23 INFLUENCER MARKETING

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Eco della Viralità: Connettere, Coinvolgere, Esasperare

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Traditional and New Media

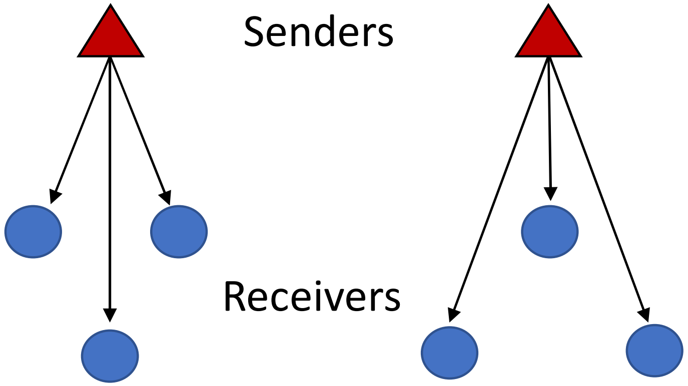
- Intermediated
- Few sources
- Vertical communication
- Linear information consumption

- Disintermediated
- Countless sources
- Horizontal communication
- Non-linear information consumption

Attention Economy

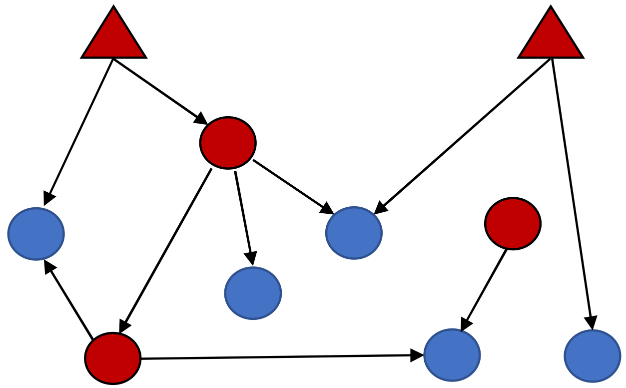
"A family of senders which employ costly signals to attract the attention of receivers characterized by their limited capacity." [1]

Traditional Media



"An information-rich world creates a poverty of attention" [2]

New Media



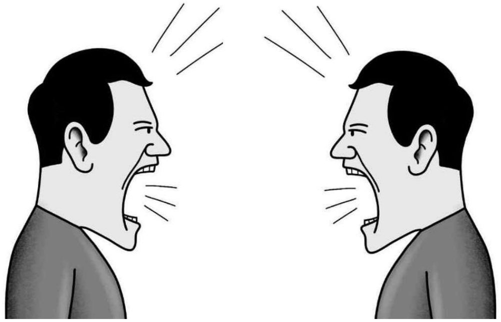
[1] - Falkinger, J. (2003). Attention Economies. *Behavioral & Experimental Economics*.
[2] - Simon, H. A. (1971). Designing organizations for an information-rich world. In M. Greenberger (Ed.), *Computers, Communications, and the Public Interest*. Johns Hopkins Press.

Major emerging dynamics on Social Networks

Echo-chambers

Groups of like-minded users framing and reinforcing a shared narrative. [3]

Polarization



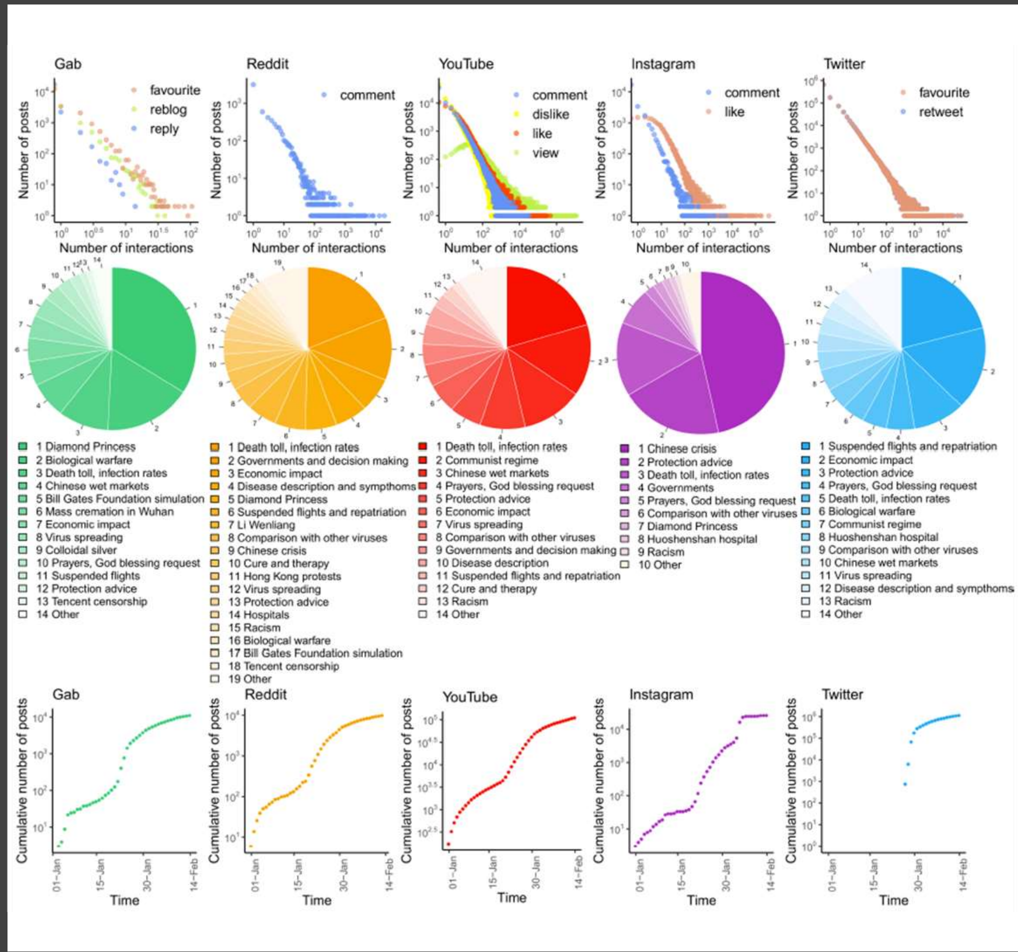
The tendency of users to interact with only a single type of information[4], usually strongly rejecting opposite points of view.

[3] Cinelli et al. (2021). *The echo chamber effect on social media*. Proceedings of the National Academy of Sciences. 118.

