Journal of Communication ISSN 0021-9916

ORIGINAL ARTICLE

Time to #Protest: Selective Exposure, Cascading Activation, and Framing in Social Media

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In social media, sharing posts exposes a larger number of users to the preferred content of their peers. As users select or discard content, they collectively highlight facets of events or issues as to promote a particular interpretation. This article describes how social media users frame political events by selectively sharing content that is cognitively congruent with their beliefs. We model cognitive dissonance modeling time-to-retweet and exemplify the proposed theory with a study of recent protest events in Argentina.

Keywords: Protests, Social Networks, Twitter, Framing, Survival Models.

doi:10.1093/joc/jqy007

Introduction

In social media, acceptance equals propagation, as the act of sharing posts exposes a larger number of users to the preferred content of their peers. As algorithms identify trends and dashboards inform editors on the news they should prioritize, issue salience depends critically on the users' decisions to publish[1] or to share content they deem worthy. More important, as users select or discard content published by peers, they collectively highlight facets of events or issues as to promote a particular interpretation that frames political events. In this article we take on the challenge of analyzing how social media users frame political events by selectively sharing or discarding content that is cognitively congruent or dissonant with their beliefs.

Entman (2003, 2004) coins the term *cascading activation* to describe the act of framing social events by selecting or discarding information offered by the White House in the aftermath of 9/11. In his analyses, media organizations withheld cognitively dissonant content and activated congruent frames. In a similar vein, we hypothesize that users frame social events by selecting or discarding messages from their peers. As content reaches the users' walls, cognitively congruent messages

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spread more readily. As a result, social media users frame social events by affecting the frequency of words, images, and embedded links that circulate among connected peers. We propose a novel methodological strategy to model this process, using *time-to-retweet* as a measure of cognitive congruence that explains the propensity of users to share content with peers.

Chaffee and Metzger (2001) and Bennett and Iyengar (2008) note that new technologies,[2] which allow users to signal their preferences for issues and content they want to read, may yield a new era of "minimal effects." In this new era, traditional media organizations, already incapable of changing readers' minds, may also be unable to set the agenda (Artwick, 2012). Indeed, in an era where social media serves a key role in the delivery and propagation of content, communication theories need to explain why and when do users share media posts as well as the effect of this decision on the selective exposure of content among peers (Himelboim, Smith, & Shneiderman, 2013). In this article, we take on the challenge raised by Chaffee and Metzger and inquire about the effect of new technologies on the production and propagation of social media frames.

With this goal in mind, we study the *#Tarifazo* protests in Argentina (i.e., the "*great rate hike*"), a political crisis triggered by the decision of Mauricio Macri's administration to increase public utility rates by 400%. As we show, social media featured prominently in the organization of the *#Tarifazo* demonstrations and in the delivery of protest messages. Users in well-defined pro- and anti-government communities framed the *great rate hike* by selecting or discarding posts that included words, hyperlinks, and hashtags, they agreed with.[3] We show which areas of the *#Tarifazo* network light up with different hashtags, the semantic clusters in each community, and the media outlets embedded by users. More importantly, we provide evidence of longer *time-to-retweet* for frames favored by government authorities, such as corruption, that failed to propagate among users aligned with the government's network.[4]

Our novel methodological strategy provides a mechanism to model faster or slower *time-to-retweet* for content that is cognitively congruent or dissonant with the users' prior beliefs. This strategy allows researchers to explore which posts elicit stronger or weaker responses from networked peers, which is critical to understanding how content propagates in social media data. For communication scholars, it provides a strategy to explore which social media frames propagate through the accepting or discarding of networked content.

Argentina provides a hard test for our argument, as it has a large base of social media users with consolidated government and opposition communities (Calvo, 2015) and clearly aligned media organizations (Becerra, 2015; Waisbord, 2014). Experienced social media users are less sensitive to new information as well as less likely to change their social media behavior when faced with dissonant messages (Bharucha & Stoeckig, 1986; Lodge & Taber, 2005). Therefore, Argentina provides a hard test for our argument and estimates will likely be conservative when compared to those in less polarized environments.

Selective exposure and cascading activation in social media

Research in communication studies shows that not every item of news has a reader. In traditional media, there are frequent gaps between the production and consumption functions of information (Althaus, Cizmar, & Gimpel, 2009; Boczkowski, Mitchelstein, & Matassi, 2017). This *news gap*, researchers argue, is the result of differences in the production function of news, the editorial interests of media organizations, and the consumption preferences of readers (Boczkowski & Mitchelstein, 2013). As this gap increases, traditional media products go unsold or unseen. This is also true in social media, where some posts are widely read while others fails to attract the public's attention. In social media, however, production costs are lower and consumption leads to propagation. Therefore, online behavior such *sharing* posts alters the frequencies of words, hashtags, and embedded links that networked users observe on their walls.

Selective exposure to social media content, as described by Himelboim et al. (2013), occurs when individuals actively seek content that is cognitively congruent with their preferences and prior beliefs. By connecting with like-minded peers and ideologically aligned media, users are exposed to a disproportionate number of publications that validate their own assumptions. More importantly, users can alter the frequencies of content that is displayed in the walls of like-minded peers by sharing content they prefer. Therefore, social media bubbles do not just expose users to information that is consistent with their beliefs but also augment the frequency of particular frames that circulate among networked peers. Selective exposure, therefore, requires users that share information that is cognitively congruent or dissonant with their preferences and prior beliefs (*selection effect*). The resulting social media frames, on the other hand, are the result of how content propagates across different network topologies (*composition effect*).

The consequences of sharing social media content are theoretically and substantively important. Editorial dashboards light up, signaling to journalists which news are in high demand. Algorithms interpret sharing behavior and draw attention to *trending* issues, reaching new audiences as well as an ever-larger number of readers. These algorithms tailor information to each user by interpreting past online behavior and mixing it with the revealed preferences from networked peers (Lecaros & Greene, 2014). Therefore, as noted by Chaffee and Metzger (2001), users today "vote" on the issues they want to see and, through content selection and its propagation in networks, frame political messages in social media networks.

Framing through cascading activation

Let us consider the following thought experiment. A single media outlet in Argentina, *La Nación*, publishes two articles and delivers two posts on a social protest event (*e.g., the #Tarifazo*). The first article frames the social protest as a response to a corruption event, featuring prominently the word "corruption." The second article frames the protests as a response to "wasteful spending." If a single user shares the first article while 10 users share the second article, frequencies observed in the walls of hundreds of networked peers (impressions) will frame the protest as a "wasteful spending" issue. By contrast, if most users share the first post, social media walls will more frequently display anti-corruption content.

