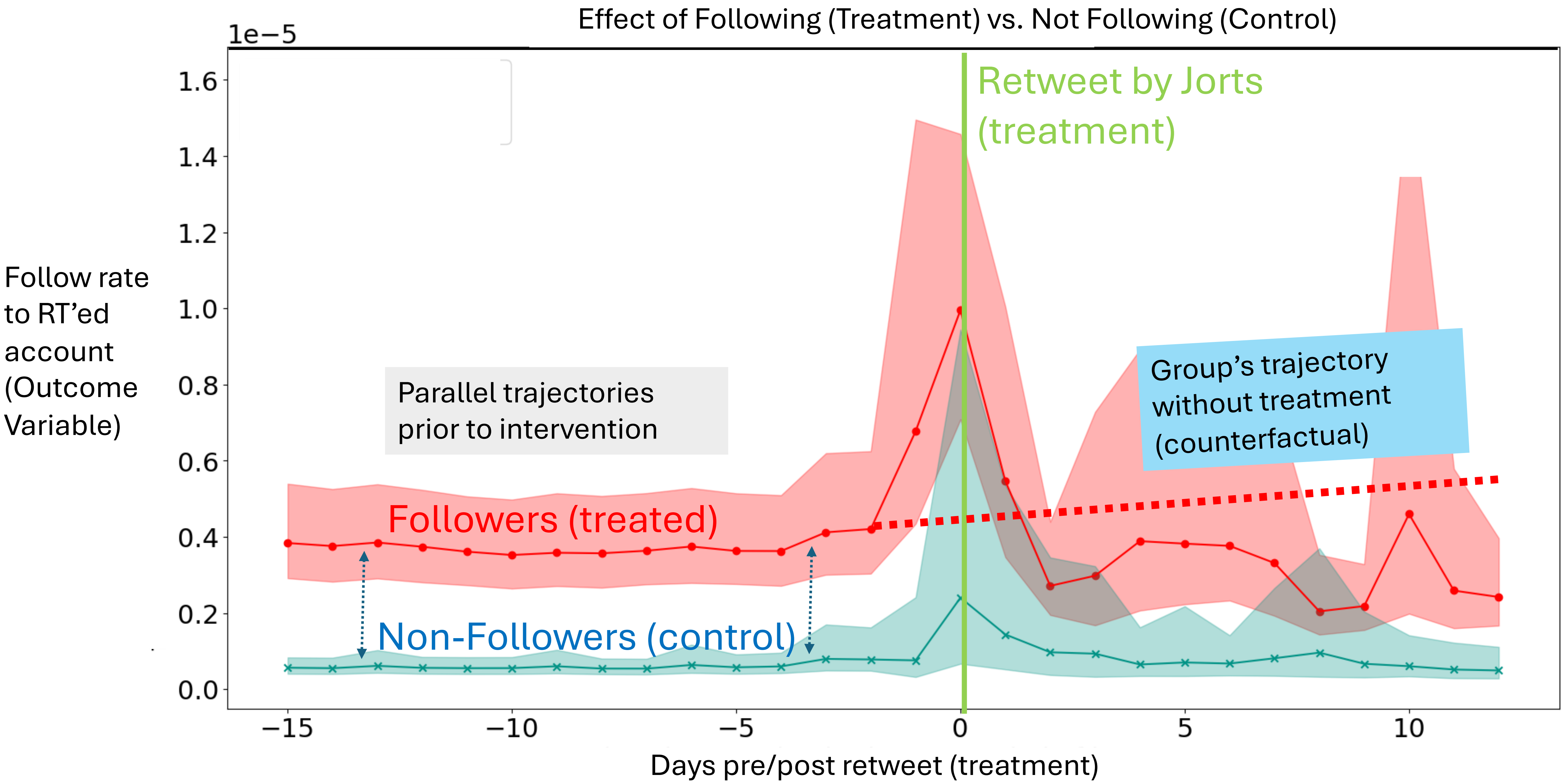

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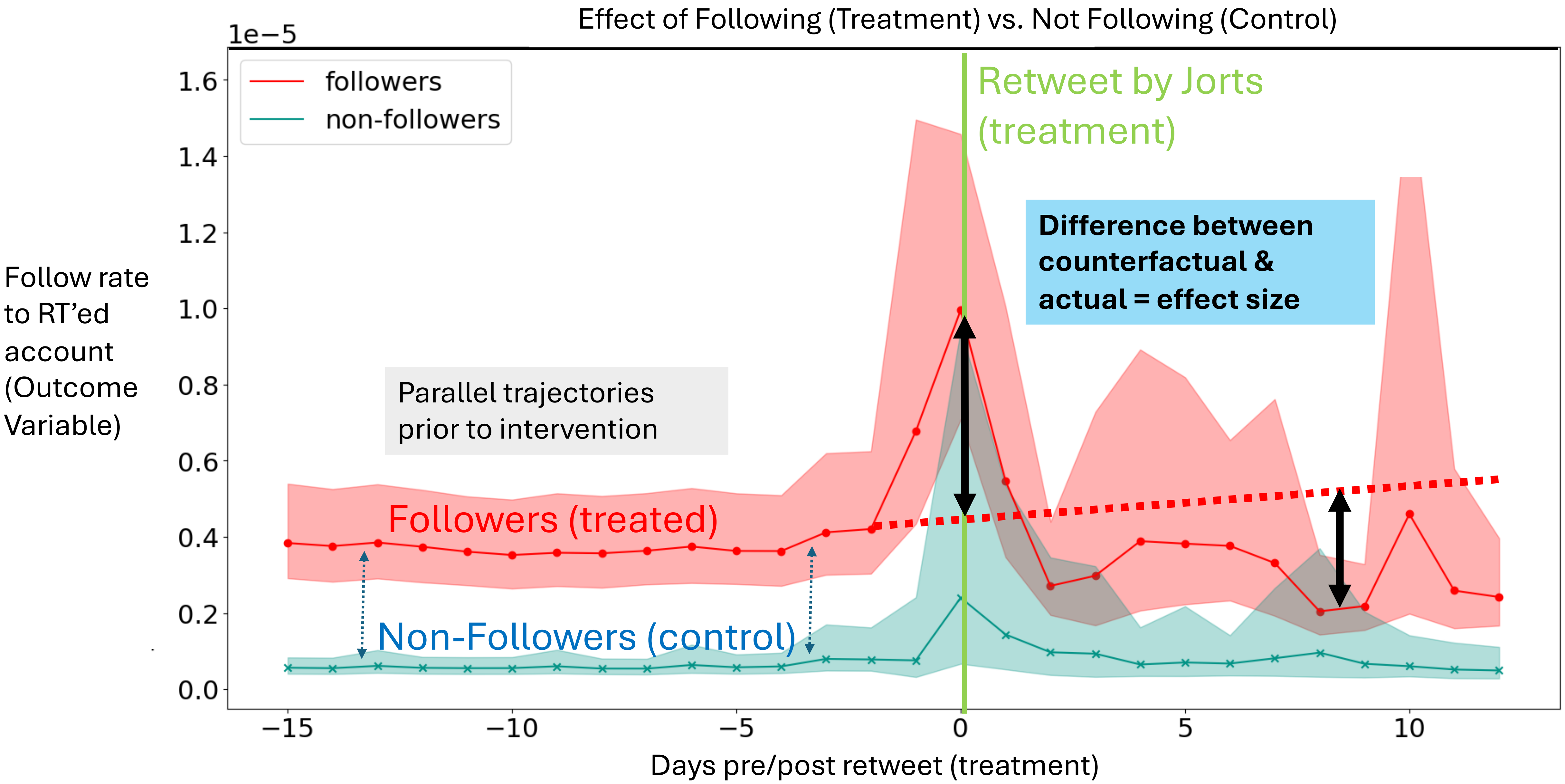
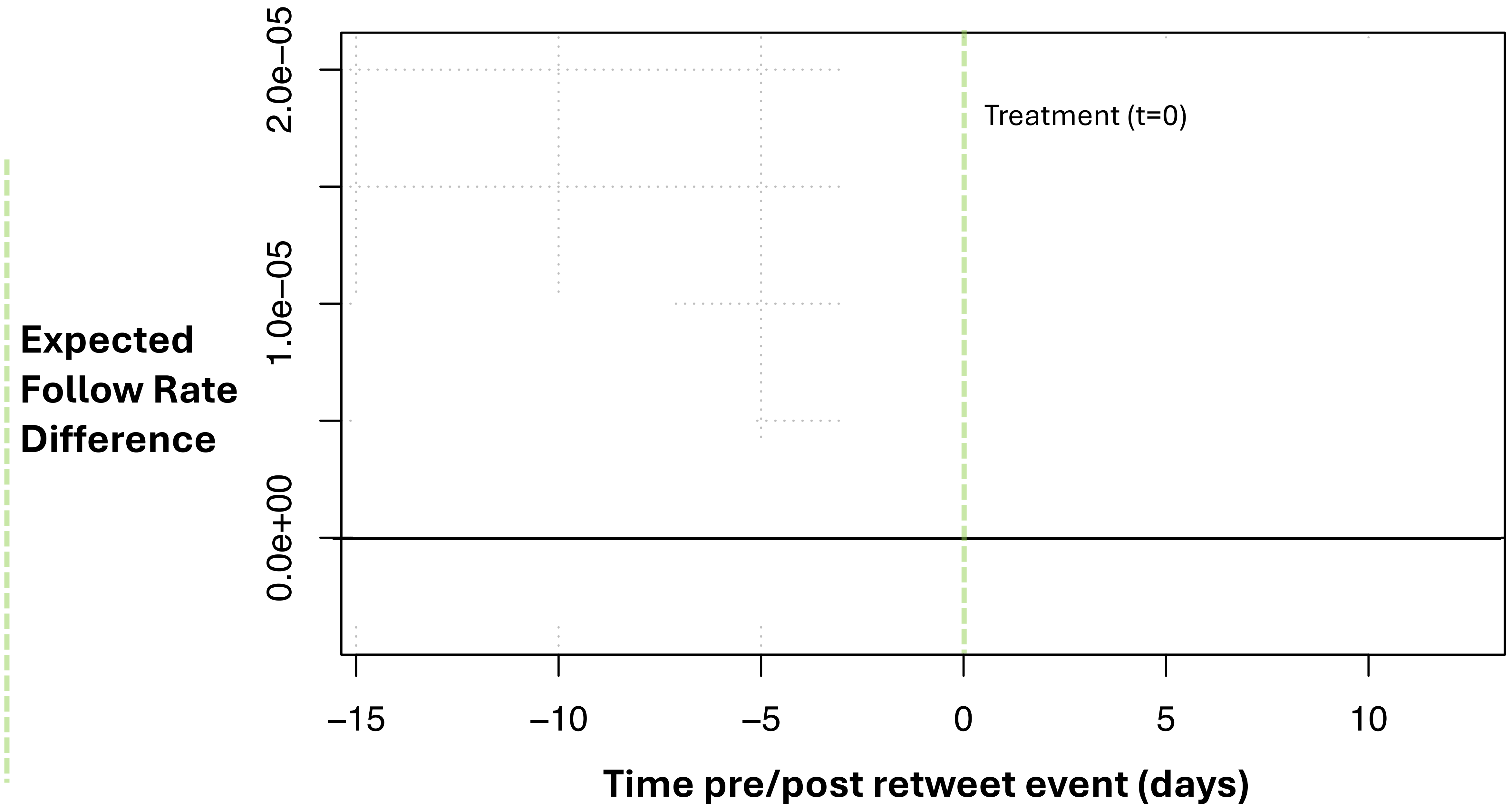


We’ve established:

- Definitions for treatment & control groups
- Parallel trends between treatment & control groups
- (Qualitative) **difference** in trajectories

We can do differences-in-differences to figure out how much of this **difference** we can attribute to Jorts

Per-Day Effect of Following Jorts (Treatment)



