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Network Histories: Methods and Measures for Studying Interdependence and Interconnectedness Within Digital Journalism

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ABSTRACT
This article details "network histories" as a methodological approach for studying organizations, teams, and individuals in digital journalism. Network histories trace the pattern of prior relationships between actors (e.g., organizations and individuals). The network histories approach provides an analytical and methodological framework that builds on extant networks scholarship and enables an examination of the role that an actor's prior histories have on subsequent activities. This approach is particularly useful for examining how changes in media and technology affect the organizations, teams, and individuals who produce digital journalism and other communication content. We detail the network histories approach in the context of analyzing the work histories and relations that shape the production of digital journalism. We also discuss future avenues for applying network histories to digital journalism research.

KEYWORDS
Digital journalism; network histories; social network analysis; big data; careers; production

This article outlines an approach to studying the interdependence among and between organizations, teams, and individuals who produce digital journalism over time in order to further understanding of the core dynamic of transformation in the field. Network histories is an analytical approach and method, first coined by Kosterich and Weber (2019) and expanded upon here, that integrates social network analysis and historical analysis of employment and biographies to examine how hiring patterns, producers of digital journalism, and organizations are evolving over time. This approach has also been extended into domains that include political communication (Kreiss and Saffer 2017). Network histories is particularly relevant to the field of digital journalism with its common reskilling of employees, rapidly changing needs in expertise, and connections to other professions in the tech and communications world (see, e.g., Kosterich and Weber 2019; Kosterich 2022).

The network histories approach aides analysis of the changes in journalistic production and outcomes, from the ways journalists perceive their audiences to the content they produce. In this Advancing Methods article, we detail the methodological

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approach, and propose a set of concrete measures and attributes for investigating the interconnectedness and interdependence among and between organizations, teams, and individuals who produce digital journalism. We then show how this approach, and the novel sources of data that it is premised upon, can open new questions in journalism research.

Defining Network Histories

Network histories is a novel method that uses a social network perspective paired with digital trace data of employment histories to examine how hiring patterns, producers of communication, and organizations are evolving over time (Kosterich 2022). Network histories integrate traditional network analysis with archival research to reveal connections between key actors and organizations. This approach captures a longitudinal perspective by applying social network analysis to digital trace data.

Social network analysis has its roots in mathematics and sociology, and especially in the work of sociologist Jacob Moreno and his development of sociometry in the 1930s (Freeman 2004). In the intervening years, social network analysis has been adopted in communication, media studies, political science, and management, among other domains, to answer a wide array of research questions. Social network analysis examines how two (or more) actors are connected through a type of common relationship such as a communicative interaction (Borgatti, Everett, and Johnson 2014). In network terminology, nodes are the vertices and ties are the connections between those vertices. A node can be any actor or unit such as an individual or organization and its connections are the relationships among them. Both nodes and connections can have attributes. A node's attribute may be a characteristic like their gender or organization type. A relational attribute might be strength of the connection between nodes. Networks form from the nodes and the connections among nodes.

Network Analysis and Organizational Studies

Extensive research demonstrates the applicability of social network analysis in the context of organizations. Organizational scholars have utilized network analysis for decades to study questions of power and to examine the roles of corporate elites in organizational management (see Scott 1991 for an illustrative example and review); this approach was expanded to consider the role of elite structure and networks in organizational decision making (Knoke 1994) and influence within organizational structure (Burt 1999, 2005). This strong foundation in organizational studies has been extended in recent years as scholars have set forth an agenda for research leveraging social network analysis to study journalism (Fu 2016). This has led to more recent scholarship applying social network analysis to understand the structural properties of networks of media organizations (Saffer et al. 2021; Sjøvaag et al. 2019), as well as studies of the gatekeeping roles of media organizations in the context of misinformation (Thapa Magar, Thapa, and Li 2024). Looking towards modern media organizations, and building on this foundation, network histories provide a key method for examining the history of alliances and partnership that have driven adaptation by news organizations.

Network History and the Context of Journalism

Network histories focuses on histories and characteristics of organizations and people by merging the sociological traditions of network analysis with historical research, where scholars have used network analysis to trace the development of past events (Brügger 2013) through social sequence analysis (Cornwell 2015). Studying sequences of network history can answer macro-level questions such as “how a diverse array of formal organizations regularize the production of cultural products and audiences” (Kreiss and Saffer 2017) and micro-level questions about changes in the types of people who become journalists and the skills necessary to enter into the profession (Kosterich 2022; Kosterich and Weber 2019)—potentially leading to changes in journalistic routines and outputs. Building on prior methodological work, network histories simultaneously account for the dynamics, nonlinearity, and multi-level nature of connections among actors.