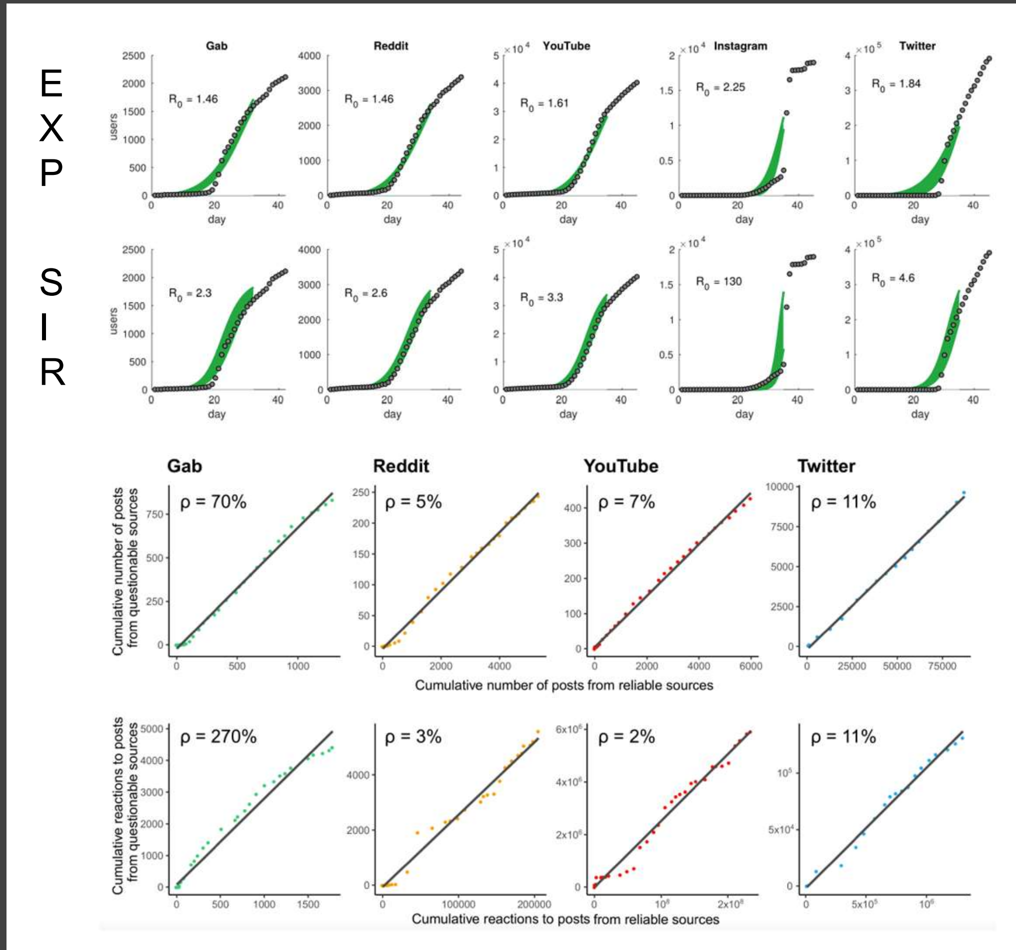
[4] Bessi et al. (2016). *Homophily and polarization in the age of misinformation*. The European Physical Journal Special Topics, 225(10), 2047-2059.

The COVID-19 Social Media Infodemic

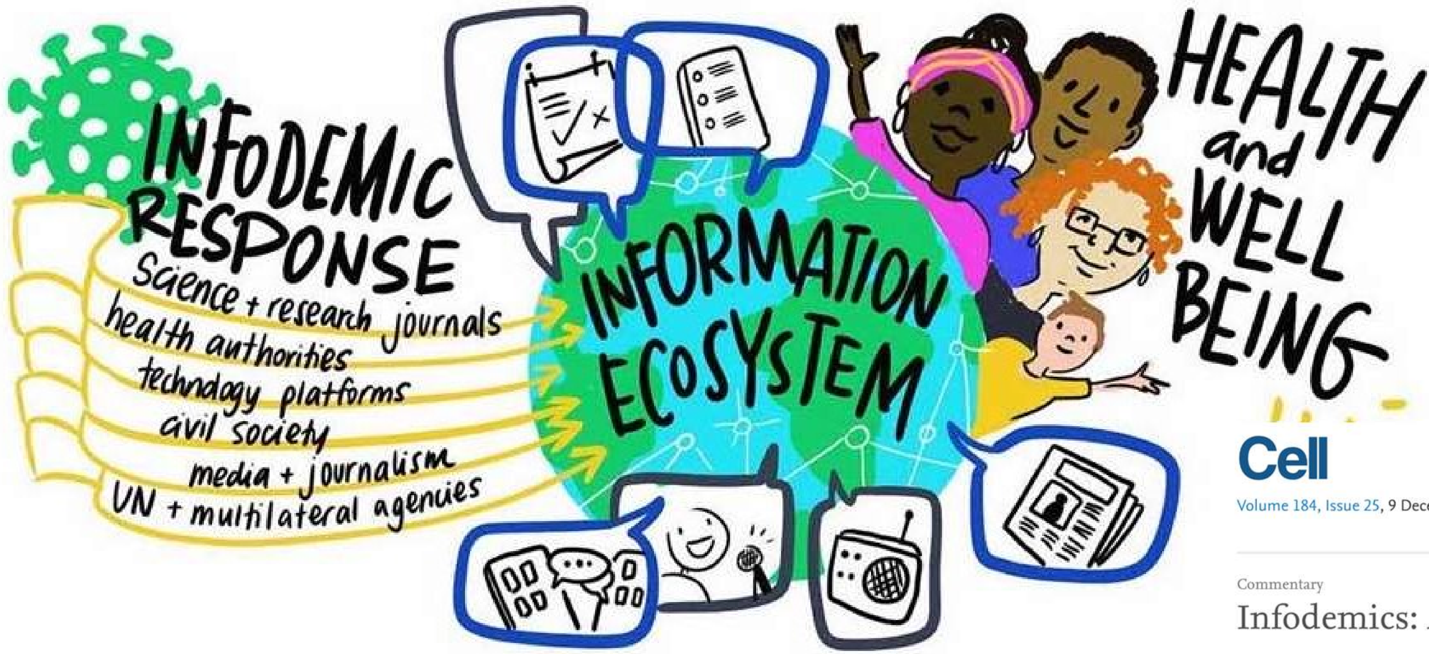
- Users behave similarly for what concern the dynamics of reactions and content consumption
- Users' interactions patterns with the COVID-19 content are similar to any other topic
- Change of behavior around the 20th of January but with different delays: social media platforms seem to have specific timings for content consumption



The COVID-19 Social Media Infodemic Results



- R0 depends on different platforms
- Questionable and Reliable source spread with the same dynamic, but differ in terms of volume.
- The ratio questionable/reliable changes from social media to social media.
- Notably, Gab is very prone to disinformation diffusion.



Cell
Volume 184, Issue 25, 9 December 2021, Pages 6010-6014

CellPress

Commentary

Infodemics: A new challenge for public health

Sylvie C. Briand [1], Matteo Cinelli [2], Tim Nguyen [3], Rosamund Lewis [4], Dimitri Prybylski [5], Carlo M. Valensise [6], Vittoria Colizza [7], Alberto Eugenio Tozzi [8], Nicola Perra [9], Andrea Baronchelli [10], Michele Tizzoni [11], Fabiana Zollo [2], Antonio Scala [12, 13], Tina Purnat [3], Christine Czerniak [1], Adam J. Kucharski [14], Akhona Tshangela [15], Lei Zhou [16], Walter Quattrociocchi [17]

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Get rights and content

The COVID-19 information epidemic, or “infodemic,” demonstrates how unlimited access to information may confuse and influence behaviors during a health emergency. However, the study of infodemics is relatively new, and little is known about their relationship with epidemics management. Here, we discuss unresolved issues and propose research directions to enhance preparedness for future health crises.

