

## **The Temporal Turn in Communication Research: Time Series Analyses Using Computational Approaches**

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Some of the most pioneering work in our field is occurring where emerging computational approaches are meeting time series analytic techniques. Combining these methods is helping scholars improve our understanding of phenomena as varied as news and issue attention cycles, physiological responses to communication exposure, changes in mass opinion, and the dynamics between social media and legacy news media. In this article, we summarize the current state of computational communication science techniques to generate sequential data for use in time series analysis and suggest directions for further development. In particular, we consider the long-standing place of temporal dynamics for our field's main theories; overview recent work combining computational science with time series analysis; present narrative accounts of two major research programs in this area;

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and review techniques of time series analysis, including major concerns for communication researchers working in the area.

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Communication research has long built time into its conceptions of influence. Yet, relative to allied fields, ours has not been especially advanced about explicating time's functions theoretically or empirically (Yanovitzky & VanLear, 2008). To be sure, solid research examining temporal dynamics has been present for decades: See the cross-lagged correlations of early agenda-setting research and its refinements (McCombs & Shaw, 1972), multidosed priming studies (Iyengar & Kinder, 1987), modeling opinion dynamics using overtime shifts in news content (Fan & Tims, 1989), and rolling cross-sectional analyses of opinion (Johnston, Blais, Brady, & Crete, 1992). But more often, time has been set aside for the limitation section of cross-sectional studies.

Today, we stand on the cusp of a new phase in our field's opportunities to incorporate temporal dynamics into research, which is a product of two advances. One is the development of computational social science (Lazer et al., 2009), and more specifically computational communication science techniques for generating sequential data (Shah et al., 2016). The emergence of these computational research techniques alongside novel sources of data and methods has opened new frontiers for examining a variety of communication dynamics in fine-grained temporal detail. Second, in recent years, communications scholars' awareness of and borrowings from other fields with expertise in modeling temporal dynamics have grown greatly. At the intersection of these developments is a burgeoning domain we call *computational communication science using time series analysis*.

The aim of this article is to (a) synthesize the work linking computationally generated data streams with other temporal data, (b) specify appropriate techniques for the analysis of this data, (c) draw attention to challenges in these processes, and (d) provide resources for scholars wishing to learn more about these intersecting approaches. The article is divided into four sections. In the first, we present theoretical considerations explaining why time is conceptually important to communication research, both historically and today; the second is an overview of pioneering research in computational communication science employing time series modeling; the third offers a narrative account of two research programs in this area; and the fourth includes greater detail about relevant time series analysis techniques. We conclude by returning to the promise of merging computational approaches with time series analytic techniques.

## **I. Time in Communication Research**

### ***Time, Process, and Causation***

Many of the major theories and models in our field contain time as a central player: the two-step flow, cultivation, spiral-of-silence, agenda-setting, framing, and communication mediation models, to name a few (Nabi & Oliver, 2009). Each articulates a set of processes that play out in time: Messages work their

way through media systems and networks, citizens perceive the world around them and decide to communicate, or not, and they make choices about participation, presumably as a product of a process that includes communication exposure. Indeed, the words that animate our field—*effect, flow, influence, dynamic, cycle*—reveal our understanding of communication as a process, and processes have temporal dimensions (Box-Steffensmeier, Freeman, Hitt, & Pevehouse, 2014). The perspective of time series analysis can help expand our notions of time's role in these dynamics. We see several ways in which we can become more attentive to time in our field.

Though we often obscure it, many of communication's major models are causal in nature. Students learn to think through establishing causality by identifying correlations, accounting for covariates, and determining temporal order. Until recently, the last of these has often been the most difficult to establish. With the spread of computationally derived data sets and advanced time series modeling techniques, this is sure to change, intensifying our need to remain aware of the other assumptions built into research of this kind. As we take advantage of these tools, we must be careful not to reduce our theoretical vistas to reductive causal stories. Responding to this tendency, Lang and Ewoldsen (2010) write,

If, as a discipline, we continue the habit of thinking that scientific, quantitative research in communication must be focused on effects, we will never begin the complex and necessary work of theorizing about long-term, systemic, complex, dynamic, interactive processes that make up the science of how communication works. (p. )

A more expansive conception of time is essential to understanding the dynamic processes that connect the communication system.

Further, most models are conceived in terms of the simplest causal temporality—linearity—which is often a usefully parsimonious, if narrow, starting point (Hindman, 2015). More sophisticated time series techniques can help us test and inform other theoretical ideas about how dynamics play out. Some may not be linear, but instead rely on an accumulated effect over time (as cultivation theory postulates); many effects have some kind of decay function by which they disappear, a tendency often absent from communication theories (cf. Fan, 1988). Still other effects may not manifest immediately, only appearing after time passes, and yet others may require surpassing a threshold to manifest (Gotlieb, Scholl, Ridout, Goldstein, & Shah, 2017).