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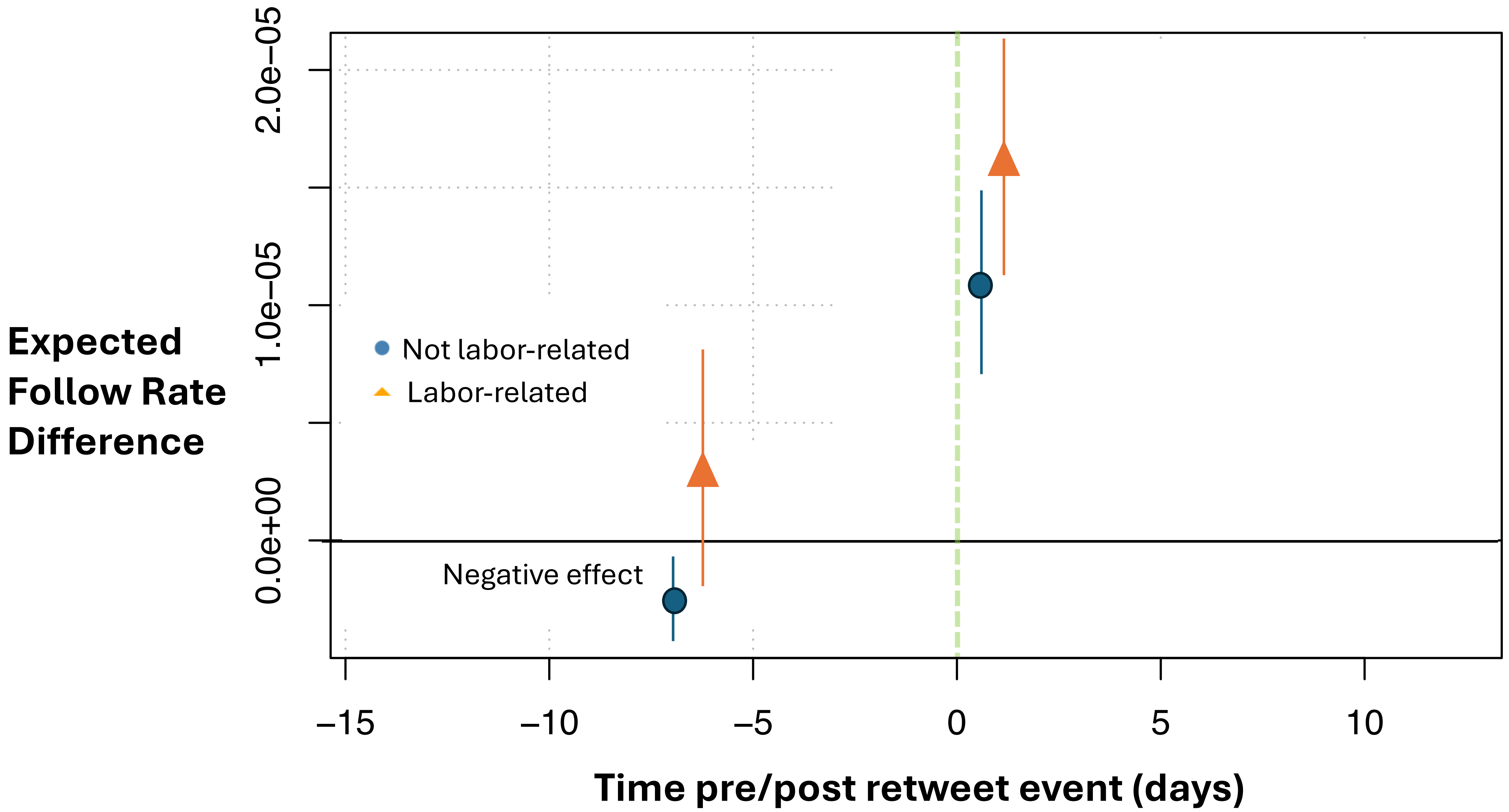
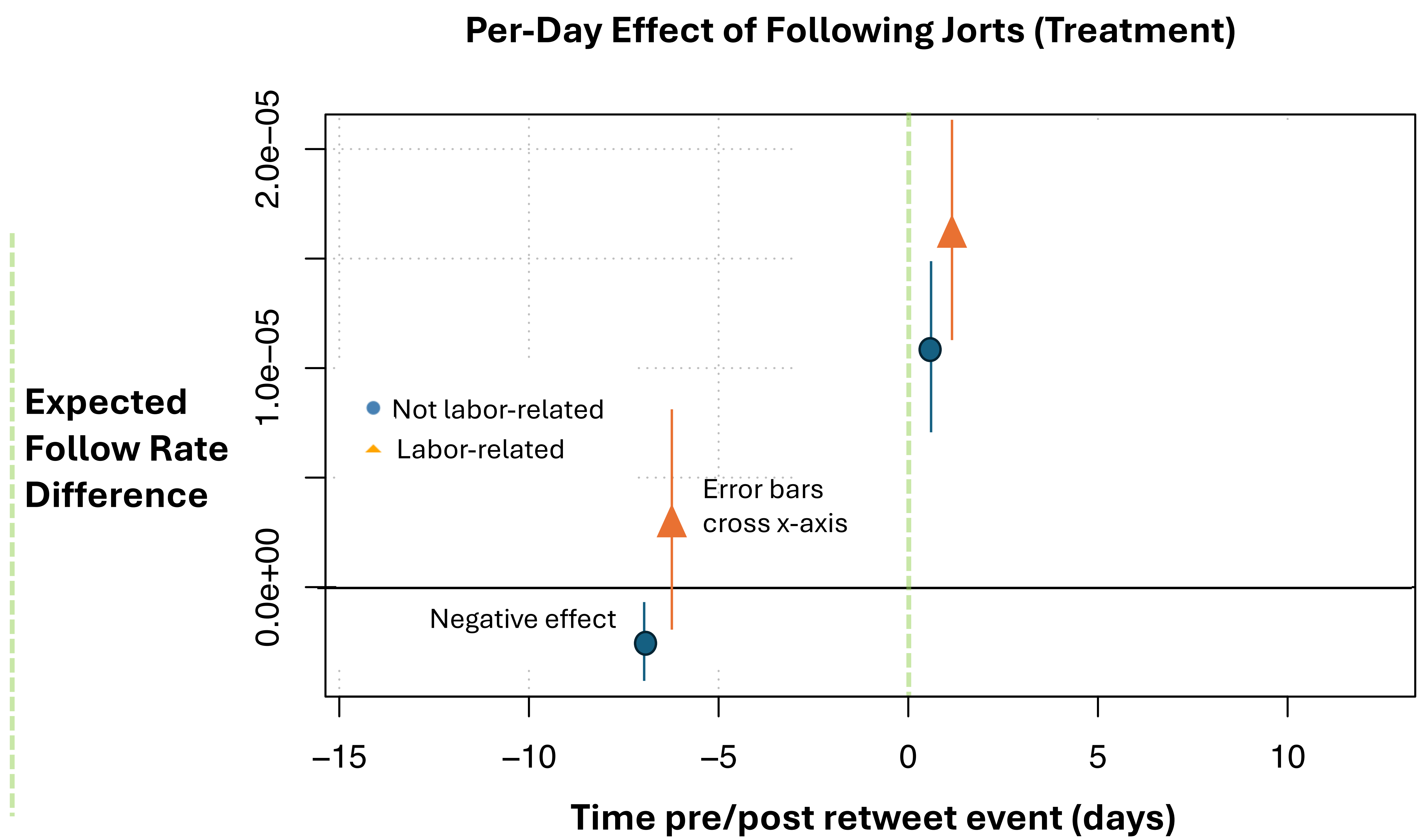
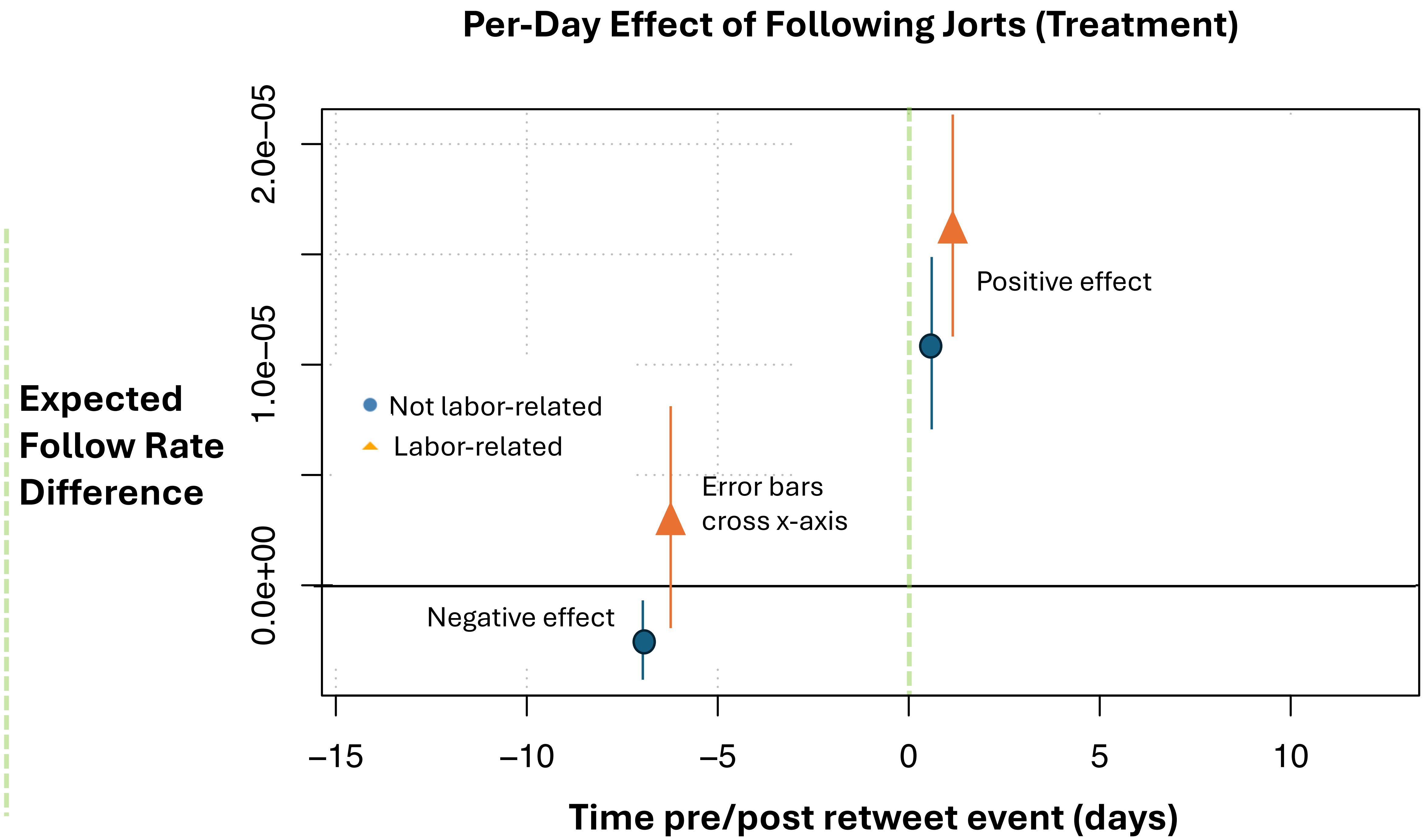
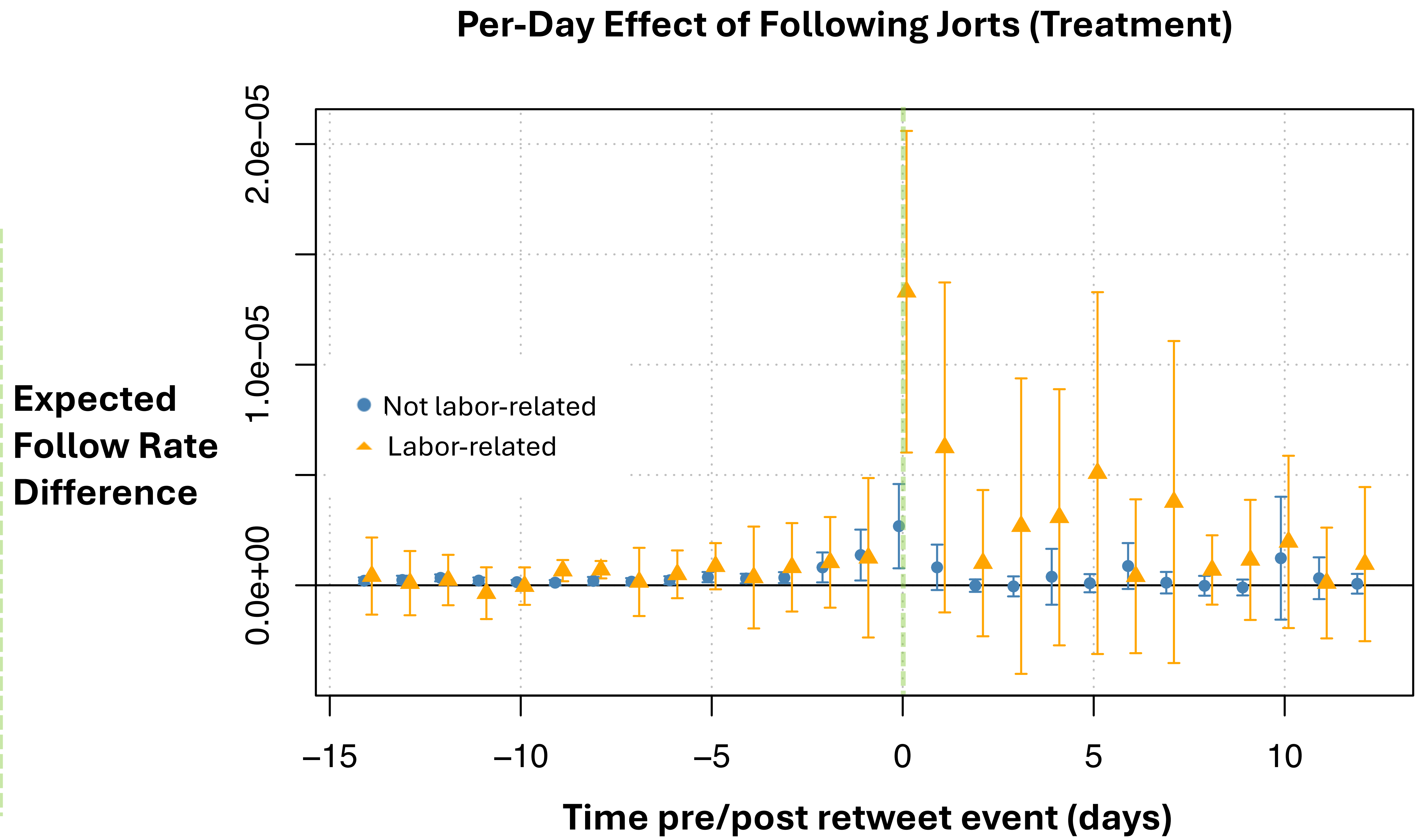




Per-Day Effect of Following Jorts (Treatment)
Expected Follow Rate Difference
2.0e−05
1.0e−05
0.0e+00
Not labor-related
Labor-related
Error bars cross x-axis
Negative effect
−15
−10
−5
0
5
10
Time pre/post retweet event (days)



Per-Day Effect of Following Jorts (Treatment)
Expected Follow Rate Difference
2.0e−05
1.0e−05
0.0e+00
Not labor-related
Labor-related
Positive effect
Error bars cross x-axis
Negative effect
−15
−10
−5
0
5
10
Time pre/post retweet event (days)



Per-Day Effect of Following Jorts (Treatment)
Expected
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2.0e−05
1.0e−05
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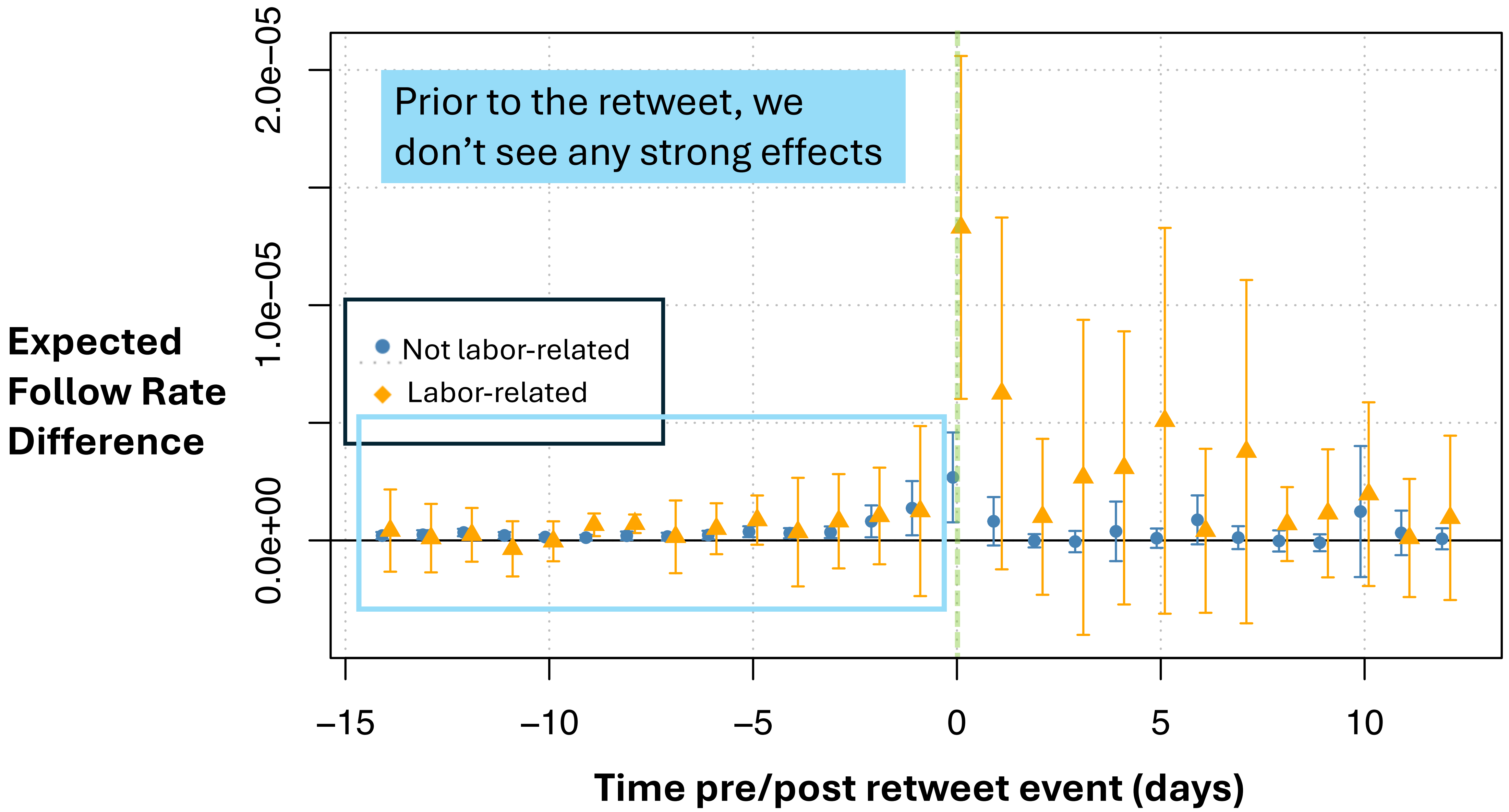
5
10
Time pre/post retweet event (days)

Per-Day Effect of Following Jorts (Treatment)