In our approach to network histories of digital journalists, organizations are connected *via* the exchange of resources (e.g., funds, employees) flowing between them. Organizations are the nodes connected by their employees’ work sequences. For example, two media outlets become connected *via* journalists with prior employment at both organizations. The patterns of these employment connections position organizations in a larger network. And, they reveal the extent to which organizations are sites for recombining journalists’ expertise and the cognitive diversity in an organization or field (Vedres and Stark 2010). At the same time, individuals are connected to their employers and become connected to other individuals when they have an employer in common. For instance, two journalists working on the product team for the BBC become connected by their shared work history and their digital production routines. Importantly, “groupings of individuals within organizations influence their capacity to produce innovations. This occurs through the recombination of individuals’ prior production experiences” (Kreiss and Saffer 2017, 522).

Network histories can also leverage biographic information to reveal the attributes of nodes and connections. Media outlets may have attributes like their type (i.e., digital-first or legacy), number of employees, or ownership structure, just to name a few. Employees’ biographic information may contain attributes like their employment tenure, education background, gender, or skills. Such attributes provide a richer picture of a network than just the nodes and connections, and may be used to explain why some nodes connect and others do not (e.g., homophily suggests that nodes with common attributes will be more likely to connect). Given that much of the data we are focused on captures connections over a substantial duration of time, it can also be critically important to include time as a variable. The exact nature of the time variable will depend on the granularity of the data, but conceivable could range from years to months; anything more granular is likely to lose meaning in an employment network (where job tenure is generally measured in years and months). The connections among nodes also can have relevant attributes. For instance, the connections among media outlets maybe characterized by their number of shared employees (i.e., tie strength). Likewise, the connections among employees may be categorized by the types of organizations they have been employed by. The relational attributes can provide great specificity about the nature of how and to what extent nodes are connected.

Utilizing the Network Histories Method in Practice

As we demonstrate, a network histories approach advances research in a number of areas, including interrogating individuals' work histories and biographies, examining the emergence of new organizations involved in journalism, and studying the changing nature of ties between them through their employees' work histories. In doing so, researchers can analyze the ways production is changing from the perspective of the "actors"—individual and organizational—that digital journalism scholars have identified as key influences (Lewis and Westlund 2015). The examples of network history research that follow focuses first on the news industry and the production of journalism at the individual level. Second, we show how network history research on partnerships and alliances provides an organizational level perspective, including detailing macro-level resource networks.

Professional Journalists and Skills

Kosterich and Weber (2019) analyzed the impact of prior work relationships on the production of digital journalism, as developments in digital technologies continue to impact who and what organizations produce news and how they produce it. The impact of digital technology on production is evident as news media organizations increasingly recruit individuals with non-traditional news industry work experience such as programmers, coders, and data analysts. Although these people account for a small percentage of overall hiring, these organizational changes are significant in shaping journalistic content and give rise to broader shifts in production practices. Indeed, these micro-innovations are drivers of larger scale innovation within journalism. Intersecting technical and journalism work histories merge within certain newsrooms to help drive digital disruption and adaptation.

Organizational Alliance and Partnership Networks

News organizations are slow to evolve; the highly institutional nature of journalism and the need for public legitimacy are two key mechanisms that hinder innovation efforts (Lowrey 2011). Research calls attention to how engagement with industries adjacent to journalism is altering the news industry topography, creating opportunities for innovation and adaptation (Lowrey, Sherrill, and Broussard 2019). Through interactions with other organizations, within the industry and adjacent to it, news organizations mimic the practices of others (Boczkowski and Santos 2007; Lowrey 2011).

Alliance formation in an effort to gain renewed legitimacy in the eyes of other news organizations and future investors can give rise to innovation (Dacin, Oliver, and Roy 2007). Network histories examine the history of alliances and partnerships that have driven adaptation and innovation by news organizations. For instance, by tracing the publicly acknowledged partners of news organizations (both non-profit and for-profit), news industry organizations (e.g., Society of Professional Journalists, Poynter, Institute for Nonprofit News) and technology organizations (Facebook and

Google), it is possible to recreate the network history of partnerships that exist between media organizations.

