Networks, creativity, and time:
Staying creative through brokerage and network rejuvenation

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Nurturing and preserving individual employees' creativity over time has become increasingly important for firm innovation and success (Amabile & Pratt, 2016; Anderson, Potočnik, & Zhou, 2014; Zhou & Hoever, 2014). In today's competitive environment, in fact, producing a single creative contribution might not be enough: as the cycles of innovation-exploitation are shortening, bumpy dynamics in employees' creativity can generate negative performance consequences and financial troubles for organizations (Ahuja & Lampert, 2001; Tortoriello & Krackhardt, 2010). This trend imposes on individuals and organizations alike to find a way to guarantee a sustainable flow of ideas over time – something that in reality seems extremely challenging (Simonton, 1984a, 1988).

Individuals' ability to stay creative over time is shaped by many factors, but their social system of relationships plays a particularly central role (Brass, 1995; Brothers, 2018; Burt, 2004; Simonton, 1984b; Perry-Smith & Mannucci, 2017). Research has shown that individuals whose network structure (i.e., *who* they talk to) and/or network content (i.e., *what* they are exposed to) gives them access to non-redundant perspectives and ideas are more likely to generate creative ideas (Burt, 2004; Carnabuci & Dioszegi, 2015; Fleming, Mingo, & Chen, 2007; Rodan & Galunic, 2004). Specifically, this non-redundancy can come from having a network rich in structural holes, bridging otherwise disconnected social circles (Burt, 2004; Burt & Soda, 2017), and/or from a network that provides access to diverse, heterogeneous knowledge (Aral & Van Alstyne, 2011; Goldberg, Srivastava, Manian, Monroe, & Potts, 2016; Zaheer & Soda, 2009).

Overall, this would suggest that the recipe to maintain a certain level of creativity over time is to keep up network non-redundancy, in terms of both structure and content. However, this is no easy task. Ties bridging structural holes are fragile (Baum, McEvily, & Rawley, 2012; Burt, 2002; Burt & Merluzzi, 2016; Stovel, Golub, & Milgrom, 2011), and are thus characterized by diminishing returns over time (Soda, Usai, & Zaheer, 2004). Similarly, knowledge and information tend to homogenize quickly within a network (Aral & Van Alstyne, 2011).

This poses a conundrum: if structural holes and content heterogeneity are difficult to maintain and their creative returns decay, what is the best strategy to keep them "alive" and conducive to creative ideas? Despite the recognition that individuals' ability to accrue advantages from their network is contingent on how they reconfigure the network over time (Burt, Kilduff, & Tasselli, 2013; Cannella & McFadyen, 2016), networks and creativity scholars so far have mainly looked at the benefits of having a certain network structure at a given point in time.

In this paper, we attempt to solve this issue by proposing that the creative benefits of open network structures and heterogeneous content at any given point in time are less likely to be accrued if actors do not add new ties. Specifically, we theorize that structural holes and content heterogeneity will have a more positive effect on individual creativity when network stability is low – i.e., when individuals rejuvenate over time the composition of their network by adding new ties. We base this prediction on the idea that, over time, stable networks result in a homogenization and entrenchment of cognitive structures (cognitive rigidity) and interaction patterns (social rigidity). If network composition does not change, over time the creative advantages provided by structural holes and heterogeneous content will thus be lost due to the increased mental closure toward new perspectives and knowledge and the increased rigidity in coordination and collaboration patterns. On the contrary, the addition of new ties introduces a positive "shock" that pushes individuals in the network to change the way they look at and process knowledge, as well as the way they interact and collaborate (Ferriani, Cattani, & Baden-Fuller, 2009; Rand, Arbesman, & Christakis, 2014; Shirado & Christakis, 2017). These new, fresh outlooks and collaboration patterns in turn enable them to accrue the creative advantages provided by open network structures and heterogeneous content.

We test and find support for our hypotheses in a setting specifically suited for our research question: the population of core artists behind the British TV series *Doctor Who*, the longest-running *sci-fi* series in the world (e.g., Moffat, 2017; Moran, 2007; Petruzzella, 2017).

THEORY AND HYPOTHESES

Network Structure, Network Content, and Creativity

Creativity occurs when an individual breaks free from his or her previous way of thinking, which can happen for a variety of individual and social reasons. Network theory focuses on the social: breaking free from your usual ways is more likely when you are exposed to people whose opinions and behaviors are different from your own. Others' opinions and behaviors can be dismissed as irrelevant, or engaged so as to see what you know in a new way. When this happens, new ideas arise like "productive accidents": the way one person makes money with product X becomes a revelation to a person selling product Y, so a new way to distribute product Y is born.

Network theory has argued and found that the more disconnected the people in an individual's network, the more heterogeneous their knowledge and perspectives, and thus the higher the chance of a productive accident in which differing opinions or behaviors collide to produce a good idea (Burt, 2004; Fleming et al., 2007; Hargadon & Sutton, 1997; Lingo & O'Mahony, 2010). For example, Picasso's innovations in Cubism were vastly the byproduct of him being embedded in a diverse, disconnected network (Sgourev, 2013). On the contrary, the more homogenous the opinions and behaviors in a network, the lower the chance of creative accidents. Highly interconnected people are drawn together by similarity in their opinions and behaviors, and socialize one another into even more similar opinions and behaviors (Festinger, Schachter, & Back, 1950; Katz & Lazarsfeld, 1955). A closed network of interconnected colleagues implies limited variation in opinions and practices, as well as emphasis within the network on the propriety of discussion limited to the socially accepted opinions and practices.

In the aforementioned studies network openness (closure) was often conflated with knowledge and content heterogeneity (homogeneity) – a well-known creativity booster (hinderer) (e.g., Mannucci & Yong, 2018; Taylor & Greve, 2006). The underlying assumption was that structure always embodies and reflects content, and thus structural holes reflect heterogeneous content, and closure reflects homogenous content. Recently, however, this equation has been called into question, with scholars arguing and showing that structure does not necessarily embody content, and thus the two dimensions, while deeply interconnected, can also act independently and thus have similar yet distinct effects. For example, Zaheer and Soda (2009) used the content of TV scripts to categorize content heterogeneity in the networks of TV production teams, and showed that network content homogeneity and structural holes had separate and even opposite effects on team performance. Aral and Van Alstyne (2011) used the information content of email messages among people in an organization and showed that, while networks bridging structural holes do carry more diverse information, network and information diversity have separate positive effects on performance. Furthermore, there is more to the effect of information heterogeneity than is captured by network structure: performance is enhanced by diverse information provided either by an open network, or by one very strong connection ("diversity-bandwidth trade-off"). Finally, Goldberg and colleagues (2016), analyzed email networks and content over a five-year period among several hundred employees and discovered a trade-off between network and content homogeneity: people in closed networks receive less positive job evaluations when they exchange information using a language that is homogenous in terms of style and topics to their colleagues', but people in open networks obtain more positive job evaluations when they exhibit this language homogeneity. Building on these insights, networks researchers have argued that the benefits of brokerage go beyond content: brokerage provides a vision advantage, a flexibility in cognition and practices that allows brokers to "see things", spotting connections that others do not see (Burt & Soda, 2017; Burt, 2008). This issue is particularly relevant for creativity: in the words of Steve Jobs, "when you ask creative people how they did something, they feel a little guilty because they didn't really do it, they just *saw* something. It seemed obvious to them after a while" (Wolf, 1996).

While creativity scholars have studied the effects of these two dimensions in isolation, they have yet to precisely disentangle the creative consequences of network structure (who individuals talk to and collaborate with) from the effects of network content (what type of knowledge they are exposed to). Considering them together is thus needed to understand whether the effect of structure on creativity is entirely dependent on content (e.g., Rodan & Galunic, 2004), or if the creative benefits of open networks go above and beyond the effect of content in that they provide a vision advantage (Burt, 2004). We thus focus on network structure and network content as separate predictors in our theorizing and analysis.

The Moderating Role of Network Stability

Extant studies on networks and creativity have mostly adopted an agnostic view on the role of network change in shaping the creative returns of non-redundant network structure and content. For example, papers looking at creative outcomes such as academic publications or patents conceptualize creativity as the aggregate sum of these outcomes produced within a certain time period (e.g., 3 years), even when they adopt a longitudinal angle (e.g., Burt, 2004; Fleming et al., 2007; McFadyen & Cannella, 2004). By focusing on aggregated patterns, we lose sight of how network composition changes or remains the same over the years – something that varies significantly across creative individuals (Phelps, Heidl, & Whadwa, 2012; Simonton, 1988, 1997). Adopting a dynamic perspective is highly important because it puts into question whether the creative benefits provided by network non-redundancy can be taken for granted also over time. Extant research shows in fact that the benefits of open networks and heterogeneous content are more easily accrued in the short term than in the long term (Aral & Van Alstyne, 2011; Baum et al., 2012; Burt, 2002; Soda et al., 2004). Brokerage positions are fragile (Burt, 2002; Stovel et al., 2011) and subject to change (Burt & Merluzzi, 2016; Sasovova, Mehra, Borgatti, & Schippers, 2010), and knowledge and content tend to homogenize quickly and have diminishing returns (Aral & Van Alstyne, 2011).