Another temporal simplification is an assumption of temporal stability: that effects play out at a steady rate at different moments in time. Regression-based time series analysis makes this assumption in the sense that it averages across all time points as though they were the same. In reality, not all time is created equal: As Dayan and Katz (1992) demonstrated decades ago, media events are extraordinary moments that attract disproportionate attention and effects, even in the digital age (e.g., Shah et al., 2016).

If a study involves aggregating data that were collected over time while neglecting the role of time, a large volume of data generated in short and intense periods may overshadow the patterns from the nonintense moments. Studies of presidential debates or election seasons have often justified themselves on the basis of this intense attention, but the notion of differentially important time plays little role in theoretical

models. In addition, communication has not done an adequate job of considering how dynamics change at different phases in a process, such as during different segments of a debate or between the primary and general elections campaign. Here, communication may take inspiration from punctuated equilibrium theory's (True, Jones, & Baumgartner, 1999) call to distinguish moments of stability from those of rapid change; the notion of media storms having unique properties and unique effects is a helpful step in this direction (Boydston, Hardy, & Walgrave, 2014).

### ***Complexity and Instability, Unpredictability and Instantaneity***

We must also remain aware of the many ways in which time's place in communication, and in society, is becoming more complicated. Sociologists of the last two decades have described the changing nature of time resulting from the conditions of postindustrial, digitally networked society. Whether "liquid modernity," "timeless time," or "time-space distancing," these notions assert that individuals and social practices are being forced to adapt to communication processes approaching instantaneity. Moreover, people at different locations within the network society vary in their ability to adapt to, and benefit from, these new conditions (Castells, 2010). These are dynamics that directly impact the lived experiences of creators and audiences of communication and shape the practice of communication itself.

Chadwick's (2017) is one of the richest articulations of the implications of time's new nature for political communication. His "political information cycle" makes clear that politics can now play out in near simultaneous real time, incorporating myriad actors who emerge from unexpected corners of the hybrid media system. When combined with time-stamped digital media artifacts, time series analyses offer techniques for studying behaviors that occur in micro-increments of seconds or milliseconds, though the simultaneity and complexity of the contemporary media system may defy untangling.

This spontaneity and unpredictability challenges theories of regularity and routinization. Today, news comes out all the time at a relentless pace and is immediately met with responses by a wide range of communicative actors. Yet, our theoretical frameworks—as well as our often regression-based empirical techniques—are only beginning to come to terms with this complexity (Karlsson & Strömbäck, 2010).

We present these considerations as a call for communication scholars to attend to matters of time more conscientiously in both theory and method and to encourage empirical modesty as we exploit new tools for measuring and modeling communication dynamics.

## **II. Time Series and Computational Methods in Communication Research**

A time series is a way of indexing or graphing data in temporal order, creating a sequential pattern of the level of a given variable over time. Units of time vary widely—from milliseconds in some physiological research to years or decades in analyses of systemic social or media change. As noted earlier in the article, time series techniques have been present in our field for decades, but have only recently become common in communication research training. Today, with the development of computational communication science techniques to generate sequential data, the use of time series techniques is rapidly expanding. By "computational" research, we refer to data collections and analytic techniques that (1) generate or use large,

complex databases, (2) involve computing variables from trace data available through social media, mobile devices, or other digital databases, and (3) often use machine or algorithmic solutions to generate patterns and inferences from these data (Shah, Cappella, & Neuman, 2015). More detail on the unique properties of temporally ordered data is offered in Section IV and supplementary materials.<sup>2</sup>

Further, data created through “always on” (Salganik, 2017) computational processes frequently include records of the time of creation. Unlike data collection from the prior era, where the main source of data was one-time responses to a survey, interview, or experiment, digital trace data inherently lend themselves to time series analysis. Increasingly, that synthesizes multiple forms of data—for example, event data, news coverage, public opinion, and/or social media texts—into a unified data set amenable to new forms of modeling.

In this section, we present an overview of ways in which computationally collected or derived data are being used within time series techniques (see Table 1 and discussion below). Though space constrains us from comprehensively treating the computational approaches mentioned here, more detail on them can be found in the article’s supplementary materials.

**Table 1. Illustrative Uses of Computationally Derived Data Sets in Time Series Analysis.**

<b>Media/Event data used</b>	<b>Published works</b>	<b>Data sources</b>	<b>Analytic techniques</b>
News media (Associated Press) + public opinion data	Fan & Tims (1989)	Nexis	Ideodynamic model, computer-assisted syntactical coding
News media + social media (Twitter)	Guggenheim, Mo Jang, Bae, & Neuman (2015)	Sysomos, Topsy	Keyword proportion, Granger, VAR
	Conway, Kenski, & Wang (2015)	Lexis, ProQuest, Twitter API	Wordstat, correlation analysis
News media + blogs + social media (Twitter)	Neuman, Guggenheim, Mo Jang, & Bae (2014)	Sysomos, Topsy	VAR, Granger
News media + partisan media + “fake news websites”	Vargo, Guo, & Amazeen (2017)	GDELT	Automated content analysis, network analysis, Granger
News media + social media activists + political leaders’ Twitter use	Freelon, McIlwain, & Clark (2018)	Twitter data purchase	Hashtag counts, Latent Dirichlet allocation, Granger