Therefore, by sharing more widely one of the two articles, the walls of the interconnected network of social media users will feature key words, images, and links, which cue readers on one of the two potential frames ("corruption" or "wasteful spending"). This raises a critical question: Should we consider *La Nación* as responsible for framing the protests as a "corruption" or as a "wasteful spending" issue? Or should we consider users as responsible for the resulting social media frames?

Let us now extend the previous thought experiment and consider a multitude of media outlets and a large number of potential frames. As users share content, impressions in social network walls will propagate particular combinations of words, images, and links to media outlets, altering their frequency and propagating frames selected through the act of *sharing* posts. Indeed, users will take as input the available content but express as output particular combinations of this information through the sole act of sharing content they like and discarding that which they dislike.

In his analyses of the White House media strategy after 9/11, Entman (2003) coins the term *cascading activation* to theorize on phenomena similar to the one we describe in this article. As he notes, media organizations were more than a mere receptacle of the narratives provided by the White House. Instead, they framed the response to 9/11 by accepting or discarding information offered by the Bush administration to the benefit of readers that rejected some White House explanations as cognitively incongruent. As he notes:

> Framing entails selecting and highlighting some facets of events or issues, and making connections among them so as to promote a particular interpretation, evaluation, and/or solution. The words and images that make up the frame can be distinguished from the rest of the news by their capacity to stimulate support of or opposition to the sides in a political conflict. (Entman, 2003, p. 417)

Drawing from Benford and Snow (Benford & Snow, 2000), he then proposes that frames "that employ more culturally resonant terms have the greatest potential for influence. They use words and images highly salient in the culture, which is to say noticeable, understandable, memorable, and emotionally charged" (Entman, 2003, p. 418). In social media, however, it is the preferences and sharing behavior of the users that alter the mix of information and, thereby, the frames impressed in the walls of networked peers.

Research hypotheses

If we accept the premise of Chaffee and Metzger—that social media users "vote" on the issues they would like to read—our communication models need a behavioral correlate that explains why users accept or reject information. Frames in social media reflect these behavioral responses leading to the selective propagation of content.[5] Selective exposure, in consequence, depends on: (a) users accepting or discarding content they agree with (*selection effect*), and, as a result (b) variation in the frequencies of content that frames social events (*composition effect*).

> *H1a: Selection effect: Users share information that is cognitively congruent, increasing the frequency of congruent frames among networked peers.*
> *H1b: Selection effect: Users do not share information that is cognitively dissonant, decreasing the frequency of dissonant frames among networked peers.*

To measure cognitive dissonance, we propose a methodological innovation that considers the length of time elapsed between when a message has been posted and the time at which it is shared by users (*time-to-retweet*). We consider *time-to-retweet* in observational data as a proxy for *latency*, which researchers frequently use in experimental settings as a measure of cognitive dissonance.

Cognitive congruence or dissonance, we argue, alters the rate of posts shared by users, the frequency of content embedded in social media data, and, consequently, how social media communities frame social events. A network authority with a significant number of followers may be interested in framing a social media event to her advantage. However, if the content is not cognitively congruent with the users' beliefs, it will be shared infrequently and fail to propagate among peers. The consequence will be a decline in the social media activity or, alternatively, a substitution of the cognitive dissonant frames by content from other sources. As the frequency of shared posts varies, communities collectively frame political events by altering the frequencies of words, links, and hashtags that propagate.

> *H2: Composition effect: Content in social media communities will differ according to how connected users (communities) vary in their propensity to share congruent messages.*

In what follows, we will describe the case, data, and methodological strategy that we use to test these hypotheses. First, in the next section, we describe the *#Tarifazo* protests in Argentina. We then describe the properties of the #Tarifazo network, including keywords, hashtags, and embedded links promoted by network authorities. Finally, we model the *time-to-retweet* of social media posts, measuring the *selection* and *composition* effects in the #Tarifazo networks.

#Tarifazo politics in Argentina

Social media has become a powerful device to organize social protests and to deliver political narratives among voters (Barberá, Jost, Nagler, Tucker, & Bonneau, 2015; Bastos, Mercea, & Charpentier, 2015; Gerbaudo, 2012; Neumayer, Rossi, & Karlsson, 2016; Theocharis, 2013; Treré, 2015; Tucker et al., 2016). Across the developed and developing world, activists use social media to advertise their demands, keep their brands current, and react to changes in the public's mood (Earl

& Kimport, 2011). Further, social media now allows activists and politicians to observe what messages are well received by the public and propagate in social media communities (Bastos et al., 2015; Hilbert, Vásquez, Halpern, Valenzuela, & Arriagada, 2017; Lee et al., 2015; Romero, Meeder, & Kleinberg, 2011). This has also been the case in Argentina, where activists organize an increasing number of protests through social media.

On 14 July 2016, protesters took to the streets of Argentina's wealthiest and largest provincial capitals. Small-scale protests spread across neighborhoods in the cities of Buenos Aires, Córdoba, and Santa Fe, followed by a larger demonstration at the Plaza de Mayo, the urban plaza that sits in front of the Pink House in downtown Buenos Aires. In a very polarized political environment, pro- and anti-government media outlets provided starkly different rationales for the *great rate hike* as well as widely different estimates of attendance.

Media pundits agreed on two basic features of the *#Tarifazo* protests. First, the demonstrations were the first true challenge to the incoming administration, which enjoyed significant support among the public and had been able to approve rather quickly much of its legislative initiatives. While holding a minority of seats in the House and the Senate, the president had successfully used the bully pulpit to publicize his agenda and bargained effectively with a divided opposition. Second, social media networks played a key role in publicizing and coordinating the *great rate hike* protests.

Protest posts circulated extensively on Facebook and Twitter, the two social media outlets with the largest user bases in Argentina. As reported in the Argentine National Electoral Survey (ENPEA/UNSAM), 17% of Argentine voters identified social media as their main source of news, second only to TV and comfortably ahead of newspapers and radio, which drew just 14% and 10% of the attention of voters respectively. Indeed, Twitter alone recently announced that it had reached 11 million unique Argentine users and had a smart phone penetration of 70% of mobile users.[6]

The *#Tarifazo* protests drew considerable support from independent voters, who six months earlier propelled non-peronist Mauricio Macri to the presidency. While a mere 15% of Macri voters reported negative views of his administration, almost 45% of them opposed the *great rate hike* and supported an order by federal justice Martina Isabel Forns to suspend all energy price increases. Opposition to the policy was far more extensive among supporters of peronist Daniel Scioli, the losing candidate in the 2015 presidential election, 73% of whom opposed the *great rate hike* and favored the federal justice's decision.