THE EFFECT OF ALGORITHMS

Check for updates

The echo chamber effect on social media

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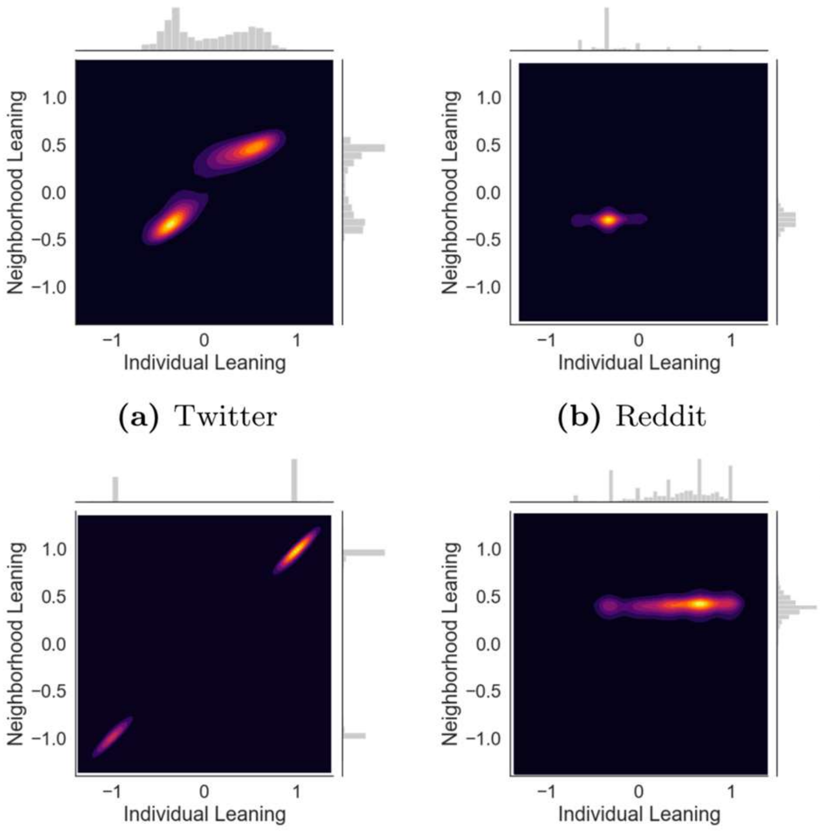
Edited by Arild Underdal, University of Oslo, Oslo, Norway, and approved January 14, 2021 (received for review November 15, 2020)

Social media may limit the exposure to diverse perspectives and favor the formation of groups of like-minded users framing and reinforcing a shared narrative, that is, echo chambers. However, the interaction paradigms among users and feed algorithms greatly vary across social media platforms. This paper explores the key differences between the main social media platforms and how they are likely to influence information spreading and echo chambers' formation. We perform a comparative analysis of more than 100 million pieces of content concerning several controversial topics (e.g., gun control, vaccination, abortion) from Gab, Facebook, Reddit, and Twitter. We quantify echo chambers over social media by two main ingredients: 1) homophily in the interaction networks and 2) bias in the information diffusion toward like-minded peers. Our results show that the aggregation of users in homophilic clusters dominate online interactions on Facebook and Twitter. We conclude the paper by directly comparing news consumption on Facebook and Reddit, finding higher segregation on Facebook.

tion and public opinion formation. In this paper, we explore the key differences between social media platforms and how they are likely to influence the formation of echo chambers or not. As recently shown in the case of selective exposure to news outlets, studies considering multiple platforms can offer a fresh view on long-debated problems (34). Different platforms offer different interaction paradigms to users, ranging from retweets and mentions on Twitter to likes and comments in groups on Facebook, thus triggering very different social dynamics (35). We introduce an operational definition of echo chambers to provide a common methodological ground to explore how different platforms influence their formation. In particular, we operationalize the two common elements that characterize echo chambers into observables that can be quantified and empirically measured, namely, 1) the inference of the user's leaning for a specific topic (e.g., politics, vaccines) and 2) the structure of their social interactions on the platform. Then, we use these elements to assess echo chambers' presence by looking