<sup>2</sup> [https://osf.io/dhb3q/?view\\_only=480a8981cfcf4094a8dba2425e2dbe99](https://osf.io/dhb3q/?view_only=480a8981cfcf4094a8dba2425e2dbe99)

News event (presidential debate) + social media (Twitter)	Shah et al. (2016)	C-SPAN, Twitter API	Keyword counts, Granger, VAR
Newspapers + search trends	Boydston, Hardy, & Walgrave (2014)	Human collection of newspapers, Google Trends	Human content analysis, univariate time series analysis
Physiological + TV	Soroka & McAdams (2015)	Skin conductance, heart rate, TV news segments	ANCOVA, OLS regression
Online news (msm + niche) + search trends	Gruszczynski & Wagner (2017)	MemeTracker, Google Trends	VAR, Granger
TV + public opinion	Searles & Smith (2016)	News Coverage Index, NAES	VAR, Granger
Newspapers + news events (death penalty) + public opinion	Baumgartner, De Boef, & Boydston (2008)	Lexis, Gallup/Roper	VAR, Granger, error-correction models
Democratization and communication technology diffusion	Mays & Groshek (2017)	Polity data series; World Bank, International Telecommunication Union data	ARIMA, selected case study analysis

### ***Text as Data***

Within the field of communication, much of the innovation in computational time series research is occurring in the area of text processing; this is largely because computational tools enable the processing of the large volumes of text necessary for multi-timepoint analyses (Schwartz & Ungar, 2015). This possibility was emergent even 30 years ago, as Fan's work on tracking change in media content using time series methodology and text-coding methods demonstrated (Fan, 1988; Shah, Watts, Domke, & Fan, 2002).

Sometimes, time series analysis of text is conducted on text data as simple as the automated counting of keywords, phrases, and hashtags (Salganik, 2017). For example, Freelon, McIlwain, and Clark (2018) explore the prevalence of hashtags and keywords relevant to the Black Lives Matter movement, comparing their prominence to the attention devoted to police brutality in both the mainstream press and policy makers' discourse. Early studies of social media response to presidential debates, discussed next, sought to understand what factors spurred Twitter users to mention candidates' names during debates (Shah et al., 2016).

Variations on simple counts have served as the basis for more significant headway in the area of intermedia agenda setting. Neuman, Guggenheim, Mo Jang, and Bae (2014) derived topical keyword lists using open-ended responses to American National Election Studies surveys, then counted mentions of those issues from traditional media coverage, Twitter posts, blogs, and discussion board conversations to test how the dynamics of public attention differ across topics. Guo and Vargo (2018) measured the co-occurrence of candidate and topic-word mentions to derive the "issue ownership networks" of the 2016 U.S. presidential campaign. Modeling the shifts in those networks in different media over time offered insight into the agenda-setting capacities of various media (see also Harder, Sevenans, & Van Aelst, 2017). Combining human content analysis of text with factor analyses conducted over time, Baumgartner, De Boef, and Boydston (2008) automated the identification of issue frames and how they change over time.

Machine learning and advanced natural language processing techniques have further increased the range of variables that can be derived from text data. These include classification tasks used to evaluate whether a text or speaker fits into a given category, such as "positive" or "negative," "liberal" or "conservative" (see Petchler & Gonzalez-Bailon, 2015, for an overview). This makes it possible to analyze more complete concepts that do not rely on repeat uses of words or phrases (Grimmer & Stuart, 2013). Once data are classified and labeled (e.g., for sentiment), they can be analyzed to see how discourse changes temporally (e.g., sentiment about a politician over the course of his or her term). Importantly, these data can then be combined with nontext data to understand the antecedents and consequences of language-in-communication. For example, researchers found a significant temporal correlation between tweet sentiment and Obama's support rate during the 2008 presidential election and his job approval in surveys in 2009 (O'Connor, Balasubramanian, Routledge, & Smith, 2010).

Other studies have used unsupervised machine learning techniques to identify key issues in discourse and to analyze the presence (or absence) of topics over time. For example, Cerchiello and Nicola (2018) analyzed a corpus of economic news stories using structural topic modeling, an unsupervised machine learning strategy, and then used Granger causality tests to analyze the spread of financial news stories across different countries. In another analysis of economic news (but focusing on stock markets), Strycharz, Strauss, and Trilling (2018) found that certain topics positively Granger-caused stock price fluctuations.

Multiple computational text analysis tools can be used to extract different types of information from text. Freelon et al. (2018), for example, used both a keyword strategy and topic modeling. Strycharz et al. (2018) used both Latent Dirichlet Allocation (LDA) topic modeling and sentiment classification to understand news about stock markets. These studies show that time series methods can be used to analyze different layers of text data, enhancing the analytical use of computationally analyzed text.