The #Tarifazo data

Between 8 July and 20 August 2016, we collected three waves of Twitter data using the string "tarifa" (rate), a term that is politically neutral and was used by both the pro-government and the opposition in their messages.[7] To collect this data, we connected Twarc (Summers, 2016) to Twitter's backward search application programming interface

(API), gathering tweets in the five days that preceded and the five days that followed the demonstrations of 14 July and 4 August. We added a shorter collection in the three days before and after the Supreme Court injunction of 18 August. Our data includes 606,248 posts by 114,616 unique Twitter users. Of this sample, 71.9% (436,690) were retweets of the original content in 50,156 tweets. The average tweet, consequently, was retweeted 8.72 times. Out of all accounts active in *#Tarifazo*, we selected for our analyses those nodes that participated multiple times and that were in the primary connected network,[8] resulting in 53,454 accounts that were responsible for 375,528 tweets. Although only half of the accounts participated multiple times, the primary connected network still holds approximately 86% of the original dataset. This is the result of the primary activity of most unselected nodes being retweets.

Together with the text of each tweet, we collected 17 variables reporting the users' screen names, followers, followees, the time of the tweet and the time of the retweet, the status of the users' accounts (verified or not verified), and all embedded links. As in prior research, Twitter data shows a remarkable degree of concentration. The Gini index for all tweets was .75, with less than 5% of the total accounts being responsible for 44% of the content that circulated in the network.

To create the layout and identify the communities in the *#Tarifazo* network, we implemented the following procedure:

1. We loaded all 375,528 edges of the primary connected network, with the author of the original tweet set as the authority and the author of the retweet set as the hub, $H_{retw} \rightarrow A_{tw}$.
2. We estimated a layout of node coordinates using the Fruchterman-Reingold (FR) forced-directed algorithm in R 3.2 *igraph* (Csardi & Nepusz, 2006) and identified communities in the *#Tarifazo* network via random walk community detection. The FR algorithm facilitates the visual inspection of the network, communicating information about the proximity between nodes (data reduction pull) while preventing nodes from overlapping (force directed push).

#Tarifazo network: the pro-government and pro-opposition communities of users

The random-walk community detection algorithm identifies two primary communities among the 53,454 high activity users: the opposition network, which includes 23,905 nodes, and the pro-government network of 10,133 nodes. The remaining communities, ranging in size from 1 to 635 users, add another 19,416 nodes (Details in the Online Supplementary Information, Appendix A). Dominant actors in these smaller communities included both foreign and domestic traditional media, top bloggers, and prominent public figures in the sports, arts, and culture.

Figure 1 presents the basic FR layout of the *#Tarifazo* network. We describe the opposition community with blue triangles (23,905), the pro-government community with golden diamonds (10,133), and the unaffiliated users with gray dots (19,416). The size of the nodes describes the nodes in-degree (authority), with larger

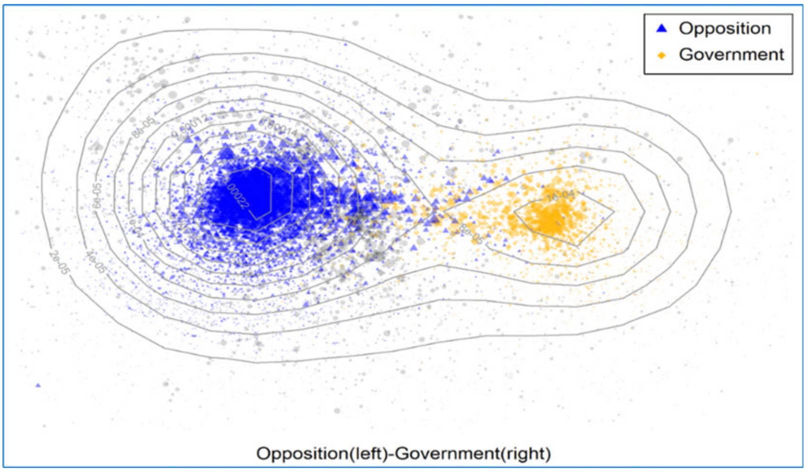

Figure 1 Network of high-activity users in the network #Tarifazo. Blue triangles describe opposition nodes (23,905), gold diamonds describe pro-government nodes (10,133), and gray dots describe unaffiliated nodes (19,416). Size of the node reflects the relative authority, expressed by the number of times they have been retweeted or in-degree, log(in-degree). Network layout done using Fruchterman-Reingold algorithm and communities identified by random walk community detection using R and igraph (Csardi and Nepusz, 2006).

nodes indicating users retweeted by a larger number of followers. Figure 1 also shows large differences in the in-degree importance (size of nodes) across communities. Such differences are the result of higher retweet activity by opposition users.

High polarization in the *#Tarifazo* network explains the sparsity of exchanges between pro-government and opposition users. Of all the edges in the primary connected network, 96.4% (259,850) of opposition's retweets are classified as Opposition→Opposition and 90.3% (49,589) of Government's retweets are classified as Government→Government exchanges. Meanwhile, a mere 1.5% (4,011) are Opposition→Government edges and 6.9% (3,792) are Government→Opposition edges. The results provide clear evidence that information circulates overwhelmingly within each communities.

As noted above, the opposition vastly out-retweeted pro-government users. The top account in the opposition network, the media conglomerate *@C5N*, was retweeted five times more frequently than the top user in the pro-government subnetwork, the television account of Clarin's conglomerate *@todonoticias*. It is also interesting to note that the pro-government network had few politicians of notice. Rather, the government was happy to see their bidding carried out by aggressive independent bloggers such as *@lanataenel13* and *@Coculo*. By contrast, some of the most prominent users in the opposition network include former Chief of Cabinet *@anibalfernandez*, former UCR Senator *@Leopoldo_Moreau*, current Diputada Gabriela Cerruti *@gabicerru*, and former Minister of Public Works *@JuliodeVido*.

Selective exposure in the #*Tarifazo* networks: contents in the information bubbles

The previous section shows that pro-government and opposition users in Argentina coalesced into two well-defined communities that exchanged information almost exclusively with likeminded users. We also show the opposition community as larger, more active, and featuring greater numbers of prominent political figures. We now turn our attention to the content of the messages that circulated in the pro-government and opposition subnetworks. First, we provide a visual inspection of the areas of the network activated by different hashtags. Second, we discuss how keywords cluster into distinct pro-government and opposition narratives. Third, we measure the penetration of different traditional news media through links embedded in the tweets.

Network activation

To map the propagation of hashtags in the *#Tarifazo* network, we count the frequencies of hashtags adjacent to each node (Details in the Online Supplementary Information, Appendix B). We then smooth these counts over contiguous (connected) nodes to facilitate visual inspection.