The question thus becomes whether an open network would yield creative advantages over time and under which conditions. We argue that answering this question requires considering the composition of the network and how it evolves – i.e., network stability. We define network stability as the degree to which individuals maintain their existing ties or add new ones. Brokers can in fact maintain their open network structures either by retaining their existing brokerage positions with the same people, or by creating new ones through the addition of new ties (Sasovova et al., 2010). These strategies have very different implications for the accrual of creative returns over time.

Scholars have argued that network stability can have both positive and negative effects on social exchanges and, consequently, performance. On the one side, network stability provides coordination and communication advantages (Ferriani et al., 2009; Perretti & Negro, 2006) that are beneficial for the efficiency of social interactions, especially on complex tasks (Ferriani et al., 2009; Soda et al., 2004), and can thus facilitate an actor's ability to exchange knowledge and execute her/his work. Moreover, recurring ties are "old timers" who possess more expertise in the task and in the social domain more broadly, something that their contacts can benefit from

(Perretti & Negro, 2006, 2007). On the other side, however, network stability can also make social interactions excessively rigid and routinized, making teams increasingly rely on the same exchange and interaction patterns, without exploring new ones (Ferriani et al., 2005; Soda et al., 2004). On the contrary, new ties can "shake up" existing cognitive patterns and thus push individuals to reconsider their ways of mentally organizing and use knowledge, as well as engender the reshaping of collaboration patterns through their sheer presence (Morrison, 2002; Perretti et al., 2006). These advantages are present regardless of whether new ties bring new content (one of their oft-argued, yet never tested advantages) or not (Shirado & Christakis, 2017). Moreover, research has called into question one of the benefits of stability, namely that it improves collaboration quality. In a series of large-scale experiments, scholars have shown that networks with high stability yield no collaboration benefits (Traulsen et al., 2010), and that networks that are not rewired through the addition of new ties actually see cooperation sharply decline overtime (Rand et al., 2011).

We argue that, when it comes to the moderating role of stability on the relationship between non-redundant network structure and content on creativity, the downsides of stability will prevail. Specifically, we propose that this will happen because network stability engenders homogenization and entrenchment of (a) mental models and structures (cognitive rigidity); and (b) of interaction patterns (social rigidity) – all which severely undermine, to the point of potentially eliminating, the creative advantages provided by brokerage and content heterogeneity.

Network Structure. As mentioned above, one advantage of brokerage beyond access to heterogeneous content is premised on having contacts that come from different social circles, and that thus hold diverse worldviews and mental models. This provides the broker with a diversity of viewpoints that allows her/him to look at things in different ways and adopt multiple angles to address the same issue, thus fostering cognitive flexibility (Burt, 2004). If those contacts remain the same over time, however, mental models and cognitive structures are likely to homogenize and become more rigid (Morrison, 2002; Soda et al., 2004). This increased cognitive rigidity will hamper the vision advantages that brokers enjoy thanks to their position (Burt, 2004, 2008), thus diminishing their ability to generate creative ideas. Moreover, network stability is also likely to reduce individuals' ability to engage with and even recognize different point of views. Research has in fact theorized and shown that highly stable collectives tend to be characterized by rigidity and resistance to new perspectives and approaches (Dunbar, 1993; Perretti & Negro, 2006, 2007; Rollag, 2004; Skilton & Dooley, 2010; Sytch & Tatarynowicz, 2014). Having an open network with highly stable membership would thus result in structural holes providing little to no creative advantage: brokers will increasingly fixate on their ways of doing things, thus limiting their ability to recognize and utilize the non-redundant perspectives and views he/she exposed to, to the point of ignoring them entirely.

New ties, on the other side, stimulate the adoption of new perspectives and ways of seeing (Ferriani et al., 2005; Morrison, 2002), thus fostering brokers' vision advantage and ability to successfully apply old notions in different ways. This advantage of new ties is not premised on their social capital, and specifically on them bringing new content: it is instead rooted in the fact that they do not possess the shared mental models and views that characterize the existing network they are entering. Because of this, they ask issues that others do not see and take for granted (March, 1991). It is precisely their "naïveté" that ensures that individuals in the network reconsider their ways of doing things and restructure their mental models. Network reconfiguration should thus benefits brokers by increasing the likelihood that they consider new frames and "lenses" to see the world, allowing them to recognize new opportunities and new potential recombinations, even within the same knowledge base. Moreover, being exposed to "new" actors, belonging to previously unexplored social circles, would increase an individual's psychological readiness to new perspectives and mental frames (Perry-Smith, 2014). This reasoning is consistent with both empirical and anecdotal evidence on how being exposed to something or someone new leads to the reconfiguration of mental structures. Taking on unusual work assignments (Kleinbaum, 2012), migrating to a different country (e.g., Hunt & Gauthier-Loiselle, 2010) and interacting with people from different cultures (e.g., Maddux & Galinsky, 2009) have been shown to favor these processes. Similarly, creatives at Pixar identify the moment Brad Bird, the first director to join them as an "outsider" after his experiences at Warner Bros and Fox, as a key moment for their continued creativity, as his addition forced them to change the ways they looked at things (Rao, Sutton, & Webb, 2008).

Another advantage of structural holes resides in the fact that interactions with disconnected individuals increase the chance of creative friction (Burt, 2004) because of the sheer fact of interacting with others that have different modes of work. Having a stable network, however, can lead to an increased social rigidity and routinization of interaction patterns, both in terms of whom actors interact with and how they interact. This routinization will result in individuals becoming entrenched and fixated in their ways of collaborating and coordinating (Morrison, 2002; Perretti & Negro, 2006). They will thus become blind to new ways of coordinating and working together, losing in part or entirely the potential creative sparks that result from having to reconsider your interaction and collaboration habits (Ferriani et al., 2009; Skilton & Dooley, 2010).

On the contrary, the addition of new ties to an existing network represents a positive shock that pushes individuals in the network to reconsider the way they work together and coordinate. Once again, the ability of new ties to generate this shock is not premised on the novelty and non-redundancy of content they can directly provide. The mere addition of new people is in fact enough to force other individuals in the network to reconsider the way they do things, if only to explain them to the newcomers. In so doing, they are forced to explore, cognitively or practically, new coordination paths, thus changing the old ways and "shaking things up". Consistent with this reasoning, Shirado and Christakis (2017) have shown that even the addition of new agents without any competence (such as "noisy" bots) to a network is enough to change the way network members interact and organize to execute complex tasks. The addition of new agents shapes not only the interactions of other actors with them, but also the way other actors interact among themselves, changing their coordination strategies and routines.

All in all, these arguments suggest that network reconfiguration to create new structural holes represents a more effective strategy for accruing the creative benefits of structural holes compared to the stabilization of existing holes. We thus expect network stability to weaken the creative benefits provided by open networks, whereas we expect changes in network composition to strengthen them.

Hypothesis 1: Network stability moderates the relationship between open networks and creativity. The positive association between open networks and creativity is weaker in more stable networks, and stronger in less stable ones.

Content Heterogeneity. A similar reasoning applies to the heterogeneous content shared through the network. One creative advantage of the exposure to heterogeneous content is premised on providing new "raw materials" that fuel the recombinatory process at the heart of the generation of novel and useful ideas (Campbell, 1960; Mannucci & Yong, 2018; Taylor & Greve, 2006). Maintaining the same network composition over time can lead to heterogeneous content to age more quickly and become obsolete (Aral & Van Alstyne, 2011), thus limiting both the novelty and usefulness of generated ideas (Soda et al., 2004). Furthermore, the likelihood of content to change over time, both in terms of composition and how it is structured and organized, is lower if the network is stable. The creative returns of heterogeneous content are likely to diminish over time if it does not change, as there are only so many creative permutations that you can derive from the same content and cognitive structures (Campbell, 1960; Simonton, 2003). Finally, network stability is likely to engender rigidity in mental structures, hampering even the mere ability to recognize and use new content (Schulz-Hardt, Frey, Lüthgens, & Moscovici, 2000; Scholten, van Knippenberg, Nijstad, & De Dreu, 2007). Always interacting with the same alters creates inert cognitive structures, which in turn reduces individuals' ability to identify and willingness to integrate diverse knowledge and content (Morrison, 2002; Skilton & Dooley, 2010). This resistance means that, even if exposed to heterogeneous content, individuals in stable networks will be less receptive to it and even ignore it entirely (Ferriani et al., 2009; Perry-Smith, 2014).