### ***Physiological Measures***

Longitudinal studies of human physiological response to communication stimuli have constituted another area of growth. Affordable data acquisition systems allow researchers to collect continuous responses such as electrodermal activity and facial electromyography by the millisecond, making time series tools useful (Ravaja, 2004; Soroka & McAdams, 2015; see also Lazer et al., 2009).

### ***Networks and Connections***

In network analysis, although researchers have acknowledged that the composition and structure of networks may change over time, they have typically ignored the temporal dynamics when the network process is in a steady state (Borge-Holthoefer & Gonzalez-Bailon, 2017; Snijders, 2005). However, a myriad of digital trace data coming from online forums, e-mail, and social media provide not only information about the relationships of the interaction, but also moment-by-moment time stamps (Lazer et al., 2009). In addition, the speed of online communications, such as the emergence of memes (Weng, Menczer, & Ahn, 2013), mass protest organized with mobile interactions (Chan & Fu, 2017), and a real-time response from social media to a televised national event (Shah et al., 2016), can accelerate the rate of change in network topology. Computational social scientists suggest inspecting time-evolving networks by incorporating more sophisticated methods, such as temporal exponential random graph models, stochastic actor-based models, or continuous-time Markov chains, or simply providing multislice representations of networks (Borge-Holthoefer & Gonzalez-Bailon, 2017).

Despite the diversity of time series applications by political communication scholars, the methodological literature remains sparse. We believe that more concerted attention to time series methods within communication is essential for working with rich, finely grained data with increasing temporal specificity. More guidance on best practices to guide data set construction, analysis, and modeling will help to advance this field.

### **III: Doing Computational Communication Research Using Time Series**

Here we offer narrative accounts of the development of two research programs, while referring readers to published articles for fuller explication and project details.

#### ***Presidential Debates and Social Media Response***

In 2012, our team at the Mass Communication Research Center at the University of Wisconsin–Madison began archiving tweets from Twitter’s “gardenhose” streaming API. Observing the granularity of time and content present in millions of tweets time-stamped to the second, we began exploring possibilities of connecting social media activity to other events in the political-media system. Initial analyses assessed the response generated by Obama and Romney on Twitter during the first presidential debate of 2012 by breaking the 90-minute event into 30-second increments and measuring counts of mentions of each candidate’s name during each period alongside assessment of partisan alignments and polarization (Hanna et al., 2013).

Next, to analyze why social media response varied during the debates, a team led by Erik Bucy at Texas Tech conducted an extensive human content analysis of the debate, using the split-screen presentation broadcast by C-SPAN. Coding assessed candidate statements, tone, gestures, and facial expressions during each 30-second block. These data were merged with two series of Twitter response, one a raw count of candidate mentions, and another a supervised machine learning sentiment analysis of those tweets. Time series analysis, particularly VAR, Granger causality tests, and Prais–Winsten

estimation, enabled us to assess the relationships among these series (Shah et al., 2016). The result demonstrated the “biobehavioral” nature of social media response: Volume of debate discussion on Twitter was strongly driven by facial expressions and gestures of the candidates, while word choices and policy statements had little effect. A follow-up study (Wells, Thomme, et al., 2016) partially disaggregated the Twitter “public” to distinguish the behavior of “elite” (journalists, party leaders) and “average” users and offered a cross-national comparison between the United States and France. That analysis revealed the additional role of elite opinion leaders in shaping real-time Twitter users’ experience of the debate.

Studying phenomena playing out in the span of 30-second periods introduced data-alignment challenges. To know how Twitter messages related temporally to coded moments in the debate, our team aligned Twitter data to the C-SPAN video based on several key moments of the debate, such as the starting moment of the debate and specific questions from the moderator. Although not everyone watched the televised debate at the exact moment given different broadband speeds or broadcasting delays, a large volume of Twitter responses was key to aligning the different data sets because it provided an indicator of real-time attention with the lags built into social media response. As this suggests, establishing clear criteria on which to synchronize often relies on establishing time lags within these sorts of time-stamped data from different sources.

### ***The Hybrid Media System and the 2016 Election***

The ubiquity of social media in the 2016 presidential primaries spurred many questions about the relationship between social and traditional media, especially given Donald Trump’s success in using Twitter to shape the national conversation. Accordingly, we conducted a series of studies examining news media attention directed at Donald Trump during the presidential primaries in 2015–2016. Building on the experience using time-organized social media data, we (Wells, Shah, et al., 2016) assembled a wider and more varied data set to account for the factors that might lead to news media attention of a renegade candidate. The data set included social media (Twitter) data (that is, tweets from Trump and retweets of him); news media coverage of Trump, operationalized as counts of articles mentioning the candidate two or more times; and several other campaign variables, including debates, rallies, interviews, and media appearances.

Time series analysis was essential to understanding these series’ relationships. Because news media and social media attention are often responsive to one another, it was particularly important to disentangle the temporal relationships among these series. Indeed, we found these to be highly correlated, speaking to the overall unity of the larger media system. Granger causality tests helped establish that social media buzz about Trump (in the form of retweets of him) tended to anticipate news media coverage more than the reverse.