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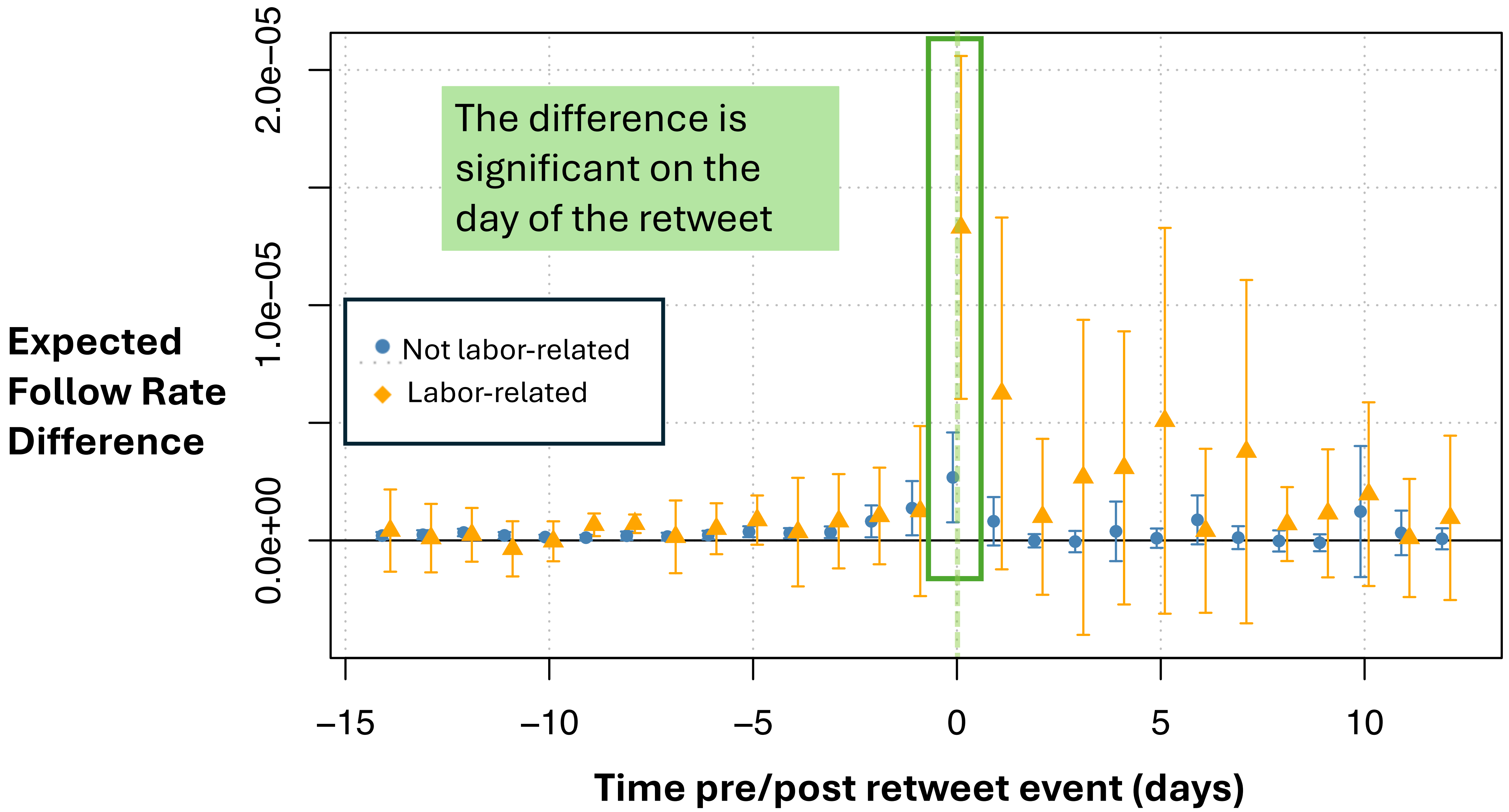

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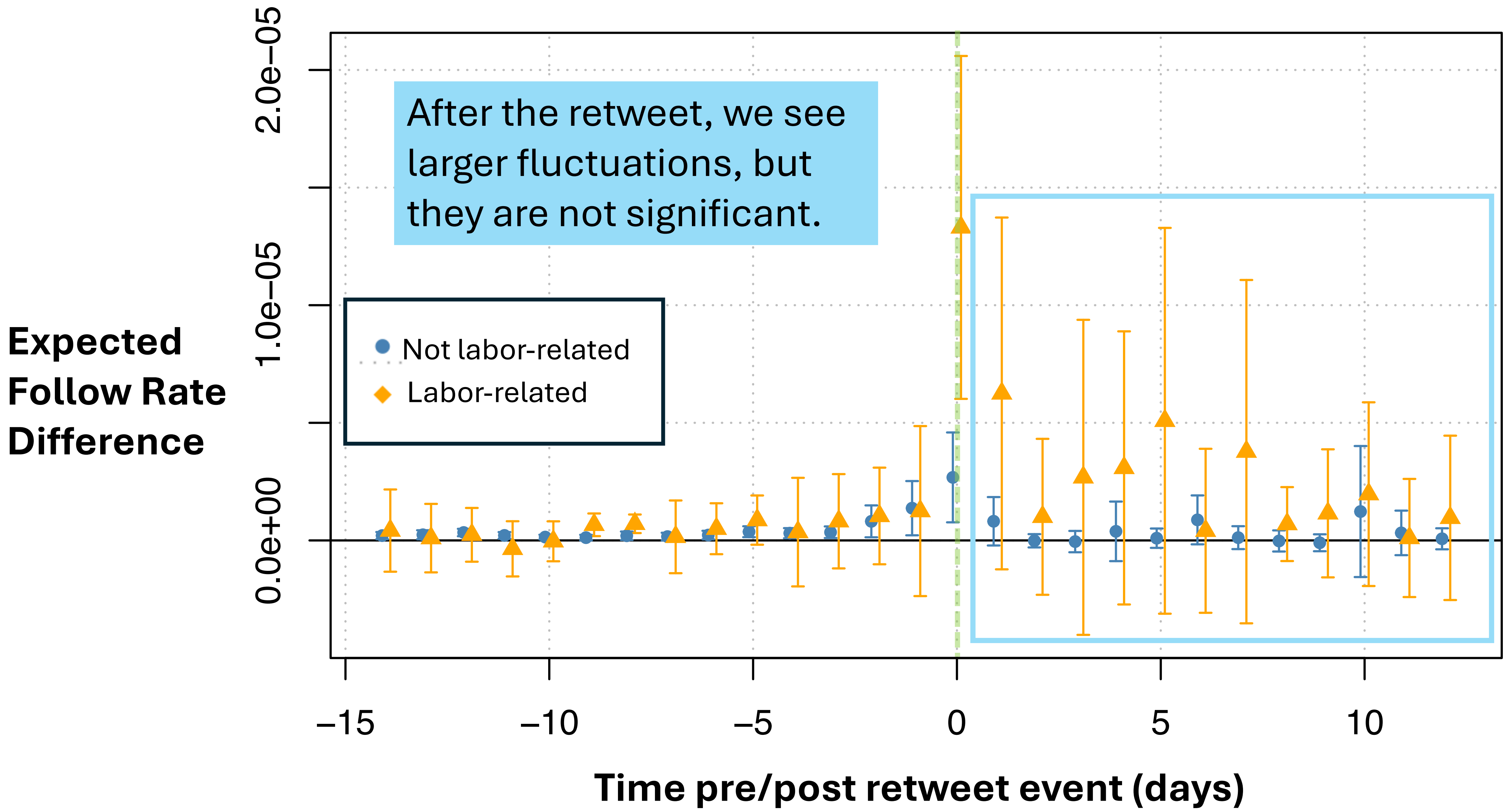


Why Does This Matter?

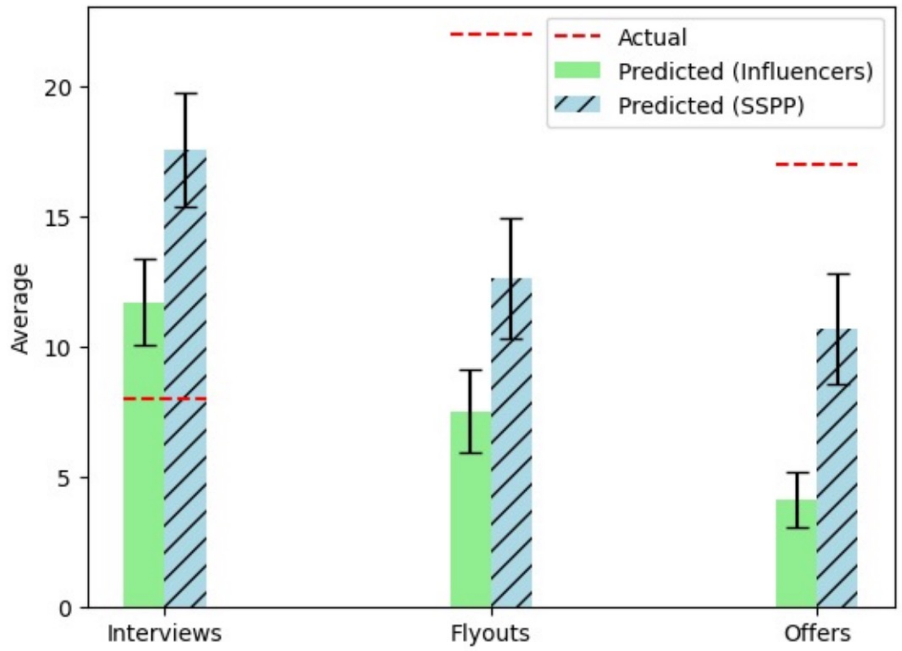
Economic Consequences

Social Media and Job Market Success: A Field Experiment on Twitter

106 Pages • Posted: 20 May 2024 • Last revised: 23 Mar 2025

- Attention brokers = trusted gatekeepers of quality
- Induce changes in {social, economic} capital

Figure 4: Predictions by Economist Influencers and SSPP Experts



→ Qiu et al. (2024)

Incitement + Radicalization

- Attention brokers are trusted curators of information
- What happens when they curate disinformation?
- Trusted figures inciting violence

Bomb threats follow Libs of TikTok's campaign against Planet Fitness

Dozens of locations across the country have reported bomb threats since the gym began receiving viral attention

EDUCATION, NEWS

After Libs of TikTok post, multiple bomb threats have been made at Waukesha middle school

School district, Waukesha police say threats are not credible

BY CORRINNE HESS • MARCH 18, 2024 • UPDATED MARCH 18, 2024 at 4:33 PM

EXCLUSIVE

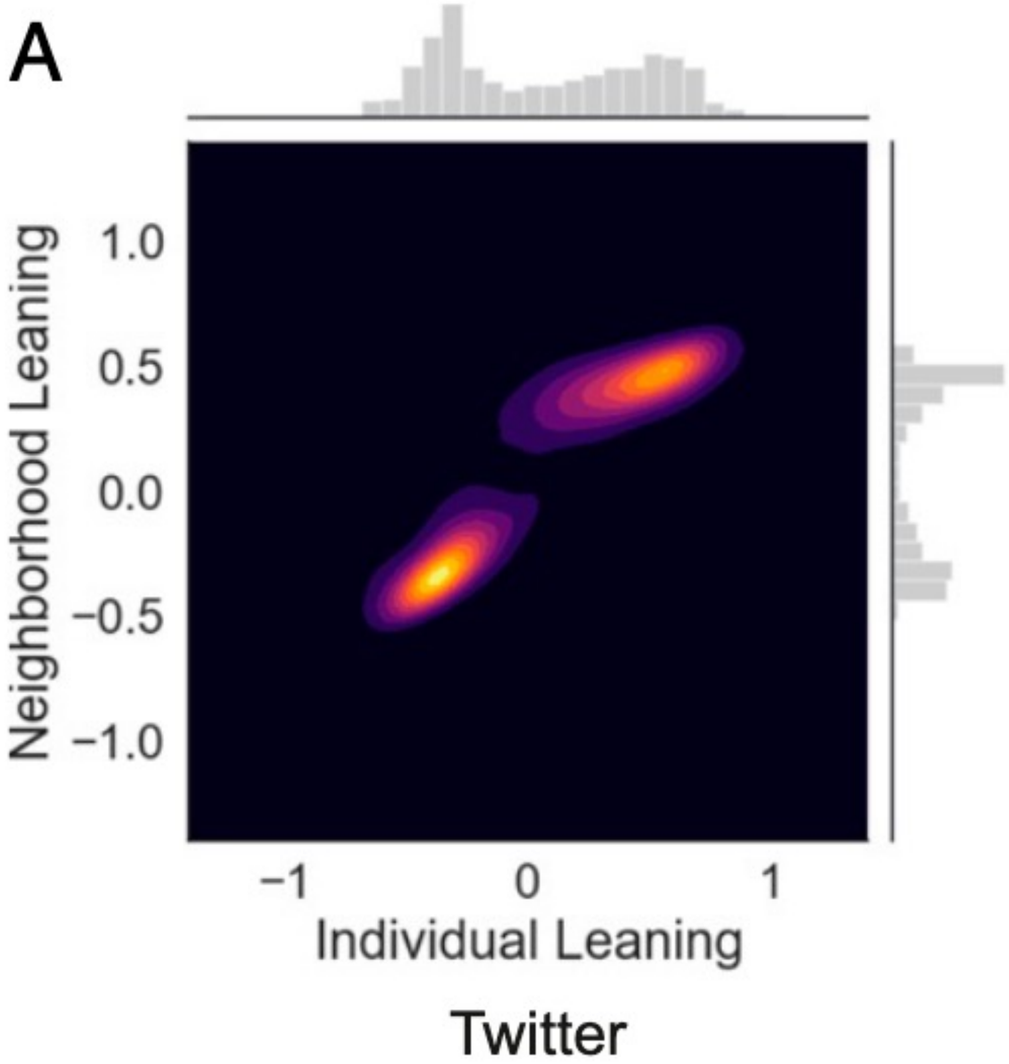
INTERNET

After Libs of TikTok posted, at least 21 bomb threats followed

The FBI and local law enforcement said bomb threats across the country have tied up government resources even when they turn out to be hoaxes.

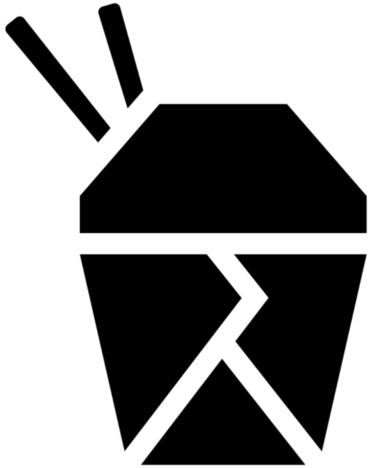
Polarization

- Over time, attention brokerage can create feedback loops
- Communities arise where people only share content that confirms their worldview



→ Cinelli et al. (2021); Green et al. (2025)

Takeaways



Attention Brokerage:

- Analyzed Twitter retweet & following data
- Found that attention brokers (re)shape attention

Ongoing & Future Work:

- Information reach
- Structures of attention
- Interdisciplinary research

Future Work

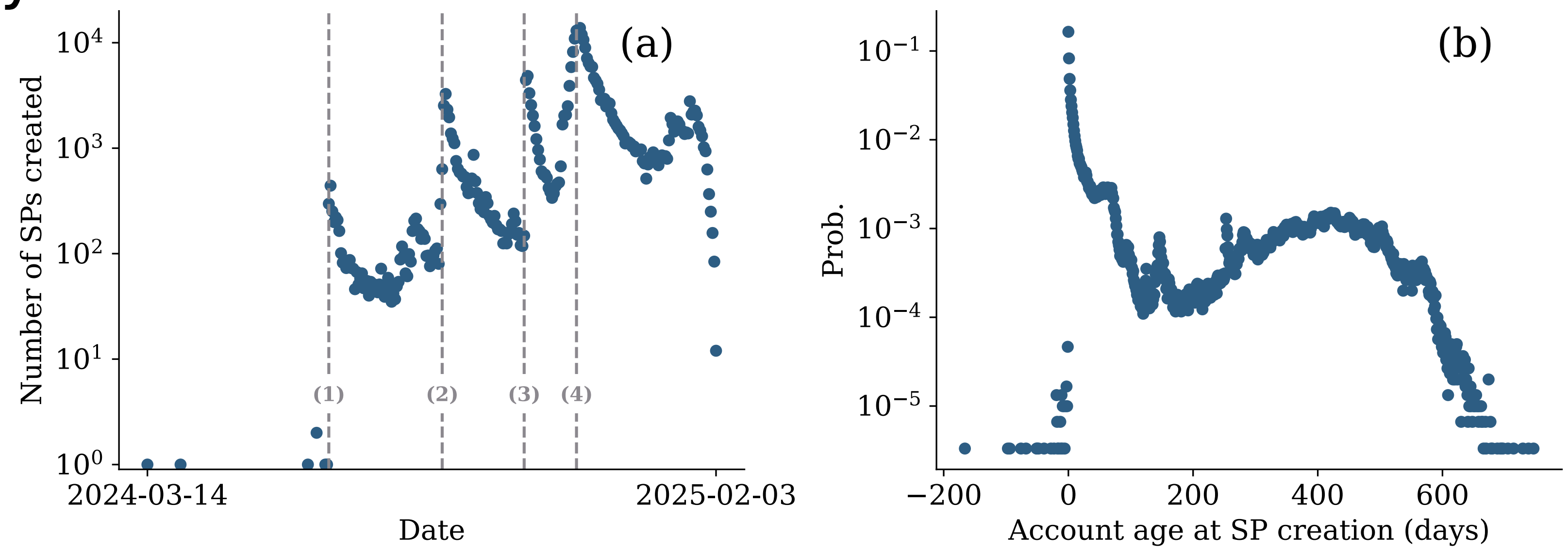
Analyzing power/attention structures & systemic harms

