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Adoption *and* adaptation: A computational case study of the spread of Granovetter's weak ties hypothesis

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ABSTRACT

How do new scientific ideas diffuse? Computational studies reveal how network structures facilitate or obstruct diffusion; qualitative studies demonstrate that diffusion entails the continuous translation and transformation of ideas. This article bridges these computational and qualitative approaches to study diffusion as a complex process of continuous adaptation. As a case study, we analyze the spread of Granovetter's Strength of Weak Ties hypothesis, published in *American Journal of Sociology* in 1973. Through network analysis, topic modeling and a close reading of a diffusion network created using Web of Science data, we study how different communities in this network interpret and develop Granovetter's hypothesis in distinct ways. We further trace how these communities originate, merge and split, and examine how central scholars emerge as community leaders or brokers in the diffusion process.

Introduction

In the 1960s and 1970s, the question of how new scientific ideas diffuse was high on the agenda of science studies. Primarily using survey methods, researchers at the time discovered some key dynamics in the spread of ideas. They found that the diffusion of a scientific idea bears similarities to the diffusion of other types of innovation, for example, in that both follow an S-shaped growth curve (Crane, 1972; Holton, 1962; Price, 1963; Mulkay et al., 1975). Research of this time also brought attention to the role of interpretation in science: studies revealed the central role of informal communities—sometimes called "invisible colleges" (Crane, 1972) or "coherent groups" (Griffith and Mullins, 1972)—in the organization of scientific research. Such communities develop separate vocabularies and narratives through which their members interpret scientific findings (Fisher, 1987). While science studies of the 1960s and 1970s opened a new field of research, scholars faced limitations in their data and methods.

An explosive development in the availability of both data and sophisticated analytical techniques since the 2000s has reinvigorated the field of science studies, allowing researchers to study the development of science at scale (Fortunato et al., 2018; Zeng et al., 2017). But computational analyses come with their own sets of research questions, since they focus on the structural properties of scientific networks while leaving the interpretative work to more qualitative researchers (Pachucki and Breiger, 2010). Combining computational and interpretative analyses in this article, we contend, can help reveal how scientific ideas spread and change in the process of diffusion. This takes us away from what Latour (1984) calls a "diffusion model" of science, in which researchers are passive nodes in a network through which ideas circulate, to what he calls a "translation model," according to which researchers shape the idea to their different projects, resulting in a continuous transformation of the diffusant.

To enable an in-depth and systematic study of how ideas change as they diffuse, we focus on a single idea that has diffused far and wide in academia: Granovetter's (1973) Strength of Weak Ties hypothesis, published in *American Journal of Sociology*. We employ citation network analysis, topic modeling and close reading to study the way this scientific idea was transformed during its spread as a result of the collective behavior and interpretations of scholars. First, we trace the structural spread of Granovetter's hypothesis and analyze its macroscopic patterns using a network representation of citation data. Next, we examine how different communities in this diffusion network developed specific interpretations of Granovetter's hypothesis and focus on the role of individual scholars in this process.

Our work advances the literature in three ways. Theoretically, we develop the notion of a diffusion network and conceptualize how

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scientific innovations are variably adapted throughout their growth trajectory. Our methodological contribution is to develop an approach that bridges the gap between computational analysis of network properties and the interpretative analysis of meaning (cf. Fuhse, 2009; Pachucki and Breiger, 2010). Finally, our substantive contribution is to show that the spread of scientific ideas entails a complex process of translation in which scholarly communities emerge as meso-level mediators, cultivating divergent interpretations of the diffusing idea in line with the different research projects in which they are engaged. During this process, some scholars—brokers and leaders—perform key roles in translating and introducing the new scientific idea into their circles and across academic boundaries.

The structure of our argument is as follows. The next section outlines the gap between computational and interpretative approaches and suggests how these two types of studies might be combined into an interpretative computational approach. The subsequent section summarizes our methods and explains how we used citation and publication metadata to create a diffusion network. The following three sections analyze: (1) the community structure of this network; (2) the interpretative function of these communities; and (3) the evolution of communities over time, spurred by leading academics with different roles in the diffusion process. The concluding section discusses the implications of our case study for the diffusion of science.

Perspectives on the diffusion of science

The groundwork for the study of scientific diffusion was laid in the 1960s and 1970s by scholars, such as Crane (1972), Goffman (1966), Griffith and Mullins (1972), Merton (1968), Mulkay (1974), Price (1963), and Small and Griffith (1974). Their research demonstrates that academics are organized in communities[1] that perform pivotal functions in the diffusion and development of ideas. Scholarly communities tend to be organized around one or several academic stars whose status is reinforced through mechanisms of cumulative advantage (Merton, 1968; Newman, 2009; Price, 1976). These star researchers function in their scholarly circles similarly to how opinion leaders function in marketing: recognized as intellectual leaders by the community, they serve as its representatives to the broader scientific world (Collins, 1983; Crane, 1972; Griffith and Mullins, 1972; Price, 1963). This parallel between academic stars and opinion leaders in marketing is in part inspired by Everett M. Rogers's (1983) diffusion of innovations theory and Elihu Katz's concept of the two-step flow of communication, which posits that innovations first spread to opinion leaders, who in turn spread them to consumers (Coleman et al., 1957; Katz, 1957).

While these early science scholars are often credited with formalizing the study of science through the development of mathematical models (Goffman, 1966; Goffman and Newill, 1964; Merton, 1968; Price, 1976), their work contains both quantitative and interpretative insights by addressing the co-evolution of scholarly networks and scholarly cultures. Since then, the study of diffusion has bifurcated. On the one hand, computational scholars have leveraged the explosive growth in the availability of data and sophisticated analytical methods to study the structural properties of academic networks (Fortunato et al., 2018; Zeng et al., 2017). On the other hand, institutional scholars and more qualitatively minded researchers have emphasized the importance of meaning and interpretation in science and diffusion (Knorr Cetina, 1999; Latour, 1987; Strang and Meyer, 1993). We discuss these research trends separately before exploring how they might be brought into conversation.

Recent computational work on citation and co-author relations has focused on uncovering the relational structures underpinning the development of science and new discoveries (Fortunato et al., 2018). By applying advanced methods to large digital datasets, this research has reaffirmed some of the findings of earlier studies, including that science is organized into communities (Lambiotte and Panzarasa, 2009; Newman, 2001b, 2004a) that revolve around academic stars, who are more likely to receive new references and engage in new collaborations (Barabási et al., 2002; Dahlander and McFarland, 2013; Newman, 2001b, 2004b). Fortunato et al. (2018) review these and other findings and outline a research field they call "SciSci"—the Science of Science—which uses computational methods, large datasets, and modeling to identify relational structures and mechanisms of discovery in science. A key premise underlying this computational work is that science is a complex system in which interactions on a microscopic level result in non-linear dynamics and the emergence of unintended and unexpected macroscopic patterns (Fortunato et al., 2018; Shi et al., 2015; Zeng et al., 2017). In line with this premise, many scholars working in this field do not discriminate between social and natural systems. They adopt their methods from the natural sciences, drawing parallels between the diffusion of scientific knowledge and evolutionary processes or the spread of diseases (Bettencourt et al., 2008; Goffman and Newill, 1964; Kiss et al., 2010; Morgan et al., 2018; Zeng et al., 2017). Related research uses agent-based simulations in which the behavioral patterns of individuals are translated into simple rules for agents in the simulation, such as "adopt when more than three of my friends adopt," and interactions between agents determine the speed and reach of diffusion. A common research question in this field is how different network structures obstruct or facilitate diffusion (cf. Centola, 2015; Centola and Macy, 2007; Watts, 2002). This kind of computational work, focused exclusively on the structural aspects of diffusion, generally assumes that the object of diffusion remains constant as it spreads.

At the same time, interpretative studies of the diffusion of science have shown that the spread of scientific ideas entails not just adoption but also adaptation, similar to re-invention (Rogers, 1983) or exaptation (Bonifati, 2010). Knorr Cetina (1981) describes how the content of knowledge depends on the different subcultures or epistemic communities in which it is practiced. Latour, 1984 similarly sets out how objects and ideas take on different forms and meanings depending on the local context in which they are adopted, and calls for a paradigm shift from the diffusion model to a translation model (see also Latour and Woolgar, 1979). Latour describes the spread as a chain, with the diffusing idea as a 'token':

> Each of the people in the chain is not simply resisting a force or transmitting it in the way they would in the diffusion model: rather, they are doing something essential for the existence and maintenance of the token. In other words, the chain is made of actors—not of patients—and since the token is in everyone's hands in turn, everyone shapes it according to their different projects. This is why it is called the model of translation.
>
> (Latour 1984; p.267–268)

In the translation model, not only does the spread come about as a result of collective action, as described in the structural complexity approach, it also involves adaptations of the idea as a consequence of the interpretations and interactions of actors. More recently, Greenhalg's (2005) study of the diffusion of the innovation paradigm shows that different research traditions develop distinct stories and sometimes contradictory interpretations of the same research findings. Kaiser (2009) examines the development of the Feynman Diagram in postwar physics and illustrates how even the meaning of scientific inscriptions such as diagrams are not "immutable" as Latour (1986) postulates—but

[1] A multitude of conceptualisations and operationalizations of community is maintained in the literature. The generation of authors discussed here, predominantly looks at relational communities (Emirbayer and Goodwin, 1994), with direct ties between scientists which are typically discovered by means of survey data. However, these authors do not use the concept of community strictly relational, simultaneously trying to get at the cognitive links between members of the same community, see for example (Griffith, 1989; Small and Griffith, 1974).

depend on the scholarly social circles in which it spreads. Theorists of institutions such as Zilber (2008), Strang and Soule (1998), and Strang and Meyer (1993) draw attention to the collaborative and interpretative work involved in diffusion. Strang and Meyer (1993) consider diffusion as a sense-making process in which actors must jointly construct an understanding of a practice or idea before they can adopt it. In other words, adoption requires adaptation and largely depends on the social context.