On the contrary, reconfiguring the network by adding new ties should ensure that the advantages offered by heterogeneous content are accrued. New ties are more likely to bring points of view (Morrison, 2002; Perretti & Negro, 2006, 2007; Sytch & Tatarynowicz, 2014), and can thus shake up mental structures, changing the way the creator looks at available knowledge. The "elements of ingenuity" brought by new ties (Perretti & Negro, 2006: p. 761) shake up individuals' mental structures and pressure them to re-consider what they thought they knew and look at it in new ways. Moreover, being exposed to "new" actors, belonging to previously unexplored social circles, would increase an individual's psychological readiness to attend to and use heterogeneous, diverse content (Perry-Smith, 2014). Consistently, research has shown that the addition of uninformed individuals to social groups ensures that all information is equally attended to, eliminating biases towards dominant points of view and content (Couzin et al., 2011).

Another reason why stability could hamper the relationship between heterogeneous content and creativity lies in the fact that it could diminish the chances that this content is actually shared. The routines and operating procedures for coordination and knowledge sharing shape also the type of knowledge that is shared (Hansen, 1999; Reagans & McEvily, 2003). The rigid, routinized procedures that characterize stable networks thus lead to the sharing of commonly-owned knowledge, turning the advantage of having access to heterogeneous knowledge from actual to potential and thus reducing its creative returns.

Overall, these arguments suggest that network stability should weaken the creative benefits provided by heterogeneous content, whereas changes in network composition should strengthen them. Thus, we predict:

Hypothesis 2: Network stability moderates the relationship between content heterogeneity and creativity. The positive association between the exposure to heterogeneous content and creativity is weaker in more stable networks, and stronger in less stable ones.

METHODS

Setting: The *Doctor Who* Production World

Testing our hypotheses required a research setting characterized by creatives who continuously engage in collaborations to generate creative outcomes. We found such a setting in the network of creatives involved in the realization of the episodes of *Doctor Who*, a British science-fiction television show and the longest running in the world. Since its launch in 1963, *Doctor Who* has been a ground-breaking success in British television (Howe, Stammers, & Walker, 1994). It is currently broadcasted in more than 50 countries and is one of the top grossing shows produced by the BBC (O’Connor, 2008). The series tells the adventures of an extra-terrestrial being called “The Doctor” who explores the universe thanks to a spaceship called TARDIS, which allows him to travel in space and time. He is joined in his adventures by a variety of companions, who help him fighting foes in different planets, times, and civilizations.

The increased importance, scope, and success of *Doctor Who* over the years has led the showrunners to elaborate a narrative ploy to keep the show running even when the actor interpreting the Doctor would decide to quit: when he is deadly wounded, the Doctor’s body regenerates to take a different appearance. Regeneration is thus at the core of *Doctor Who* in terms of characters, plots, and themes. The show has attracted a lot of praise for its creativity and ability to reinvent itself (e.g., Moran, 2007; Petruzzella, 2017). For example, this is how Steven Moffat, one of the most successful showrunners in British television, described the classic series of *Doctor Who* in a recent interview (Moffat, 2017):

> The classic series […] has more good ideas in it, the classic ones of *Doctor Who*, than any other television series in history. They invented the TARDIS! Somebody sat in a room and said: "It's bigger on the inside and looks like a police telephone box". They invented the Doctor who's never caught, whose name is shown to be Doctor Who but isn't Doctor Who, which is in itself a weird and charming idea. They invented the regeneration, they invented the Daleks, they invented the Cybermen, they invented a different version of a show where the Doctor was a benevolent alien living on Earth working through the UNIT and saving the planet. All these are different series contained within *Doctor Who*. […] There are more good ideas there than in, look, *Breaking Bad*, the *West Wing*, and these are two things among the best things television has ever done. *Doctor Who* has more ideas in a couple of episodes than I have ever had in an entire life.

Doctor Who is also an ideal context in that it represents a single cultural product realized for a long period of time within the same company (BBC). As such, it provides a controlled context for creativity and it allows us to rule out product-specific or company-specific characteristics that could be affecting creativity (e.g., Soda et. al, 2004; Cattani & Ferriani, 2008; Mannucci & Yong, 2018). Moreover, focusing just on *Doctor Who* enables us to identify precise boundaries for defining collaboration networks and content domains (see Clement, Shipilov, & Galunic, 2018, for a similar approach)[1], while at the same time controlling for creators' collaborations and exposure to content outside these boundaries. Finally, the time required for creating and shooting

[1] More broadly, this approach is consistent with the large majority of extant network studies in cultural industries that focus on a single product (e.g., movies, television shows, Broadway shows – Cattani & Ferriani, 2008; Soda et al., 2004; Uzzi & Spiro, 2005), and thus do not consider the work artists might have done in other fields. For example, an actor playing a role in a TV show might have worked also in a movie at the same point in time.

Doctor Who episodes was very important for our focus, as it allowed for a fine-grained exploration of the stability versus change in network composition, with time windows covering only few months rather than one or more years.

Data and Sample

The sample consists of the entire population of core crewmembers who worked in at least one of the 273 episodes produced between 1963 – the year the show started – and 2014. While recognizing that a television episode is the result of the creative effort of multiple professionals, we followed a diffused practice in network and creativity research (e.g., Cattani & Ferriani, 2008; Mannucci & Yong, 2018; Perretti & Negro, 2007) and focused on the individual artists that are in charge of the most critical aspects of creative work. The "core" artists for each episode include three creative roles: one producer (sometimes called a showrunner), one or more directors, and one or more writers. In our sample, "core" teams vary in size from two to five, with the majority containing three people (81%).

We identified individuals associated with each role by looking at the credits of each episode as reported on BBC website. We then crosschecked the reliability of this information with other sources, such as specialized publications on *Doctor Who* (e.g., Fleiner & October, 2017; Howe, Stammers, & Walker, 1992, 1993, 1994) and *Doctor Who*-dedicated Wikis (e.g., TARDIS Wiki). We then cleaned the data, removing duplicates and checking for other inconsistencies. Since not every artist is involved in every episode, the final sample included 866 observations for 200 individual artists.

Social Network Structure of *Doctor Who* and Artists' Cohorts

To unveil the social network structure of the *Doctor Who* production world, we analyzed the affiliation network between artists and episodes. An affiliation network is a network of vertices connected by common group memberships such as projects, teams, or organizations.

Examples studied in the past include collaborations among television professionals (Soda et al., 2004), Broadway artists (Uzzi & Spiro, 2005), and Hollywood film professionals (Cattani & Ferriani, 2008). In our network, a link between any two artists thus indicates that they have worked together on the making of an episode.

Like many cultural industries, and in particular television, the *Doctor Who* collaboration network is structured as a “latent organization” (Starkey, Barnatt, & Tempest, 2000), with an interplay of artists that come together for a given project, seemingly dissolve, and then come together for another project at a later date. Artists come to work on these projects in different ways: sometimes they self-propose for a project, and sometimes the content buyer actively pursues them. In *Doctor Who*, for example, Neil Gaiman self-nominated for writing the episode “The Doctor’s Wife”, but it was BBC executives that selected Verity Lambert as the first producer of the show (Fleiner & October, 2017; Howe, Stammers, & Walker, 1992).

Within latent organizations, the large majority of collaborations takes place within the project boundaries, akin to what happens within a regular organization (Starkey et al., 2000). Consistent with previous work (e.g., Clement et al., 2018), we thus defined the boundaries of our network as the production world of our focal product, thus limiting our analysis to artists’ collaborations while working *Doctor Who*. With such an extended run, the social network of artists working on *Doctor Who* was naturally characterized by different cohorts based on the time these artists worked on the show. Figure 1 is a sociogram of the artists involved in *Doctor Who* in our observation period (1963-2014). Symbols represent the 200 artists distinguished for their primary role by color, and primary cohort by symbol shape. Larger symbols distinguish artists who worked on more episodes. Thin lines connect artists who worked together on only one episode, while bold lines connect artists who worked together on two or more episodes. Artists are located in the space close to other artists with whom they worked (spring embedding algorithm, Borgatti, 2002). We use Graeme Harper (the red triangle in the center of the sociogram) as an example to illustrate what network connections mean in our context. Graeme directed a total of 14 episodes, three of which were produced by John Nathan Turner in the second cohort (yellow square in the center of the second cohort cluster). The bold line connecting Graeme and John indicates that they worked on more than one episode together. The thin lines connecting Graeme with three other artists indicate that they worked together on one episode.