Figure 2 provides eight different plots with a selection of top hashtags that circulated extensively during the protests: *#Tarifazo* (47.7% of tweets), *#Ruidazo* (26.4%), *#TeTomanDeBoludo* (2.6%), *#NoAlTarifazo* (4.6%), *#CorrupcionK* (.27%), *#AngustiaLasPelotas* (.58%), and *#TimbreoNacional* (.49%). The layout of the network is identical to Figure 1 with nodes as a function of the tally of each hashtag, i.e., *log(#Tarifazo)*.

As shown in Figure 2, the two most widely circulated hashtags, *#Tarifazo* and *#Ruidazo*, were prevalent in both the opposition and pro-government networks, even though there are few edges connecting users across the two communities. As expected, *#Ruidazo*, with the implied meaning *make noise!*, is considerably less prevalent in the pro-government community. Hashtags with a larger presence in the pro-government subnetwork include *#CorrupcionK, #Frenazo*, and *#JuevesIntratable*. Indeed, the government narrative defended the *great rate hike* as a needed remedy to the corruption and mismanagement of the previous administration, which left the country's infrastructure in shambles after years of disinvestment and profiteering.

Keywords in each community

As with the hashtags above, we may compare how the pro-government and opposition communities frame the protests using the cross-correlation matrix of keywords in published posts. That is, measuring the extent to which different keywords correlate with each other. To this end, we proceeded to collect all news articles in the top four newspapers in Argentina and select 120 keywords frequently used in the written media to describe arguments in favor and against the *great rate hike* (Details in the Online Supplementary Information, Appendix D)

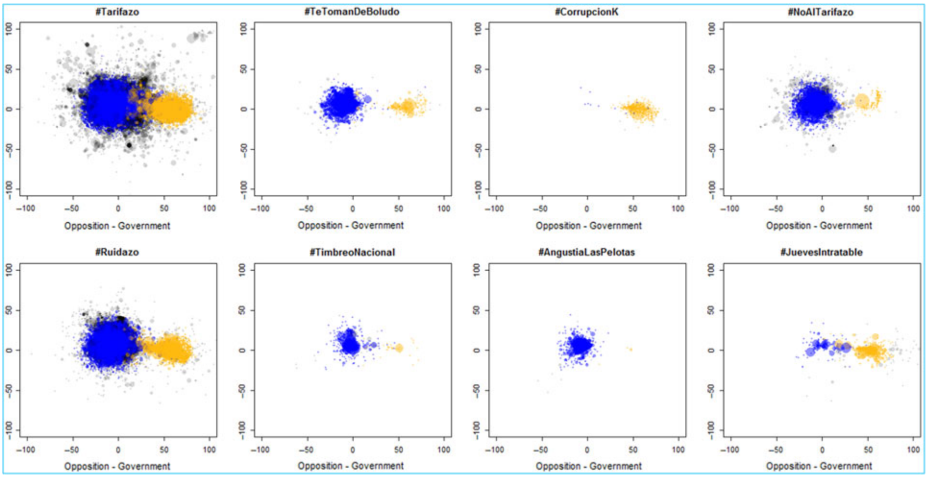

Figure 2 Activation of user accounts by hashtag content in tweets estimated by transferring information from the edges (tweet) to the nodes (user accounts). Network layout done using Fruchterman-Reingold algorithm and communities identified by random walk community detection using R and igraph (Csardi and Nepusz, 2006).

As expected, the pro-government newspapers[9] *La Nación* and *Clarín* favored frames proposed by the government, framing the *great rate hike* as a response to the corruption and economic mismanagement of the previous administration. Meanwhile, the opposition media *Ambito Financiero*, *C5N*, and *Página/12* decried the consequences of the *great rate hike*, presenting the policy as a giveaway to big businesses. As described by Joaquin Morales Sola, a leading Argentine journalist and a dependable supporter of the current administration:

> Two very different political and economic views collided [in Congress]. The old peronist interventionism permeated speeches from almost all sides of the movement founded by Perón. A more modern conception was articulated by [Minister of Energy] Aranguren, who still, willfully or not, wasted the perfect opportunity to demonstrate that excessive state regulation was responsible for the demise of the Argentine economy. (Joaquín Morales Sola, 17/8/2016, *La Nacion*)[10]

The dendrogram in Figure 3 perfectly captures these competing frames. To compute this dendrogram, we extracted the frequencies of the aforementioned keywords from the text in each of the tweets and computed a dissimilarity matrix. We then implemented agglomerative nesting algorithm'. Figure 3 shows that pro-government posts include issues such as "unpredictability," "calculus," "care," "rumors," "investment," "responsibility," "effort," and a large collection of terms appealing to civic duty and to "sound" economic management.

By contrast, opposition tweets highlight connected keywords such as "malaise," "adjustment," "activism," "lies," "fear," "access," and a variety of other terms that describe the social costs of the new energy policy. Indeed, the issues highlighted by

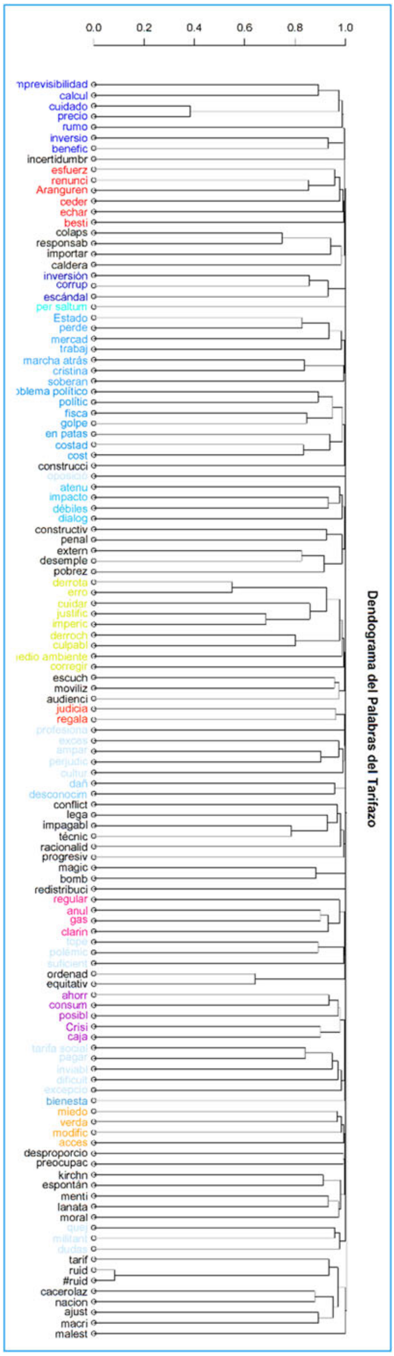

Figure 3 Dendrogram of Keywords.

pro-government and opposition users express different normative principles to justify or reject the proposed policy, such as "responsible" policy on the part of the government contested by a call for "social fairness."