A Methodological Approach to Network Histories

In order to illustrate this approach, we use two sets of data. We make reference to data used in Kosterich and Weber (2019) manuscript on newsroom employment; their network data provides a useful testbed for some of the measures discussed in the following (see Kosterich and Weber 2019, for additional details). Second, we use a set of data from 2016 tracking employment histories of digital journalism professionals to illustrate the utility of our analytical and methodological approach. The purpose of this illustrative study is to provide an initial examination of work histories at a subset of media organizations near the New York City metropolitan area (the data presented here is part of a broader effort to track media organization work histories.) The sample organizations include the Asbury Park Press (in Asbury Park, NJ; representative of a legacy, local news organization), Vox Media, Inc. (in New York City; representative of a digital-first startup news organization), and the New York Daily News (in New York City; representative of a legacy regional news organization). These three organizations represent a cross-section of news-function, market-size, and budget in a major metro area. We analyzed the work histories of 100 randomly sampled employees at each of these three news organizations. The dataset includes 300 individuals and 725 job roles prior job roles occupied by those individuals (which we analyze as connections between actors). Information on the employment histories of journalists working for these sample news organizations was aggregated through a process of hand-coding public data gathered from LinkedIn. This approach enables a preliminary analysis of employment networks in the digital news media ecosystem, the variety of digital journalist skillsets, and how the requisite skills differ by type of news media organization. The use of this limited sample and dataset provides a more focused snapshot for illustrating the Network Histories approach to data collection and analysis.

We conducted a search *via* LinkedIn's interface for each organization, and recorded employee work histories including job titles, organizations, dates of employment, and educational information in a separate Google sheets database. Data were de-identified and anonymized immediately following completion of data collection to protect individual identities. Organizations and positions in the dataset were categorically coded to summarize the data. We coded organizations by industry and positions by general function. We used manual coding in this case study, similar to other work (see, e.g., Kreiss and Saffer 2017; Kosterich and Weber 2019; Kosterich 2022); however, there are also options for computational approaches for gathering partial data through LinkedIn's API, depending on a researcher's abilities and access. A data coding sample is shown in Figure 1 to guide future researchers.

A	B	C	D	E	F	G	H
Search Date	Name	Position	Current Company	Current Position	Date Started	Date Ended	Location
2/10/2016	14152	5	New York Daily News	Stringer, News Desk	2011	2012	Greater New

Figure 1. Sample network history spreadsheet entry.

As illustrated, each employment position is coded. In this case, employee #14152's fifth job is coded. It is useful to leverage computational resources such as web scraping to automate the data collection process (especially if the researcher is interested in a larger sample size).

Additional fields coded include education (university and major) and self-identified skills and areas of expertise. These are coded as attributes in addition to the primary network data. The selection of attributes is a critical component of the construction of network histories because they amount to explanatory variables. For instance, in the case of journalists, the major of a reporter could help to explain the type of reporting produced by a journalist (e.g., financial reporters will be more likely to have a background in economics, in addition to journalism).

Ethical Considerations

Our data were collected with Institutional Review Board (IRB) approval, but despite IRB oversight there are ethical issues that may arise collecting these types of data. As noted above, we deidentified all actors in our dataset. In addition, we only reported summary data to protect individual work histories. In some countries, such as those in the European Union, regulations such as the General Data Protection Regulation are likely to limit the ability to collect these data without individual approval. These types of data could be collected *via* a survey, which is often done in sociological studies, but sites such as LinkedIn offers a more complete range of observational data not dependent on response rates, and likely better reflects individuals' professional resumes.

We use these data to demonstrate our approach and provide guidance on implementing Network Histories in practice. The following steps build on lessons from prior work (Kosterich and Weber 2019; Kreiss and Saffer 2017) and demonstrate how to examine each type of data to better understand the evolving nature of these critical journalism institutions. Each step in this process of developing network histories is detailed in the following sections.

Analytic Scope & Boundary Specification: Whole and Ego Networks

One of the initial challenges in network research is determining the eligibility criteria for the nodes and connections that will be included (Marin and Wellman 2011). This is a key issue for network histories as well. This process of boundary specification is similar to the challenge of accurately defining the population upon which results are generalized. Network histories take a relation-based approach, which is more common with ego networks (where data collection focuses on networks extending from a single actor or set of actors). This relational approach focuses on all actors connected by a predetermined number of steps to a focal set of actors. The approach begins with a set of focal nodes whose relations are traced to other nodes using snowball sampling.