——— Figure 1 About Here ———

The sociogram of collaborations in Figure 1 displays four clusters. These clusters empirically identify four artist cohorts that correspond to different time periods of the shows. Artists are more densely interconnected within cohorts, and each cohort is connected only by occasional bridge relations between artists belonging to multiple cohorts. "Cohort one" artists are clustered together to the west (circles). Below them are the "cohort two" artists (squares). To the right of them is the cluster of "cohort three" artists (triangles), and to the further right is the cluster of "cohort four" artists (diamonds). The artists' population that created the *Doctor Who* episodes is thus more precisely a set of four separate populations, variably overlapping, and ordered in time.[2] The Figure shows that the few instances of artists working across cohorts generate numerous interpersonal collaborations across cohorts, but the cohorts remain visible as separate populations. The table in Figure 1 shows that most interpersonal collaborations are within cohort, with almost no connection between artists in the first two cohorts versus the last

[2] The *Doctor Who* network in Figure 1 meets the criteria of being a small world in that (1) the average network density around individual artists is much higher than would be expected by random chance and (2) the path distance (i.e., the shortest chain of indirect connections linking artists) is about as short as would be expected by random chance (Watts & Strogetz, 1998). The average density of collaborative ties between artist contacts in Figure 1 is 65.6% — two thirds of the average artist's contacts have collaborated with each other. The expected average density if the same number of collaborations were distributed at random would be a much lower 3.1%. The average path distance between any two artists in Figure 1 is 3.8 steps, which is about the same as the 3.1 steps expected if the same number of collaborations were distributed at random.

two. The latter is due to the fact that the show was effectively cancelled in 1989 because of falling viewing numbers and a less-prominent transmission time (Ley, 2013). This resulted in a 14-year gap between cohort two's last episode in 1989 and cohort three's first episode in 2004 – a gap depicted in Figure 1 by the deep structural hole between the first two cohorts and the last two, spanned only by Graeme Harper, who is connecting cohorts two and three.

Dataset Construction: Cross-sectional vs. Panel

We constructed two datasets. The first one is a cross-sectional, constructed by taking the approach, common in networks and in creativity research (e.g., Burt, 2007; Simonton, 1984b), of measuring one's network over a given observation period and aggregating all outputs (in this case, their creative contribution to each episode) she/he realized during this time. This dataset thus consisted of the aggregation over time of all network and creativity data, with the 200 artists as the unit of analysis. We constructed this dataset for two reasons. First, we wanted to verify that the well-known positive relationships between non-redundant network/content and creativity that are usually identified when taking this aggregative approach were present in our setting. Given the peculiarity of our setting, there was the chance that some idiosyncrasies related to the setting could be affecting our hypothesis testing. Replicating these well-known relationships would make us confident that our results were not driven by these idiosyncrasies. Second, we wanted to offer an in-depth overview and description of the collaboration network that developed over years of creative production of *Doctor Who*.

The second dataset is a panel that we used to conduct our main analyses and test our hypotheses. This dataset is an unbalanced panel, with number of episodes per artist ranging from 1 to 50, with an average of 4, and included 866 artist-episode pairs as units of analysis.

Dependent Variable: Creativity

We measured creativity following the consensual assessment technique, a well-established method in creativity research (Amabile, 1982, 1983). This method is rooted in the idea that creativity is not an objective property: in order to be considered creative, a product has to be judged as such by appropriate expert observers belonging to the field (Amabile, 1996; Csikszentmihályi, 1999). We thus recruited two expert judges to assess the artists' creativity. Judges were recruited for their expertise with British television and *Doctor Who* in particular. Both were critics with many years of experience, and both had written essays and articles on the history of *Doctor Who*. The judges provided their assessment consistently with the suggested best practices in the consensual assessment technique (Amabile, 1982). First, to establish similar frames of reference, they were provided with a definition of creativity as the generation of novel and appropriate outcomes. Second, they provided their assessments independently.

Television episodes are the sum of the creative effort of different individual creators, each contributing with her/his specialized knowledge and talents. This feature allows experts such as our judges to identify and isolate each individual's creative contribution, independently from the overall creativity of the episode (see Cattani & Ferriani, 2008, and Mannucci & Yong, 2018 for a similar approach). For example, an episode can feature outstanding directing but a poor script. For each episode, judges were thus asked to rate the creativity of the producer, of the director, of the writer, and overall episode creativity[3] on a 1-5 scale (1=not creative, 5=very creative). The fact that the ratings were provided two years after the last episode was broadcasted allows us to minimize issues of reverse causality (see Mannucci, 2017). However, the time separation could

[3] We treated episode creativity as akin to being a co-author of a significant work, and assigned the same episode creativity rating to all artists who worked in a given episode.

also create memory problems: we thus asked judges to re-watch episodes they have not watched in more than three years.

We provide the frequency counts of the creativity ratings in the Online Appendix (Table A1). We measured interrater agreement using Cohen's (1960) weighted kappa, which is more appropriate in the presence of ordinal variables (Bakeman & Gottman, 1997). The kappa scores for the three roles and the episodes varied between .79 and .83, significantly higher than the threshold of 0.61 generally accepted as a good level of overall agreement (Kvalseth, 1989).

For the panel dataset, we used the creativity of the creator's role as a measure of her/his creativity in the given episode. If the creator covered more than one role, we took the average of the two scores. For the cross-sectional, we computed four different measures of an artist's creativity over her/his career within *Doctor Who,* two measured at the individual level and two measured at the episode level: (a) maximum individual creativity exhibited by the artist, (b) maximum episode creativity for episodes the artist has worked in, (c) number of highly creative individual contributions, and (d) number of highly creative episodes the artist has worked in. We considered a contribution as "highly creative" when the creativity score as assessed by our two judges was equal to or higher than 4.5.

Independent Variables

For the panel dataset, we constructed the network of each artist at time *t* as the network composed of every other person who worked with the artist over a four-episode time window – the episode at time *t* plus the immediately preceding three episodes. As an episode is produced in about one month, a four-episode window could be seen, on average, as a four-month time window[4]. We ran sensitivity analysis by reducing and expanding the four-episode window, but

[4] It is important to note that while producers often worked on consecutive episodes (the record being John Nathan Turner, who produced 50 consecutive episodes – see Figure 1), directors and writers typically worked on non-

found no substantive differences in results. We thus report only analyses with the four-episode windows. For the cross-sectional dataset, we constructed the network of each artist by looking at the network composed of every other person who worked on the same episodes as the artist over her/his time working on *Doctor Who*. The connection between each pair of people in the network is the number of episodes on which they ever worked together. The size of these 200 networks ranges between two and 47, with a mean of 5.93 and a median of four.

Network openness. We computed network constraint to measure the extent to which an artist's network is closed (Burt, 1992). Constraint increases from zero to one with the extent to which a person has few contacts (size), those contacts are strongly connected directly to one another (density), or strongly connected indirectly through their connections to the same other person in the network (hierarchy). Scores approach 1 when an artist works with collaborators who often work with one another. Scores approach zero when an artist works with different people who themselves work with different people. We computed constraint within four-episode time windows for the panel dataset, and over all of an artist's time with *Doctor Who* for the cross-sectional dataset. The patterns of these two measures are illustrated in the Online Appendix (Figure A3). To ease interpretation, we operationalized our independent variable as 1-constraint, so that high scores reflect openness and low scores reflect closure.

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consecutive episodes. The table below shows how unusual it was for a director or writer to work on consecutive episodes. Even when a director or writer worked on only two episodes, the episodes were separated by a median of three — mean of nine — intervening episodes. This supports the idea that the *Doctor Who* collaboration network is a "latent organization" (Starkey et al., 2000).

Artist's number of episodes (N)	Artists with consecutive episodes	Artists with more than one episode in one season	Minimum number of episodes between consecutive episodes	Median number of episodes between consecutive episodes	Maximum number of episodes between consecutive episodes
One (65)	65	65	1	1	1
Two (45)	9	25	2	5	60
Three (21)	1	2	3	11	62
More (51)	0	4	7	47	109

Content heterogeneity. We measure the content heterogeneity in terms of how similar the episode content is compared to other episodes the artist has worked in. To compute this variable, we first identified content categories that we could use to describe each *Doctor Who* episode. Following an approach already validated in other studies set in the cultural industries (e.g., Cattani & Fliescher, 2012; Taylor & Greve, 2006) and in the television industry in particular (e.g., Clement et al., 2018; Zaheer & Soda, 2009), we consulted domain-specific sources to establish relevant content categories. Specifically, we searched through published reference works and essays (e.g., Fleiner & October, 2017; Howe et al., 1992, 1993, 1994), magazines (e.g., Doctor Who Magazine, Radio Times) and online sources (e.g., Tardis Fandom) focusing on *Doctor Who*. By cross-comparing these sources, we were able to identify four content categories that were consistently used to classify *Doctor Who* episodes: story type, setting, incarnation of the Doctor, and type of alien foe.