As the study of the diffusion of scientific ideas bifurcated, a divide opened up between structural and interpretative approaches—the former often made use of computational methods and large datasets, the latter tended to be theoretical and privileged case studies. In study of science, some efforts are made more recently to explore the interaction between the—structural—evolution in scientists networks on the one hand and their—cultural—intellectual advancements (Moody, 2004) on the other hand, theorizing on regularities in the patterns that unify these two dimension (Abbott, 2001). Scholars in fields such as social network analysis, information theory, opinion dynamics and relational sociology have similarly sought to bridge this broader structural and cultural chasm (Pachucki and Breiger, 2010). One such approach in social network analysis investigates socio-semantic networks designed to capture the joint dynamics of social and socio-semantic structures (Roth and Cointet, 2010). Information theory scholars seek to expand their frameworks to incorporate meaning into the analysis of scientific communication (Leydesdorff et al., 2018, 2017). For instance, Vilhena et al. (2014) find that structural holes (cf. Pachucki and Breiger, 2010) and cultural holes overlap but not coincide in science, underlining the importance of studying not only citation networks but also the content of scientific communication. In the fields of opinion dynamics and diffusion modeling, disease as an analogy is under increasing criticism, as scholars seek to incorporate meaning in previously structurally driven models. For example, Goldberg and Stein (2018) advance a model based on associative diffusion, in which the objects of diffusion are associations between beliefs and behaviors, showing how cultural differentiation can arise without relying on structural fragmentation or homophily among agents. Theoretical attempts at bridging the structural-cultural divide in relational sociology have also been made. Martin (2002) argues for a formal investigation of the relation between beliefs and social structure, while Fuhse (2009, 2015), building on the work of Harrison White, systematically explores the meaning structure of social networks. These contributions all provide clues as to how structural and interpretive methods might be best combined to examine the co-evolution of meaning and social relations.

We build on this literature by developing the notion of a *diffusion network*—the network that maps the spread of a particular innovation, in this case Granovetter's hypothesis on the Strength of Weak Ties, between adopters. Like scholars in Science of Science, we view the diffusion of science as a complex process, and use computational methods and citation-based diffusion networks to study its micro-macro dynamics. However, like interpretative scholars, we consider every citation to involve interpretation and adaptation, as Granovetter's hypothesis is inserted into particular narratives that aid researchers in identifying and answering the questions of interest. As this process of translation is the outcome of collective interpretative work, we hypothesize that researchers self-organize into distinct diffusion communities. We are interested in the spreading patterns of Granovetter's hypothesis and how this idea is reinterpreted and adapted during the diffusion process. Our main hypothesis is that diffusion networks are comprised of structural communities that advance the same scientific ideas in distinct ways. In addition to testing this general hypothesis, we seek to understand what gives rise to these structural-cultural patterns in the diffusion network. Accordingly, we examine the network's evolution over time and identify the roles of key actors in brokering diffusion and developing specific interpretations of the Strength of Weak Ties.

Data and methods

Our strategy is to apply network analysis to citation data of Granovetter's hypothesis in order to identify structural patterns in diffusion processes and then to use topic modeling and close reading of publications to understand the interpretative work scholars engage in. While previous research examines aggregate knowledge flows between fields or institutions, confirming the self-organization of science into communities (Rawlings et al., 2015; Noyons and van Raan, 1998; Rosvall et al., 2009), our interest is in the dynamics of the diffusion of a particular scientific idea, shaped by both structural and cultural forces. This entails interest in the specifics of interpretation and therefore requires the type of fine-grained analysis enabled by the in-depth study of a single case of scientific diffusion. We thus conduct what might be thought of as a computational case study. Like computational researchers, we use advanced computational techniques to search for relational structures in the spread of a scientific idea, and like qualitative researchers, we rely on interpretative methods to develop a nuanced understanding of qualitative differences in how Granovetter's hypothesis has been adapted by scholars in different communities.

To construct the diffusion network, we collected data on publications referencing Granovetter (1973) from the Web of Science.[2] For each publication, we retrieved the following metadata: author(s), title, journal, publication date, research areas, keywords, abstract, and references. The dataset contains 8198 publications from May 1973 until November 2017. We used this data to construct a network that represents the journey of Granovetter's hypothesis through the academic landscape. Previous studies on academic citation networks typically use edges to represent either direct citation (Price, 1965), co-authorship (Newman, 2001a) or co-citation (Small and Griffith, 1974) relationships among scholars. With our edges, we aim to capture the formal scientific communication between authors that involved the idea in question. We therefore combine both co-authorship and direct reference relations between scholars, since both are signals that an exchange of ideas has taken place between these scholars on the Strength of Weak Ties.[3] That is, edges are drawn from scholars new to the Strength of Weak Ties hypothesis to the scholars they cite who have previously used the hypothesis, hence representing influence[4] of prior authors (edge target) to newly adopting authors (edge source). As we are interested more in the spread of the idea than the intensity of its use, we only create outgoing edges for publications in which authors reference Granovetter (1973) for the first time. Similarly, we draw directed edges of authors' first publication that references Granovetter (1973) to their co-authors on that publication, on the assumption that co-authors work together to position their work in relation to others, including Granovetter. For incoming

[2] Although the Web of Science's coverage is relatively broad, it primarily includes publications from journals and contains fewer books and book chapters.

[3] Reference and co-authorship relations might signal a different type of communication about the diffusing idea. References might signal a simple information flow between weak ties in which the edge target informs the edge source about the novel idea, similar to Granovetter's (1973) study on job vacancies. A strong tie co-authorship relation might reveal more about how the novel idea gets embedded in the literature and research methodology by the edge target. However, both types of communication are integral parts of the diffusion, are hard to discern and can take place in both types of relations. We therefore do not discriminate between these two types of relations in our network.

[4] It is difficult to gauge the extent of influence of prior authors upon new authors referencing the Strength of Weak Ties. Some scholars cite articles without reading them; others use cited articles extensively (for an overview of theories of citation, see, for example, Moed (2005)). For our analysis—which focuses upon the meso- or community level rather than upon micro-interactions among scholars—it is sufficient to state that prior authors have 'some influence' over new authors.

edges, in contrast to outgoing edges, we consider later publications. This procedure generates a diffusion network that includes 8198 publications, 15,056 scholars (nodes), and 142,227 edges.

To determine whether communities indeed mediate the diffusion of innovation, we first test whether the modularity of the diffusion network is significantly higher than a random network with the same degree distribution and sequence. We then use topic modeling to identify principal themes and frames in the literature (Bail, 2014; DiMaggio et al., 2013), and examine how these relate to the structural diffusion communities in the network (as identified through community detection). Finally, we do a close reading of key contributions to investigate how the application and adaptation of Granovetter's hypothesis differs between three large communities. To study how these structural-cultural patterns emerge, we examine the development of communities over time and the role of influential scholars within them. To do so, we ran a temporal community detection algorithm to locate communities in different time slices (1995–2000–2005–2010–2017) (Mucha et al., 2010) and explore the paths of key figures in the diffusion of the Strength of Weak Ties hypothesis. These key scholars play crucial roles in the formation and linking of communities. They do not perform this work on their own, but serve as focal points for scholars who constitute specific communities (Collins, 1998). In other words, their leadership is not an individual property but emerges from the references of numerous scholars in their communities—more precisely, the communities are formed through the references (Collins, 1998). Some communities are quite closed and constructed around key scholars important only to members of that community; other communities have porous boundaries. By examining the role of these key scholars, we form a better idea of the mechanisms by which diffusion communities are constructed as a result of academics' referencing practices.

Communities in the diffusion network

A key premise of our argument is that the diffusion network contains clusters corresponding to communities of scholars who collaboratively interpret and cultivate Granovetter's hypothesis in various directions. Before turning to the question of collaborative interpretation, however, we first need to ascertain that the network indeed exhibits significant clustering. We identify network communities using the Louvain algorithm (Blondel et al., 2008; Traag, 2015), a community detection algorithm which stochastically optimizes modularity. The Louvain algorithm provides slightly different approximations of the optimal partitions in different runs. To improve the robustness of our results, we ran 10,000 instances of the algorithm and compared the resulting community structures by focusing on scholars with a high indegree (>200) (81 scholars representing 0.5% of the sample) and how they are grouped together. We selected an instance where high indegree scholars who are grouped together in the majority of configurations (>60% of 10, 000), are grouped together, and high indegree scholars who are never or only rarely grouped together (<10% of 10,000) are not grouped together, as an appropriately robust partition.

When we examine the community structure of the diffusion network (Fig. 1), we see that it consists of communities of scholars, defined as groups of scholars with more edges between members of the same community than between members of different communities. We refer to these communities as "diffusion communities." Fig. 2 shows the distribution of the size of the diffusion communities, which is very uneven: the three largest communities comprise 45% of all scholars in the giant component; the largest twelve communities (size >200), 86% of all scholars in the giant component. Our analysis focuses on these 12 communities.

To gauge whether this community structure is indeed significant, we need to compare its level of modularity with a plausible benchmark. Since the structure of any network—and particularly networks with an uneven degree distribution—will have some degree of modularity, finding a plausible benchmark is essential. For this, we use an adjusted version of the Havel-Hakimi graph (Hakimi, 1962; Kleitman and Wang, 1973). We compare the modularity of our empirical network to the average modularity of 10,000 Louvain partitions of adjusted Havel-Hakimi networks with an identical degree sequence as the empirical network. We treat reciprocal and singular links separately and match their degree sequences to create our adjusted graphs. This is necessary as our network has notably few reciprocal links, which is not the case in the regular Havel-Hakimi graph. By design and logic of the diffusion network, earlier links are not reciprocated. Only scholars who reference Granovetter (1973) for the first time in a co-authored publication have a reciprocal link in the diffusion network.