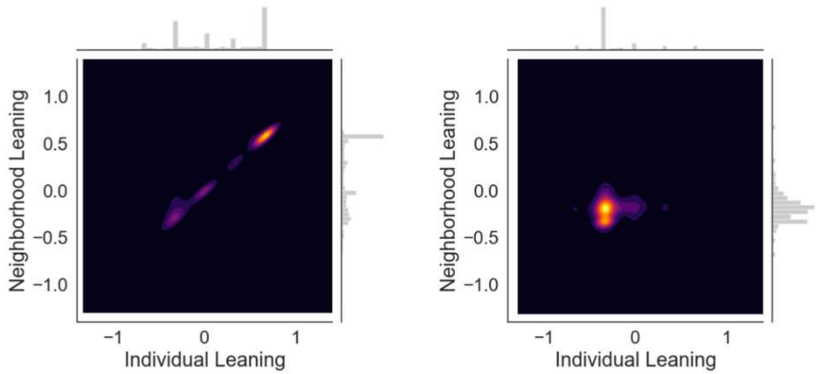
POLARIZATION ON DIFFERENT PLATFORMS



(a) Twitter (b) Reddit

(c) Facebook (d) Gab

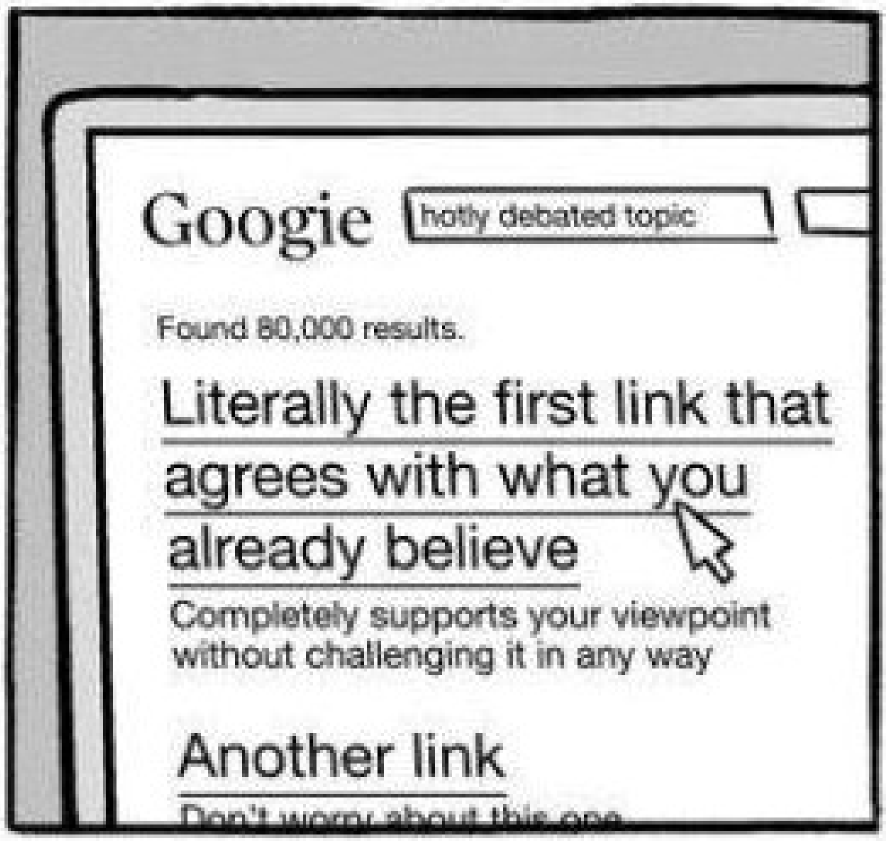
NEWS AND POLARIZATION



A., Quattrociocchi, W., & Starnini, M. (2020). Echo chambers on social media: A comparative analysis. *arXiv preprint arXiv:2004.09603*. under revision to Science Advances

Selective Exposure

The tendency of users to ignore dissenting information and to interact with information adhering to their preferred narrative.[5]



[5] Cinelli et al. (2020). Selective exposure shapes the Facebook news diet. *PloS one*, *15*(3), e0229129.

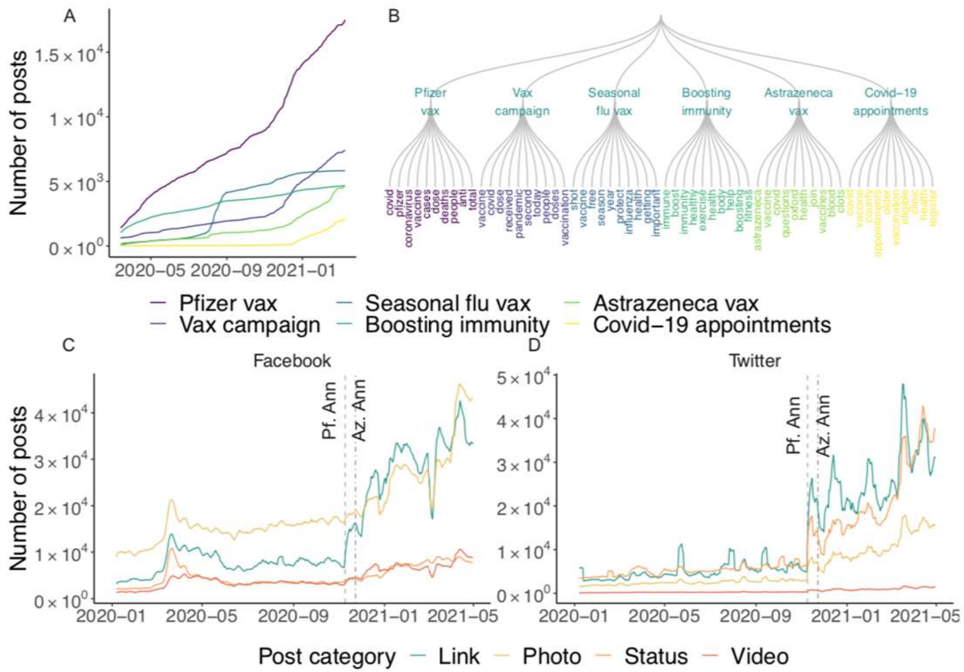


Figure 1: **Vaccine debate on social media platforms.** Panel A: evolution of debated topics over time. Panel B: Keywords representing the main topics. Panel C and D: seven days moving average of posts divided by category for Facebook and Twitter respectively. Dashed lines represent the announcement of Pfizer and AstraZeneca COVID-19 vaccine effectiveness occurred on 18 November and 23 November 2020, respectively.

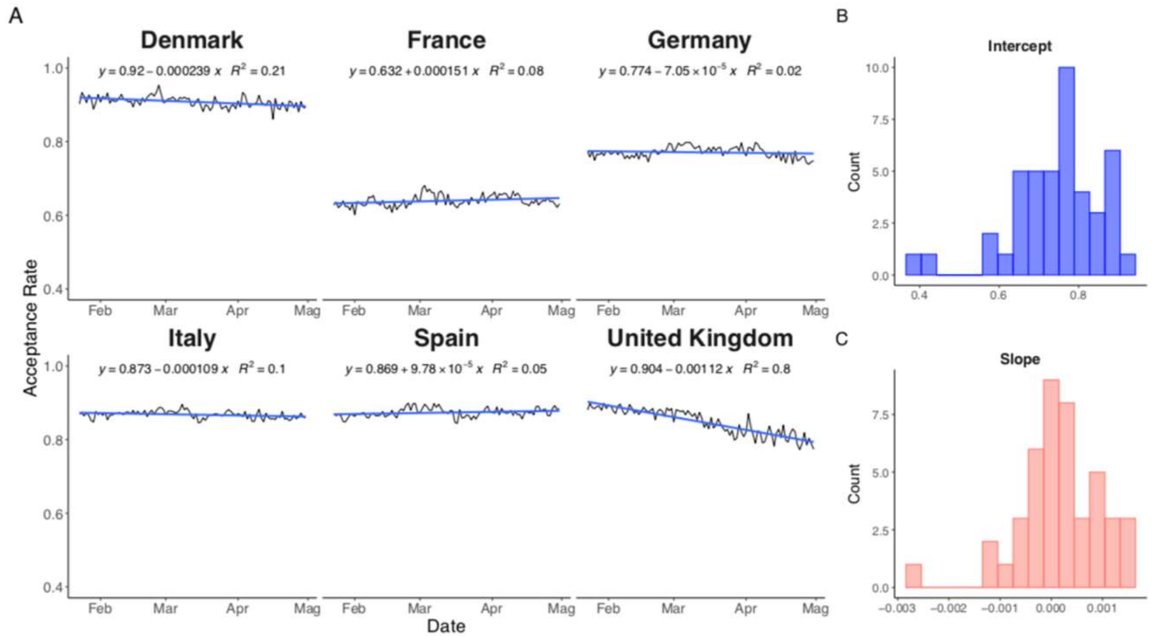


Figure 3: **Steady acceptance of COVID-19 vaccines.** Panel A: Black lines represent three days moving average of vaccine acceptance rate for Denmark, France, Germany, Italy, Spain, and United Kingdom from 23 January to 30 April 2021 according to Facebook COVID-19 Trends and Impact Survey. The blue lines are the linear fit on the trend. Panel B (C): Histogram of regression intercepts (slopes) for countries with more than 500 average daily respondents.