↓

Making online platforms more just, more safe, and more vibrant

Endorsement & Attention on Bluesky

- Endorsement on Bluesky via the starter pack feature
- Released a network dataset & preprint
- <u>**Future work: how do starter packs affect network evolution?**</u>



Starter pack (SP) creation per day

→ Smith et al. (2025) *(arXiV Preprint)*

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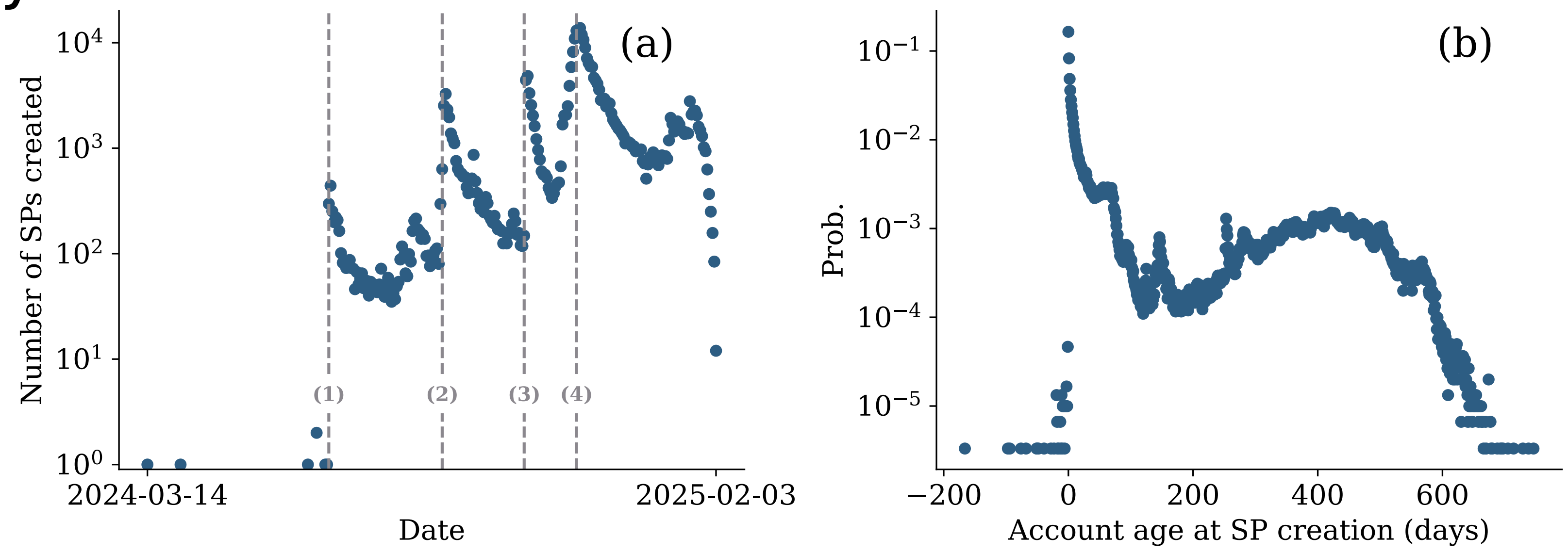


Starter pack (SP) creation per day

What features help online social networks grow, thrive, and facilitate exchange?

→ Smith et al. (2025) *(arXiV Preprint)*

Endorsement & Attention on Bluesky

Example Projects:

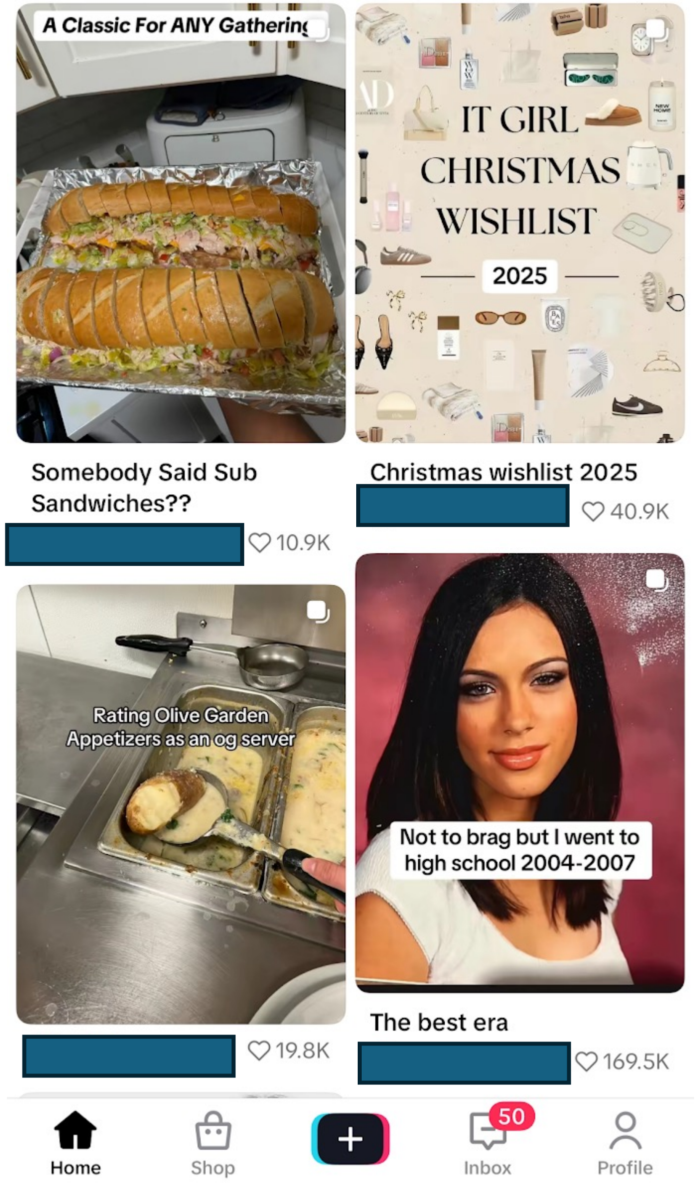
- Comparing spreading processes on the starter pack + following networks
- Simulating network evolution based on starter pack patterns
- Visualizing the Bluesky following network

Tools:

- Network {science, modeling, epidemiology}
- Data visualization

Folk Theorizations

- Algorithmic *folk theories* are how people intuitively explain how algorithmic curation works.
- **<u>Future work: what folk theories exist about attention brokerage?</u>**
  - **Semi-structured interviews**
  - **Analyzing social media posts**



→ DeVito et al. (2017)

Folk Theorizations

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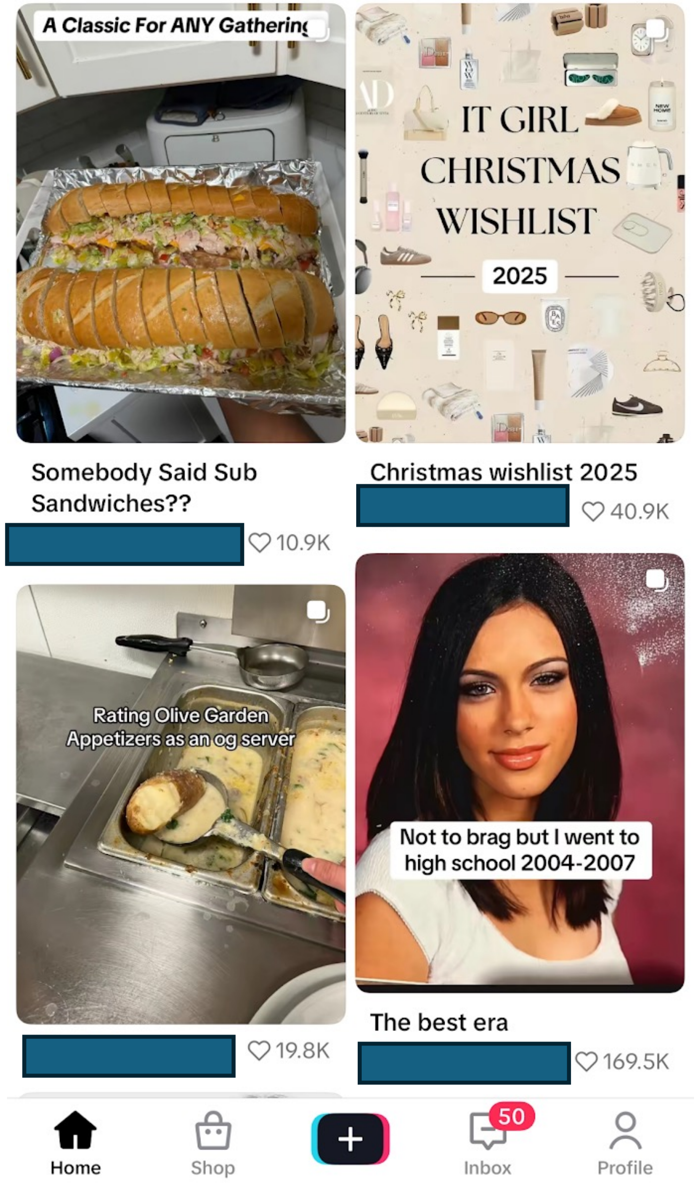
- **<u>Future work: what folk theories exist about attention brokerage?</u>**
  - **Semi-structured interviews**
  - **Analyzing social media posts**

What ways of thinking about attention reduce polarization & facilitate open dialogue on social media?



→ DeVito et al. (2017)

Folk Theorizations

Example Projects:

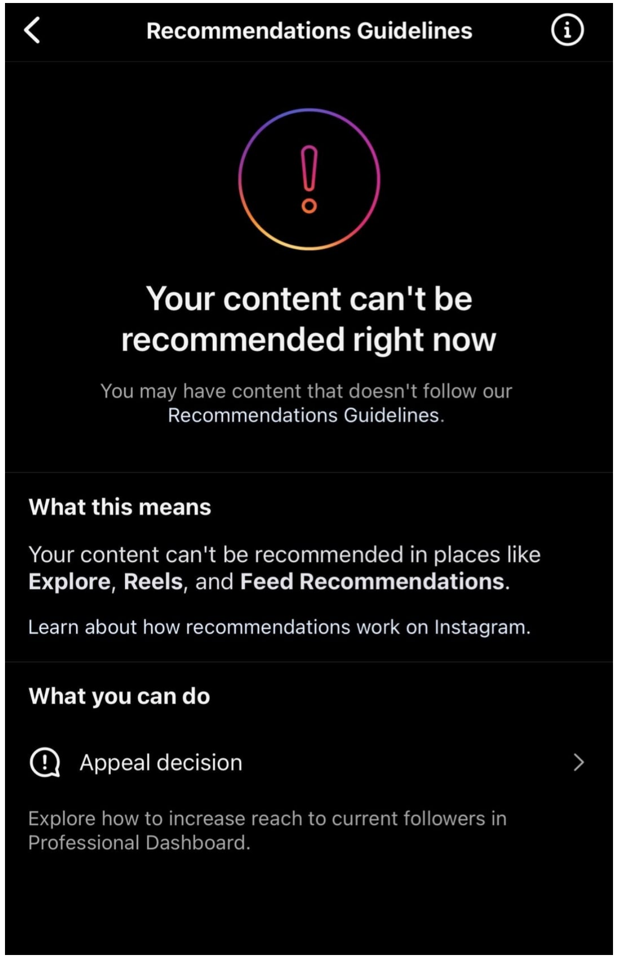
- Semi-structured interviews with attention brokers on Bluesky
  - How do they see their role on the platform?
  - How do they think about attention?
- Analyzing TikTok duet + stitch videos
  - Who gets amplified in duets vs. stitches?
  - What do these accomplish relationally & attention-wise?

Tools:

- API use + data engineering
- Qualitative methods

Algorithmic Curation/Suppression

- Some contentious topics experience reduced reach and engagement on social media.
- **<u>Future work:</u>**
  - How do people avoid algorithmic suppression?
  - Do avoidance tactics work?
  - Can we audit algorithmic suppression?



Algorithmic Curation/Suppression

- Some contentious topics experience reduced reach and engagement on social media.
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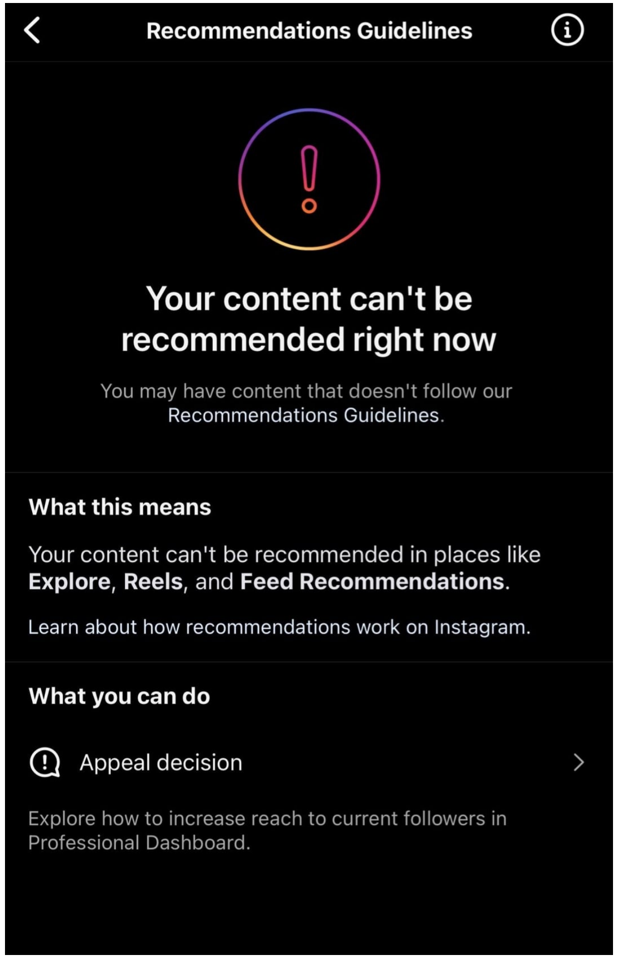
  - How do people avoid algorithmic suppression?
  - Do avoidance tactics work?
  - Can we audit algorithmic suppression?

How can we make social media a more vibrant, safe place for activist engagement?



Algorithmic Curation/Suppression

Example Projects:

- Compare posts with obfuscated & non-obfuscated language
  - Differences in engagement?
  - Qualitative differences in content?
- Within-community algorithmic audits
  - In tandem with activists?
  - Data donation programs

Tools:

- Natural Language Processing
- Databases
- Community partnerships

Thank you so much for your attention!

I look forward to your questions.