The adjusted Havel-Hakimi graph serves as a benchmark for our network, as it represents the hypothesis that the structures of these networks are products of a first-mover advantage (Newman, 2009), positing that the first publications and scholars in a new research area receive citations at a much higher rate than later ones. This hypothesis is modeled as follows: the network grows over time as more scholars discover Granovetter's idea. Each new generation of researchers cites Granovetter as well as previous generations of scholars: the first generation cites only Granovetter; the second cites Granovetter and the first generation; the third cites Granovetter and the first two generations, and so on. This is the process that the Havel-Hakimi algorithm represents: it generates graphs by successively connecting nodes of the highest degree to nodes of the second highest degree, ordering the remaining nodes by degree from high to low, and repeating the process. The Havel-Hakimi graph thus captures how a scientific diffusion network would be structured, were it only organized by the timing of publications and scholars, without scientific communities playing any role in the diffusion process.

By comparing the Strength of Weak Ties diffusion network with the adjusted Havel-Hakimi graphs, we find that the former has significantly more community structure (0.62, p-value$<$0.001). Fig. 3 shows our diffusion network on the right and a random instance of the Havel-Hakimi graph on the left with identical degree distributions (both for singular and reciprocal links), demonstrating a marked difference in network modularity.

Comparing these networks points to another structural feature that the first-mover advantage model leaves out. Fig. 3 shows how scholars with highest indegree are located at the center of the adjusted Havel-Hakimi graph, whereas they are spread out over different communities in the Strength of Weak Ties diffusion network. Scholars with high indegree are authors[5] of publications containing a reference to Granovetter (1973) that are often referenced by scholars new to the Strength of Weak Ties. Examining the growth of communities and the indegree of scholars over time (Fig. 4), we see that the first-mover advantage does not seem to drive the diffusion process. Numerous scholars cite Granovetter (1973) much later—for example Brian Uzzi in 1999, Albert-László Barabási in 2000, and Örjan Bodin in 2006, respectively twenty-six, twenty-seven, and thirty-three years after Granovetter's publication—but nevertheless receive many citations from the next generation of adopters, making them important figures in the diffusion of Granovetter's hypothesis.

While these academic stars are cited by scholars in the entire network, they are mostly—sometimes even exclusively—cited by scholars from their own communities. These findings show that the spread of Granovetter's idea was not a simple process of contagion, but that scholarly communities containing key figures played an important role in its diffusion to a broader scholarly audience. The distinctive feature of high-indegree scholars may not be simply timing—as the first-mover advantage theory proposes—but their status (Cole, 1970; Morgan et al., 2018; Way et al., 2019) or their ability to apply an existing idea in a novel context, so that it speaks to scholars in other research communities (Lane, 2011). The latter point is part and parcel of the idea that

[5] References to publications are included in the network as edges to all authors of the referenced work, not only to the first author.

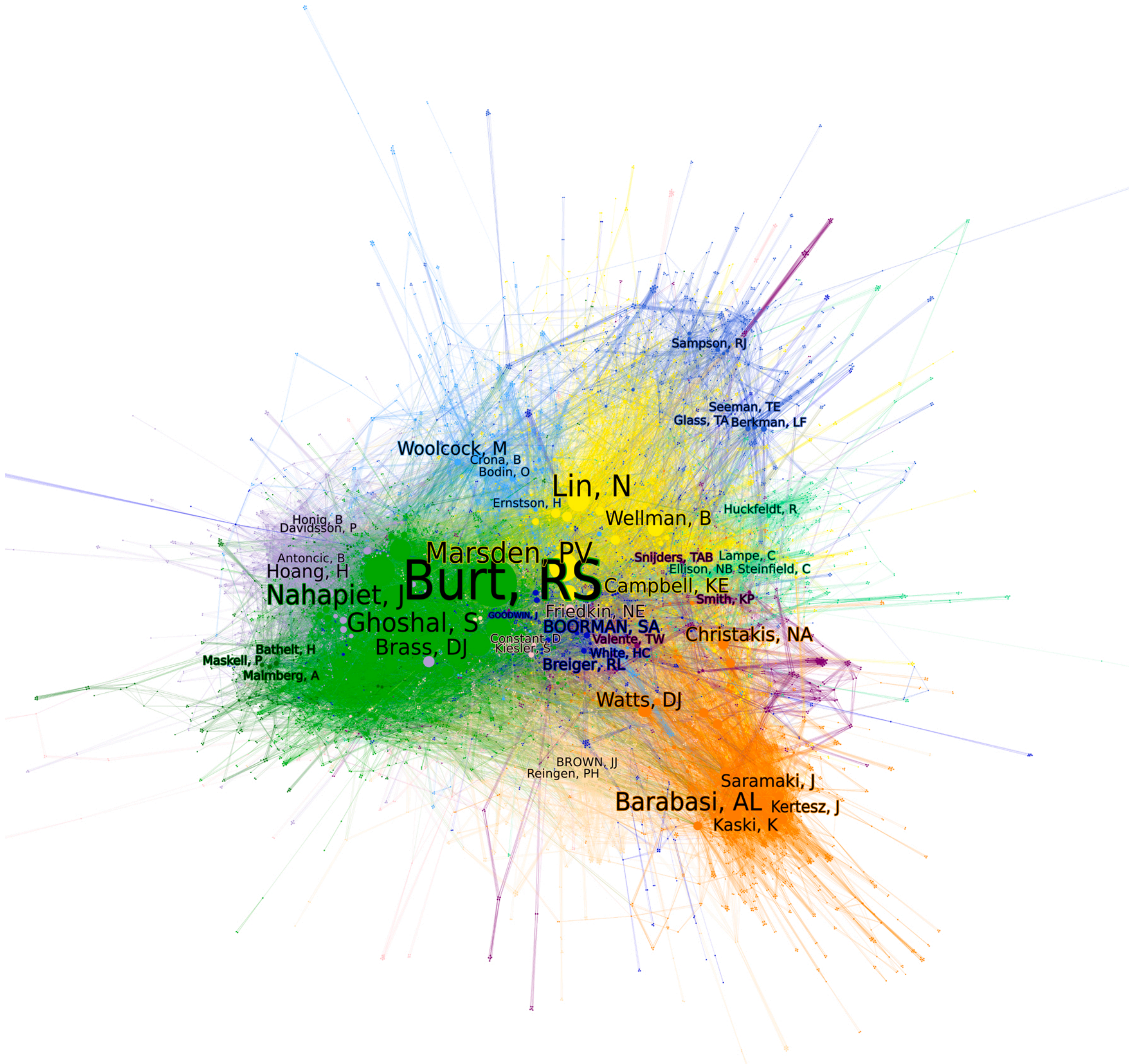

Fig. 1. The largest 12 communities of the diffusion network in 2017, containing 10,787 scholars and 121,132 edges. The nodes are colored by their community and the scholars with highest indegree of each diffusion community are labeled. The labels are sized according to their indegree.

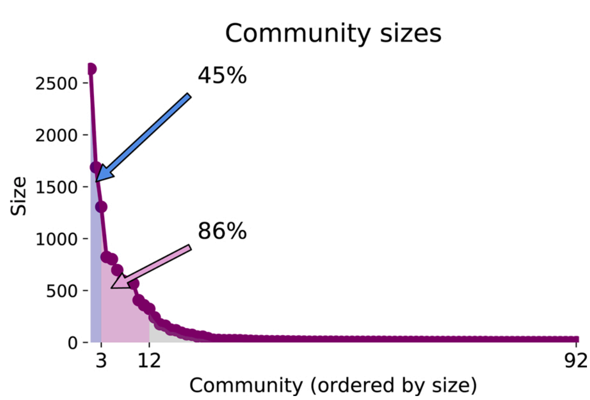

Fig. 2. Distribution of community sizes in the diffusion network, with a small number of large communities and a large number of small communities. The largest three and twelve communities consist 45% and 86.4% of all scholars in the giant component of the diffusion network.

innovation takes place throughout the diffusion process, and not just at its initiation (Lyytinen and Damsgaard, 2011).

Communities' interpretative work: The development of narratives

We applied topic modeling to the abstracts of publications in the twelve largest communities and explored correlations between topics and communities. The resulting correlation matrix in Fig. 5 shows the degree to which scholars in the twelve communities discuss various topics. It reveals that different communities do indeed apply Granovetter's idea to different topics (Chi-squared = 2057, df = 154, p-value< 0.1^5), albeit to different degrees. Communities addressing similar topics tend to be more connected in the citation network (Pearson correlation = 0.23, p-value = 0.06) (see Fig. 6). For example, Community 4's topics are similar to those of Community 11, and these two communities are strongly connected in the diffusion network based on citations (see appendix for details on topics).

We find that communities comprise distinct combinations of scholars from different research fields (Chi-squared = 177,432,451, df = 1100, p-value< 0.1^5) (Fig. 7), with communities closer in their research interests exhibiting stronger connections in the citation network (Pearson correlation = 0.39, p-value<0.001) (Fig. 8). We can get a sense of a

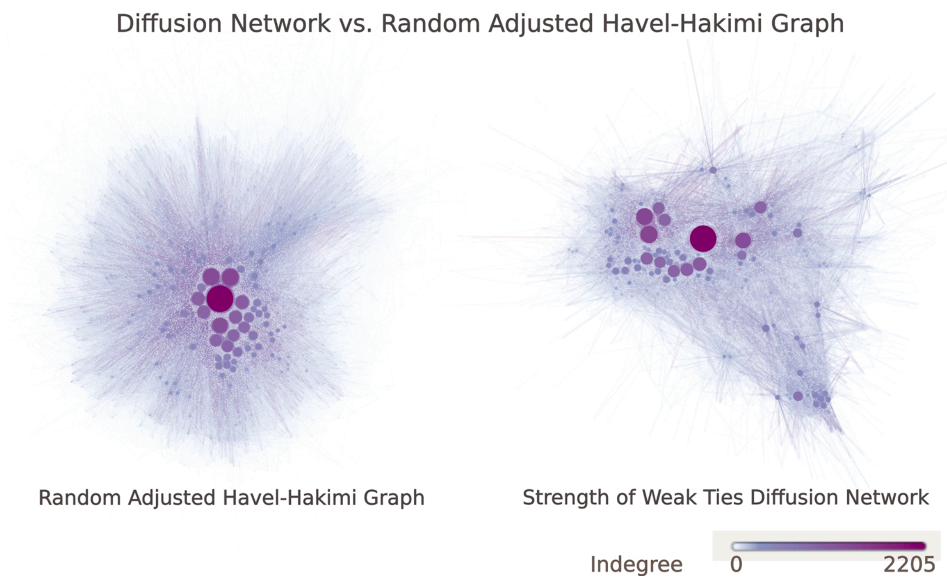

Fig. 3. The Strength of Weak Ties diffusion network in 2017 (right) and a random adjusted Havel-Hakimi graph with identical degree distribution (for both reciprocal and singular edges). Both visualizations have identical settings, with nodes sized and colored by their indegree and the same layout algorithm (Gephi's Force Atlas 2). The diffusion network is more clustered (0.623 p-value<0.001) than the adjusted HH graph. The high indegree scholars are highly centered in the HH graph and more spread out over different communities in the diffusion network.

given community simply by looking at topics and disciplinary backgrounds (Fig. 9). Scholars in Community 9, for example, appear to be active in the field of communication science, discussing words associated with Topic 12, including "information," "online" and "media."