As argued earlier in this article, in social media acceptance leads to propagation. As users *share* information, new users are exposed to the media content of their peers. On Twitter, significant time is spent sharing, rather than creating, content. Indeed, 29.9% of the tweets in the *#Tarifazo* network include embedded links to content already on circulation in the web. Such links redirect users to existing social media posts on Twitter, Facebook, and Instagram; niche political and business media such as www.eldestapeweb.com and www.mundoempresarial.com.ar; and traditional newspapers such as *La Nacion*, *Clarin*, *Ambito Financiero*, and *Pagina/12*.

Descriptive information shows that pro-government and opposition users embed links at roughly similar rates. However, there is little overlap of the most frequently embedded links in their tweets. While the top hyperlink embedded in both the pro-government and opposition communities originated from Twitter, content analyses showed that these tweets were different. Beyond Twitter, the top link in pro-government posts directed readers to the top conservative newspaper, *La Nacion*, and the TV channel of the other major pro-government newspaper, *Clarin*. By contrast, the main links embedded in opposition posts included relatively marginal news outlets such as *Mundo Empresarial* and *El Destape Web*.

Time-to-retweet: modeling cognitive dissonance in Twitter data

So far, we have shown that the *#Tarifazo* network included two well-defined pro-government and opposition sub-networks. We noted that these two sub-networks exchange little information between them and that the text, hashtags, and embedded links that circulated in each community are different. We then showed that the hashtags and keywords activated different regions of each sub-network, with pro-government users highlighting responsible behavior and opposition users highlighting redistributive fairness.

We now take on the task of evaluating what types of messages were more rapidly retweeted by users in each community. Following a significant literature on information processing, we test whether latency increases or decreases for a variety of user traits and tweet content. Our key findings show that corruption, a wedge issue expected to energize the pro-government community, failed to do so. In fact, as we will show, *time-to-retweet* lengthened when authorities in the pro-government network included variations of the keyword "Corrup+" in their messages. Results also show that "Corrup+" was a term that lengthened time-to-retweet among opposition users. Differences in the time-to-retweet differed by a variety of content- and user-level variables.

As we proposed at the beginning of this article, consumption leads to propagation and propagation to selective exposure. Critical to selective exposure, consequently, is cognitive congruence with content that is posted by community peers. Measures of *time-to-retweet*, we argue, provide evidence of cognitive dissonance that prevented pro-government users from advertising the core message that government authorities sought to promote.

The dependent variable

The dependent variable reports the number of seconds elapsed from the time a user (authority) posts a tweet to the time a second user (hub) retweets the same post. This information is available for every observation in our dataset, given that edges describe the link between the original tweet and a retweet, both of which have a registered time by Twitter's API. Because users sometimes retweet older posts, we eliminated from the sample all observations with a count above 20,000 seconds.[11] The median time to retweet in our sample is 1,599 seconds, a little over 26 minutes. The data is skewed right, with a mean time-to-retweet of 3,797, slightly over one hour.

	Min.	1st Q.	Median	Mean	3rd Q.	Max
Time-to-Retweet (Seconds)	0	355	1,599	3,797	5,577	20,000

Differences in the *time-to-retweet* by users are extremely informative. Figure 4 displays the *#Tarifazo* network with node sizes that are inversely proportional to time-to-retweet. In Figure 4, larger nodes describe users that retweet information more rapidly. At the center of the two communities are the authorities, which produce the most important tweets but do not retweet as often. They also display longer *time-to-retweet* than peers in their own communities.

More interestingly, to the left of the opposition and to the right of the pro-government subnetworks we see the "soldiers" of each group: The users that are ready to retweet the posts of the authorities in their respective communities. *Time-to-retweet* shortens as we move away from the "other" community, providing reassurance of its value as a proxy for cognitive congruence.

The independent variables

We consider three different types of independent variables: (a) user-level data, (c) embedded links, and (d) keywords and hashtags. The first group of independent variables includes user-level data by both the user that posted the original tweet (authority) and the user that retweeted that message (hub). This includes the number of friends and followers. Important users have large numbers of followers while following very few people. President Mauricio Macri, for example, has over 3.5 million followers but just 637 friends. High numbers of friends and almost no followers, by contrast, tends to be the signature of bots and trolls. As a proxy for the importance of a user in the network, we compute the ratio between the followers of the user that posted the tweet (authority) and the followers of user that retweeted (hub). We also include the ratio of friends to sort out the effect of bots. Finally, we

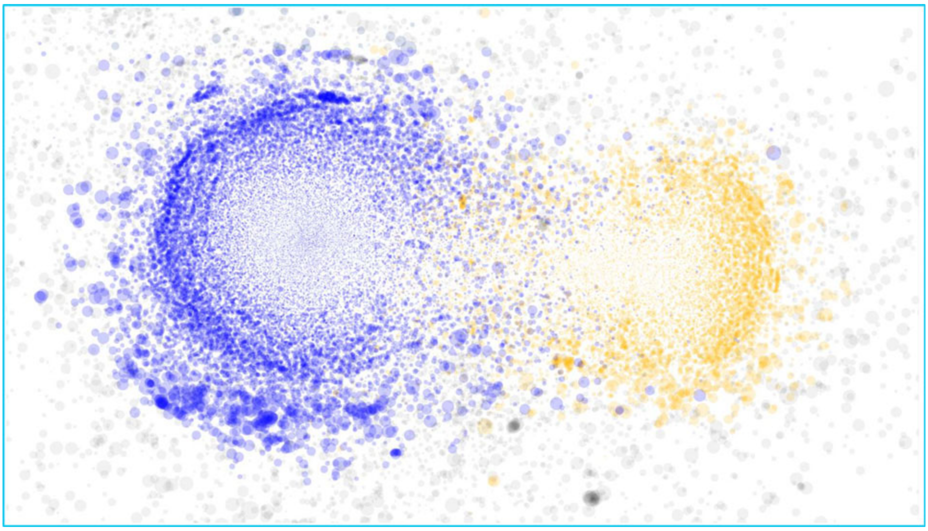

Figure 4 Network of high-activity users in the network #Tarifazo. Blue dots describe opposition nodes (23,905), gold dots describe pro-government nodes (10,133), and gray dots describe unaffiliated nodes (19,416). Size of the node is inversely proportional to the time-to-retweet, with larger sizes indicating that users retweet information more rapidly. At the center of the two communities are the authorities, which produce the most important tweets but have little retweet activity.

include the *verified* status of the account, expecting verified accounts to result in lower time-to-retweet.