How long does attention survive?

Dataset

Users	Posts	Total Interactions		Analysis Period	
2.224.430	57.031.026	8.015.177.602		1/1/2018 – 31/12/2021	
Total	**Topics**	**Events**		**National**	**International**
296	209	87		184	112
	Person	**People**	**Organization**	**Place**	**Undefined**
	100	61	69	45	32
	Art-Culture-Sport	**Economy**	**Environment**	**Human Rights**	**Labor**
	34	50	52	89	47
	Politics	**Religion**	**Social**	**Tech-Science**	**Health**
	141	28	140	36	24
Victims	**Crime**	**Disaster**	**Scandal**	**Violence**	**War-Terrorism**
64	57	38	91	44	40

Geographical

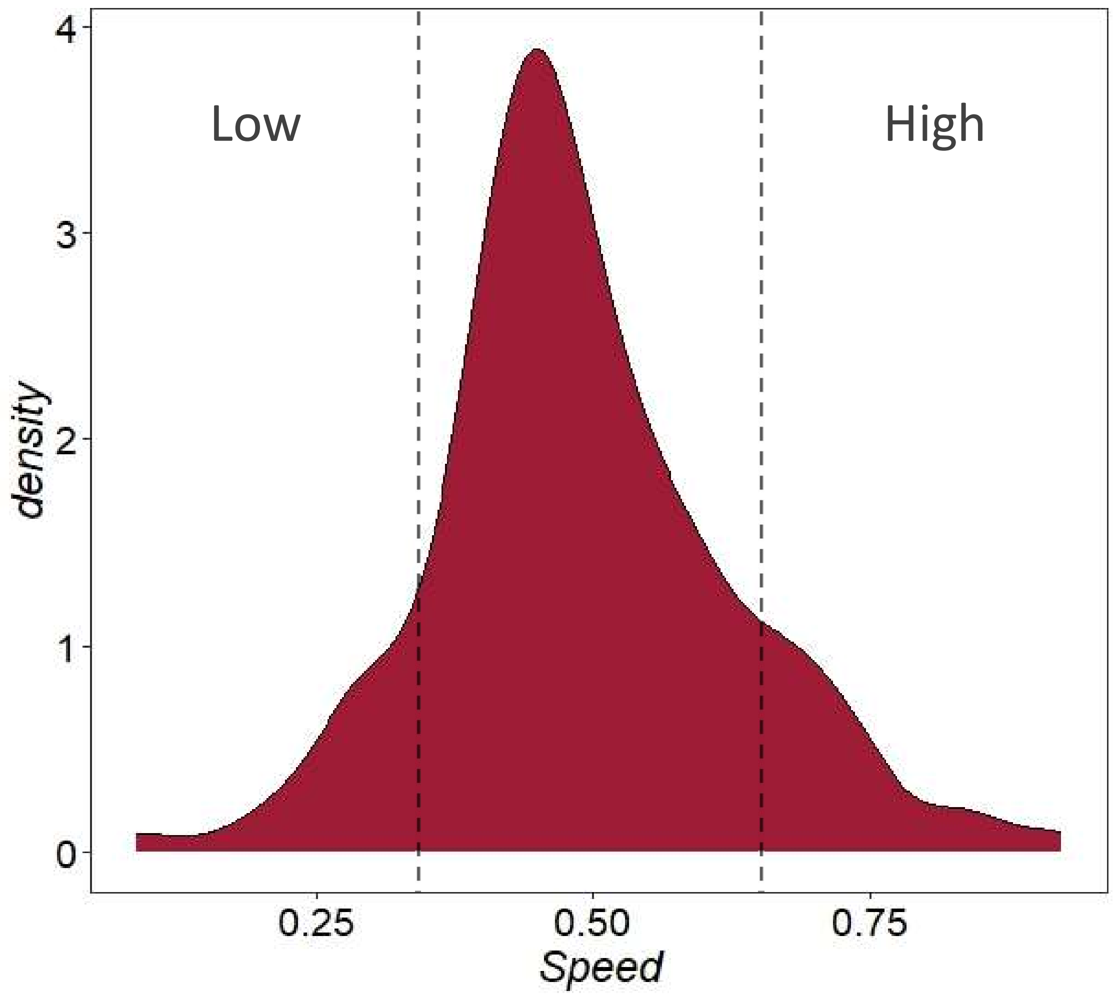
Subject

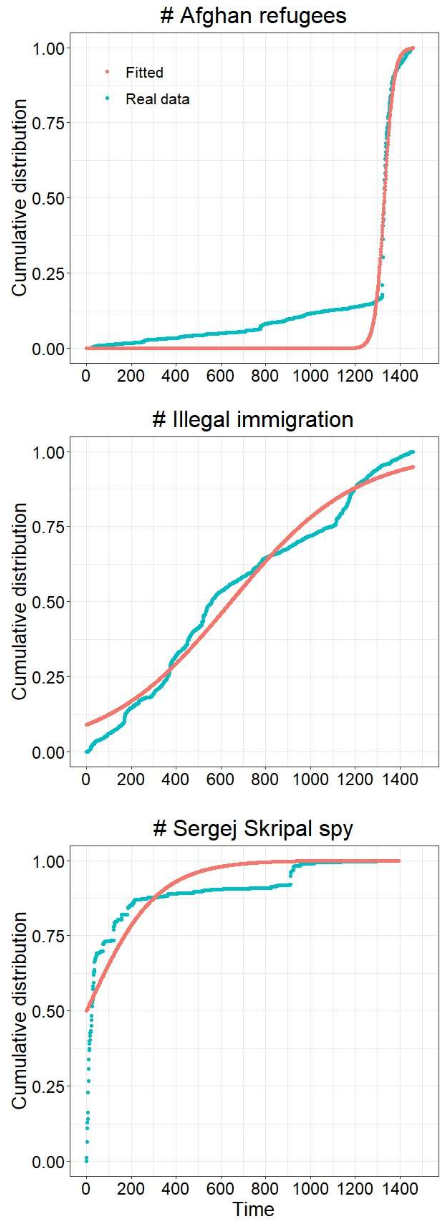
Category

Harmfulness

Results – 1) Engagement Dynamics

Distribution of topics' saturation speed





Low

Medium

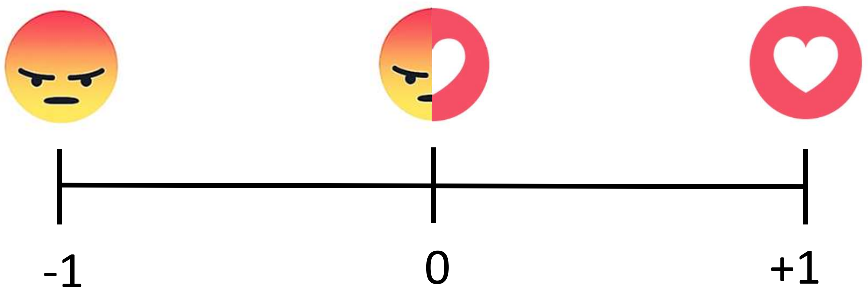
High

Results - 2) Sentiment Dynamics

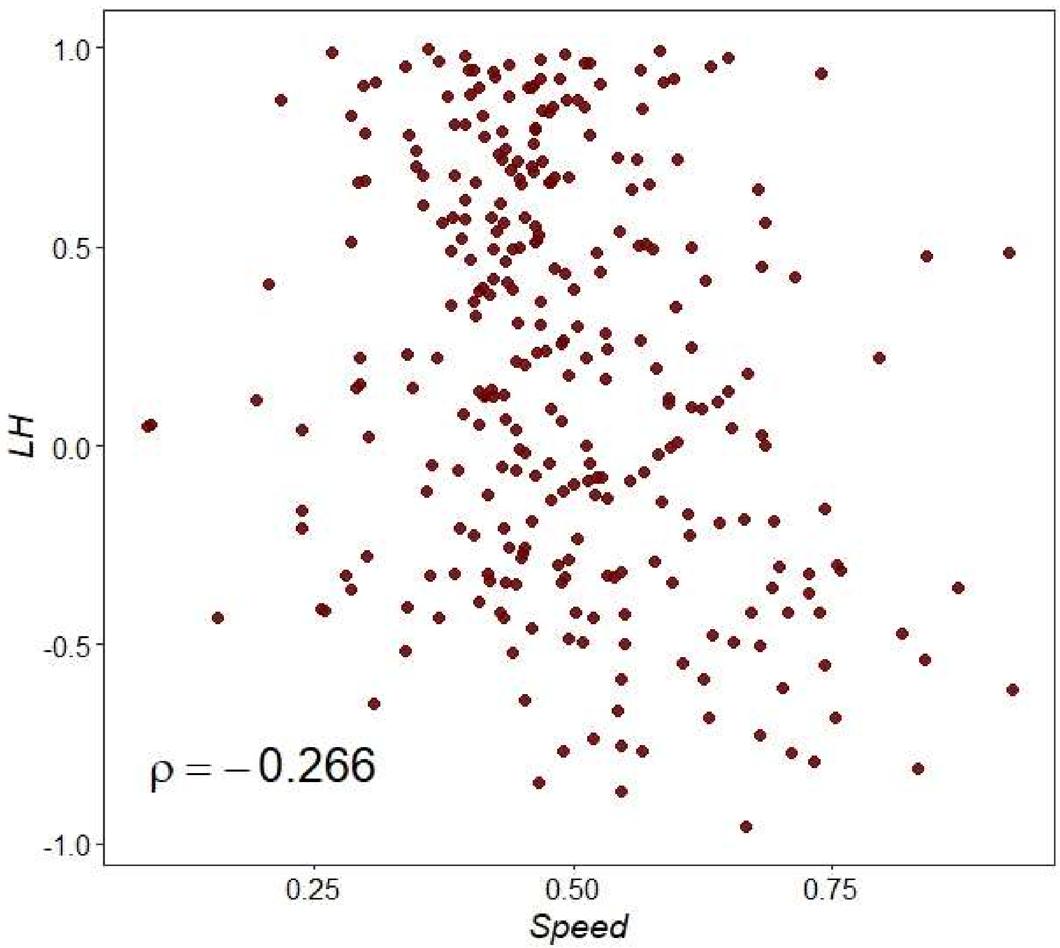
Love-Hate score

Relying on **Love** and **Angry** reactions of Facebook's posts, we define a sentiment ratio as:

$$LH = \frac{1}{n}\sum_{i=1}^{n}\frac{Love - Angry}{Love + Angry}$$



Speed - LH Score Correlation



Results – 3) Sentiment across categories

Spearman correlation between LH Score and Speed per category