These findings provide *prima facie* evidence that the diffusion of a scientific idea is mediated by scholarly communities—previously existing or newly formed—with different disciplinary perspectives and research interests. While correlations between topics and research fields do not demonstrate that scholars only cite within their field or that they limit themselves to specialized topics, they do show how the diffusion of a novel idea via citations is closely linked to its contextual understanding and applications. While topic modeling provides us with the contours of interpretative schemas, a close reading of key publications—identified by the number of references they receive in their communities—is necessary to better understand how scholars integrate Granovetter's hypothesis into their frameworks and apply it in their research. As we shall see, Granovetter's 1973 article planted a seed for a number of research avenues and understandings of the Strength of Weak Ties, which have each developed and diverged during the diffusion process.

We now turn to a more detailed analysis of the three largest communities in the diffusion network, which each leverage and develop another use case and interpretation of the Strength of Weak Ties. We refer to them as the *Organizational Advantage Community*, the *Ego-Network Community*, and the *Complex Networks Community*.

Community 1. The Organizational Advantage Community

Granovetter (1973) points out that weak ties are more likely than strong ties to be bridges between socially cohesive clusters, and suggests they are therefore crucial for the flow of information. This observation is taken up by the Organizational Advantage Community in the context of management and organizations. Most scholars in this community publish in the fields of management and organization. The central scholar is Ronald S. Burt, followed by Sumantra Ghoshal, Janine Nahapiet, Daniel J. Brass, Bill McEvily, Rob Cross, Ray Reagans, Stephen P. Borgatti, Seok-Woo Kwon, and Paul S. Adler (see Fig. 10 for the structural development and position of scholars in this community).

The vast majority of empirical studies in this community use firm-level data and focus on innovation-based competitive advantage for organizations (e.g. Reagans and McEvily, 2003; Nahapiet and Ghoshal, 1998; Brass et al., 2004; Adler and Kwon, 2002; Burt, 2000). According to scholars in this community, innovation occurs when extant knowledge and experience are combined in new ways and they relate this to the structural patterns within organizations: innovation and good ideas are more likely to appear near structural holes where the knowledge of different social collectives intersects (Burt, 2004). The Strength of Weak Ties is a pillar of knowledge creation in this community, and is the basis for Burt's notion of structural holes: "The structural hole argument draws on several lines of network theorizing that emerged in sociology during the 1970s, most notably, Granovetter (1973) on the Strength of Weak Ties" (Burt, 2000, p. 340). Burt thus interprets, adapts, and extends Granovetter's notion of the Strength of Weak Ties so that it becomes relevant to a community of scholars who seek to understand why some organizations, corporations, and managers have advantages over others.

As this Organizational Advantage Community grows, social capital becomes its most central concept, understood as "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit" (Nahapiet and Ghoshal, 1998, p. 243). "Social Capital, Intellectual Capital, and the Organizational Advantage" by Nahapiet and Ghoshal (1998) is the most frequently cited article by new adopters in this community. While this resonates with the work of scholars such as Robert Putnam and James Coleman, scholars in this community are specifically interested how social capital may confer organizational advantages to corporations or managers. They link concepts such as social capital and weak ties to notions like intellectual capital, knowledge, and innovation, also drawing upon other works of Granovetter such as his writing on embeddedness (Granovetter, 1985).

Community 2. The Ego-Network Community

In his 1973 article, Granovetter illustrates his theoretical argument with empirical evidence about job attainment that shows individuals more often find jobs through weak ties than through strong ones. Members of the Ego-Network Community build on this to conceptualize weak ties as a type of individual asset which enhances this individual's status in society. The majority of scholars in this community publish in sociology and are interested in how different types of social relationships can confer advantages to individuals, particularly in terms of status (e.g. Lin et al., 1981; Lin, 1999; Campbell et al., 1986). This focus on individuals corresponds to the main data source for these scholars, namely surveys. The central figures in this community are Nan Lin, Peter V. Marsden, Barry Wellman, and Karen E. Campbell. These scholars laid the groundwork for this community in the 1970s and 1980s and some are directly connected to Granovetter, such as his thesis supervisor Nan

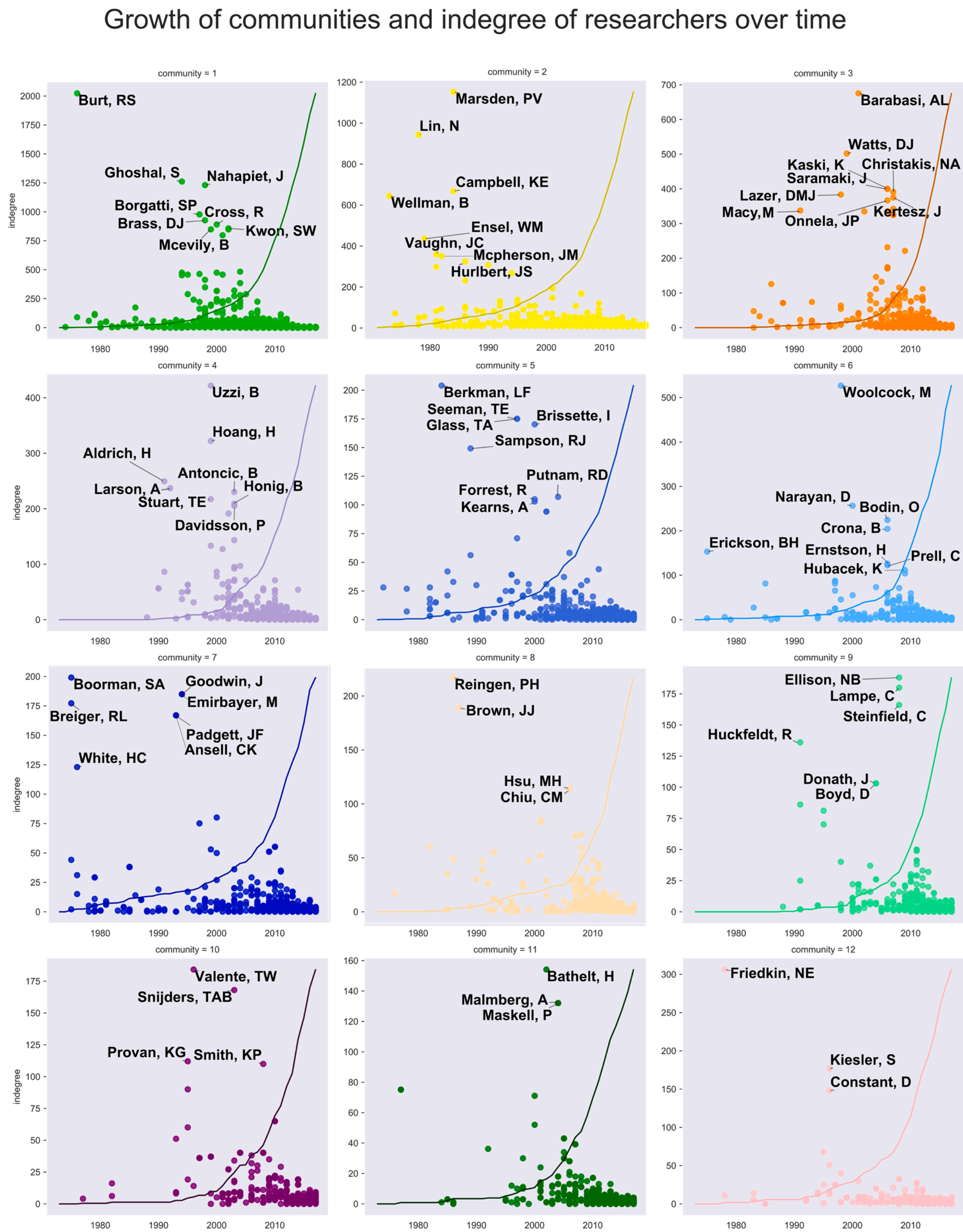

Fig. 4. The growth (line) and indegree of researchers (scatter) in each community of the Strength of Weak Ties diffusion network over time. The *y*-axis for growth—in terms of community size—runs from 0 to 100%, but is not shown for the sake of legibility. The scatter points of the eight scholars with highest indegree per community (and indegree>100) are labeled. Most communities have at least one important high indegree scholar, and the timing of these scholars' first publication referencing Granovetter's hypothesis varies significantly: not all are first movers.