Let's stay in touch:

Bibliography →→→

Website: asmithh.github.io
Email: smith.alyss@northeastern.edu
Bluesky: cetaceanneeded.bsky.social

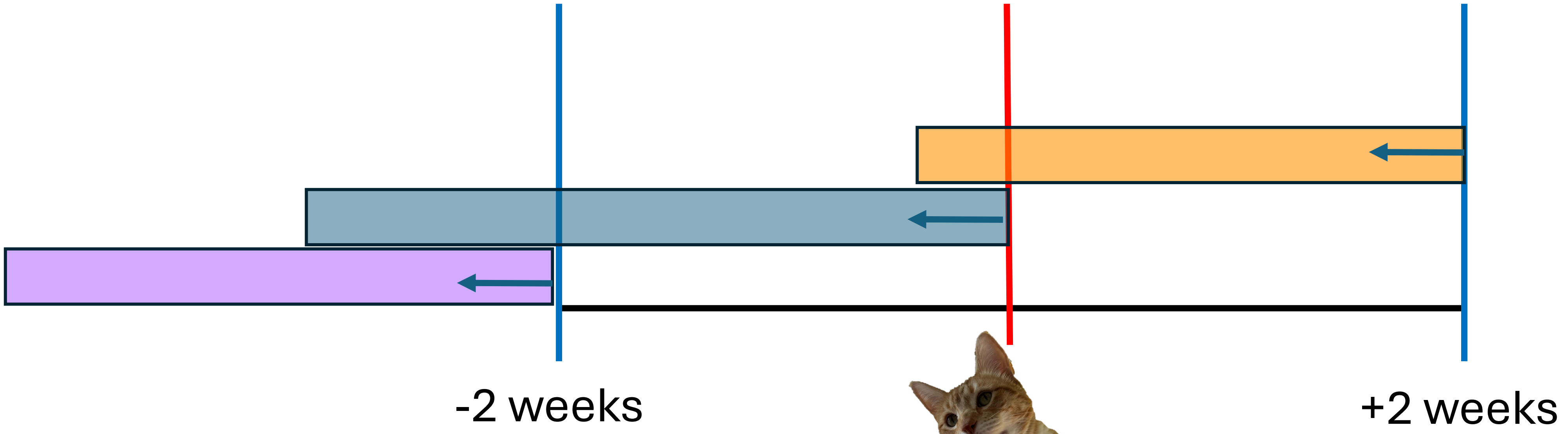
Backup Slides

High-level methods overview

- Two attention broker case studies, Jorts and J.K. Rowling
- We collected their retweets over a few months (Jorts) and a few years (Rowling)
- For each retweet, we did the following*:
  - Figured out who followed the retweeted account in the 2 weeks before & after the retweet
  - Figured out whether each follower was following Jorts **before** they followed the retweeted account
- We estimated attentive follower and non-follower populations using mark-and-recapture techniques from population ecology.
- We used causal inference (two-stage differences-in-differences) to figure out whether users following an attention broker when the attention broker retweeted an account followed the retweeted account at a higher rate than non-followers.

* (there's a cool hack we used with the Twitter V1 API (RIP) to put arbitrarily exact time bounds on when a following event occurred)

Data Collection/Twitter API Hack



- Specify timestamp cursor to API
- Follow events returned in reverse chronological order
- Align lists to get time-bounded follower list
- Linear interpolation used if necessary

Two-Stage Differences in Differences

- Event study → model changes in effect size over time
  - Expect decreasing effect size after retweet
- Staggered timing for interventions (i.e. retweets aren't simultaneous)
  - Regular diff-in-diff doesn't provide a consistent estimator for the treatment effect.
  - The two-stage implementation first estimates individual & temporal fixed effects using non-treated and not-yet-treated data points.
  - Then it estimates the treatment effect using the full dataset.

→ Butts, 2021

Backup: DID2S Math

$$\boxed{Y_{it}} = \boxed{\mu_i} + \boxed{\mu_t} + \sum_{k=-14}^{-1} \boxed{\tau^k} \boxed{D_{it}^k} + \sum_{k=0}^{14} \boxed{\tau^k} \boxed{D_{it}^k} + \boxed{\epsilon_{it}}$$

Following Rate

Account-level fixed effects

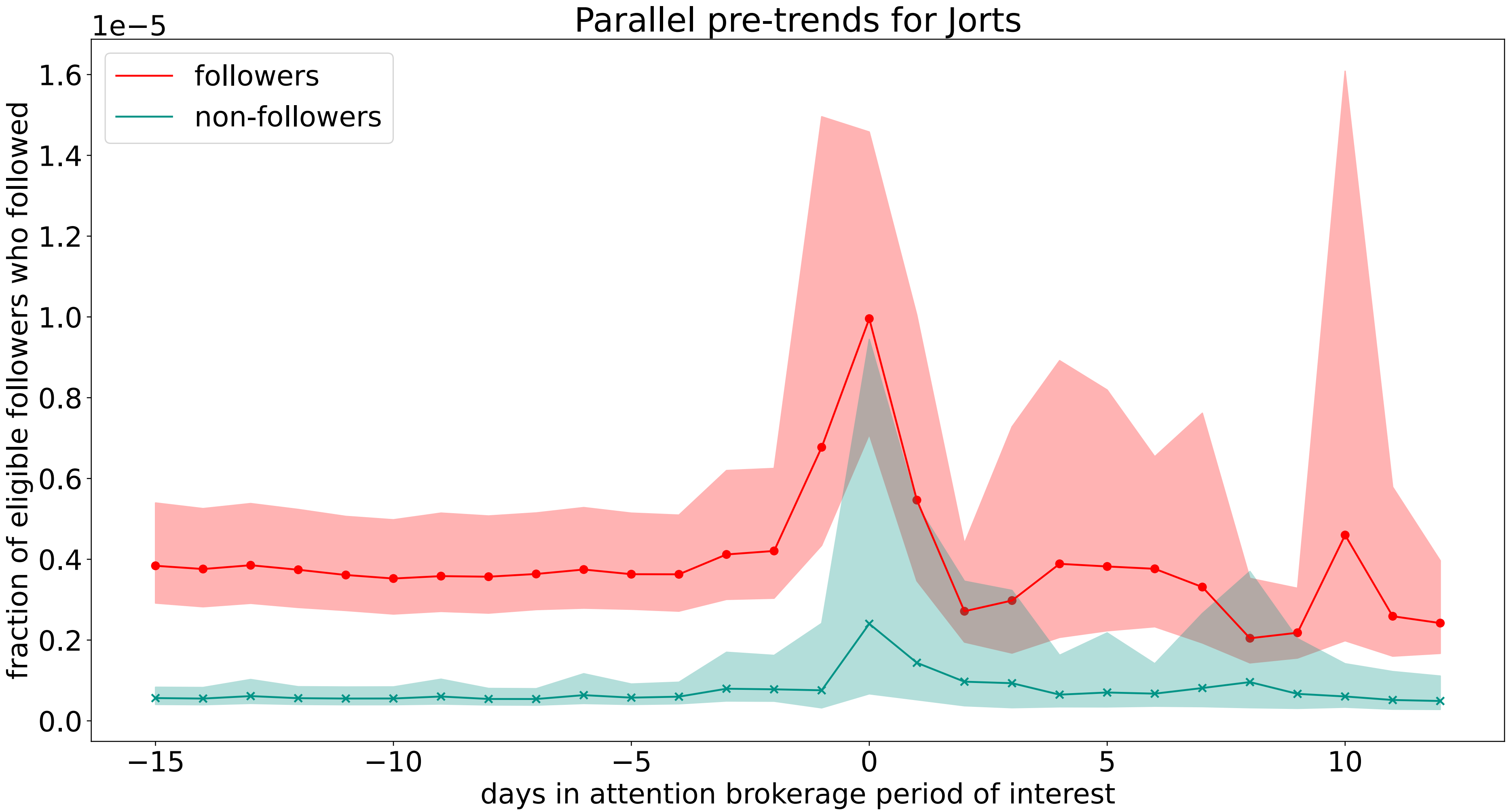
Temporal fixed effects

Effects of attention brokerage through day *k*

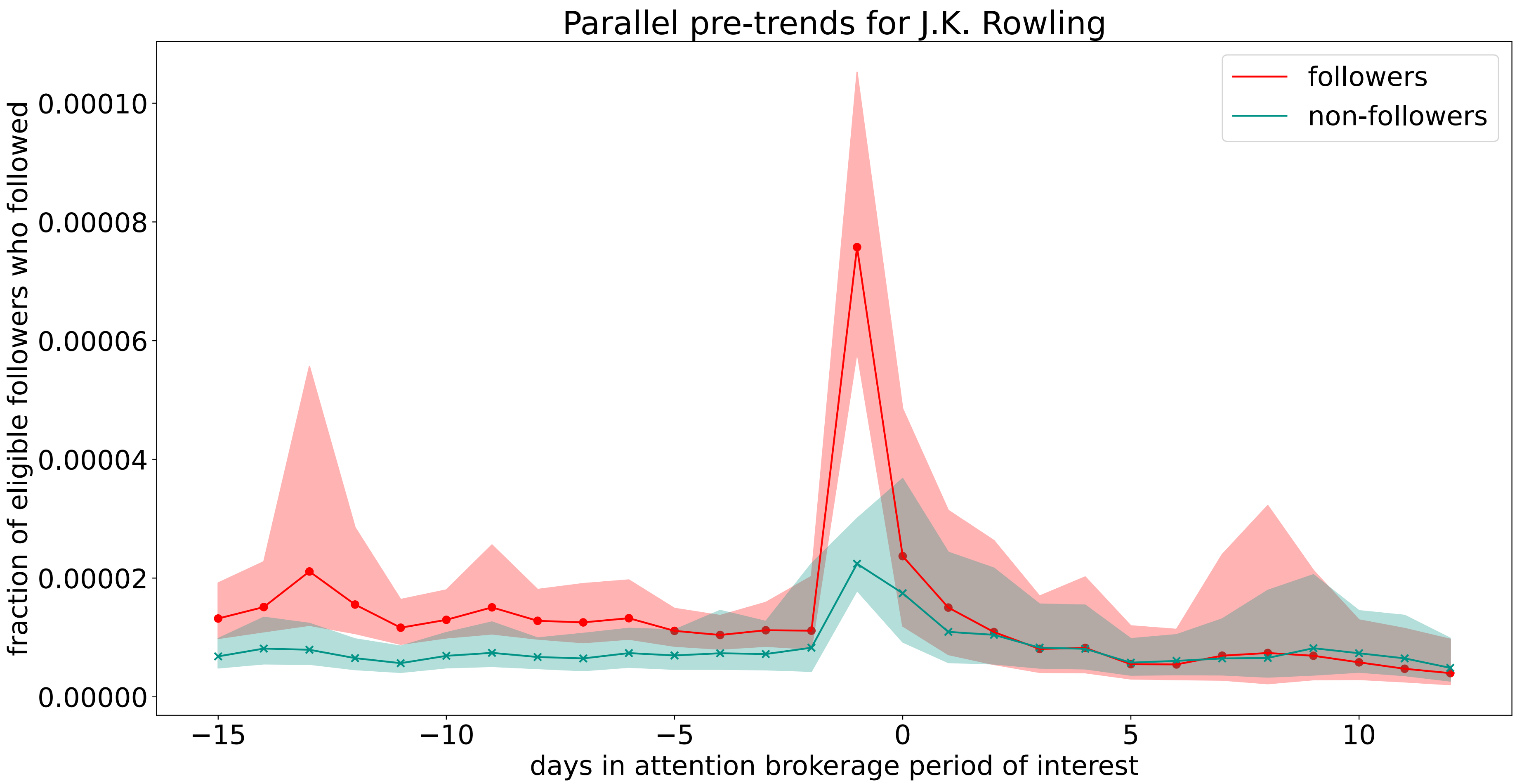
Treatment lead/lag variable

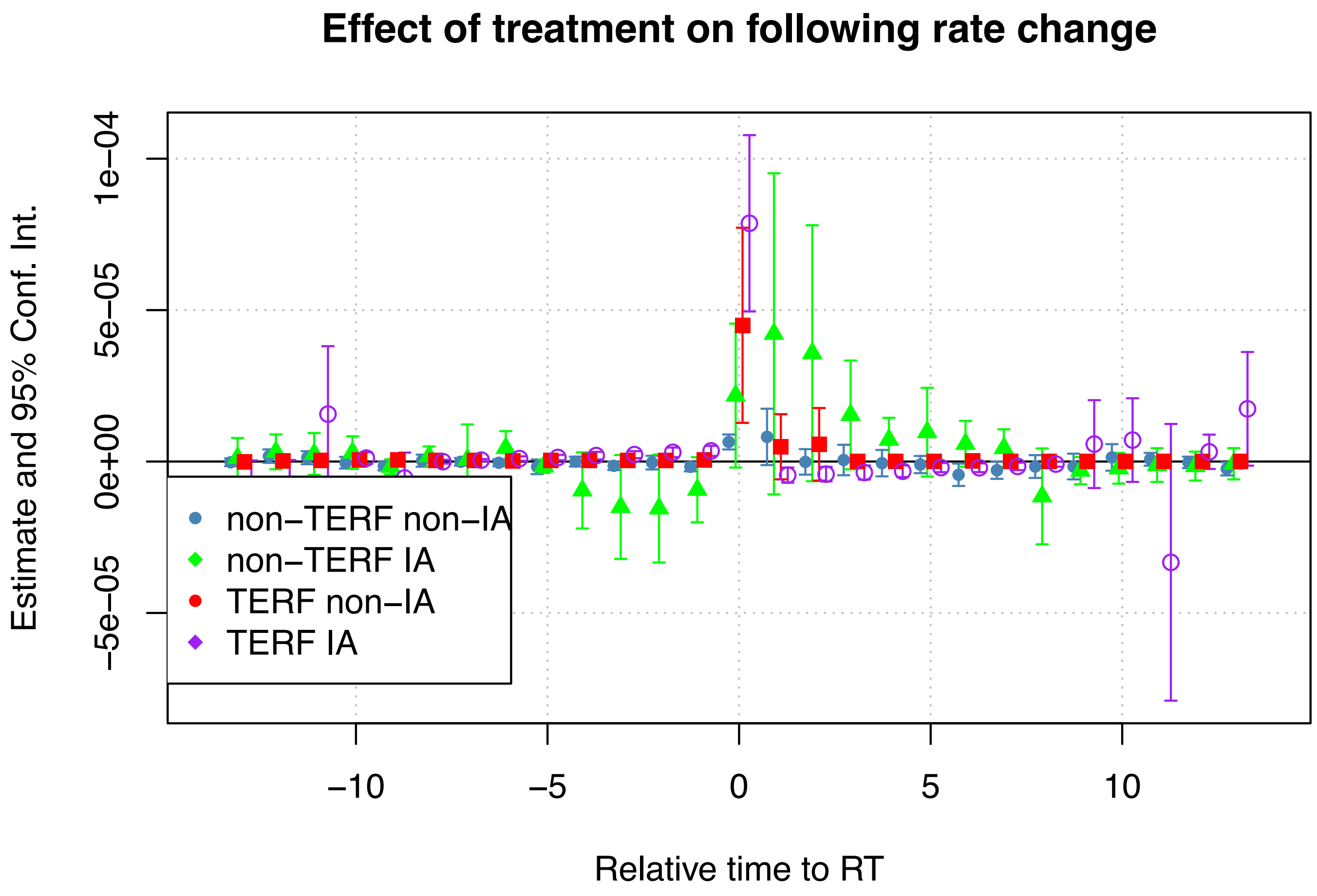
Error term

Initial Average Trends



Initial Average Trends





- Accounts are broken out by type
- The effect of following Rowling is significant on day 0 for all types
- After day 0, the effect size is not obviously significant.