## **IV. Time Series Techniques in Communication Research**

Until now, we have described how techniques combining computational communication science with time series analysis can enrich the study of communication phenomena. Next, we review some techniques of time series analysis. Our purpose is not to offer instruction in the use of these techniques (see

this article's supplementary materials for references to technical sources<sup>3</sup>), but rather to identify concepts that any scholar wishing to investigate social processes will need to be familiar with. We hope that this section will provide readers with a working knowledge to understand existing studies and begin to contemplate conducting their own time series analyses, even those without an extensive background in regression methodology.

### ***Foundations of Time Series***

Modern time series techniques were synthesized and popularized in the social sciences by Box and Jenkins (1976). The key insight of the Box–Jenkins modeling approach is that researchers must apply various statistical filters to a univariate time series to ensure that the variance explained in regression models represents the social process of interest rather than a statistical artifact. For example, if the stories a journalist covers today are influenced by what stories he or she published yesterday, then some portion of the variance in a time series of that news coverage will simply be explaining itself, rather than an independent variable(s) of interest.

The Box–Jenkins approach accounts for these self-driven processes by decomposing individual time series using a set of statistical tools to diagnose the types and extent of temporal dependency. Typically, the first tool is a set of correlograms that plot the autocorrelation function (ACF) and the partial autocorrelation functions (PACF) of the time series. These plots form the basis for identifying one, or a combination of, three possible processes: autoregressive (AR), moving-average (MA), and/or integration (I). The resulting models, known as autoregressive integrated moving-average (ARIMA) models, diagnose what kind of self-driven behavior is present in a time series. While ARIMA models are decompositions of single univariate series, diagnosing and addressing these properties form the foundation of multivariate time series. Before addressing multivariate cases, we discuss each component of an ARIMA model to better illustrate its complexity, importance, and application to communication.

### ***Autoregressive Processes***

AR processes are present when a strong predictor of behavior in one time period is a function of the behavior during previous time periods. That is, changes in a time series have a “memory” that decays progressively. For instance, wall-to-wall news coverage of a politician's campaign gaffe one day may justify significant follow-up coverage the next day, and even additional news analysis later that week, but the event eventually decreases in journalistic value as other issues push it off the news agenda. AR processes describe this gradual, often exponential, decay in the influence of a shock to a process. AR processes are very common in social data and are almost always present in time series of media data (see Wells, Shah, et al., 2016).

Failing to account for AR processes leads to model misspecification and/or biased parameter estimates in traditional (OLS) regression contexts. The traditional response to finding an AR process in a data set is to treat it as a nuisance—a statistical problem to be solved via specialized regression techniques. Often, these approaches rely on generalized least squares (GLS) models like the Cochrane–Orcutt or Prais–Winsten, which

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<sup>3</sup> [https://osf.io/dhb3q/?view\\_only=480a8981cfc4094a8dba2425e2dbe99](https://osf.io/dhb3q/?view_only=480a8981cfc4094a8dba2425e2dbe99)

differ from ordinary least squares (OLS) in that they can identify and correct for autoregression present in the error terms of a regression model (Hester & Gibson, 2007; Shah et al., 2016).

These GLS approaches, however, suffer from two limitations. First, from a theoretical point of view, they treat temporal dependence as an estimation problem to be corrected rather than a meaningful component of the regression equation itself. Second, AR processes can be of varying lengths, or orders. GLS approaches (along with traditional regression diagnostics) can only detect and correct for an AR(1) process—that is, when the AR property of a series lasts only one time period before becoming statistically insignificant. They thus miss higher order AR(2) or AR(3) processes, in which an event may generate independent influence beyond a single period, even when controlling for its one-period effect. When handling higher order AR processes, GLS approaches should be avoided. Recent work comparing OLS, Prais–Winsten, Cochrane–Orcutt, ARIMA, and lagged dependent variable (LDV) models recommend higher reliance on ARIMA and LDV models because they “produce the best estimates under the widest number of experimental conditions” (Keele & Kelly, 2006, p. 196).

Moreover, Cochrane–Orcutt and Prais–Winsten approaches cannot account for other properties of time series data: moving-average and integration.

### ***Moving-Average Processes***

MA processes are familiar to many analysts, but often as a tool for smoothing data rather than as a property of the data themselves. They are defined as a linear function of past random shocks. Unlike AR processes, which diminish in explanatory power over time, MA processes disappear from a system quickly and after a finite period; they are thus considered short term (Box-Steffensmeier et al, 2014). Yet these properties also have important implications, suggesting that the data-generating process has a relatively short memory.

### ***Stationarity and Integration***

Integrated series are less familiar to the typical analyst, but are arguably the most important. In a stationary (nonintegrated) series, shocks influence the process under observation and the quantity of interest shifts, but over the time series, these shocks have diminishing effects, bringing the series back to the equilibrium.