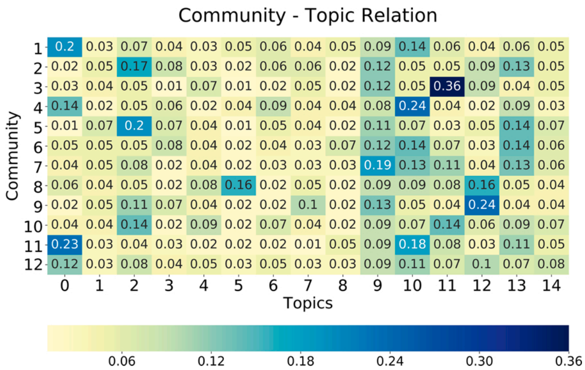

Fig. 5. The topics (columns) addressed by communities (rows) in the Strength of Weak Ties diffusion network. Cell numbers indicate coverage by all community publications, e.g. 36% of publications in the Complex Networks Community (community 3) address complex models (topic 11). The parameters for topic modeling are set to find 15 topics and to discard words that occur in less than 30 articles or in more than 80% of articles. See appendix for details of topics.

Lin.

In this community, a central research topic is how individuals derive different kinds of benefits from strong and weak ties; some of its most-cited publications are devoted to measuring tie strength using survey questionnaires (Marsden and Campbell, 1984). The central concept of this community is "social resources": different kinds of ties offer different kinds of support to individuals (Wellman and Wortley, 1990). A central theoretical notion is the social resource proposition, explained by Lin and Dumin (1986, p. 366) as: "an individual who uses a contact of higher socioeconomic status should find a better job than someone else whose contact has lower status." Scholars in this community likewise explore the hypothesis that weak ties confer distinct advantages: "for two individuals at the same or similar initial positions, it is hypothesized that the one who uses weak ties rather than strong ties will tend to reach better social resources. This is called the strength of ties proposition" (Lin and Dumin, 1986, p. 367).

Ties are seen as an individual's property, as stated in the following passage from one of the most cited publications in this community: "The friend may use his/her position or network to help ego to find a job. These are 'borrowed' and useful to achieve ego's certain goal, but they remain property of the friend or his/her friends" (Lin, 1999, p. 468). Whereas scholars researching organizational advantage find strength in weak ties by viewing them as a collective property, scholars studying ego-networks consider weak ties as individual property that can strengthen individual status.

Community 3. The Complex Networks Community

The Complex Networks Community shifts the focus from social networks to networks in general. Granovetter (1973) presents the Strength of Weak Ties as part of a broader argument for using structural networks to link micro and macro levels of society. This ties in with the central focus of this community: the study of complex networks, in which individual properties and micro-interactions coalesce into sometimes surprising macro-patterns. This community consists primarily of physicists, science and technology scholars, and computer scientists. The community's main figure is Albert-László Barabási, a physicist interested in detecting and modeling the universal properties of complex

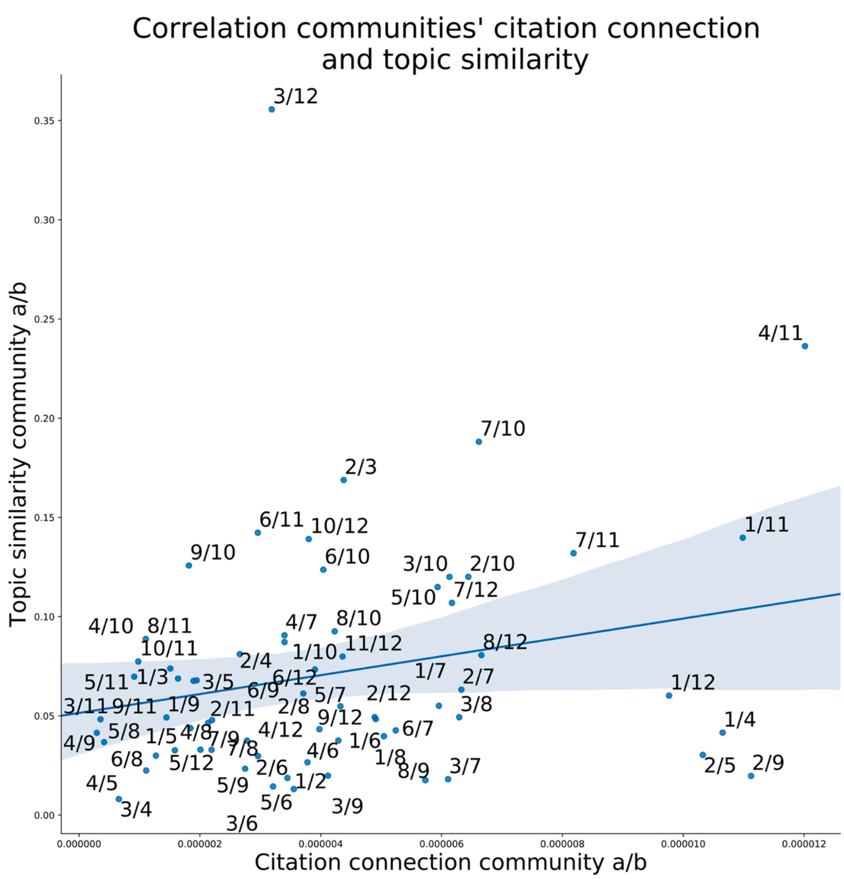

Fig. 6. The relation between communities in the Strength of Weak Ties diffusion network expressed by their direct citations (*x*-axis) vs. their similarity in topic coverage (*y*-axis), Pearson correlation = 0.23, *p*-value = 0.06. The citation relation is calculated as the number of edges between communities a and b, divided by the product of the sizes of communities a and b. The topic similarity is calculated as the correlation between the topics covered by communities a and b.

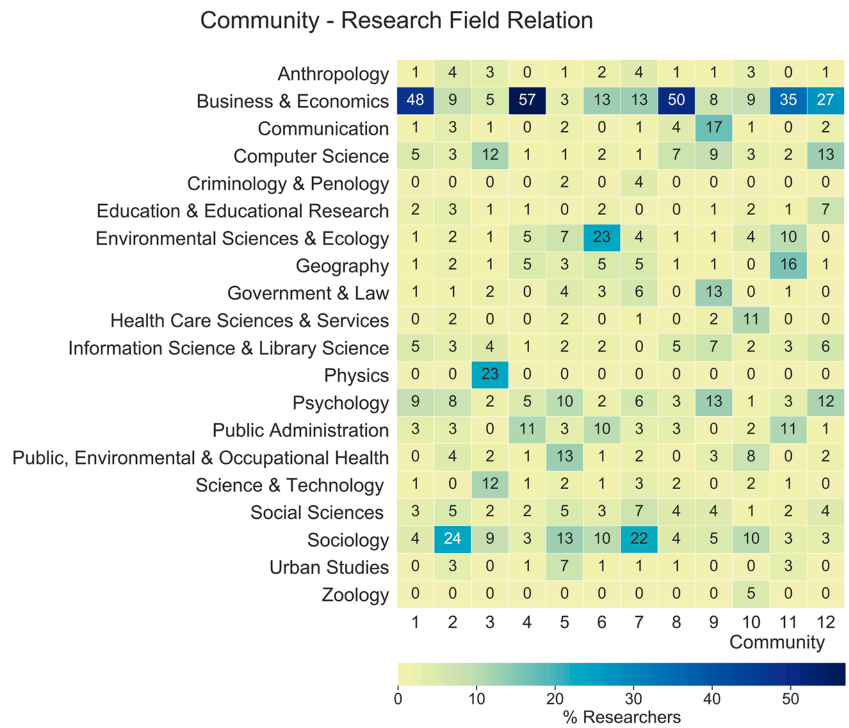

Fig. 7. The disciplinary background of communities in the Strength of Weak Ties diffusion network. Each cell value and color represents the percentage of community researchers of a particular field (e.g. 57% of researchers in community 4 publish on business & economics). The figure only contains research fields where at least one community significantly deviates from the overall network (two-sided Z-test) and which involve at least 5% of the community's scholars.

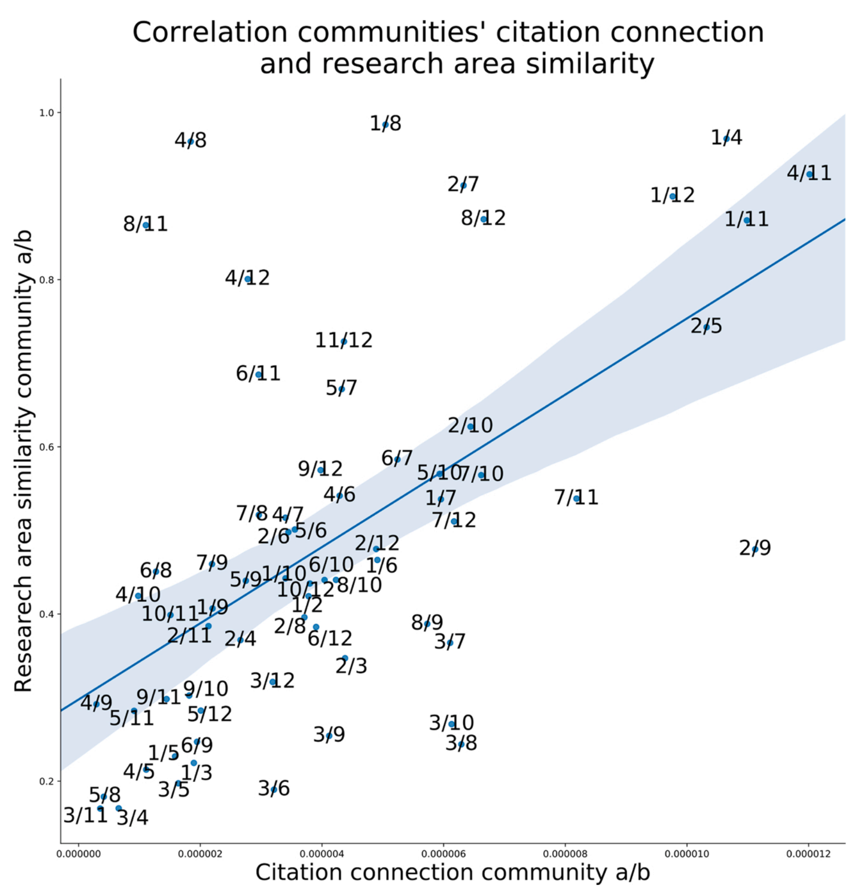

Fig. 8. The relation between communities in the Strength of Weak Ties diffusion network expressed by their direct citations (x-axis) vs. their research areas (y-axis), Pearson correlation = 0.39, p-value = 0.001. The citation relation is calculated as the number of edges between communities a and b, divided by the product of the sizes of communities a and b. The research area similarity is calculated as the correlation between the research areas of communities a and b.