We then followed a two-step procedure to corroborate the appropriateness of these content categories. First, we reviewed the plots of each episode to ascertain that the four content categories could be indeed applied to each episode, and verified that this was the case (see Zaheer & Soda, 2009, for a similar approach). Second, and most importantly, we asked our expert judges to separately validate our list of categories. They both confirmed that these four categories were capturing the "language, messages, narrative, and identity" of each episode (Zaheer & Soda, 2009: p. 16), and that they significantly affected episodes' key features such as narrative style, visual appearance, and characters. For example, episodes with the seventh incarnation of the Doctor have a darker, secretive atmosphere, whereas episodes with the third incarnation are characterized by more down-to-earth, investigative plots. Similarly, episodes that include the aliens called Daleks often take place in war-ridden planets and sets, with a gloomier cinematography; whereas episodes that include the aliens called Time Lords take place in luxurious, sci-fi interiors, with a cinematography characterized by saturated colors (Howe et al., 1992; Howe & Walker, 1998). Table 1 provides a detailed description of each content category and of the relative sub-categories.

——— Table 1 about Here ———

The second author and a research assistant blind to the research hypotheses then used these four categories to independently code the content of each episode. In the few instances where disagreement arose (about 2% of the cases), they resolved it through discussion.

We then split each category into a set of binary variables, each describing one sub-category. Each episode was thus characterized by a profile of 41 binary variables: three of the variables distinguish story type, three distinguish story setting, 12 distinguish incarnations of the Doctor, and 23 distinguish the kind of alien opposing the Doctor. The content on which an artist has worked is thus defined by M content profiles, where M is the number of episodes the artist has contributed to, either within the four-episode time window (panel dataset) or across all her/his work on *Doctor Who* (cross-sectional dataset). To the extent that an artist's M content profiles are identical, the artist has a history of homogeneous content; the more the artist's M content profiles differ, the more he/she has a history of heterogeneous content.

We use Jaccard coefficients to measure dissimilarity between pairs of the M profiles, which together define an (M, M) symmetric matrix of association like a correlation table. We average the M^2 elements in the table to measure an artist's content heterogeneity. In our setting, a low coefficient means the artist worked on stories of the same type, in the same setting, with the same Doctor protagonist, against the same kind of alien. The resulting measure has construct validity both in terms of what is assumed in network theory and what should be expected from previous research: content heterogeneity increases with the level of network openness (*r*=.92, compared to, for example, *r*=.71 in Aral & Van Alstyne, 2011: p. 118)[5].

The way the Jaccard index is computed means that one-episode artists would naturally receive heterogeneity score of 0. Given that the minimum mean Jaccard for multi-episode artists is .333, this score would set one-episode artists far apart from the rest of the population, potentially creating outlier problems in the analysis. We thus shifted the content heterogeneity score for single-episode artists from 0 to a .33, which puts them at the lowest level of content heterogeneity, but only just below the rest of the population.

Network stability. In the panel dataset, network stability was measured as 1 – ($n_{\text{new ties}}$ / $\max_{\text{new ties}}$). New ties were computed as the number of new faces on the creative team the artist is working with on a given episode, where a collaborator was treated as new if the artist had not worked with her/him before the current episode. Given the small team size, the new faces in a given episode are typically one or two, with many instances of no new faces (13.39%) and an equal number of three or four (12.89%). For the cross-sectional dataset, we computed network stability as the average of the panel measure across the episodes on which the artist worked.

Control Variables

We included control variables to account for factors that can influence the creators' likelihood of generating a creative contribution and/or the characteristics of their network structure and content.

Panel dataset. We controlled for artists' level of *expertise*, a well-known creativity precursor (e.g., Amabile, 1983; Dane, 2010; Simonton, 2003). The variable was computed as the

[5] We also run a principal component analysis (PCA) of each artist's (*M*, *M*) matrix of Jaccard coefficients as an alternative way to summarize content homogeneity (ratio of first eigenvalue to *M*). The PCA and mean Jaccard measures were so highly correlated (r = .99) that we report only results with the more widely used Jaccard measure.

number of episodes the artist has worked on up to the focal one. We also included a measure for *input non-redundancy* to control for the experiences of the people in the focal artist's network. We computed it as the number of content elements that the artist's alters had experience in while the artist did not, divided by the total number of content elements alters had experience in. We also controlled for an artist's *outside experience*, measured as the number of TV shows outside *Doctor Who* the artist has worked on during the focal year. Including this control was warranted for two reasons: first, non-redundant content and thinking styles can in fact come not only from network position and exposure, but also from working in unrelated areas and products. Second, while focusing on the collaboration network of a single TV show allowed us to control for potential confounds at the product or company level, it did not allow us to assess the role played by outside experience, a potentially powerful creativity precursor (e.g., Perry-Smith & Shalley, 2014; Reagans, Zuckerman, & McEvily, 2004).

Additionally, we controlled for the *previous creativity* of the artist, measured as the average creativity of her/his prior contributions as rated by our judges[6]. The inclusion of this control was warranted because prior creativity can affect current creative performance (e.g., Audia & Goncalo, 2007). Moreover, including this variable allows to control for unobserved variables and for other potentially important, but omitted, predictors of creativity (Greene, 2011).

We also controlled for *previous outside collaborations* between the creator and her/his ties, and for the *outside ties* of each creator with other artists in the television industry outside *Doctor Who.* As mentioned above, focusing on the collaboration network of a specific product is

[6] For the first contribution, where no prior rating was available, we tried two different specifications of this variable. First, we assigned to the first contribution a value of zero, in order to reflect the fact that no contribution had yet taken place. Second, we assigned to the first contribution a value of 3, i.e. the mid-point of the scale on which judges rated artists' creativity. Results for our focal relationships remained identical across the two specifications. The effect of the prior creativity variable was also the same, in terms of direction and significance, across specifications. We report results based on the first specification.

standard practice in general (e.g., McFadyen & Cannella, 2004), and in studies set in the cultural industries in particular (e.g., Clement et al., 2018). However, our focus on new ties prompted us to control for the number of pre-existing ties due to collaborations outside *Doctor Who*. We computed previous outside collaborations as the number of people in each artist's network that the artist has already worked with on other projects outside *Doctor Who* prior to the focal episode. Controlling for outside ties is a standard practice in network research, and in networks-creativity in particular (e.g., Fleming et al., 2007; Perry-Smith, 2006; Tortoriello & Krackhardt, 2010) as it allows balancing the need to set up boundaries for mapping the focal network with the need to account for actors' outside experience (Laumann, Marsden & Prensky, 1989). We measured outside ties as the number of people not included in the network that the focal creator has worked with on other productions during each 4-episode time window.

Finally, we included dummy variables for the *role* covered by the artist in the focal episode and for the *cohort* to which the focal episode belonged to. Controlling for roles was important because roles have implications for the way artists work. Producers were often hired to work on a sequence of consecutive episodes. In contrast, directors and writers were usually hired on a per-episode basis. As a consequence, a third of the writers and directors worked on only one episode (35.7%), and another third worked on only two or three episodes (36.3%). Controlling for cohorts was also relevant for two reasons. First, we observed significant differences between cohorts. The first cohort created and established the template for the show. Artists in the first cohort produced the most episodes (108, versus 59 in the second most active cohort), involving the largest number of different artists (86, versus 46 in the second largest cohort). The second cohort is instead characterized by the presence of a single producer, John Nathan Turner (the large yellow square in Figure 1), against eight in the first one, with directors and writers experiencing shorter employment periods than in the other cohorts. Half of the writers and directors in the second cohort worked on a single episode (48%), versus a third in the other cohorts (35%, 30%, and 28% respectively in the first, third, and fourth cohorts). The third cohort enters after the 14-year hiatus in the show production: artists in this cohort thus enjoy some of the freedom and license enjoyed by the first cohort. Production in the third cohort is also relatively centralized in a single producer, Phil Collinson (yellow triangle in Figure 1), who produces 84% of the third cohort's episodes. The fourth cohort followed immediately in the wake of the third, embedded in the opinion and practice of the third cohort without the leadership of Phil Collinson's experience. Second, controlling for the cohort was particularly important in the panel dataset because each cohort represents a network community. A stable community is characterized by high connectivity and high knowledge flow, and is at higher risk of homogenization (Gulati et al., 2012; Sytch & Tatarynowicz, 2014). Thus, transitions between cohorts can be disruptive experiences that make artists in the subsequent cohort more likely to re-think previous opinions and behaviors. Conversely, the shorter and less disruptive the transition from one cohort to another, the more the subsequent cohort is embedded in the first, making only incremental adjustments to established opinion and behaviors.