	Art-Culture-Sport	Economy	Environment	Human Rights	Labor
	-0.23	-0.27	-0.24	-0.21	-0.44
	Politics	**Religion**	**Social**	**Tech-Science**	**Health**
	-0.33	-0.07	-0.26	-0.37	-0.55
Victims	**Crime**	**Disaster**	**Scandal**	**Violence**	**War-Terrorism**
-0.22	-0.33	-0.39	-0.39	-0.21	-0.02

Topics and categories show similar evolution patterns
but sentiment dynamics differ between categories

Take-Home Message

- Emergence of a persisting bulk of on-going topics which hold the attention constantly over time

- Topics with sudden saturation tend to trigger more negative and heated interactions

- Some categories show a stronger relationship between speed of saturation and users’ sentiment

Dataset

- **Entire history** of Facebook posts (2008 - 2023)
- More than **1000 news outlets** in **4 languages**
- Sourced from Newsguard, obtained through Crowdtangle

	Pages	**Posts**
English	223	11.482.164
French	245	11.762.328
German	257	12.105.772
Italian	357	22.201.370
Total	1082	57.551.634

Theoretical Framework

Defined by Robert Gibrat in 1931, **Gibrat's law** states that [4]

the growth rate of a firm is independent of its absolute size.

Growth can be formalized by the random multiplicative process:

$$S_{t+\Delta t} = S_t\,(1+\varepsilon_t)$$

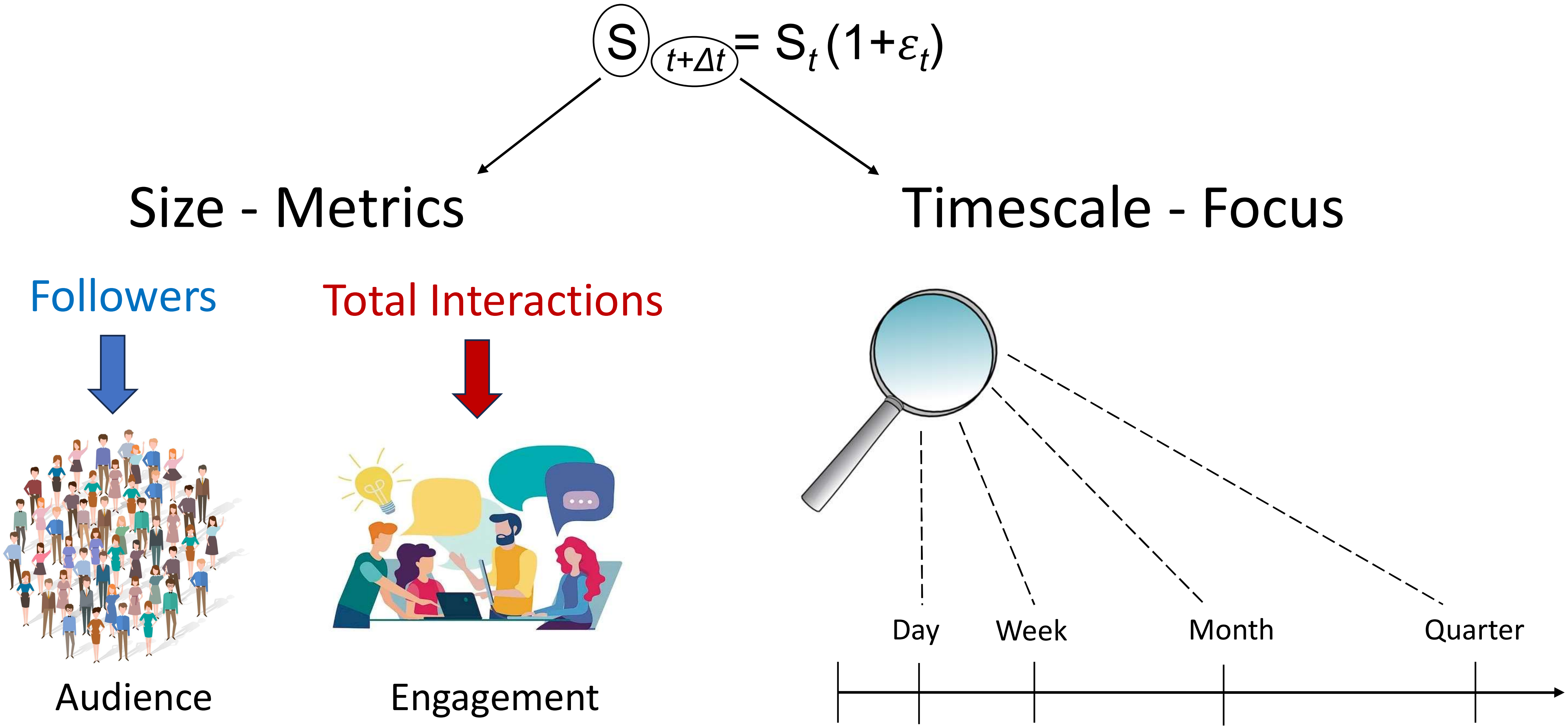
where $\mathbf{S}_{\boldsymbol{t}}$ and $\mathbf{S}_{\boldsymbol{t+\Delta t}}$ are the size of the company at time $\boldsymbol{t}$ and $\boldsymbol{t+\Delta t}$, and $\boldsymbol{\varepsilon_t}$ is an uncorrelated random variable with $\boldsymbol{\mu} \cong 0$ and $\boldsymbol{\sigma} \ll 1$.

Gibrat assumed that:

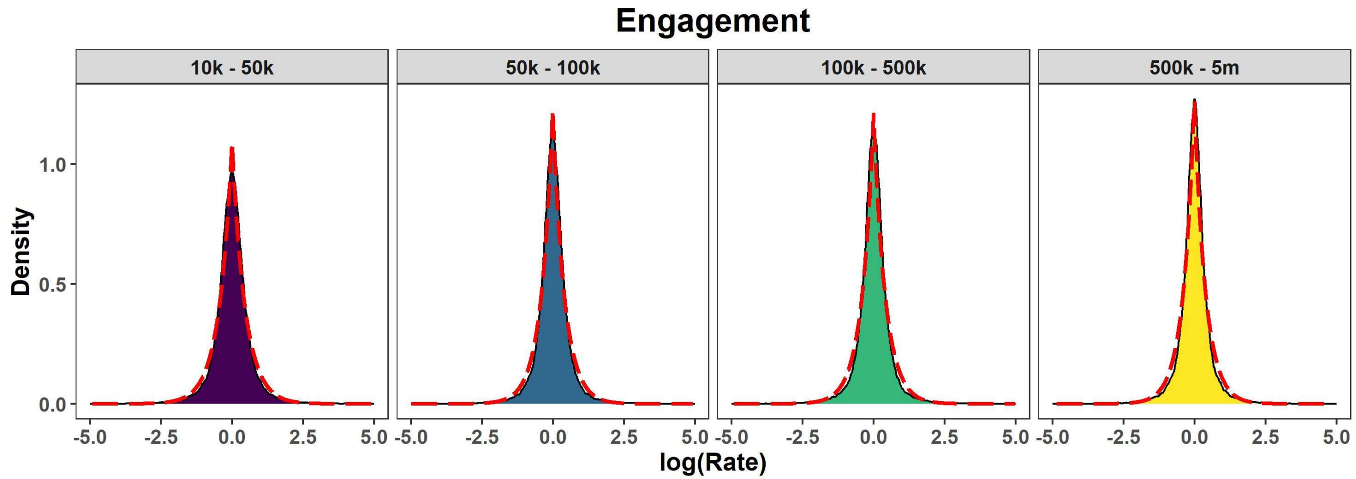
1) $\boldsymbol{\varepsilon_t}$ **is independent of** $\mathbf{S}_{\boldsymbol{t}}$ (Gibrat’s Law)
2) ε_t has no temporal correlation
3) There is no interaction between firms

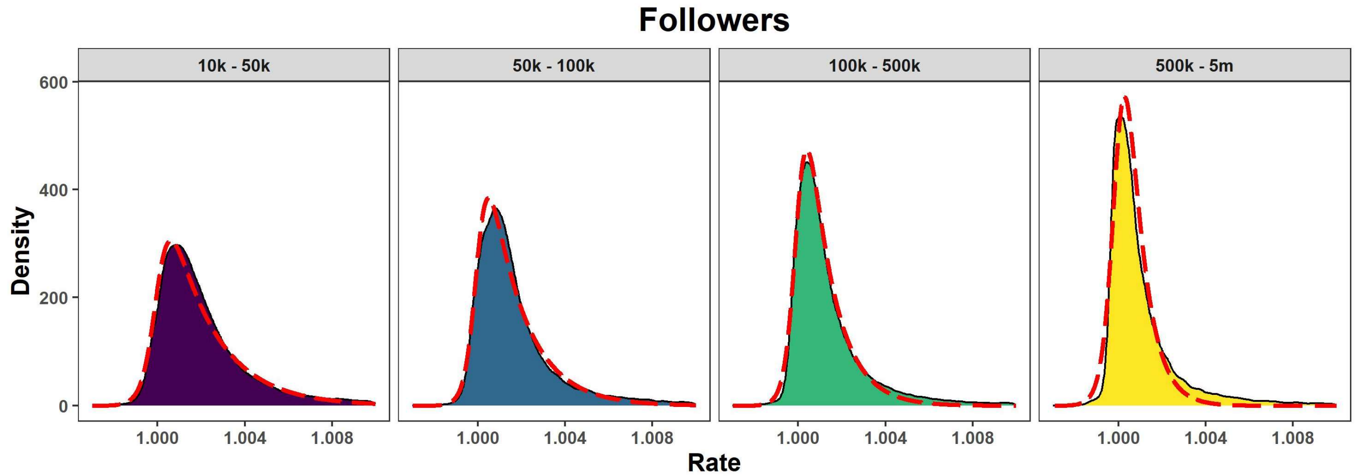
[4] Gibrat, R. (1931). Les inégalits économiques. *Sirey*.