With an ego network scope, researchers study focal nodes or a set of nodes (i.e., individuals or organizations), egos' connections to "alters" (i.e., other nodes connect ego), and the attributes of those egos and alters (Borgatti, Everett, and Johnson 2014). Such an approach is useful for studying individuals' or organizations' ties. In Kosterich and Weber (2019) study, a random sample of news media companies headquartered in NYC led to the snowball sampling of other related nodes in the news media employment ecosystem. This enabled an analysis of journalists' employment networks that provided insight into the organizational, educational, and skillset trajectories of professionals in digital journalism.

Collecting and Coding Data

Network histories draw on novel data sources and measures of employee biographical information (e.g., labor intermediaries like job websites, professional social networking sites, credits on creative projects, social media, etc.). It is possible to collect network history data from qualitative approaches such as interviews, although such an approach is likely to limit the scope of data collection because of the time-intensive nature of the process. The growth of online recruitment and hiring practices has created a vast repository of digital data tracing employment histories and practices, which can be used to examine changing skills within journalism or shifts in the employment patterns.

Converting Data for Network Analysis

It is necessary to convert the information from a database format to a network format. Data can be transformed into two-mode affiliation networks that contain two types of vertices or one-mode networks (i.e., one type of vertex). Generally, the process for the type of affiliation data collected in network histories research is to convert the data into a two-mode network (actors to employers), and then once the data is in network format a conversion can be made to a one-mode network (actors to actors, or employers to employers). In our case study, a two-mode network was created with a '1' used to indicate that a journalist worked at a particular organization and a '0' used to indicate that no relationship existed. Network packages including statnet (Handcock et al. 2008) and igraph (Handcock et al. 2008) were used in the open source R framework to transform the two-mode network into a one-mode network of organizations.

The two-mode network shows the employees who are connected to target employers (i.e., Vox, Asbury Park Press and the New York Daily News). Figure 2 shows the ego-network specifically for the Asbury Park Press. In this case the network is illustrated as a one-mode network of employers. Two employers are connected if an employee was hired from one organization to another. In this case, there is a strong connection between Gannett and the Asbury Park Press (a Gannett-owned paper), showing that a larger number of employees moved from Gannett to the Asbury Park Press. This illustrates a clear connection between these organizations, and the movement of employees between the two media companies. Network visualization can be important as a means of quickly identifying key features in a given network and providing context to the data derived in subsequent analyses.

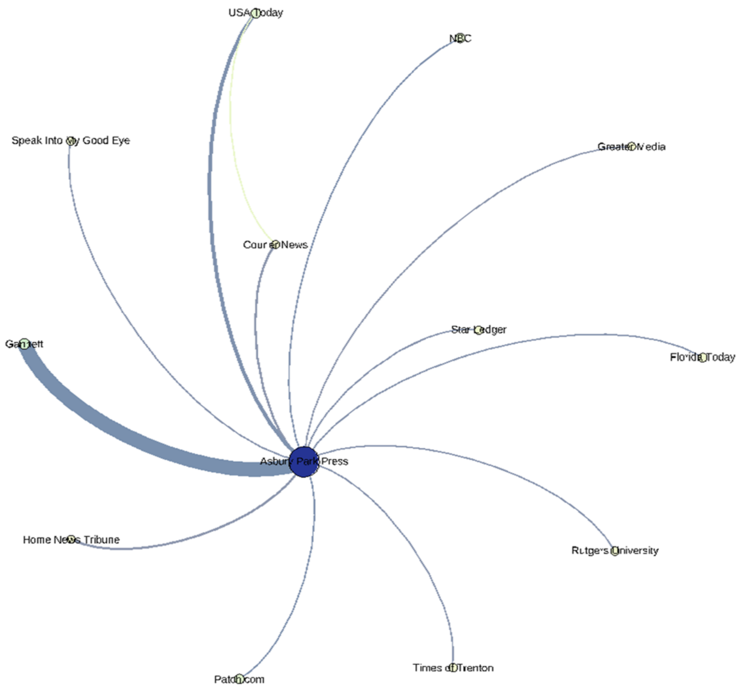

Figure 2. Sample ego-network illustration for Asbury park press.