Cross-sectional dataset. For the cross-sectional, we controlled for an artist's level of expertise, outside experience, creative role, and cohort. Expertise was computed as the number of episodes an artist has worked on during her/his entire run in *Doctor Who.* We measured outside experience as the number of TV shows an artist has worked on during their career that are not related to *Doctor Who*.

We also included dummy variables for creative role and cohort in order to control for unobserved role-specific and cohort-specific characteristics. If an artist had worked in more than one role or cohort, we assigned her/him to the role he/she more frequently covered and to the cohort they spent more time in.

RESULTS

Preliminary Analysis (Cross-sectional Dataset)

Table 2 presents the correlations and descriptive statistics for our variables in the cross-sectional dataset. The correlations of network openness and knowledge heterogeneity with our four measures of creativity are positive and significant, ranging between .540 and .572 for constraint ($p < .001$) and .519 and .593 for heterogeneity ($p < .001$). This shows that open networks and non-homogeneous knowledge are positively related to creativity also in our setting, thus replicating the well-known relationships in extant research.

——— Table 2 and Figure 2 about Here ———

Figure 2 presents a visual depiction of our findings: the more closed the network around an artist, the less creative her or his work[7]. Figure 2A compares artists for their most creative work, while Figure 2B compares artists for the number of creative contributions. There is a linear association with the number of very creative works up to about 70 points of network openness, above which there is a concentration of creative work in the artists with the most open networks.

To further explore the relationship, we also conducted regression analyses. While our cross-sectional design and variable aggregation do not allow us to claim causality, regression analyses provide a more robust test of the relationship between our predictors and creativity. We used ordinary least squares regressions for the analyses focusing on maximum creativity, and Poisson regressions to predict the frequency with which an artist produced highly creative work[8].

[7] To facilitate the Figure's interpretation, we multiplied the fractional constraint scores by 100. This allowed us to discuss points of constraint.
[8] Given that our dependent variable was overdispersed, we initially tried a negative binomial specification. However, the dispersion parameter alpha was not significantly different from zero, thus suggesting that the data were better estimated using a Poisson rather than a negative binomial model.

For each measure of creativity, we entered variables into the analysis at two hierarchical steps: (1) control variables, (2) predictor variables.

Table 3 presents the regressions analyses. The results are highly consistent across different operationalizations of creativity. Looking at Models 2, 4, 6, and 8, we can see that network openness has a positive and significant effect across all the operationalizations of creativity but the number of highly creative episodes ($p < .01$ for maximum role creativity; $p < .05$ for maximum episode creativity; $p < .01$ for number of highly creative individual contributions). On the other side, content heterogeneity did not have a significant effect on any of our operationalizations of creativity. Finally, it is worth noting that the effect of network stability is always positive ($p < .05$ for both maximum creativity measures, $p < .01$ for both creative contributions measures): artists working in stable networks generated more creative work.

——— Table 3 about Here ———

We also conducted analyses entering each predictor separately, both with and without control variables. These analyses were warranted given the high correlation between two of our predictors (network openness and content heterogeneity). Full results are not reported due to space constraints and are available in the Online Appendix (Table A2). The effect of brokerage and stability when added in isolation was almost identical to our main analyses: both variables displayed a positive and significant effect for all operationalizations of the dependent variable ($p < .001$ for all), both when control variables were present and when they were absent. Content heterogeneity instead displayed a different pattern compared to the one reported in our main models (2,4,6, and 8). Its effect was significant for all operationalizations of the dependent variable ($p < .001$ for all) both when control variables were present and when they were absent, suggesting that the non-significant effect found in the main analysis is due to brokerage "washing out" its effect.

Main Analysis (Panel Dataset)

Table 4 reports the correlations and descriptive statistics for the panel dataset. For this dataset, the use of linear regression was not appropriate for two reasons. First, the presence of repeated observations for the same creators over time violates the OLS assumption of independence of observations. Second, the variance of the error terms might be heterogeneous across different cross-sectional units, presenting a heteroscedasticity issue. The final model for the panel dataset was thus a conditional fixed-effects linear model, which controls for inherent differences in creator's skills and ability. We performed a Hausman test (1978) to choose between fixed- and random-effects models. The test was significant, indicating that the random-effects estimator was not consistent. We report significance levels based on Huber-White robust standard errors to control for any residual heteroscedasticity across panels. Using robust standard errors is equivalent to clustering on the creator, further accounting for the presence of repeated observations (Arellano, 2003; Wooldridge, 2016).

We entered the variables into the analysis at four hierarchical steps: (1) control variables, (2) predictor variables, (3) each interaction separately, (4) both interactions together. We did not center the predictor variables, and thus our interaction coefficients can be interpreted as the effect of the independent variable when the moderator is equal to zero (Allison, 1977). Table 5 summarizes the results. We checked for multicollinearity by computing the collinearity diagnostic procedures illustrated by Belsley and colleagues (1980), the most appropriate approach for computing collinearity using panel data (Hill & Adkins, 2001). These procedures examine the "conditioning" of the matrix of independent variables, producing a condition number that is the largest condition index. The condition number for the full model was 13.11, far below the value of 30 considered problematic by conventional standards (Belsley, 1991), indicating that collinearity was not an issue.

——— Table 4 and 5 about Here ———

Model 1 includes all the control variables. We find that previous creativity ($p < .01$) has a negative effect on creativity. Model 2 shows the results after we entered the independent variables and the moderator. Neither network openness nor network stability has a significant effect on creativity, but content heterogeneity has a positive and significant effect ($p < .05$)[9]. Model 3 reports the results after including the interaction between network openness and network stability. As expected, the coefficient is negative and significant ($p < .01$), indicating that the effect of open networks/structural holes becomes less positive as network stability increases. This is consistent with our Hypothesis 1. Model 4 reports the results after including the interaction between content heterogeneity and network stability. The interaction coefficient is negative and significant ($p < .01$), indicating that the effect of content heterogeneity becomes less positive as network stability increases. This is consistent with our Hypothesis 2. Model 5 presents the results after including both interaction variables: results are consistent with those of Models 3 and 4, with both interaction coefficients that remain negative and significant ($p < .01$ and $p < .01$ for both). The overall fit of the model improves as compared to the baseline, but also with respect to Model 2, indicating that the full model better fits the data. The F-test for one degree of freedom shows that Model 5 improves significantly on Model 2 (Pr > F is < .001).

——— Figure 3 and Figure 4 about Here ———

Figure 3 and Figure 4 plot the marginal average effects. Figure 3 shows that the effect of network openness is positive when network stability is low ($p < .05$), and becomes increasingly less positive as network stability increases, to the point of turning negative when the network is characterized by zero change ($p < .01$). Figure 4 shows that the effect of content heterogeneity is

[9] As with the cross-sectional dataset, we tried also adding our core predictors separately, one by one. Results on their main effects were identical to those reported above and in Table 5, Model 2.

positive and significant when network stability is low ($p < .01$), but becomes increasingly less positive as network stability increases. The analysis of marginal effects provides further support for our Hypotheses 1 and 2.

Figure 5A and Figure 5B provide a visual depiction of the observed pattern of results by mapping the distribution of creativity ratings across different configurations of network openness and network stability (Figure 5A) and of content heterogeneity and network stability (Figure 5B). Figure 5A shows that creativity is highest for people embedded in open networks working with multiple new teammates (far left columns). The benefits of maintaining an open network are lower if half the team is unchanged (middle columns), and reverses to negative if the team is unchanged or contains only one new member (far right columns). A similar pattern can be observed for content heterogeneity in Figure 5B: creativity is highest for people with diverse content experience working with multiple new teammates, and decreases as the number of new teammates decreases.

——— Figure 5A and Figure 5B about Here ———

Robustness Checks

First, we controlled for the effect of a different operationalization of our independent variable. We thus computed structural holes using the effective size measure developed by Burt (1992). This measure reflects the number of non-redundant contacts in one's networks, and is thus posited to have opposite effects as compared to constraint (which instead measures the degree to which an individual is "constrained" within a redundant network). The results were identical to the ones presented above, with the interaction coefficient between effective size and network stability being negative and significant ($p < .01$ when entered alone, $p < .05$ when entered with the interaction between homogeneity and stability): the effect of structural holes becomes less positive as network stability increases. The coefficient of the interaction between content homogeneity and network stability stayed positive and significant ($p < .01$).