Community	Size	Central Figures	Dominant Research Fields	Dominant Topics
1	2635	Burt, RS | Ghoshal, S | Borgatti, SP	B&E	0 - Organisational Advantage|10 - Enterpreneurship
2	1687	Lin, N | Marsden, PV | Wellman, B	Sociology	2 - Survey Data | 13 - Economic Development
3	1306	Barabási, AL | Watts, DJ | Macy, M	Physics | Science & Tech.	11- Complex Networks | 9- Markets & Politics
4	823	Uzzi, B | Hoang, H | Aldrich, H	B&E	10 - Enterpreneurschip | 0 - Organisational Advantage
5	802	Berkman, LF | Seeman, TE | Glass, TA	Sociology | Public Env. & Occ. Health	2 - Survey Data | 13 - Economic Development
6	697	Woolcock, M | Narayan, D | Bodin, O	Env. sciences & Ecology	10 - Enterpreneurship |13 - Economic Development
7	597	Breiger, RL | Boorman, SA | White, HC	Sociology | B&E	9 - Markets & Politics | 11- Complex Networks
8	584	Reinigen, PH | Brown, JJ	B&E	5 - Methodology | 12 - Communication
9	567	Ellison, NB | Lampe, C | Steinfield, C	Communication	12 - Communication | 9 - Markets & Politics
10	407	Valente, TW | Snijders, TAB	Health Care Sciences	2 - Survey Data | 11 - Complex Networks
11	359	Maskell, P | Bathelt, H | Malmberg, A	B&E | Geography	0 - Organisational Advantage | 10 Enterpreneurship
12	323	Friedkin, NE | Kiesler, D	B&E | Computer Science	0 - Organisational Advantage | 10 Enterpreneurship

Fig. 9. Size, central figures, prominent research fields and topics addressed by scholars in each community in the Strength of Weak Ties diffusion network. We have named the topics to capture their essence, see appendix for more details of topics and for qualitative community descriptions.

networks.

Key words in the community's dominant topic include "model," "structure," "nodes," "properties," "degree," and "complex." The community is driven by data and models as it examines the structural patterns of networks and quantifiable emerging patterns. The first significant scholars who formed this community include Duncan Watts, Michael Macy, and Nicholas A. Christakis, whose work is partly situated in sociology and links the behavior of individuals to collective behavior and network characteristics (e.g. Centola and Macy, 2007; Centola, 2010; Christakis and Fowler, 2007; Kossinets and Watts, 2006). The Strength of Weak Ties diffused from these more social science oriented scholars towards physicists focused on numerical models, such as Albert-László Barabási, Kimmo Kaski, Jari Saramäki, János Kertesz, and Jukka-Pekka Onella (e.g. Karsai et al., 2011; Onnela et al., 2007; Albert and Barabási, 2002). This can be seen in Fig. 11, which shows the growth of this community in the network. One of the most referenced works in this community is Barabási and Reka Albert (2002)'s "Statistical Mechanics of Complex Networks," which discusses abstract properties of complex networks. The variety of environments considered in their work—cells, chemicals, and the Internet—speaks to the broad applicability of Granovetter's idea as interpreted by this community.

In contrast to the Organizational Advantage and Ego-Network Communities, which reference both Granovetter's 1973 article and his work on economic life and embeddedness, the Complex Networks Community almost exclusively references the 1973 article. The Strength of Weak Ties idea is disconnected from a social setting and is instead conceptualized as an efficiency principle for diffusion processes in complex networks. Damon Centola writes in his highly-cited article, "The Spread of Behavior in an Online Social Network Experiment": "Evidence in support of the Strength of Weak Ties hypothesis has suggested that networks with high levels of local clustering and tightly knit neighborhoods are inefficient for large-scale diffusion processes" (2010, p. 1197). Similarly, according to Barabási et al. the Strength of Weak Ties hypothesis "states that the strength of a tie between *A* and *B* increases with the overlap of their friendship circles, resulting in the importance of weak ties in connecting communities. The hypothesis leads to high betweenness centrality for weak links, which can be seen as the mirror image of the global efficiency principle" (Onnela et al., 2007, p. 7336). Consistent with an interest in emerging patterns, agent-based simulations are the preferred method of inquiry among scholars in this community.

With a deeper understanding of the research interests of these three communities (and of communities 4-12 in appendix), we see how different communities of scholars translate and advance a scientific idea in various directions. In the community examining organizational advantage, weak ties are viewed as a collective organizational resource, an antecedent and corollary of Burt's notion of structural holes which enables organizations to innovate. In the Ego-Network Community, weak ties are considered individual property, most notably a resource for individual status attainment. In the Complex Networks Community, the Strength of Weak Ties is first and foremost considered a universal property of complex networks, independent of social context.

Emergence and growth of communities

Thus far, we have ascertained that our diffusion network has a community structure; that this structure reflects the development of distinct research cultures which interpret and reuse Granovetter's hypothesis in different ways; and that most communities developed around one or several central researchers active in spreading Granovetter's idea to new audiences. We now turn to the question of what gives rise to these structural and cultural patterns. To do so, we examine the roles individual researchers play as their work collectively shapes the diffusion network over time.

To better understand the forces which shaped the diffusion network over time, we require an historical analysis which considers changes in communities over time.[6] We thus employ a temporal community detection algorithm to find communities in different time slices (1995–2000–2005–2010–2017) (Mucha et al., 2010), in which nodes in each time slice are weakly linked to the other time slices (interslice weight parameter = 0.00001).

Fig. 12 shows the evolution of the communities over time (top) and the community paths of key, highly cited scholars (bottom). Some of these hubs—for example Lin, Wellman, and Scott Feld—started out belonging to different communities but later became part of the same community, whereas Ronald Breiger and Burt belonged to the same community and then split into different communities as they are recognized for different contributions to the literature, diffusing the Strength of Weak Ties to different audiences. Burt was acknowledged for his ideas on structural holes within organizational networks (Burt, 1997, 2000, 2004), which became most popular among business and economics scholars interested in innovation (the Organizational Advantage Community). Breiger, alternatively, got known for his contributions on mathematically identifying roles and positions in networks as matrices (Breiger et al., 1975; White et al., 1976). Although his work builds less explicitly on the Strength of Weak Ties, he acknowledges Granovetter, who was also on his thesis committee. Breiger's work is picked up by scholars working in the—at that time—emergent New York School of relational sociology (Emirbayer and Goodwin, 1994; Mische, 2011) who use Breiger's concepts and algorithms for block model analysis. These examples illustrate how the structural communities in the network are

[6] While our analyses have been based on static characterizations of the data, we seek to shed light on a complex and dynamic diffusion process. Thus far, we have defined communities in the diffusion network by the configuration of edges in 2017. Our choice to use a static definition of community was not only technical, but an answer to the ontological question of what communities represent in this case study: by using the full data from 2017, we apply the most recent lens of history as the citation patterns of later researchers are used to identify the community to which earlier contributions belong.