Account Categories

Rowling:

Interest Actor (y/n): An account that talks about politics, and is influential in discussion of politics**, but is not a traditional political elite.** (Moses, 2023)

TERF (y/n): Trans-Exclusionary Radical Feminist (attacks trans women by upholding hegemonic, cissexist ideas about womanhood)

Jorts:

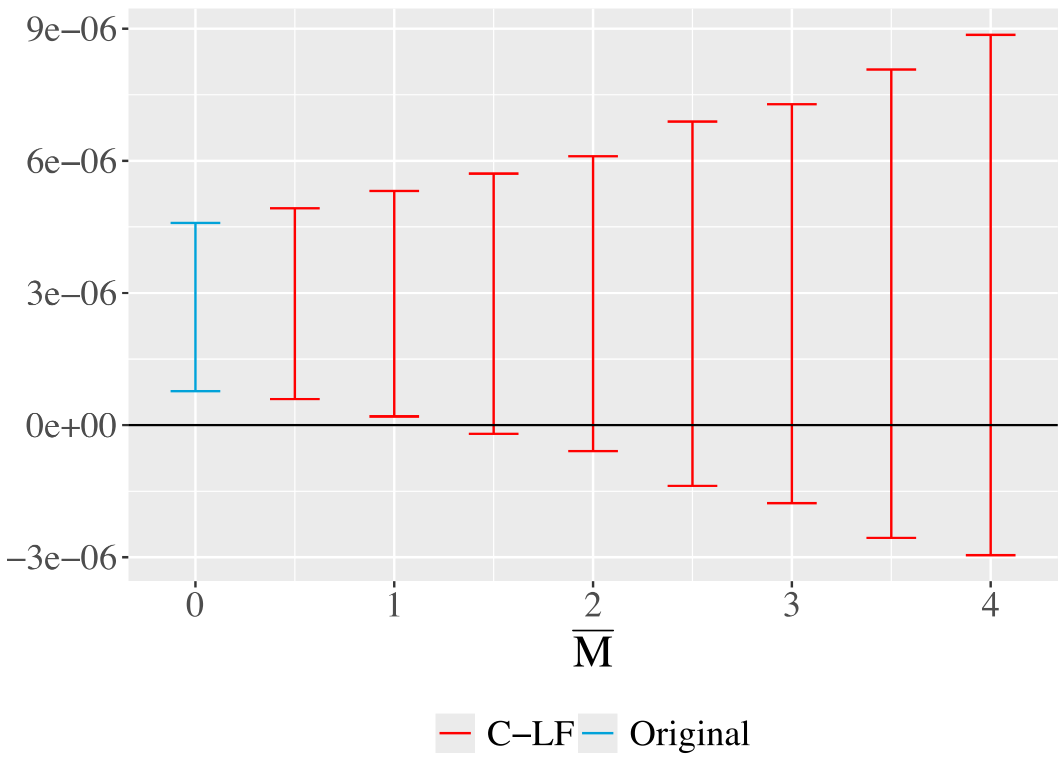
Union (y/n): Frequently (more than half the time) discusses labor activism and/or union organizing.

Robustness Checks

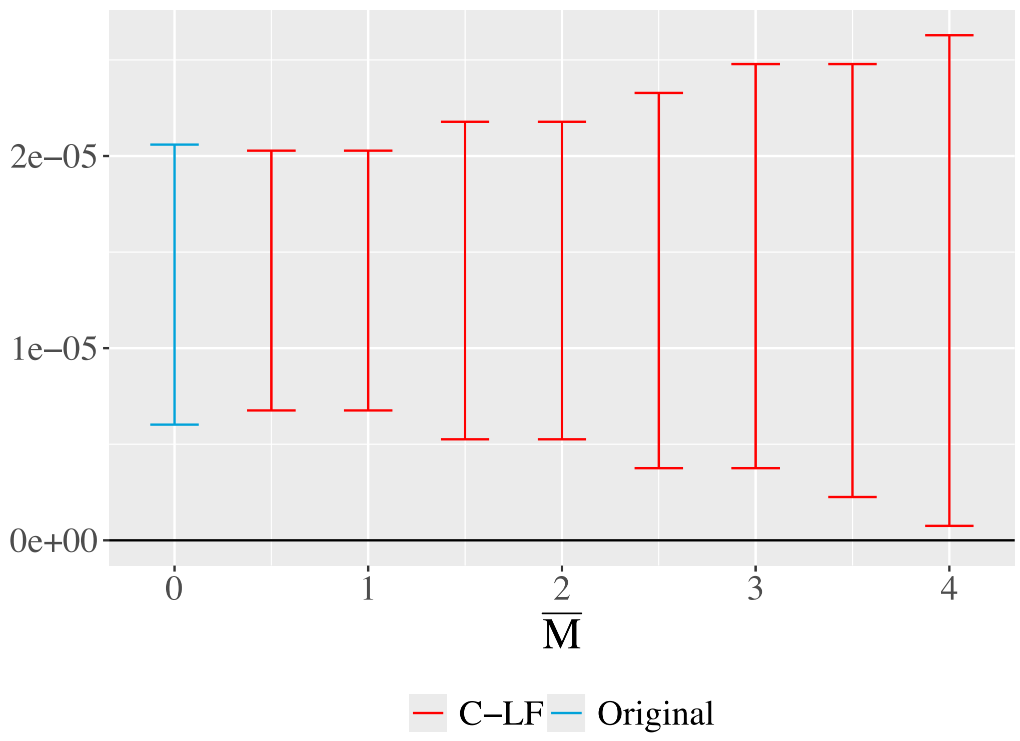
- Differences-in-differences tends to assume parallel pre-trends
- What if this isn't the case?
  - Unobserved shocks to the treatment group might violate the parallel pre-trends assumption
- Honest DiD → Rambachan and Roth (2023):
  - How much larger does the trend difference between treatment & control groups have to be post-treatment, as compared to pre-treatment, for the results to not be valid?

Robustness Checks: Jorts

Non-Union

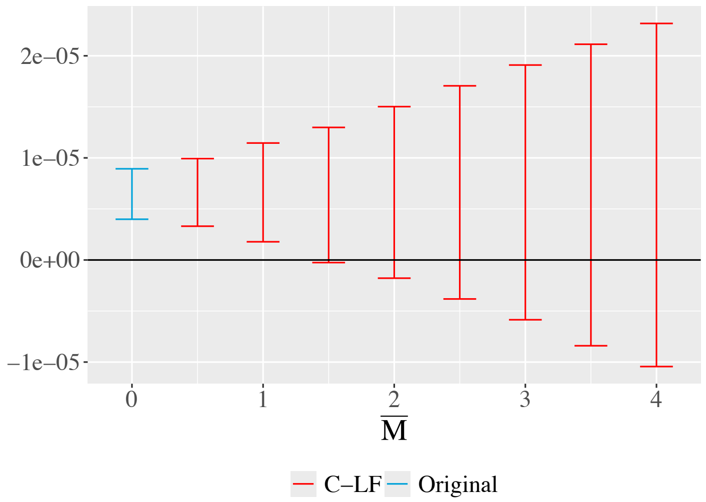


Union

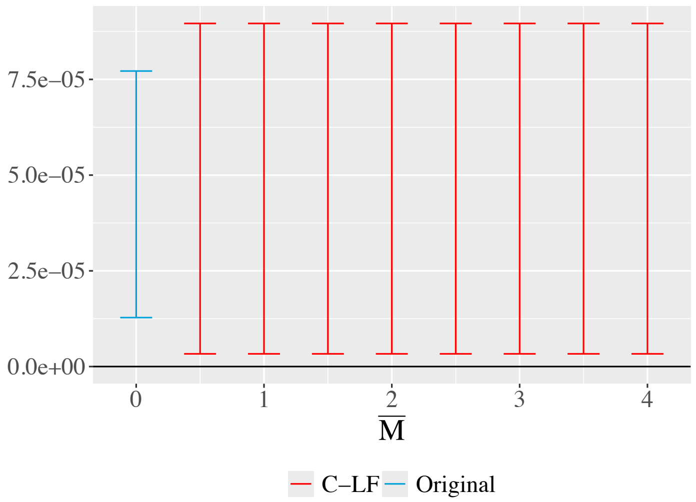


Robustness Checks: Rowling

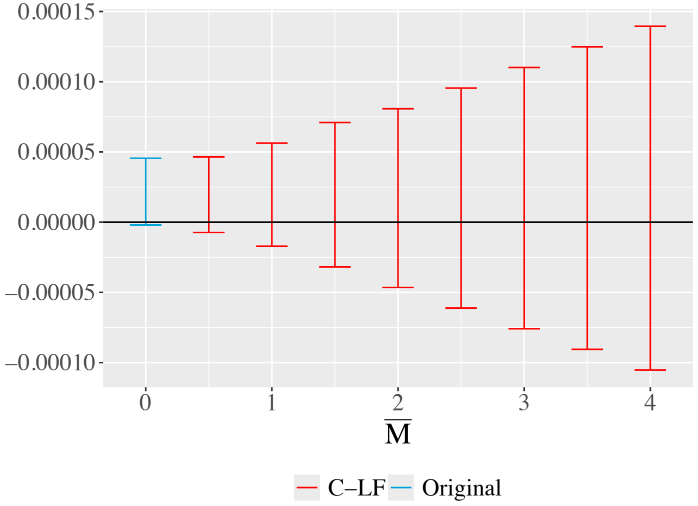
Non-TERF
Non-IA



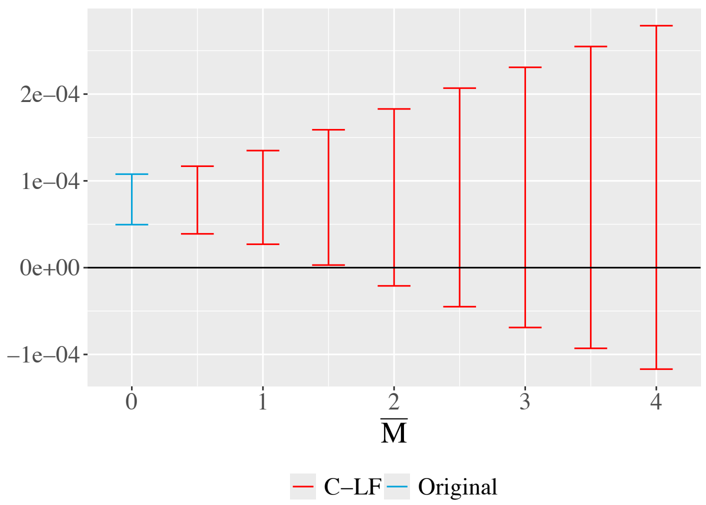
Non-IA
TERF



TERF
Non-IA



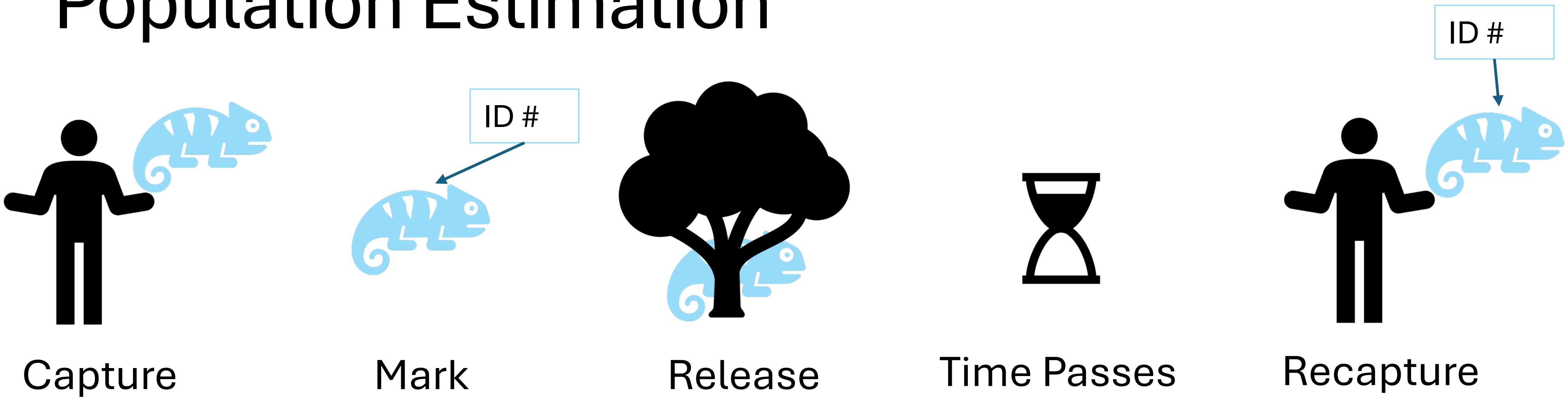
IA
TERF



Population Estimation

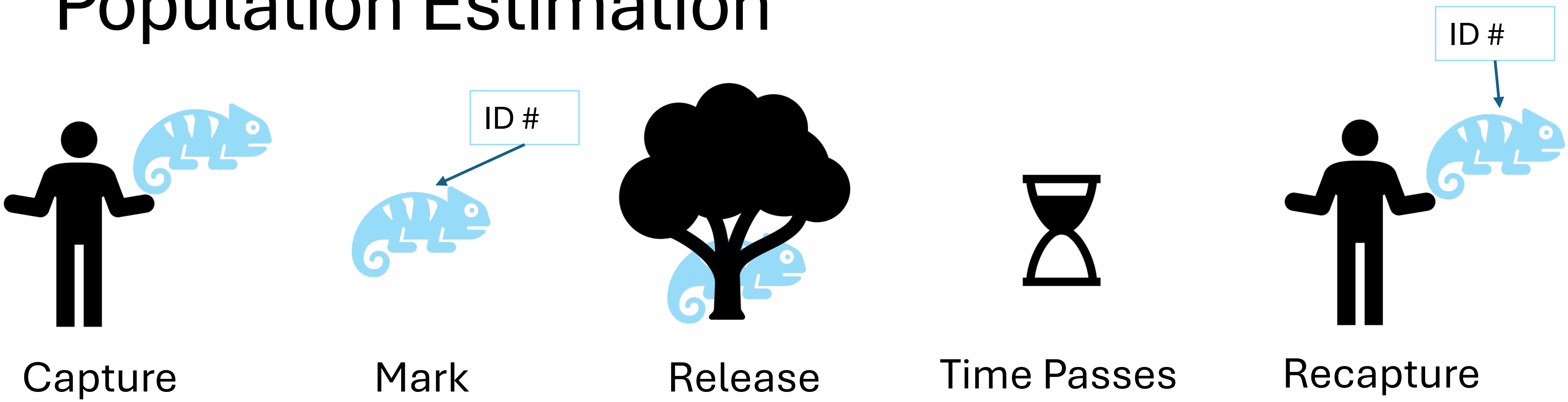
Capture   Mark   Release   Time Passes   Recapture

Population Estimation



Idea: treat each following event as a capture event

Population Estimation

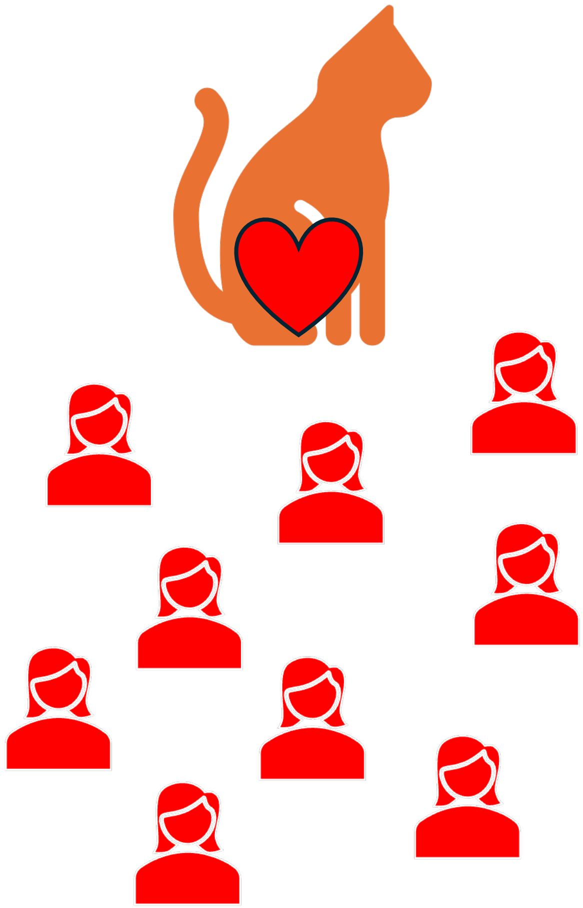


Idea: treat each following event as a capture event

Use Jolly-Seber algorithm to estimate population

Outtakes

What We're Measuring (Data)