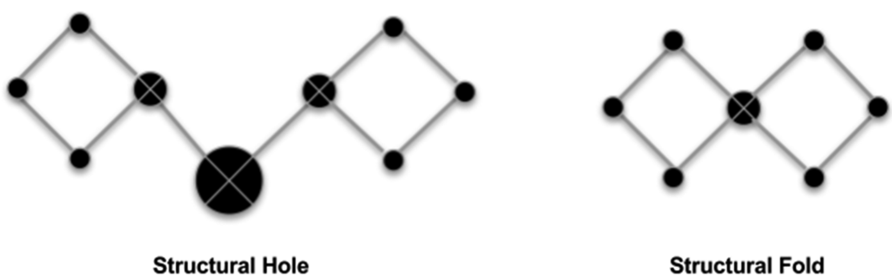

Figure 3. Structural hole versus structural fold.

Measures for Network Histories

A dominant argument among network researchers known as the "brokerage-plus-closure" perspective argues that innovations arise from the flow of new ideas and information among cohesive groups (Burt 2005). There is a balancing act at work within a network between competing tensions of brokerage and closure. Cohesive groups where nodes are well connected can allow for information to easily flow through the network. This information is often redundant and there is a need to gain access to new information. Brokers, who connect unconnected parts of a network, fill structural holes (Burt, 1992) and can facilitate the flow of new information (Obstfeld 2005). A broker can introduce a team to new information. The individuals (or organizations) brokering the exchange of ideas and information belong to distinct cohesive (well-connected) groups, as depicted in Figure 3.

Contrary to the brokerage-plus-closure perspective, the "intercohesion perspective" asserts that innovation arises from dynamic, disruptive tensions among bonded individuals, teams, and organizations. Intercohesion recognizes some nodes may be embedded in multiple cohesive parts of a network that subsequently allow for the recombination of new ideas and information. The focus is less on the flow and more on what is produced from connections. Additionally, basic network analysis measures can be applied to describe networks, including core measures of network centrality and density. There are also several novel measures that can be used to analyze patterns of production in these networks, outlined as follows.

Structural Folding

A network histories approach can assess whether news organizations are ideally positioned within a network to generatively recombine news workers' knowledge bases and productive resources. Structural folding is based on the premise that effective recombination of knowledge occurs at "the intersection of cohesive groups where actors have familiar access to diverse resources" (Vedres and Stark 2010, 1115). Here organizations are nodes and connected by employees' employment histories. Organizations are positioned in a network when their patterns of connections–employees' prior employment–come from cohesive groups with overlapping connections (de Vaan, Vedres, and Start, 2015). In other words, organizations that regularly hire employees with work histories at organizations that have also previously employed the same people can create cohesive groups that can ease the friction of recombining knowledge and accessing knowledge bases.

Those familiar with network measures may see that structural folds share similarities with the concept of brokerage from structural holes theory. Whereas brokers "fill" the structural holes between unconnected parts of a network, structural folds are the points of overlap between cohesive portions of a network (see Figure 1). Analytically, structural holes identify locations of network brokerage but structural folds reveal the network locations of recombination—the points where nodes' connections overlap with other nodes embedded in other cohesive groups (Vedres and Stark 2010). For example, a journalist with prior experience in a data analytics role brings with her connections to that firm and all the previous firms that she was employed by. This is seen in the context of an employee who worked at The Washington Post on a software development team moving into a management position at The New York Times overseeing a team of reports (Kosterich and Weber 2019). Her connections combine with the network histories of other journalists who have their own connections to previous employers. When journalists come from a cohesive set of employers (i.e., employers already have overlapping employment of multiple staffers), the organization is then positioned at a structural fold (Stark and Vedres 2006).

In the context of the case study, there are no overlapping relationships between employees of Vox and the Asbury Park Press. There are two actors who have brokerage roles in the network between Vox and The New York Daily News, but when the structural fold measure is applied neither of these brokers occupy positions bridging reinforced structural holes. Thus, Burt's Burt (2015) more refined measure helps to discern the strength of brokerage opportunities, and points to a lack of reinforced connectivity between the three organizations.

Cognitive Diversity

Where structural folding is position-based, cognitive diversity is attribute-based in that it directs attention to the variety of "stylistic elements available for reworking" (de Vaan, Vedres, and Start, 2015, 7) that can come from a node's connections. Conceptually, cognitive diversity asserts that knowledge is not solely bound to the organization, rather it is based on individuals and their prior work experiences that come with unique knowledge bases and production routines. One way to analytically investigate cognitive diversity is to determine the variety of organizational types a node's employees come from.