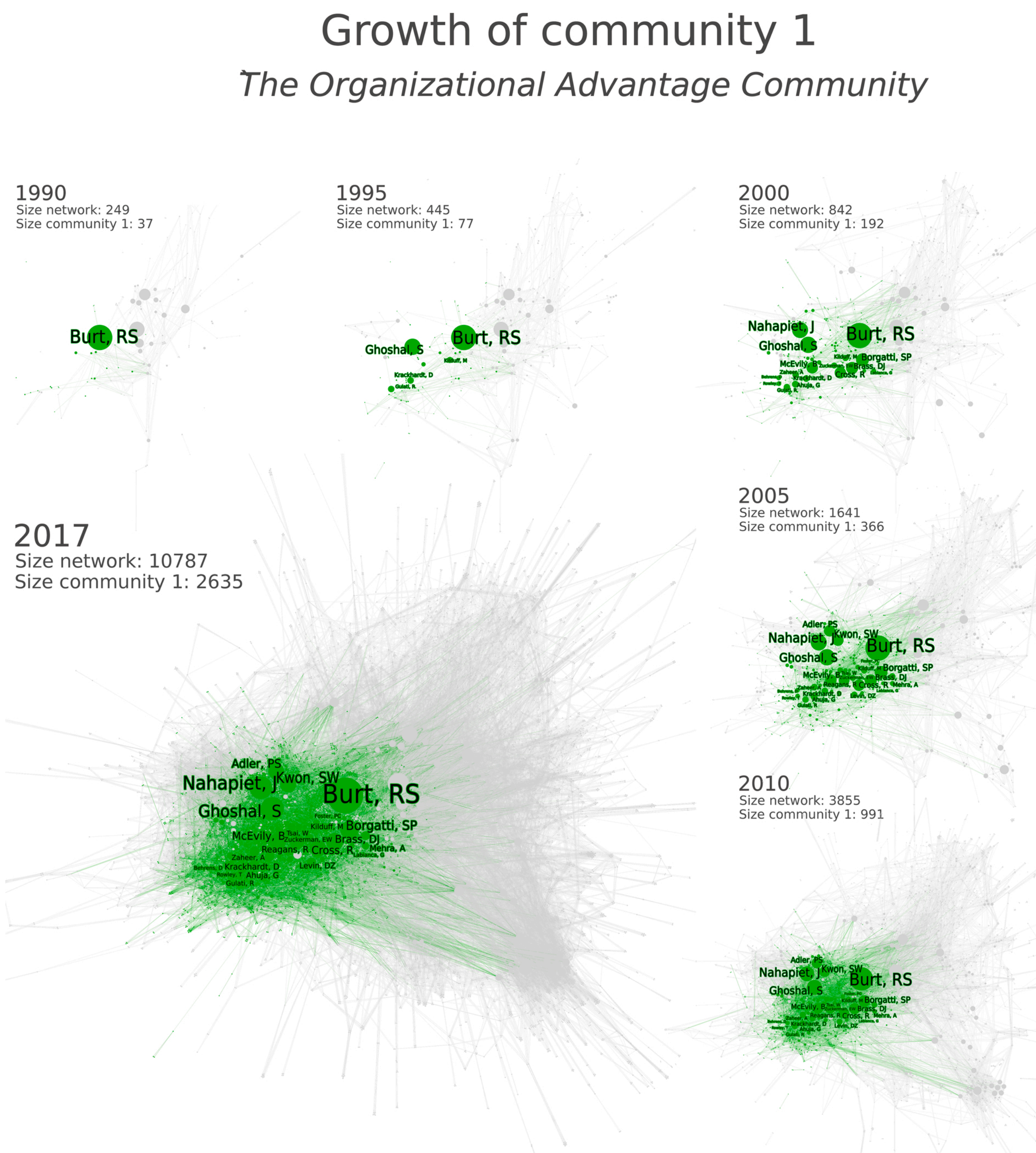

Fig. 10. Growth of the organizational advantage community (community 1). All scholars in this community are colored green. Only scholars who received at least 250 citations from future adopters (indegree > = 250) are labeled, sized according to indegree. The community develops around seminal works by central figures such as Burt (1997, 2000, 2004), Nahapiet and Ghoshal (1998), Brass et al. (2004), Levin and Cross (2004), Reagans and McEvily (2003) and Borgatti and Foster (2003). By 2005, all scholars to be most cited by this community have extensively referred to the Strength of Weak Ties. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

related to the interpretative work of the scholars that constitute them but also of scholars citing them at later points in time.

We see in these cases centrifugal forces that separate communities and fragment the network, as well as centripetal forces that bring together different communities, integrating the network. The final network structure is a balance of these opposing forces, which emerge from researchers' individual behavior. As researchers navigate the tension between novelty and conventionality, they seek to create new connections, while heeding the common practices of the discipline needed for research to have impact (Foster et al., 2015; Uzzi et al., 2013). When a new idea diffuses, researchers reinterpret it to introduce insights into existing or developing traditions, thus acting as part of the centrifugal force that strengthens the community while fragmenting the larger network. Simultaneously, researchers use new ideas as links or channels to other disciplines and bodies of literature, developing theories that combine different ideas, thereby becoming part of the centripetal force that integrates and draws the diffusion network together.

These competing interests—novelty versus contventionality, tradition versus innovation—become clearly visible if we compare Burt and Barabási's roles in shaping the network. Barabási references Granovetter in a number of highly cited publications (Barabási et al., 2002; Karsai et al., 2011; Onnela et al., 2007), incorporating the Strength of Weak

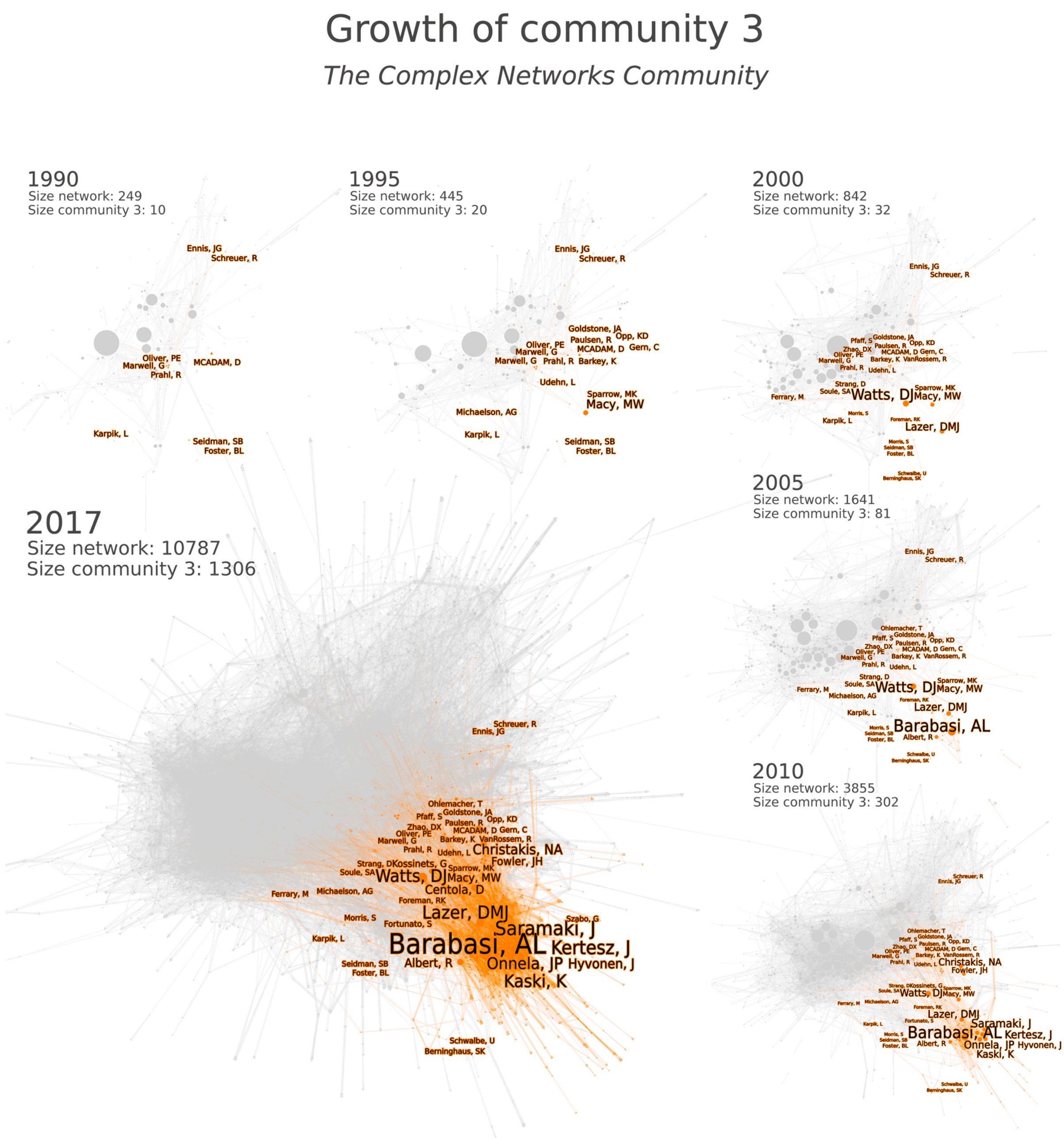

Fig. 11. Growth of the Complex Networks Community (community 3). All scholars referencing the Strength of Weak Ties before 2000, who might be considered innovators in this community, are labeled irrespective of indegree. All scholars receiving at least 250 citations by future adopters (indegree > = 250) are also labeled, sized according to indegree. Temporal networks show how this community emerged slowly in 2000, spread due to scholars such as Macy (1991), Flache and Macy (1996), Centola and Macy (2007) and Watts (1999), Kossinets and Watts (2006), and boomed after Albert and Barabási (2002), Onnela et al. (2007), Palla et al. (2007), Onnela et al. (2007) began citing Granovetter (1973).

Ties in a complex networks approach, leveraged by the Complex Networks Community. Although Barabási's star rises rapidly, he receives citations almost exclusively (83%) from within his own Complex Networks Community (Fig. 13). As Fig. 11 shows, this community only took off after 1999 and is primarily organized around Barabási's work, cited by 43% of all new scholars in this community (Fig. 13). Like Barabási, Burt is prominent in the diffusion network, but his role is different. Burt theorizes about structural holes and how brokerage enhances creativity and innovation; he is not only the most prominent scholar in the Organizational Advantage Community, but also the most central actor in

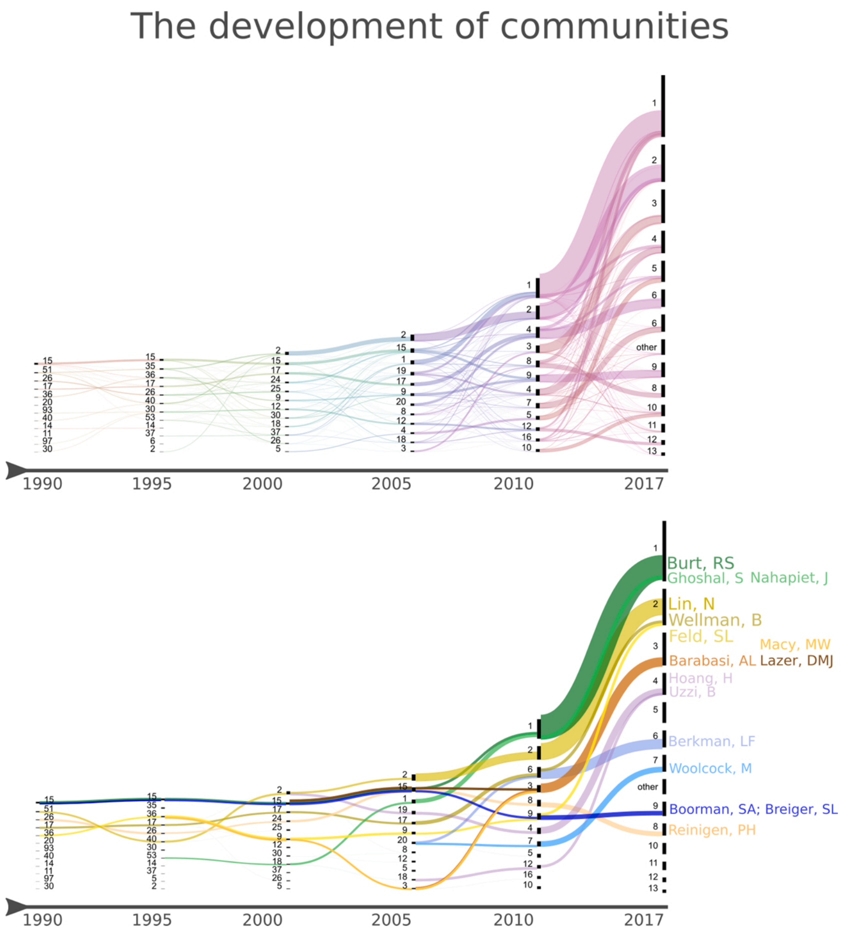

Fig. 12. Temporal evolution of communities, detected with the algorithm of Mucha et al. (2010), implemented by Vincent Traag in the Louvain Python package, using interslice_weight of value 0.00001 and 1995–2000–2005–2010–2017 time slices. The alluvial diagram shows the largest 13 communities at each time slice. Scholars in smaller communities and scholars who have yet to reference the Strength of Weak Ties in each time slice are omitted. The lower diagram shows the path of important hubs and the splitting and merging of communities over time, arising from both centrifugal and centripetal forces.