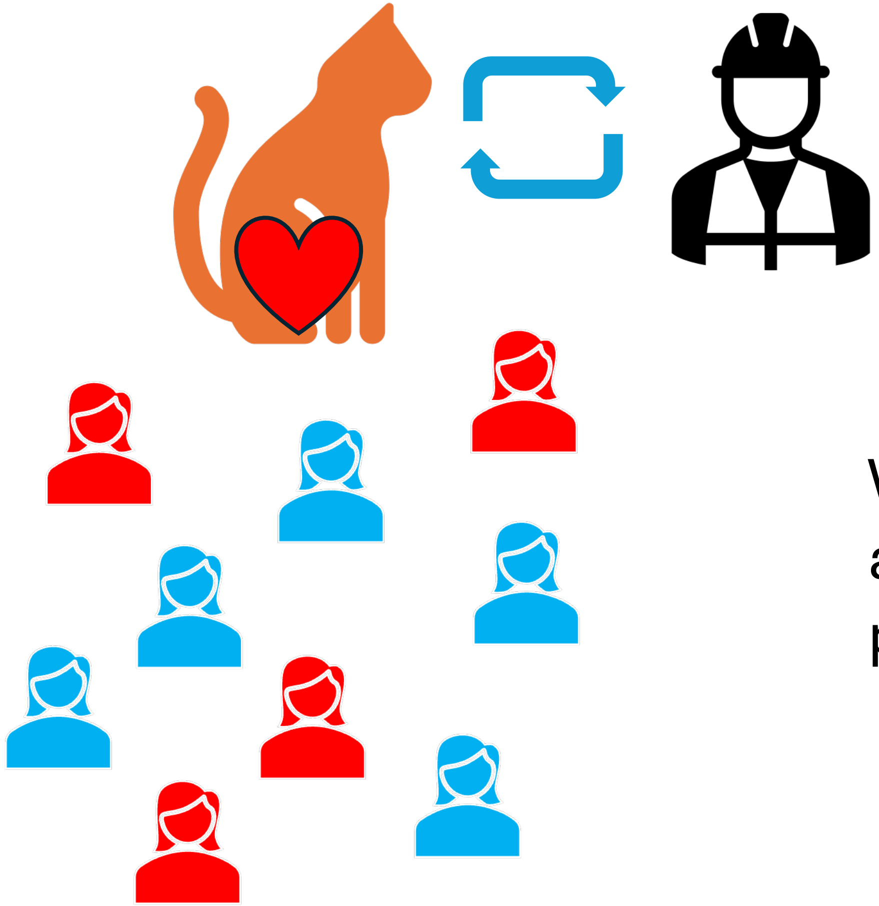


Jorts' Followers

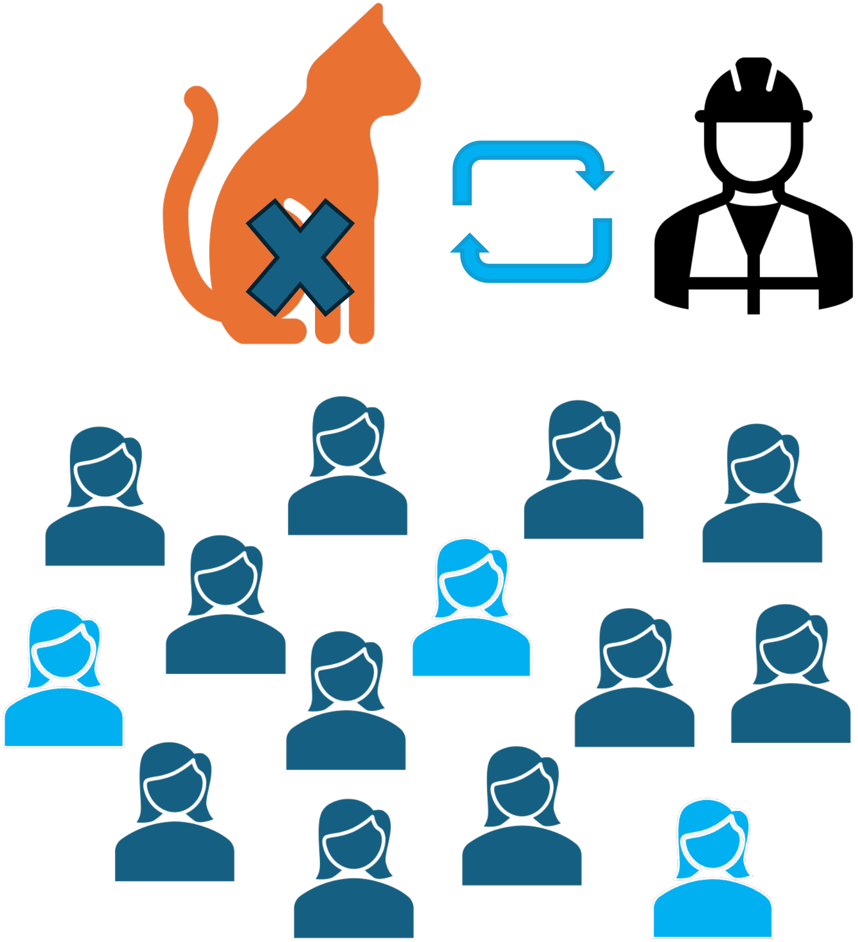
We look at Jorts' **followers'** behavior as well as his **non-followers'**.

Non-followers

What We’re Measuring (Data)



When Jorts **retweets** a user’s post, some people **see it**.



Jorts’ Followers

Non-followers

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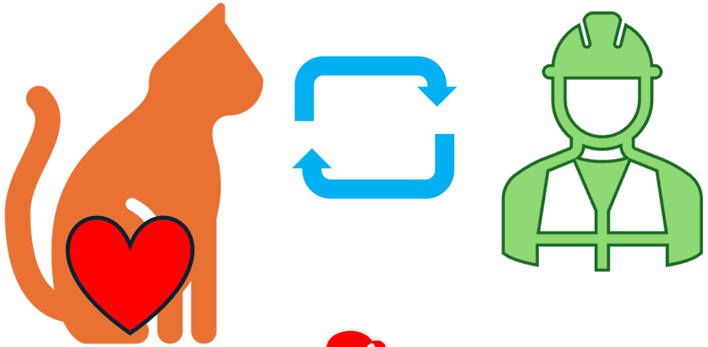
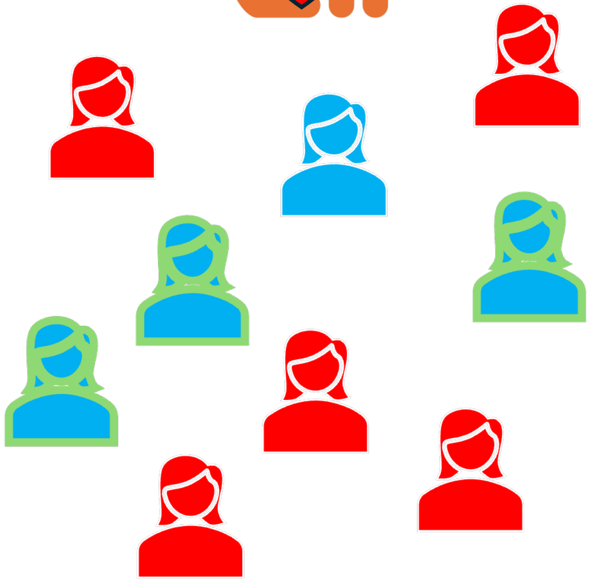


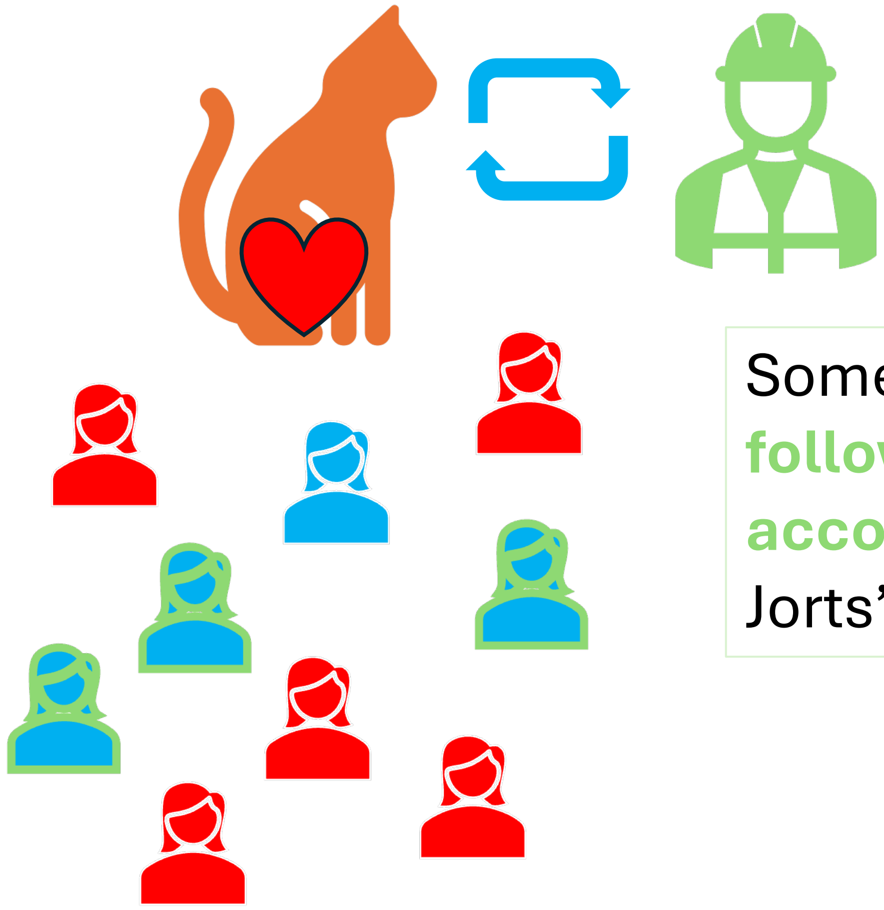


Out of the people who **see the retweet**, some might choose to **follow the retweeted account**.

Jorts' Followers

Non-followers

What We're Measuring (Data)

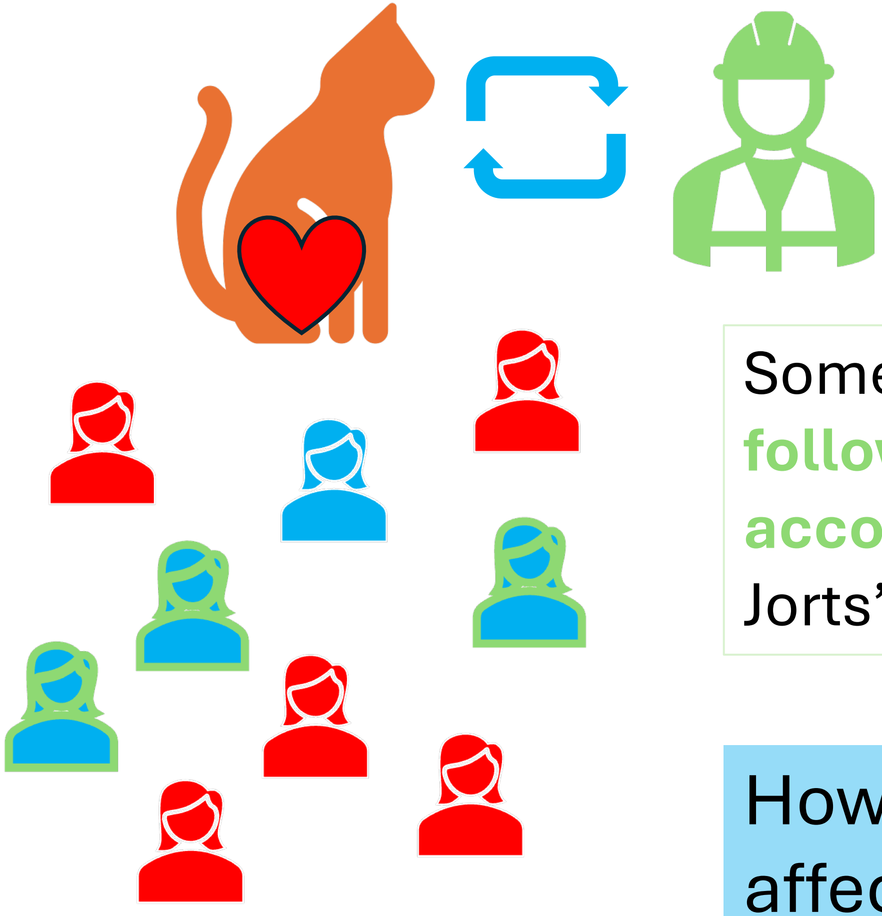


Jorts' Followers

Some people might've **followed** the **retweeted account** regardless of Jorts' **retweet**.

Non-followers

What We're Measuring (Data)



Jorts' Followers

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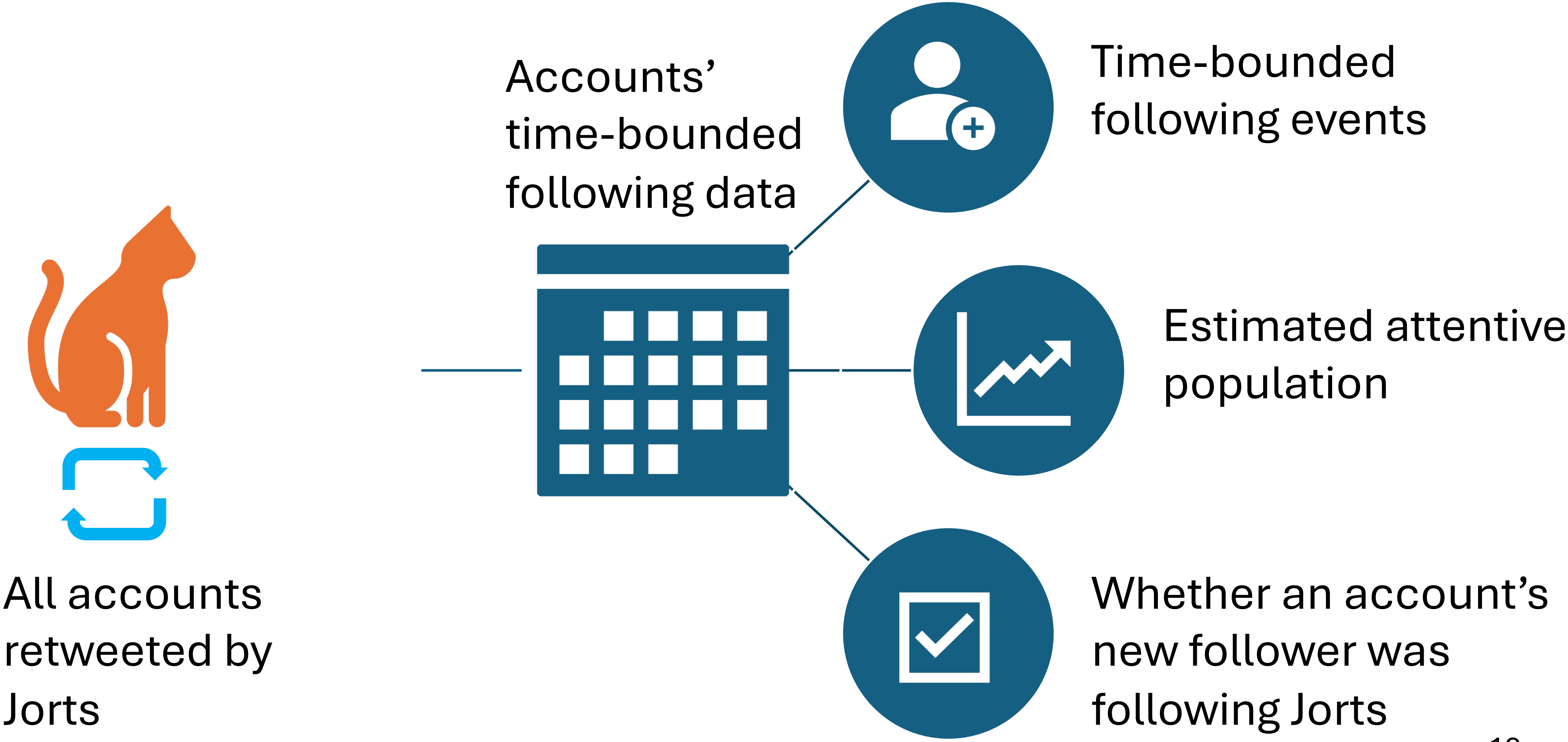
How much is **Jorts** affecting following patterns?