A second group of dummy variables identifies the most frequently embedded links in our data. This includes links to the pro-government newspapers *Perfil*, *La Nacion*, and *Clarin* as well as the pro-government television networks *TN*. We also include variables describing links to the opposition newspapers *Ambito Financiero* and *Pagina/12*. Finally, we consider links to posts by peers on Twitter and Facebook, as well as the other 16 most frequent websites in the #Tarifazo data. We expect positive hazard rates for media aligned with each community, with slower *time-to-retweet* for content that is cognitively congruent with users in each community.

The third group of independent variables identifies keywords and hashtags that were core to the frames proposed by the media aligned with the government and the opposition. This includes dummy variables for each of the 118 keywords in the dendrogram of Figure 3. Of particular interest are variations of the word corruption ("Corrup+"), the hashtag #Ruidazo, and markers for former President Cristina Kirchner, current president Mauricio Macri, and the Minister of Energy Juan Jose Aranguren. We expect the markers for corruption to speed up the time-to-retweet in the government (positive hazard rate coefficient) and to slow it down for the opposition (negative coefficient). This expectation is borne out of the strategies of each group, with government actors "owning" the issue the corruption and expecting to benefit from its use. By contrast, we expect protest calls such as #Ruidazo to speed up time-to-retweet for the opposition and to slow it down among government actors. More generally, we expect keywords associated with markets and responsible behavior to have positive hazard rate estimates in the government community. We also expect keywords associated with protests and economic injustice to have positive hazard estimates among users in the opposition.

Model and discussion

Figures 5 and 6 present estimates of the proportional hazard cox model, with unstandardized coefficients describing changes in the hazard rate of *time-to-retweet* and confidence intervals represented by lines around each estimate. The full table with all numerical estimates and model fit parameters is in Appendix D of the supplemental information file (SIF). Here, for presentation purposes, we present graphical displays of all parameters.

Proportional Hazard Cox models explain survival rates (*time-to-death* event), which in our case explains *time-to-retweet*. Positive coefficients indicate an increase

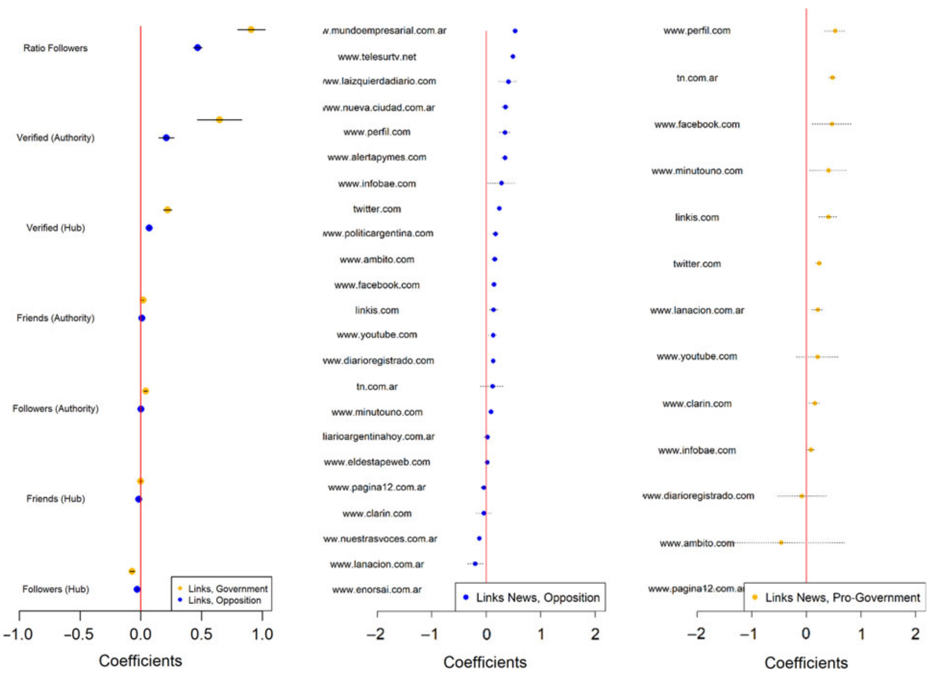

Figure 5 Hazard estimates of time-to-retweet by user traits (left), embedded news of the opposition community (center), and embedded news of the pro-government community (right). Positive numbers indicate positive increases in hazard rate and shorter time to retweet. Results of the model reported in Appendix D of the Supplemental Information File (SIF).