Analysis definition



2 – Evaluating growth dynamics





Laplace Distribution [5, 6]

$$p(x \mid \mu, b) = \frac{1}{2b} exp(-\frac{|x-\mu|}{b})$$

Burr Distribution

$$p(x \mid c, k) = ck\cdot\frac{x^{c-1}}{(1+x^{c})^{k+1}}$$

[5] Stanley, M. H. et al. (1996). Scaling behaviour in the growth of companies. *Nature*, *379*(6568), 804-806.
[6] Fujiwara, Y. et al. (2004). Do Pareto–Zipf and Gibrat laws hold true? An analysis with European firms. *Physica A*, *335*(1-2), 197-216.

3 - Modeling growth

Knowing the distributions that describe the growth of our metrics allow us to evaluate the variation of their parameters according to size and timescale.

We can therefore simulate growth on the chosen timescale,
given two starting values of Followers and Engagement, F_0 and E_0.

Step 1: Engagement growth

$$E_{t+1} = E_t(1+\varepsilon_t)$$

where:

$$f\,(\varepsilon_t \mid \mu, b) = \frac{1}{2b} exp(-\frac{|x-\mu|}{b})$$

with :

$$\mu = \beta_0 + \beta1_{\mu} \cdot ln(F_t) + \beta2_{\mu} \cdot ln(E_t)$$

$$b = \beta_0 + \beta1_{b} \cdot ln(F)_t + \beta2_{b} \cdot ln(E_t)$$

Step 2: Followers growth

$$F_{t+1} = F_t(1+\delta_t)$$

where:

$$f\,(\delta_t \mid c, k) = ck \cdot \frac{x^{c-1}}{(1+x^c)^{k+1}}$$

with :

$$c = \beta_0 + \beta1_{c} \cdot ln(F_t)$$

$$k = \beta_0 + \beta1_{k} \cdot ln(F_t)$$

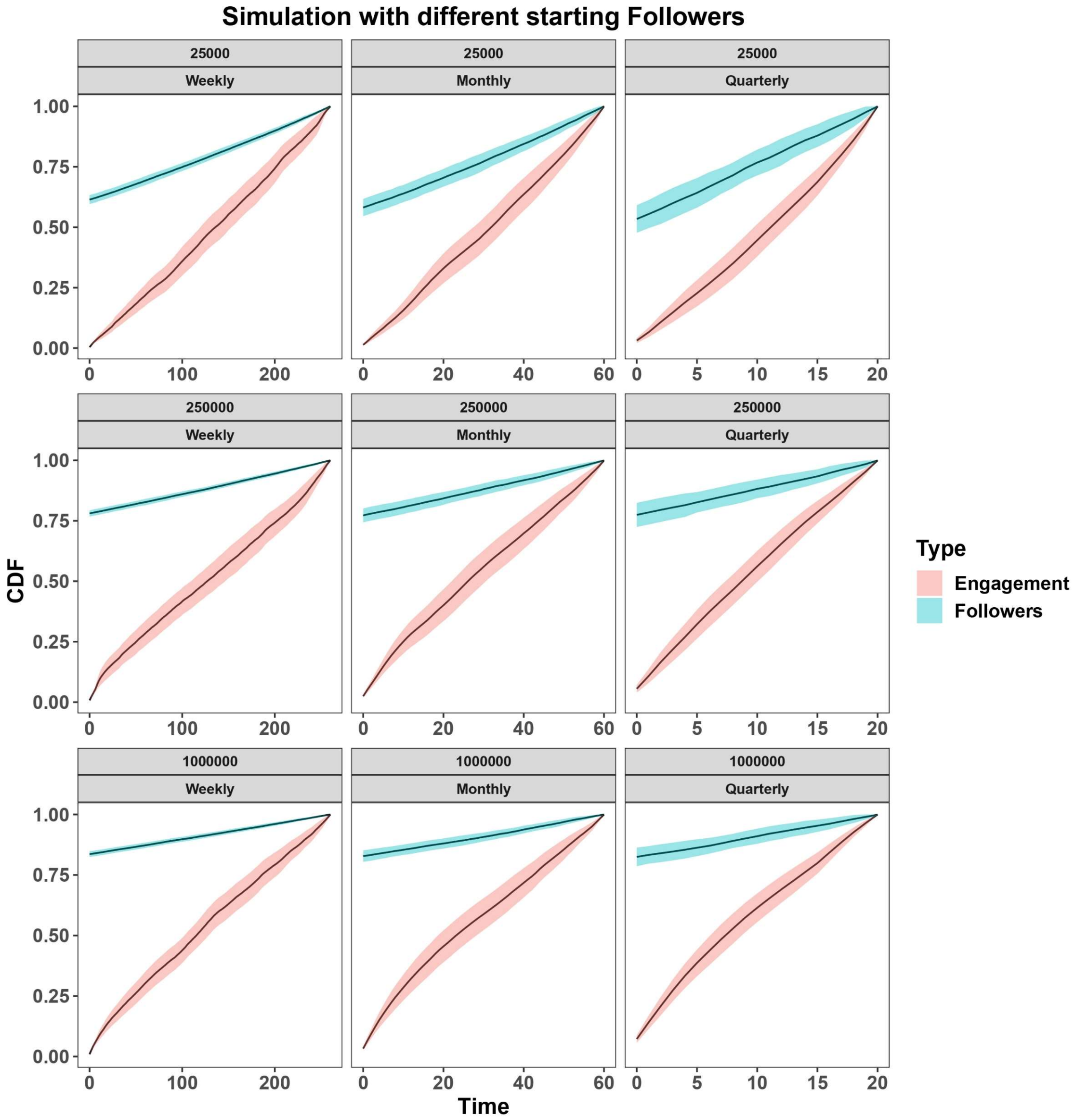
β0	β1	β2	Parameter	Timescale
-0.109	0.054	-0.062	*μ*	w
0.073	0.037	-0.051	*μ*	m
0.384	0.031	-0.065	*μ*	q
0.613	0.027	-0.054	*b*	w
0.593	0.041	-0.066	*b*	m
0.844	0.056	-0.094	*b*	q
8,420.469	-372.77	-	*c*	w
2,550.010	-127.559	-	*c*	m
1,053.905	-56.113	-	*c*	q
-0.778	0.083	-	*k*	w
-0.751	0.078	-	*k*	m
-0.714	0.073	-	*k*	q

Results

Sizes represent pages with low, medium and high number of Followers.

Even by modeling engagement probability of growth based on Followers, on a weekly timescale, the engagement growth shows similar evolution, basically steady, for all three sizes.

As the observed timescale increases, the growth of small pages begins to exhibit convex behavior, while the growth curve of bigger pages shifts toward concavity, providing evidence of how size (Followers) impacts the engagement evolution only over the long run.



Conclusion

- ❑ The possibility of **producing viral content** and reaching a broad audience **is independent of the information provider’s size**

- ❑ The engagement follows a **universal growth regime** in the short term, while the Followers’ driver effect only emerges in the long run

- ❑ **Followers do not represent** a sufficient proxy for evaluating pages’ **actual influence**

- ❑ There could possibly be the presence of **‘hidden influencers’** - pages with a broader audience than their number of Followers