Integrated series, also known as a random walk or a unit root process, have a permanent memory. These shocks persist perpetually, resulting in a series without a clear equilibrium (see Figure 1). Time series of communication phenomena are often integrated: daily growth in Twitter follower count, for example, or quantity of political-related news coverage over an election cycle. Diagnosing integration is critical to applying appropriate time series procedures. For example, a Prais–Winsten regression with integrated time series would yield incorrect estimates because only the AR properties are considered, not the integrated component.

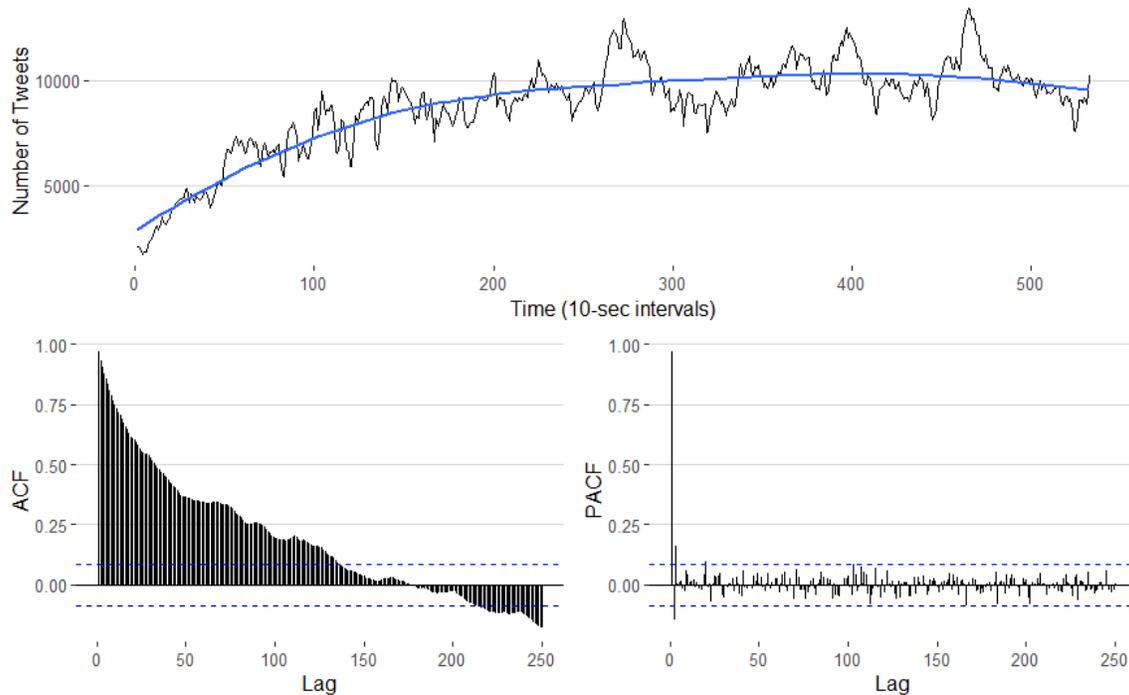
Scholars in communication have progressively improved their diagnosis and treatment of nonstationary data, though more consistent treatment would be desirable. Early agenda-setting studies visually inspected ACF and PACF plots to determine stationarity without formal statistics. A common technique to correct integration, fitting a linear trend to an OLS regression, is flawed because of the sensitivity of OLS to the first and last observations, as well as to outliers (Box-Steffensmeier et al., 2014). Recently, scholars have begun reporting results of formal tests for unit roots (Augmented Dickey-Fuller, KPSS) before analysis (e.g., Neuman et al., 2014).

To treat integration, first-differencing the series is often standard practice (Groshek, 2011; Searles & Smith, 2016). Another strategy, useful if other processes are present (AR or MA), would be to estimate an ARIMA model, saving the residuals of the model to then use as a normal, stationary time series—a process referred to as “pre-whitening.”

Cutting-edge time series econometrics have shown that integrative processes are not binary. Rather than conclude that a series is stationary or nonstationary, scholars have estimated the degree to which a series is stationary. This approach—referred to as fractional integration—more precisely measures the order of stationarity,  $I(d)$ , rather than assume  $d(0)$  or  $d(1)$  (Box-Steffensmeier & Smith, 1998). Fractional integration represents a long-memory process where memory is persistent but not permanent. For scholars interested in granular data, this may be a highly productive area for future research. Research on presidential debates, for example, has found that memes and other eruptions during debates can create persistent yet nonpermanent effects on social media response during the time of the broadcast. Fractional integration is also likely in communication data because of data aggregation. As Granger (1980) notes, the act of aggregating heterogeneous measures of individual behavior (e.g., news media, polling) will naturally produce fractional dynamics (Lebo, Walker, & Clarke, 2000).

Importantly, using modeling approaches that “ignore the presence of fractional dynamics leads to an alarmingly high rate of type I errors” (Lebo et al., 2000, p. 32). This is because first-differencing a fractionally integrated series unintentionally removes both long-run and short-run dynamics. By accounting for what are essential partial differences, short-term processes remain intact, and long (but impermanent) properties can be identified. Fractionally integrated ARIMA models (ARFIMAs), a variant of ARIMA, incorporate this consideration.