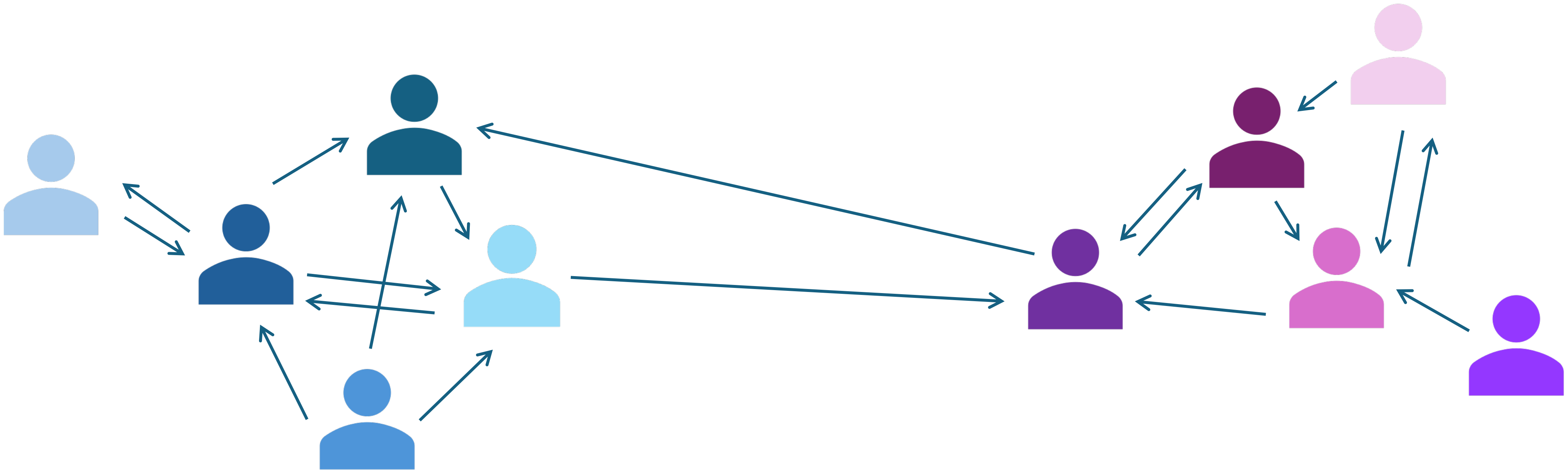
Non-followers


All accounts retweeted by Jorts
Accounts' time-bounded following data
Time-bounded following events
Estimated attentive population
Whether an account's new follower was following Jorts

Homophily

Neighbors in networks tend to be similar to each other* due to...

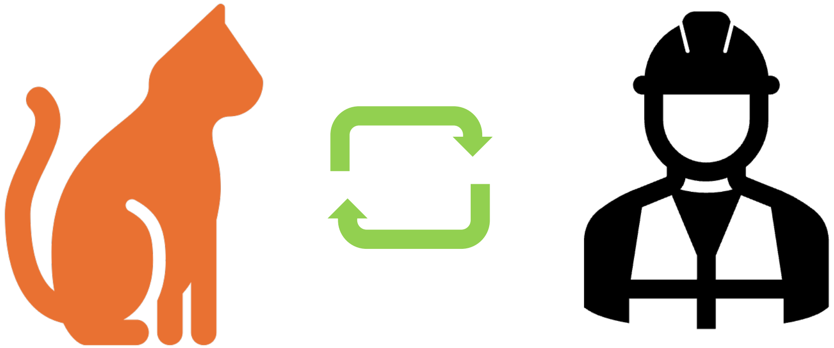
- Structural factors?
- Individual preference?



→ Kossinets and Watts (2009)

Analysis

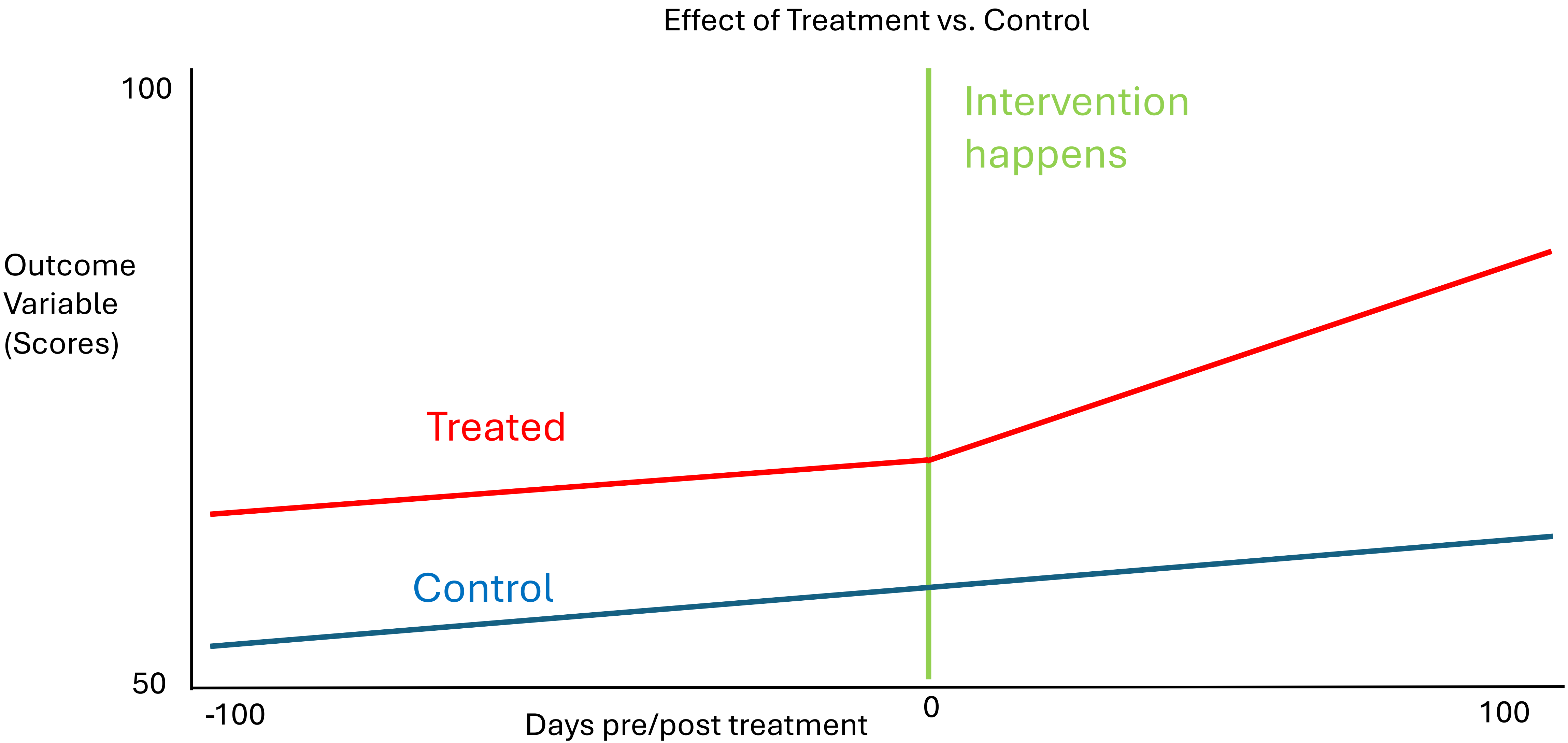
Compute per-day effect size for both account groups (labor-related & not)



Random Account A

$$\mathbb{E}\left[\underbrace{\boxed{\frac{\text{\# of follows to A / day}}{\text{\# of attentive accounts}}}}_{\text{Jorts' followers}} - \underbrace{\boxed{\frac{\text{\# of follows to A / day}}{\text{\# of attentive accounts}}}}_{\text{Non-followers}}\right] = \boxed{\textbf{Per-Day Effect Size}}$$

Differences-in-Differences (toy example)



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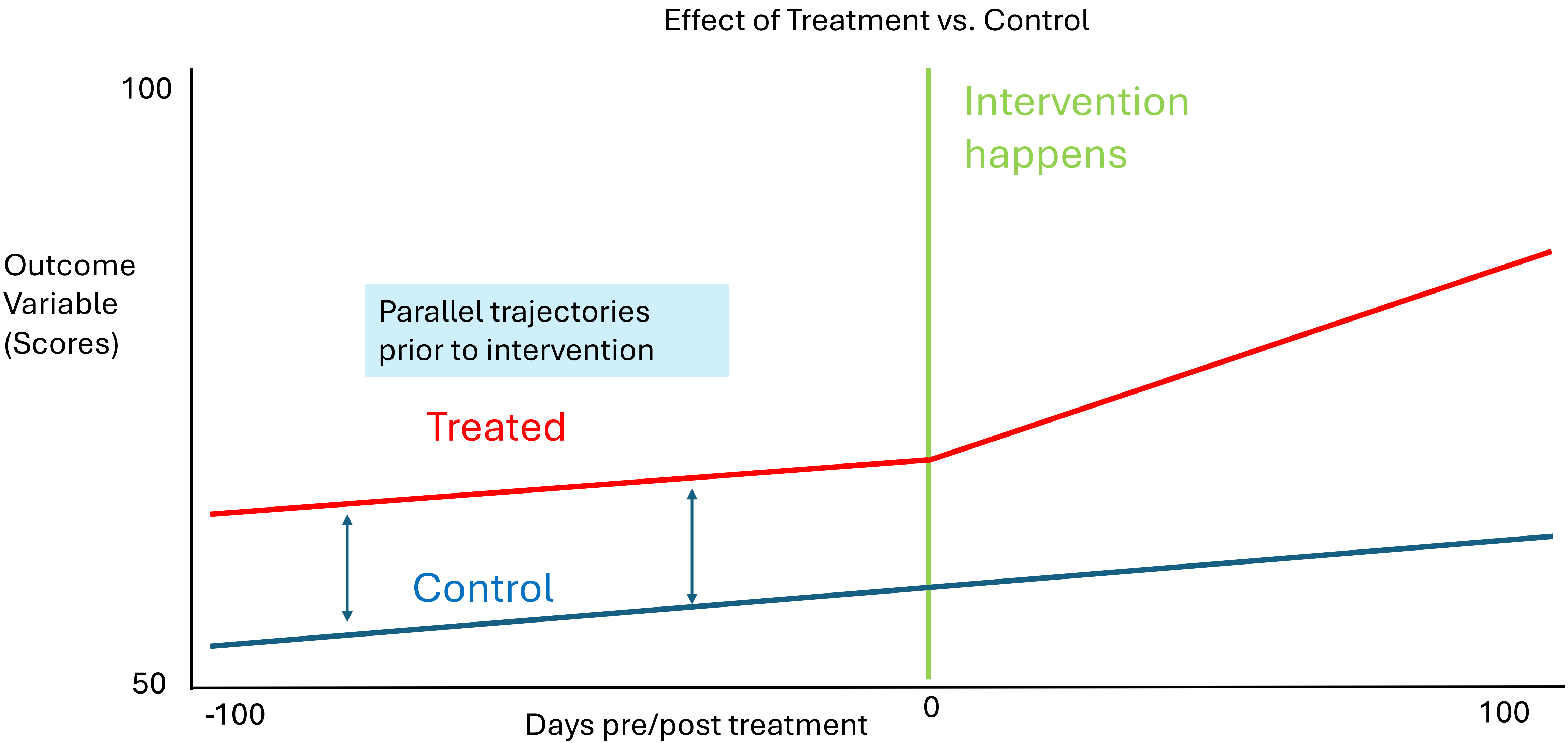

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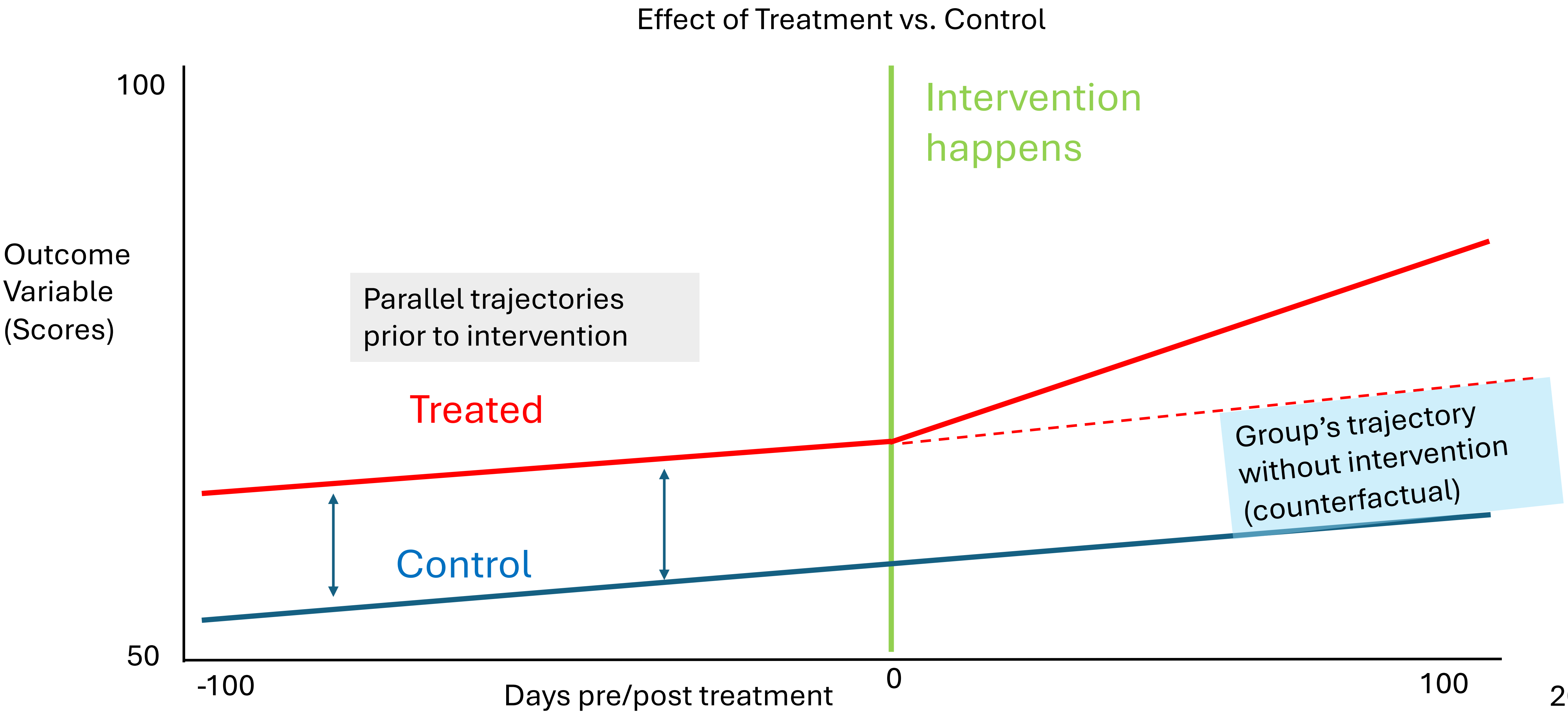

Differences-in-Differences (toy example)