A unique network statistic, an E-I (external-internal) analyses, can examine the number of connections to nodes with different (external) and/or similar (internal) attributes. That is, it assesses the diversity of connections between and among groups (e.g., organizational types) by "comparing the number of ties within groups and between groups" (Hanneman and Riddle 2005, Chapter 8, para. 37). Researchers should determine a theoretically or applicably relevant nodal attribute. In our case study, the type of news organization (i.e., legacy or digital-native) could apply.

The E-I analysis produces a normalized value ranging from −1.0 (only internal relationships to the same type) to +1.0 (only external relationships to different types) (Krackhardt and Stern 1988). When an organization only has ties to other organizations of the same type, the index would be −1.0, and vice versa. For instance, applying the E-I measures to the case study network data, one sees that an E-I index of −0.66 is generated, which indicates a trend towards internalness and translates to a tendency for employees to stay within their individual organizational networks. This calculation was run using the homophily package in R. One would expect that in larger networks with a higher degree of movement between organizations that the E-I index would shift towards the positive, signaling a more out-group approach as employees move between companies with a higher degree of frequency. For instance, testing this using the network data from Kosterich and Weber (2019) analysis of news organizations in NYC from 2011 to 2015 shows that the E-I index moves from −0.30 in 2011 to 0.11 in 2015, demonstrating the expected shift from negative to positive as the expected move to an out-group approach took place. Here the use of the time variable (representing years) is particularly helpful for capturing change over time.

Clustering

Clustering offers another perspective on the way in which employees may, or may not, move between organizations. Dense clusters are subgroups that form within the broader network. There are a wide range of measures available for assessing clustering within a network (for a complete review, see Hanneman and Riddle 2005); the various measures focus on detecting different types of clusters. A clique, for instance, is a subgroup that is more densely connected than other parts of the network. An analysis of cliques could reveal subgroups of organizations that are likely to hire employees from one another. For instance, revisiting Kosterich and Weber (2019) analysis, that data set shows a clique of NBC News, ABC News and CBS News television stations through which employees frequently move. The strength of the clique (measured by tie strength) did not change substantially over the period of data collection (2011–2015).

Discussion and Future Research

This article outlines an important analytical and methodological approach to studying the types of organizations and individual actors who do the work of digital journalism production. Network histories can be a central approach to understanding how the institutions of digital journalism are evolving, meeting Lowrey and colleagues' (2019) call to focus on the "importance of understanding the wider social, political and economic contexts within which innovation takes place" (p. 2146).

Network histories can a provide meaningful record of an organization's history as well as embedded individual actors' prior work experiences, which help explain how organizational processes evolve over time. Emergent research in this space shows that network histories provide a meaningful record of an organization's prior history as well as embedded individual actors' prior work experience and reveals key variables that help to explain how prior experience impacts both how organizational processes evolve over time (see, for instance, Tubaro's 2021 analysis of employment networks on online platforms). Only by understanding the histories of organizations *and* individual actors can we begin to understand how they come together in particular ways at moments in time within organizations can we understand variations in the production of communication across many domains and media industries. Networks provide a new set of objects for scholars to study within organizations, while enabling the analysis of organizations in relation to their environments, fields, and histories. Taken together, these measures help scholars situate production in time and across individual and organizational units of analysis. Only by understanding the histories of organizations *and* individual actors can we understand how they come together at moments in time within organizations and help account for variations in the production of journalism.

Future Research

Network histories provide a unique perspective on the changing patterns of the production of digital journalism. Our focus herein has been on media production, but we see clear connections to other domains. For instance, this type of research aligns closely with sociological studies of the nature of work and could complement that research. In labor relations, this type of method could be useful for recreating career pathways to understand how workers come to occupy certain job roles. Our approach has been focused on a specific set of examples within this manuscript, but we see clear application across domains.

Indeed, scholars can use a network history approach paired with other methods, such as content analysis, to analyze whether differential hiring patterns leads to different output in a variety of communication contexts. Scholars can also study diffusion, for instance, analyzing whether there is a transfer of technical skills from national digital journalism organizations to local ones, or across fields, and the consequential results for those local organizations. This type of approach is likely to take further advantage of the time measurement within the data. Methodologically, this type of approach could also take advantage of longitudinal data modeling in network analysis to better understand statistical relationships over time. In addition, scholars can build on recent work on phenomena such as "field crossers" (Comfort 2020) to reveal how and when the movement of journalism, staffers, or consultants across fields results in innovation in practices.

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