Figure 1 shows a diagnostic plot of Twitter mentions of presidential candidates Donald Trump and Hillary Clinton during the first 2016 general debate, measured at 10-second intervals. A visual analysis of the raw series suggested a unit root, or integrated series. The relatively linear, yet moderate, decay from high values of the ACF plot is a classic sign of fractional integration (Box-Steffensmeier et al., 2014). We estimate that the time series of Twitter mentions of both Trump ( $d = .48$ ) and Clinton ( $d = .44$ ) were fractionally integrated (i.e., neither  $d = 0$  nor  $d = 1$ ), requiring the use of ARFIMA models. Others, like Habel (2012), use ARFIMA models to test the directional influence of media opinion from *The New York Times* and *The Wall Street Journal* editorials on the policy positions of the public and policy makers over 56 weeks. However, recent experimental work recommends extreme caution for researchers considering fractional integration techniques using fewer than 100 observations (Keele, Linn, & Webb, 2016).



**Figure 1. Illustration of graphical tools used to diagnose properties of time series. Data come from counts of tweets mentioning Donald Trump or Hillary Clinton during every 10-second period of the first presidential debate of 2016.**

In short, those undertaking future work in the field should be alert to the possibility of fractional integration as a variant of nonstationary time series data. As finely grained social media data and other computationally derived measures become more common, the likelihood of pure  $I(0)$  or  $I(1)$  processes will likely decline.

#### ***Multivariate Time Series: VAR, Granger, Cointegration, Error Correction Model***

Our discussion of time series so far has centered on univariate techniques, but most analysts wish to know the influence of one process on another. Notably, multivariate time series techniques all build on the basic ARIMA techniques as a foundation. The closest analogs to univariate ARIMA models are intervention models and transfer function models, which allow for assessment of how an exogenous factor influences a time series, controlling for other possible influences (Box-Steffensmeier et al., 2014).

An important multivariate method is vector autoregressive (VAR). These models estimate the influence of multiple (stationary) time series variables on one another, including lagged values of past observations. In contrast to structural equation models, which assume exogeneity of key independent variables, VAR makes few assumptions about functional form—in VAR, the analyst can specify which

variables are endogenous and exogenous. Once a VAR is estimated, Granger causality tests can be used to verify which variables can be considered temporally prior. VAR models and Granger causality tests are popular because of their ability to account for endogenous variables, making them especially appropriate for scholars who suspect bidirectional or multidirectional relationships (Freeman, Williams, & Lin, 1989).

### ***Cointegration and Error Correction Models***

But what if a researcher discovers that more than one of his or her series are nonstationary? One approach, as discussed, is differencing a series, which retains information on short-run dynamics, but sacrifices information about long-run dynamics. However, if the integrated components of two or more series are related in some way (i.e., they are "cointegrated"), differencing the time series would remove the relationship. Cointegration and error correction models (ECMs) are used to address these issues (Durr, 1992).

Cointegration allows us to consider two or more series as related by speculating that they may have a correlation over the long term, but diverge in the short term, as in response to exogenous shocks. These shocks will push the series apart, yet in the long run, they will reequilibrate to track each other again. For example, consider coverage of two news events (political events and economic coverage), which may be correlated. At some point, an event (like a scandal) may cause excessive coverage of one event, perhaps at the cost of attention to the other; this results in an attenuation of the correlation. Yet, after some time, the two resume their close tracking of one another.

ECMs are designed to account for both of these long-run correlations, but also short-term equilibrations. A statistical test is required to determine cointegration, followed by estimation of a full model via a single equation, using the Engle and Granger (1987) approach or a multiequation VAR approach known as the Johansen (1988) method. Error correction models have been applied to evolutionary factor analysis of news frames and public opinion about the death penalty (Baumgartner et al., 2008) and how uncertainty in economic news coverage affects consumer confidence (Van Dalen, De Vreese, & Albæk, 2017).

While VAR and ECM techniques can capture and predict more complex dynamics among variables of interest, researchers should always consider whether ARIMA models or multivariate transfer functions are more parsimonious forecasting approaches based on their research questions, hypotheses, and modeling assumptions (Edlund & Karlsson, 1993).

### ***Additional Issues of Time Series in Computational Communication Research***

In addition to these issues in time series analytics, two other considerations are often present, forcing the analyst to make choices when generating and coding data to investigate particular social processes.

#### ***Temporal Aggregation***

When an analyst measures a social process using a time series, one of the first questions to be asked is: How often should the process be measured? Temporal aggregation refers to increasing the unit of measurement for a time series (e.g., from minutes to hours, months to years). Time series with low levels of

aggregation have smaller time units at high frequency, while series with larger time units are highly aggregated with low frequency (Silvestrini & Veredas, 2008). One can “increase” the aggregation of a time series by using systematic sampling or by grouping time points (Freeman, 1989).