Second, we controlled for the presence of survival bias in our model. It might in fact be that, in the long run, successful individuals are more likely to stay in the sample, whereas unsuccessful creators would have relatively less opportunities to display their creativity in the future. While our *past creativity* control variable should already account for this (Greene, 2011), we decided to directly test for the potential effect of selection based on how successful a creator's episode has been. We adopted Lee's (1983) modified version of the Heckman model (Heckman, 1979). Since we were looking at individuals dropping out of the sample because of low success, we used an accelerated failure time (AFT) model with an exponential distribution to estimate the likelihood that a creator will leave the production (and thus the sample) in year t+1 (see Henderson, Miller, & Hambrick, 2006, and Mannucci & Yong, 2018, for a similar approach). We used audience ratings for the focal episode as the selection condition. Audience ratings represent the most salient measure of success in the television industry, and are the most likely determinant of whether an individual would continue to work on *Doctor Who* or leave the production team. We obtained audience ratings from the BBC website and corroborated them using archival sources (e.g., Howe et al., 1992). The selection model included our two predictors (constraint and knowledge homogeneity) and audience ratings. Results from the first step regression are reported in the Online Appendix (Table A3).

We followed the procedure detailed by Henderson and colleagues (2006) to calculate the selection parameter, or Inverse Mills ratio (IMR), and then added it as a control to the full model. The Inverse Mills ratio does not have any significant effect on creativity when added to the full model. Moreover, our main results are robust and consistent with those presented in Model 5, with both interactions staying positive and significant ($p < .05$ for constraint and $p < .01$ for content homogeneity), and the analysis of marginal effects being virtually identical to the one presented above. This provides evidence that survival bias is not affecting our results (Certo, Busenbark, Woo, & Semadeni, 2016).

Third, we empirically verified one assumption of our theorizing on the moderating effects of stability – namely, that adding new ties would be beneficial regardless of the human capital owned by these new ties, and in particular regardless of whether they bring non-redundant content. This notion was rooted in research suggesting that the value of new ties in reshaping mental models and social interactions is independent of their expertise, knowledge, and competences (e.g., Rand et al., 2011; Shirado & Christakis, 2017). We put this assumption to the test by measuring two types of human capital owned by new ties: expertise and content non-redundancy. We measured new ties' expertise as we did for focal actors: we first computed the number of episodes each new tie has worked in; then, we took the average of these values and used it as our measure of new ties' expertise. We computed new ties' knowledge non-redundancy as a variation of our control variable *input non-redundancy*[10] - i.e., as the ratio between the number of content elements that the artist's new ties had experience in while the artist did not, and the total number of content elements new alters had experience in. We then computed two separate model for each of these variables, for a total of four models. Specifically, for each human capital variable we tested one model where we added a three-way interaction between the human capital variable, network stability, and network openness; and one where we tested the three-way interaction between the human capital variable, stability, and content heterogeneity.

[10] This variable was unsurprisingly highly correlated with our measure of input non-redundancy (r = 0.96). Thus, in order to avoid collinearity issues, we dropped input non-redundancy and used only the new ties' knowledge non-redundancy measure in this specific analysis.

The three-way interaction with new ties' expertise and stability was negative and not significant for network openness ($p = .110$), and positive and not significant for content heterogeneity ($p = .366$). The three-way interaction with new ties' knowledge non-redundancy and stability was negative and not significant for network openness ($p = .188$), and positive and not significant for content heterogeneity ($p = .938$). The full results are reported in the Online Appendix (Table A4). Overall, these findings provide support for our assumption that adding new ties will foster the network openness/content heterogeneity on creativity regardless of new ties' human capital.

Finally, we also controlled for the possibility that prior experience had a curvilinear effect on creativity, as research on creative careers would suggest (see Simonton, 1988, 1997). We thus added the squared term of prior experience to our main model. The coefficient of the squared term was positive and significant ($p < .01$), indeed suggesting the presence of a curvilinear effect. However, adding the squared term did not affect our main results, with the interactions staying positive and significant ($p < .01$ for both network openness and content heterogeneity) and the analysis of marginal effects being virtually identical to the one presented above.

DISCUSSION

Creativity often manifests as a bolt of lightning – something that strikes once and forever changes the course of what follows. Stories abound about creatives who shaped the field with only one memorable piece of work. For example, Harper Lee's novel *To Kill a Mockingbird* won the Pulitzer Prize in 1960, and remains the only work she published during her lifetime. However, as the demand for creative ideas keeps growing in organizations, producing a single creative contribution might not be enough to ensure organizational success. Understanding how employees can preserve their creativity over time is thus becoming increasingly important for organizations.

In this paper we adopted a social network lens to address this issue. We suggested that the oft-found positive association between open networks and heterogeneous knowledge with creativity is questionable when one takes a long-term view that accounts for changes in network composition. As network openness and content heterogeneity are unstable and characterized by diminishing returns, the way individuals maintain them over time becomes relevant for their continued creativity. We have theorized that constantly rejuvenating network composition by adding new ties, rather than maintaining existing ones, ensures the continued enjoyment of the creative advantages provided by network openness and content heterogeneity.

We tested and found support for our predictions by analyzing 866 creative contributions from 200 artists involved in the realization of 233 episodes of the television show *Doctor Who*. Open networks and heterogeneous content foster creativity only when they are coupled with low network stability – i.e., with the addition of new ties. These findings contribute to research on networks and creativity and on creativity over time more broadly.

Theoretical Contributions

Our study challenges and enriches our current understanding of how social networks shape individual creativity. First, we offer a theoretical framework and empirical test of how change in network composition plays into the networks-creativity relationship. In so doing, we answer the long-standing call to introduce a dynamic focus to research on creativity in general (Anderson et al., 2014; Shalley et al., 2004) and on social structures and creativity in particular (Phelps et al., 2012; Perry-Smith & Mannucci, 2015). Specifically, scholars have suggested that stability in network composition can be a potentially "important contingency variable in explaining when a particular type of structure (i.e., closed vs. open) will improve actor knowledge creation" (Phelps et al., 2012: p. 37). Our theory also speaks to research that has explored the dynamics of structural holes (Burt & Merluzzi, 2016; Sasovova et al., 2010) and of structural holes and performance in creative contexts (Soda et al., 2004; Zaheer & Soda, 2009).

Altogether, our findings pinpoint the importance of considering the interactive effect of network structure/content on one side, and network stability on the other in order to understand how it is possible to stay creative over time. Stability begets rigidity in mental structures and modes of interaction, leading to the risk of rejecting non-redundant perspectives and content and to the rigidity of collaboration patterns, thus taking away the creative spark deriving from creative abrasion. Network change instead brings a shock that forces individuals to reconsider their cognitive structures and collaboration modes, increasing their flexibility and thus enhancing the chance that they consider and utilize new frames and knowledge. It is interesting to note that this effect is not contingent on whether new ties bring non-redundant content: the mere presence of new faces disrupts existing ways of working and doing things, forcing individuals to reconsider how they interact, share, and integrate knowledge.

Similarly, network change *per se* does not engender benefits for the creativity of a given outcome: our findings show that it needs to be coupled with certain types of structures and content in order to be conducive to creative performance. In so doing, we extend and corroborate extant literature on the effects of the addition of new ties on individual creativity. First, we show that the benefits of adding new ties for any given creator are contingent on the creator being able to "tap" into non-redundant perspectives, frames, and content: while it is often assumed that new ties bring new content, this assumption is rarely tested. Moreover, extant research has also suggested potential downsides to the addition of new ties in the disruption of coordination and routines. Our study provides a potential explanation for these inconsistencies. Our results suggest that new ties are beneficial for individual creativity only when coupled with network structures and content that provide the raw materials that ensure that the "shock" they bring is a positive one

– one that activates generative recombination and reconfiguration processes rather than just being disruptive. To use a metaphor, if new ties are the spark that ignites a creative reaction, open networks and heterogeneous content constitute the chemical ingredients. This finding is consistent with extant work that has shown that the addition of new ties is beneficial for collective problem-solving only when these ties are added to a specific network structure – specifically, the core of the network (Shirado & Christakis, 2017), where they are likely to stimulate the vision advantage that this position confers.

Overall, our study points out the need to add network stability and change to the equation in order to develop a good network theory of creativity. The long-lasting intuition of the benefits of brokerage is reinforced by the idea that structural and content-based network advantages cannot be decoupled from network composition in terms of old vs. new ties – and, thus, from an actor-based view. Future research should further explore these issues by adopting a more in-depth view on network and creative trajectories, looking at how different network configurations engender different trajectories in creative productivity. One interesting avenue could be to look beyond the focal actor's network to look at how the evolution and "breaking and making" of alters' ties shape the actor's creativity. This altercentric approach has already been adopted in network and creativity research (e.g., Grosser, Venkataramani, & Labianca, 2017; Venkataramani, Richter, & Clarke, 2014) and could be fruitfully extended to focus on network dynamics and creativity over time.