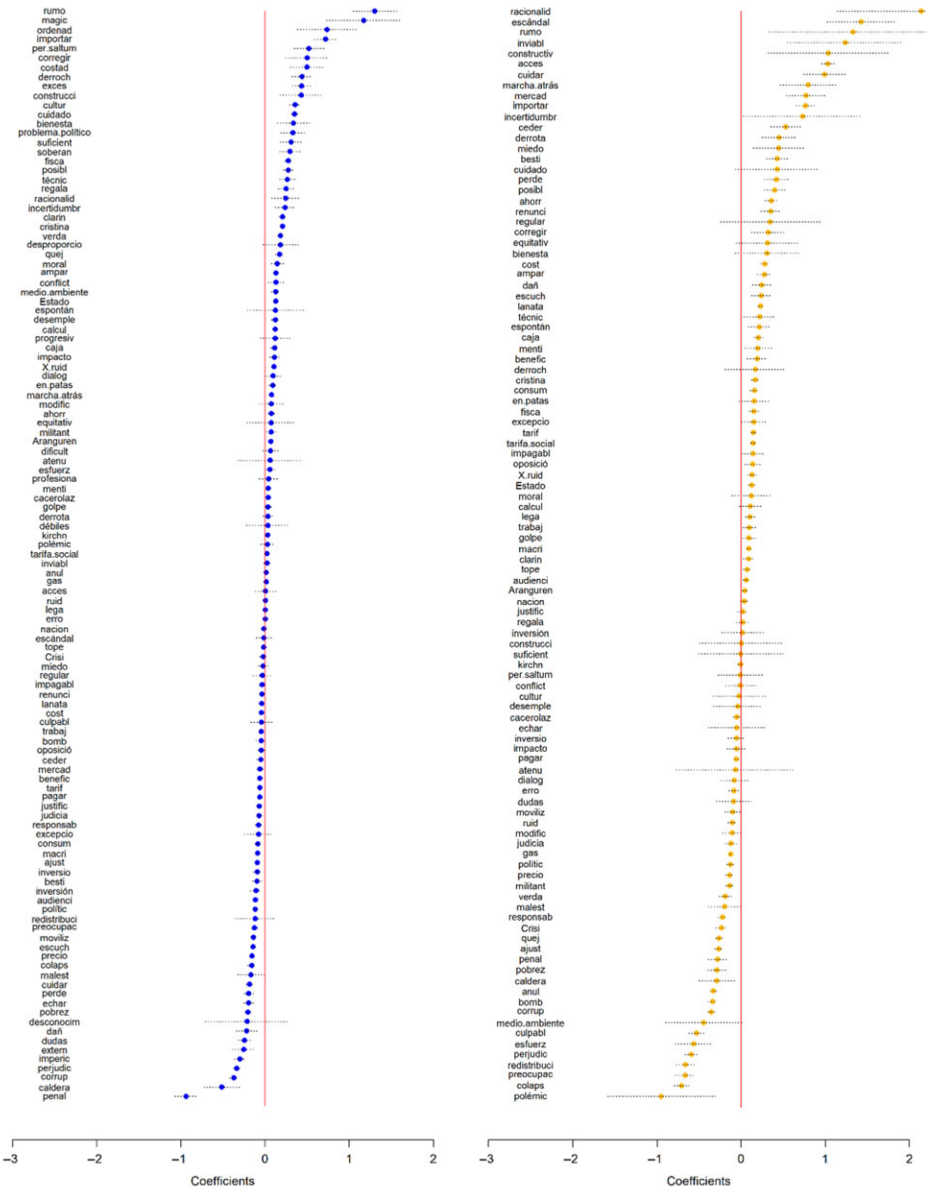

Figure 6 Hazard estimates of time-to-retweet by keywords, with the opposition community on the left and the pro-government community on the right. Positive numbers indicate positive increases in hazard rate and shorter time to retweet. Full model results reported in Appendix D of the Supplemental Information File (SIF).

in the hazard rate (faster *time-to-retweet*) while negative coefficients indicate slower times. For an intuitive interpretation of the magnitude of the effect, consider the effect of the covariate "corruption" among users of the pro-government community, which is negative and takes the value of +Corrup = −.359 in Model 2, Table D.1 of the Appendix. We may interpret the coefficient as log of the instantaneous change in time-to-retweet when any variation of the term "corruption" appears in a tweet. The exponentiated change in the hazard rate is $exp(-0.365) = 0.701$, showing that the *time-to-retweet* for posts that raise the issue of corruption is about 30% slower, 1–.701=.299. Most estimates fall in the range [−1 to 1], where −1 yields a decline of 63% in time-to-retweet while 1 yields an increase of 270% in the time-to-retweet.

Figure 5 presents estimates for the user traits (left) and for embedded links of the opposition (center) and the government (right). Given that we are interested in the propensity to share content produced by like-minded peers, the model specifications estimate the *time-to-retweet* when both the authority and the hub belong to the same community. Within-community estimates ensure our models explain cognitive dissonance in messages disseminated by fellow community members.

The left plot in Figure 5 shows that users in both the opposition and pro-government communities were eager to retweet messages posted by their own authorities. Results show that time-to-retweet is shorter as the number of followers increases. Further, for every extra unit in the ratio of authority followers to hub followers, the hazard rates increase 59% among opposition users and 248% among pro-government users. Results also show that users with larger number of followers take considerably longer to retweet, particularly for authorities in the pro-government community. Finally, results provide evidence that pro-government users were quicker to retweet content from network authorities than those in the opposition. To summarize, as expected, users with a larger following had considerably lower time-to-retweet than less important users.

The middle and right plots in Figure 5 describe estimates of time-to-retweet for links embedded by users in each community. Users in the pro-government community display shorter times to retweet for posts that embed friendly media such as *Perfil*, *TN*, *La Nacion*, and *Clarin*. Opposition users, by contrast, were eager to retweet information that included independent outlets such as *mundoempresarial* and *laizquierdadiario* as well as friendly media such as *Ambito Financiero*. Interestingly enough, the estimate of *Pagina/12* among opposition users was near zero and statistically insignificant. Therefore, while users embed media that is aligned with their own communities, time-to-retweet was below expectations for *Pagina/12* among opposition users.

Figure 6 presents estimates for over 100 keywords, with positive coefficients describing faster time-to-retweet. Results are consistent with the dendrogram in Figure 3, with pro-government users retweeting posts that feature terms such as *rationality*, *markets*, *care*, *savings*; and slower times for terms such as *crisis*, *adjustment*, *poverty*, and *corruption*. The opposition, on the other hand, was quick to retweet terms such as *excesses*, *sovereign*, *gift*, *clarin*, *Cristina*, *truth*, and slow to retweet *price*, *poverty*, *damage*, *doubt*, and *corruption*.

Findings show that corruption issues that were expected to energize pro-government users failed to do so. In fact, latency increased and time-to-retweet

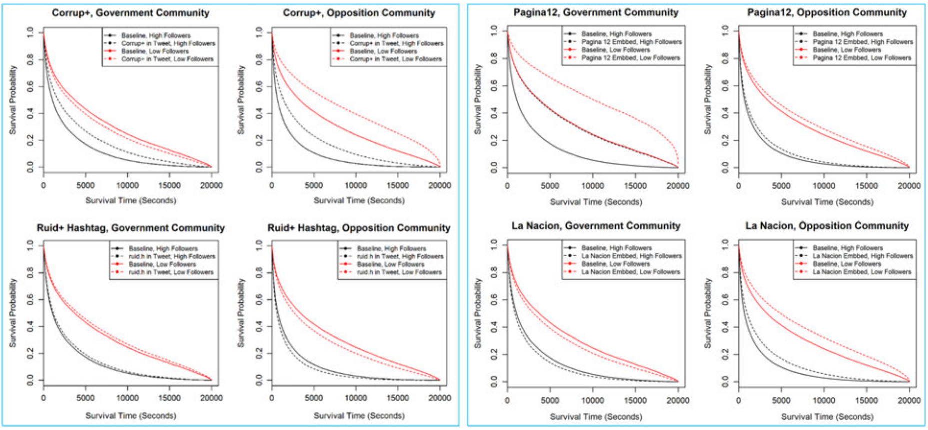

Figure 7 Survival probability of Proportional Hazard Cox models, with time-to-retweet as the dependent variable. Average survival rate in solid lines, with the effect of embedded term ("Corrup+," Ruid+) or embedded link (Pagina/12, La Nacion) in dotted lines. Lines are centered for original tweet posted by high- or low-importance user (High Followers ratio or Low Fallowers ratio).

lengthened when authorities in the pro-government network included variations of the keyword "Corrup+" in their messages. Results also show that "Corrup+" lengthened time-to-retweet among opposition users. Indeed, both pro-government and opposition users were slow to retweet messages that feature corruption.