There is some disagreement among scholars in econometrics and time series about whether temporal aggregation alters the measurement of the underlying social processes under observation (Marcellino, 1999; Silvestrini & Veredas, 2008). Low levels of aggregation can maximize the power of a model and reveal micro-processes (Haug, 2002), but Freeman (1989) also encourages researchers to devote more time to deciding the “natural time unit” of their theories. That is, researchers should have some theoretically derived understanding of the temporal dynamics at play for their case that should inform their data collection and aggregation choices. For example, Harder et al. (2017) aggregates social media data at 6-hour intervals as a middle ground among traditional daily/weekly agenda-setting models and the second/minute granularity and pace of online platforms like Twitter.

However, it is not always possible to measure processes at such a granular level. Polls, the gold standard of public opinion measurements, are collected about every three days to a week, and more sporadically during nonelection years (O’Connor et al., 2010). Most time series research involving news media is also operationalized at the day level of aggregation (Neuman et al., 2014). In addition, many dependent variables that scholars are interested in do not vary at low levels of temporal aggregation (e.g., partisanship), are very sparse (e.g., polls), or are difficult to verify when aggregated at a minute or hour level. For instance, our own exploration of the time stamps of Lexis, MediaCloud, and news organizations’ websites revealed enough discrepancy for most news outlets that we were unable to aggregate at levels lower than the day. As more and more granular media data become available to researchers, scholars should be careful in choosing a unit that makes sense for all data, and it may be optimal to test multiple levels of aggregation.

### ***Lags***

Another important consideration is the role of lags, or delays in the effects of variables on one another. In a natural setting, communication between two or more individuals does not occur simultaneously; people need to process information before they can respond. Lags are necessary to account for the time it takes for an effect or outcome to occur. Incorporating a one-unit lag in multivariate analyses is common in communication research (e.g., Bastos, Mercea, & Charpentier, 2015; Habel, 2012) and is often appropriate for communication data (Yanovitzky & VanLear, 2008). Others have tested different lag lengths to examine the relationship among different parts of the media system (Conway, Kenski, & Wang, 2015; Green-Pedersen & Stubager, 2010; Neuman et al., 2014).

The reality is that the “real” lag lengths of media effects are often not known, especially in the domain of social media platforms and the increasing churn of the news cycle, which raises thorny new questions for researchers testing for media effects. When the correct time lag for a measured response to a media platform is unknown—and it often is, especially given the early stage of much of the relevant research—there is potential for model misspecification and parameter misestimation. This is an area in need of development, both theoretical (what kind of lags does our theory lead us to expect?) and empirical (what kind of lags are our data indicating exist?).

For example, in analyzing the 2016 debates, we speculated that Twitter would respond to candidates' nonverbal and verbal populism cues at different rates; notably, nonverbal indicators would be more quickly discussed relative to verbal cues. Our initial analysis finds that visual elements took the fewest lags (1 lag, 10 seconds) to influence candidate mentions, whereas tonal and verbal elements took longer (4 lags, 40 seconds). Several information criteria are available to determine an appropriate number of lags in a time series model. The most common include the Akaike information criterion and Bayesian information criterion (Lütkepohl, 1984), which are used to compare the fit of models with different lag lengths. Of course, different information criterion may recommend different lag lengths, introducing an aspect of researcher judgment into the decision (Liew, 2004).

### **Conclusion: Supporting the Temporal Turn**

The digitization of communication technologies and media archives, alongside the development of new tools and platforms for computational methods, promises great advances in empirical work, since the process of harvesting and analyzing is now feasible on growing scales and speed. However, as databases grow larger and more complex, so do the potential caveats that accompany them.

Perhaps most critical is awareness of how choices made using the new techniques impact our conceptualization and execution of studies. How our models predispose us to think about communication phenomena may have substantial bearing on our analyses and findings. And in this connection, of course, the increasing availability of communication data, and facility with time series analysis in our field, presents risks of misuse, misspecification of models, the misinterpretation of coefficients, and the overestimation of causal processes.

However, new methods also present us with the opportunity to rethink, and sometimes empirically investigate for the first time, existing assumptions—about the “natural” time increment of a phenomenon, or how long an effect takes to trigger or fade away. We expect a wealth of new findings, some of them descriptive, demonstrating the underlying properties of communication phenomena, and others predictive, explaining the dynamics of relationships among different parts of the media system. It is our hope that this research can help to improve the sense we make of a chaotic, unpredictable, and increasingly complex communication and mass opinion system.

There are also areas in which communication will need to innovate. The challenge of summarizing textual data in a way that is conducive to time series analysis is an important problem, and one that communication scholars are already important leaders in addressing. Gaining the ability to capture meaning, changes in meaning, and the flow of units of meaning across communicative spaces is a tantalizing challenge. The problem of accounting for the complexity of the media system—both its speed and its volume and diversity—is another: With the potential of thousands of series coming from online outlets and social media, how will we choose which are most significant? What are the most appropriate techniques for aggregating them? How can we guard against Type 1 errors resulting from too many significance tests? We anticipate that time series analysis will play a growing role in the already burgeoning field of computational communication science, and we hope that this article proves helpful to some of the scholars doing this exciting work.

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