the diffusion network as a whole (with the highest authority value[7] of 0.0047). Burt publishes many articles in which he cites Granovetter's Strength of Weak Ties publication ($n = 26$) and offers contributions also beyond the role of structural holes for organizational advantage, such as insights on survey network data (Burt, 1984) and social capital (Burt, 1997). In his publications, he draws upon a wide variety of literature. Burt is strongly connected to Ego-Network Community, having been supervised by Lin for his M.A., and his ideas are much influenced by his doctoral advisor Harrison White, who features as central figure in community 7, the community that works in the lines of relational sociology. Burt receives a large number of citations (of 2.623 unique new scholars in the network) and, in contrast to Barabási, in notable amounts by members of other communities than his own, see Fig. 13 for details. Much of Burt's earlier work has become canonical not only in management science and sociology, but also in the interdisciplinary field of network analysis. Like Granovetter, Burt advances ideas that find their way into publications on diverse topics with different theoretical underpinnings and methodologies, in effect serving as a vehicle for network integration. Burt thus diffuses the Strength of Weak Ties across community borders, contributing to connecting networks of scholars. Interestingly, Burt does what he theorizes: he is a broker operating within the structural holes between communities in the academic landscape.

[7] The authority value (Kleinberg, 1999; Langville and Meyer, 2005) measures the centrality of a node by considering the centrality of its neighbors. The focus here is on the incoming edges of nodes, hence the name authority centrality. His high score on this measure thus reflect Burt's centrality in the overall network. Where some individuals are very prominent within their cluster, Burt is influential across the diffusion network as a whole, connecting its different parts.

Our analysis demonstrates how researchers play different roles that together generate countervailing forces which balance fragmentation and integration in the diffusion network. This process is driven by the work of key individuals, backed by collective citing behavior, that either integrates a new idea into existing or developing specializations or fills cultural and structural holes by connecting to other concepts and ideas. Scientific communities are a cultural and structural fabric consisting of strong ties between concepts and individuals, providing a context within which researchers can develop their work and make novel contributions that build on the community's cumulative knowledge. Through the lens cultivated by the Organizational Advantage Community, we see that whereas research communities provide a cultural context for researchers' scientific work to have meaning, the weak ties between research communities are where radical new ideas often emerge as a variety of knowledge is combined in innovative ways (Burt, 2004). The work of researchers is thus simultaneously and inextricably both cultural and structural. Employing the lens of the Ego-Network Community, scholars use both their knowledge and network as resources to advance their work and academic status (Lin, 1999; Lin and Dumin, 1986). Drawing on the Complex Networks Community's focus, we see that they inadvertently fuel the centripetal and centrifugal forces, which shape the cultural and structural network patterns we have analyzed in this article: a diffusion network in which different structural communities interpret and apply Granovetter's hypothesis in diverging ways.

Conclusion

This computational case study has studied the process by which a scientific idea is adopted and adapted as it spreads through scholarship, focusing on the case of Granovetter's (1973) Strength of Weak Ties

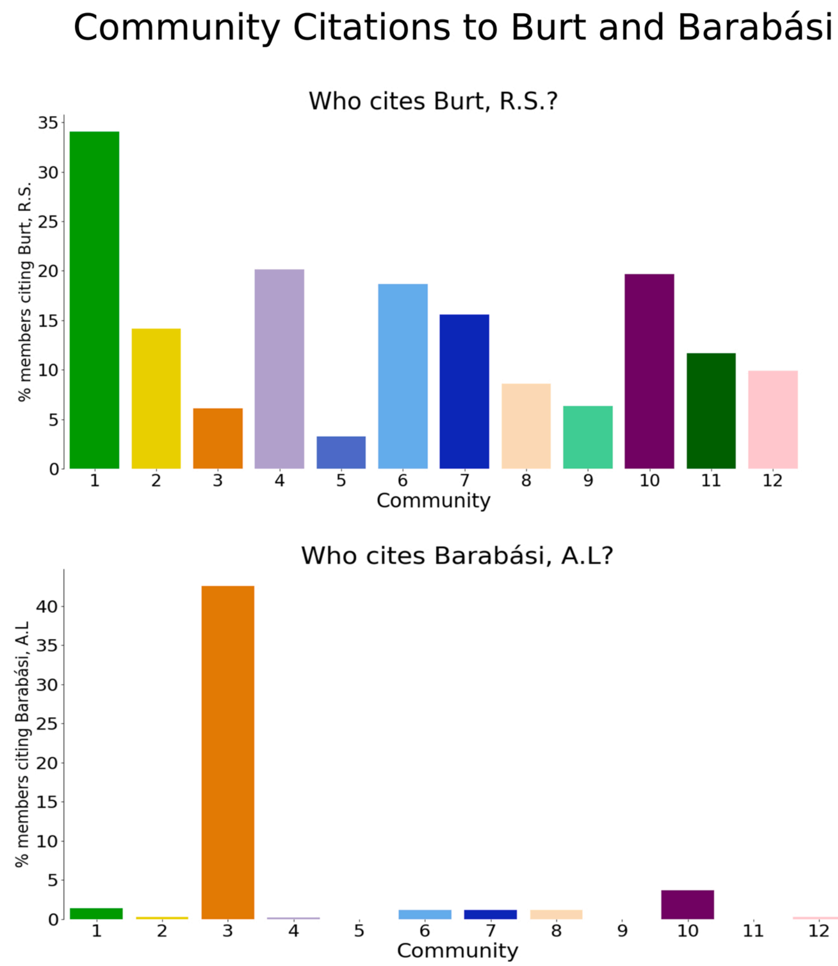

Fig. 13. Citations to Ronald S. Burt (top) and Albert-László Barabási (bottom) from scholars in the twelve largest communities in the Strength of Weak Ties diffusion network. The bars represent the percentage of scholars referencing publications by Burt or Barabási on the first occasion they refer to the Strength of Weak Ties. Burt is highly cited in all communities. Barabási is almost exclusively cited by scholars in his own community (by 43% of them).

hypothesis. We found that this hypothesis' diffusion path generates identifiable scientific communities, each of which develops its own interpretation of the hypothesis. Scholars in the various communities focus on different topics, ask different research questions, use distinct vocabularies, and advance the hypothesis in particular ways that fit into their overall research framework. Central figures around whom communities form play pivotal roles in this process; as scholars cite their publications, their work locally becomes a focal point for both the circulation and interpretation of the hypothesis.

Our analysis shows that a spreading idea is unlike viral diffusion or social contagion in that every event of transmission involves interpretation by the adopting scholar, consequently leading to a continuous transformation of the idea. Like a chameleon adopting the colors of its surroundings, the notion of weak ties takes on different guises, advanced by the interests and perspectives of the scholars redeploying and building on it. For some researchers, the Strength of Weak Ties is a universal self-organizing principle of complex networks that is not specific to any social context and can only be understood by considering and modeling the network as a whole. Other scholars find strength in weak ties due to their ability to increase the relative status of individuals in society, conceptualizing weak ties as an asset to an individual ego. Different communities use the same reference to make very different points.

Looking at Granovetter's original article on the Strength of Weak Ties (1973), we can in retrospect see the potential for the different interpretations which later emerged.[8] However, much like the varieties of plants developing from the same seed, the idea progresses in diverging directions as a result of interpretative actions and interactions of numerous scholars. This process of developing distinct interpretations of an idea functions structurally as a centrifugal movement in the diffusion network, fragmenting and separating its communities. This is in line with Burt's intuition: good ideas come about by bridging structural holes in social networks, but spread in ways that divide social groups (2004, p. 394). But we also identify centripetal forces in the diffusion process: several scholars in the network actively work across different communities, tying together ideas and fields, thus integrating the network as a whole.

In line with Latour (1984), this study suggests that translation,

[8] In fact, there are traces of this in other literatures from that time as well, as seems to be the case for most ideas—a phenomenon also referred to as simultaneous invention or multiple independent discoveries (Merton, 1961). In 1972, William Liu and Robert Duff published an article called "The Strength in Weak Ties," proposing an argument similar to Granovetter's, and drawing upon his doctoral thesis.

according to which both the circulation and the various meanings of an idea result from numerous actions and interactions among individuals, is a better model for the spreading of ideas than diffusion. Our methodology captures both the structural, macroscopic patterns that arise as a result of microscopic actions, namely diffusion communities centered around local hubs, and the changes in meaning that follow from numerous individual and collective interpretations and the development of new lines of research. Our results illustrate how these structural and cultural patterns are interrelated. We hope this will motivate researchers to look for other methodologies and approaches that integrate these insights and further our understanding of the mechanisms at play during diffusion-translation processes, in science and beyond.

One open question is to what degree the diffusion communities overlap with already existing scholarly communities or come about as a consequence of the spread and research potential of new ideas. Another avenue for future research would be to look deeper into the roles of influential scholars, to have a better sense of the extent to which they perform unique translation work or receive credit for doing so because of their status. With this article, we hope to suggest that further and more sophisticated development of these ideas will require scholars of a variety of methodological backgrounds.

Data availability statement

The data that support the findings of this study are openly available in figshare at https://doi.org/10.21942/uva.12310046.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.socnet.2021.01.001.

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