Most important, however, are the results of the interaction between the ratio of followers (user importance) and corruption, showing that the more important the pro-government user that posted "Corrup+," the larger the latency in time-to-retweet. In other words, denunciations of corruption in the pro-government network against the opposition induced higher cognitive dissonance when submitted by more important users. Figure 7 provides plots of survival time, with solid lines describing the average time-to-retweet and dotted lines describing survival for tweets that included "Corrup+" or #Ruidazo. When important users in the pro-government network included variations of the word "Corrup+," time-to-retweet slowed a statistically significant 30.8% in the case of the opposition and 29.8% among pro-government users. Survival plots of #Ruidazo, *Pagina/12*, and *La Nación*, provide a visual assessment of the level of cognitive congruence or dissonance of each community, conditional on the user that posted the original tweet being an authority or a hub. As it is possible to observe, leaders and followers behave alike in all cases except in corruption, where pro-government authorities that include terms connected to corruption see a significant slowdown in time-to-retweet. While it is true that mentions of corruption depressed time-to-retweet by a larger amount among opposition users, the surprising result is that it failed to energize the pro-government sub-network on an issue that had been featured in the presidential race just a few months earlier.

Concluding remarks: observing local frames in social media networks

Our research contributes to the communication literature by showing that social media users frame events collectively, accepting or discarding keywords, hashtags, and embedded links which are then impressed on the walls of likeminded users. Similar to the notion of *cascading activation* (Entman, 2003), we note that sharing posts in social networks alters the frequency of content that users display in the walls of community peers. Sharing, therefore, frames political narratives by highlighting facets or issues "so as to promote a particular interpretation, evaluation, and/or solution" of a political event (Entman, 2003, p. 417).

Thus, political frames differ at each location of a social network. This has been recognized by the extant literature, which expects users in different social media bubbles to be exposed to widely different content (Barberá et al., 2015). In polarized network environments, users are unlikely to observe competing frames (Chong & Druckman, 2007), which take hold in different regions of the social media network. In most networks, however, the relative prevalence of markers for these competing frames will vary, with users exposed to activated fragments of each frame. That is, competing frames are expressed with differing intensity in each region of a connected network. A fruitful extension of this research, therefore, is to test how users react to competing frames when their relative frequency varies across social media networks.

Our research takes on the challenge posed by Chaffee and Metzger (2001), measuring what issues people "vote" on as they share content among peers (selection effect). It also provides a methodological strategy to explain the compositional effect on the frames that characterize communities of users (Himelboim et al., 2013). Because the propagation of frames requires the willingness to *share* posts, social media networks may fail to deliver content that is resisted by users, even when published by community authorities.

In recent years, an emphasis on the pervasiveness of information bubbles in social media has prevented researchers from measuring whether users embrace content delivered by community peers. Communities may differ in the extent to which they share, and therefore propagate, messages from peers they like. Our research provides a rational to explain why not all information bubbles are alike, as some will successfully frame political events and propagate content while others will fail to do so.

Polarized political environments, such as those of Argentina and the United States, provide a fertile ground to explore cognitive congruence and dissonance in social media networks. Our analysis shows the benefits of comparing the performance of paired communities with distinct narratives, where we measure which frames and issues propagate among like-minded users. Using *time-to-retweet* as a measure of cognitive congruence or dissonance, the analyses of Argentina's *great rate hike* shows meaningful differences in the behavior of pro-government and opposition users. Both pro-government and opposition users interact with like-minded peers in separate information bubbles, sharing distinct posts and propagating diverging political frames. However, opposition users were extraordinarily more successful in propagating their message. Cognitive dissonance among users in the pro-government community was prevalent in every type of data we collected: fewer users and fewer retweets per user, lower agglomerative structure in their hashtags, keywords, and embedded links; and, central to our model, slower *time-to-retweet* for content posted by social media authorities.

Supplementary Material

Supplementary material are available at *Journal of Communication* online.

Acknowledgements

We would like to thank Eduardo Arriagada, Antoine Banks, Martin Becerra, Paula Clerici, Facundo Cruz, Eric Dunford, Jesus Elizondo, Luciano Gallup, Lara Goyburu, David Karol, Nadia Koziner, Neil Lund, Max McCombs, Maria Victoria Murillo, Mario Riorda, Zach Scott, Ed Summers, Shibley Telhami, Joan Timoneda, Sebastian Valenzuela, Tiago Ventura, the editor of the *Journal of Communication*, as well as four anonymous readers who made extensive suggestions to make this article better. As usual, mistakes are the exclusive responsibility of the authors.

Notes

1 Russell Neuman, Guggenheim, Mo Jang, and Bae (2014) argue that social media users and traditional media can differ in how they frame events and which issues are relevant. They emphasize how such differences reflect the preferences of users that create content. By contrast, this article focuses on the decision to share content, altering the frequency of frames observed in social media networks.

2 The new technologies include audience dashboards (e.g., *Chartbeat, Quantcast, etc.*), which allow editors to monitor the consumption patterns of readers, as well as social media dashboards (e.g., Socialflow) that provide real time information on social media usage.

3 Attention to particular frames or frame attributes could also be influenced by media messages, published outside of social networks, by the way of compelling arguments (Ghanem, 1997). We do not inquire on the origins of the user's current beliefs system but take them as given and consider them as exogenous. This relevant discussion is a promising extension to our article.

4 For research that measures message spread as a function of time-to-retweet, see Lee et al. (2015) and Romero et al. (2011).

5 Therefore, the disruptive effect of social media on frames and agenda setting varies as information is brought to the attention of peers (Aruguete, 2017; Zaller, 1992).

6 http://infotechnology.com/online/Tweetter-tiene-118-millones-de-usuarios-en-la-Argentina-20160314-0001.html.

7 We use the string "tarifa" to ensure that our search captures tweets that include variations of this string. Tweets posted on the #Tarifazo protest fall below the threshold at which the search API is restricted (Driscoll & Walker, 2014).
8 We selected tweets with in-degree >=2 and eliminated unconnected nodes.
9 Since 2008, news media in Argentina has become increasingly partisan and polarized. See Becerra (2015) and Waisbord (2014) for an analysis of news media politics in Argentina.
10 http://lanacion.com.ar/1928809-un-choque-entre-dos-visiones-opuestas.
11 We tested a variety of other truncation times, which are available upon request.

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