A second contribution of our study is that we bring the structure-content debate to creativity research. We show that being embedded in an open network has a positive effect on creativity above and beyond its benefits in terms of content heterogeneity. This finding is consistent with research that has suggested that open networks provide not only content heterogeneity, but also a "vision" advantage, changing the way individuals think and see things and allowing them to spot opportunities otherwise unseen (Burt, 2004, 2008; Burt & Soda, 2017). Maintaining an open network is "valuable as a forcing function for the cognitive and emotional skills required to communicate divergent views. It is the cognitive and emotional skills produced as a by-product of bridging structural holes that are the proximate source of competitive advantage" (Burt, 2008: p. 963). Our results corroborate this view in the realm of creativity: the interaction between network openness and stability is significant even when controlling for content heterogeneity, and both the effect of openness and the effect of heterogeneity are contingent on network stability. Given the centrality of the structure-content relationship in shaping creativity, future research could further explore their related yet independent effects by focusing on other types of structures or content. For example, scholars could explore whether and how the effect of network size and centrality is independent from the one of content: while the majority of extant theorizing on the creative benefits of centrality center on increased access to non-redundant content (Perry-Smith & Shalley, 2003), it is true that centrality is also linked to increased sense of power (Bonacich, 1987), which in turn has been shown to lead to greater creativity (Galinsky, Magee, Gruenfeld, & Whitson, 2008). Similarly, we focus on a specific type of heterogeneity, capturing the degree to which a creator is working on something different from her/his past. Future research could focus on other types of heterogeneity, such as the heterogeneity of the inputs received through the social network, for example by focusing on email exchanges (e.g., Aral & Van Alstyne, 2011).

A third contribution of our study is that it indicates that our focal relationships could play out differently depending on the breadth of the time horizon being considered. Our results suggest that aggregating creative outcomes and networks over long time horizons can result in a neglect of how network micro-dynamics in the short term shape the creative benefits of open network structures in the long run. Extant research usually focuses on time horizons of at least three-four years – a time during which individuals can adopt significantly different network maintenance strategies, which in turn can have significantly different implications for their ability to accrue creative advantages from their network structure. The existence of these differences and their implications has already been pointed out by networks and creativity scholars alike (e.g., Burt et al., 2013; Simonton, 1988), but has so far been overlooked empirically. While extant evidence emerging from focusing on relatively long time horizons (and replicated in our cross-sectional dataset) shows that open networks are related to creative achievement over time, our main findings using time windows of about four months suggest that the "network recipe" behind this macro-pattern is maintaining non-redundant networks through short-term cycles of rejuvenation in network composition (i.e., the addition of new ties).

Similarly, our findings suggest that also the effect of network stability could vary depending on the time horizon considered: we found stability to be positively related to creativity over a long-time horizon, while it has no direct effect on single creative contributions. Understanding the reasons underlying these observed differences could provide an explanation for the divergent findings on the effects of stability on creativity and innovation (e.g., Ferriani et al., 2009; Kumar & Zaheer, 2019; Sytch & Tatarynowicz, 2014). Specifically, we believe that understanding what change and stability mean for these different time horizons could provide insights into this puzzle. Change within short time horizons can come from adding a reduced number of new ties – something that would result in a rejuvenation of the network without causing too much disruption. On the contrary, low network stability over a longer time period means that the artist continuously changes her/his network composition, thus potentially jeopardizing her/his ability to maintain effective collaboration patterns. Future research could explore this issue, focusing on how much change is "too much" across different time horizons.

Practical Implications

Our study has relevant implications for practitioners. First, we pinpoint the importance of network renewal in order to accrue the creative advantages of non-redundant structures and content in the long run. Our results show that building a non-redundant network might not be enough to sustain creativity in the long run if it is not coupled with the systematic broadening of the network with new people. Preserving a brokerage role in the structure of collaboration is not enough to sustain creativity without the intellectual friction and the shock to mental structure and routines associated with newcomers. This finding has implications for both individual creators and managers who want to reduce creativity fluctuations. These fluctuations come in fact with high risks and liabilities. Creators who are not able to maintain a constant flux of ideas might be excluded from interesting projects and career advancement opportunities, or even lose their job altogether. The history of cultural industries is full of once-successful creators whose inability to continuously generate creative ideas made it impossible for them to find valuable employment: for example, director Michael Cimino was ostracized from Hollywood after the failure of *Heaven's Gates,* despite having previously directed the critically acclaimed *Deerhunter*.

Similarly, managers who cannot guarantee a regular generation of creative ideas to their organizations run the risk of hurting the organizations' chances for survival, given the increased importance of employees' creativity for organizational competitiveness. From an organizational standpoint, the key implication of our study is thus that managers can help their employees' creativity by actively encouraging their employees to maintain their collaborative structures open to newcomers, even when products are successful, ensuring the right balance between non-redundancy and stability. We believe that this idea extends beyond cultural products, as the need for fresh perspectives is a feature of creativity across many domains.

Our setting provides a perfect illustration of this idea. One of the most interesting features of *Doctor Who* is that this TV show survived, both from a business and a cultural perspective, across generations of viewers, industry and technological disruptions, and company reorganizations. Over the years, the creatives involved in this adventure have been able to transform and re-invent the "product" by capturing and adapting it to spirit of the time.

Limitations and Directions for Future Research

Notwithstanding its contributions, this study has some limitations. First, the characteristics of our setting might limit the generalizability of our findings. The *Doctor Who* production world is characterized by a strong focus on creativity, and by the adoption of collaborative project-based structures. The latter feature means that our conceptualization and operationalization of stability are rooted in the fact that adding a tie often implies breaking another one, given the fixedness of roles: a director working with a new writer on an episode likely means that he/she will not be working with someone he/she used to work with. Moreover, our setting is a creative industry, and we focus on the work of highly qualified professionals working together to produce creative outcomes. Our findings may apply more closely to settings with similar characteristics, such as consulting, scientific research, and new product design, but not to settings where creativity is not so central, roles are more flexible, and/or individuals are less qualified. However, there is reason to believe in the generalizability of our findings to a wider range of settings. Results in our cross-sectional replicated the well-known relationships between open networks, non-redundant content, and creativity. Second, many of the problems faced by employees in cultural industries are becoming increasingly common in other industries given the increased centrality of creativity and innovation to company success and survival (Ahuja & Lampert, 2001; Lampel, Lant, & Shamsie, 2000). Finally, the "shock" effect of new ties is not premised on their quality, but just on the fact that their addition disrupts established routines and cognitive structures (Shirado & Christakis, 2017). That said, we cannot definitively rule out that the phenomenon of interest plays out differently in other settings.

A second limitation stems from the fact that we focused on the artists' creative efforts and collaboration patterns within a single product category (i.e., *Doctor Who* series). This choice was made following established practices (e.g., Clement et al., 2018; McFadyen & Cannella, 2004), as this feature of the collaboration network allowed us to rule out confounding effects (e.g., different product categories, different companies) that usually affect networks focusing on multiple products. At the same time, it could be that taking into account multiple products and the relative collaboration networks would paint a different picture. For example, it could be that brokers whose network spans different product domains have a lower need to renew their network in order to accrue creative benefits from their brokerage position. However, there are three reasons that make us believe that this should not affect the robustness and generalizability of our findings. First, we controlled for creators' cumulated experience and collaboration patterns in other TV series. Second, this effect of spanning different domains should be true, at least to some extent, also for creators whose network contacts span different categories *within* the same product domain. Our results show that, while controlling for this non-redundancy, the moderating effect of network stability was still significant. Third, the definition itself of what constitutes a product domain is largely subjective (Csikszentmihályi, 1999), and this same logic could thus be applied to extant studies focusing on an entire industry. For example, network studies have focused on network of creators within cultural industries such as the movie industry (e.g., Cattani & Ferriani, 2008), the television industry (e.g., Soda et al., 2004), and Broadway musicals (e.g., Uzzi & Spiro, 2005). However, many creatives involved in these industries are likely to work in another one: for example, screenwriters write for both cinema and television, and theatre directors work on both musicals and plays. This means that, even when considering entire industries, creators can have networks spanning multiple fields. Given the importance of clearly identifying network boundaries and meaningful product categories for our analysis, we believe that the benefits of this choice outweigh its disadvantages, and that our focus on a single product category should not significantly limit the generalizability of our findings. Scholars could further explore this issue by focusing on networks spanning different product domains.

Finally, the archival nature of the data prevented us from empirically measuring the mechanisms through which structural holes, network stability, and their interaction shape creativity within different time horizons. Future research could identify these mechanisms through the use of designs such as laboratory studies or ad-hoc surveys.

Conclusion

Notwithstanding these limitations, we believe that our study offers a fresh perspective on the relationship between networks and creativity, and on creativity more broadly. By introducing a dynamic lens to network-creativity research, we hope to pave the way for more studies exploring the dynamics of social networks and creativity across different time horizons, as well as to research exploring the best network strategies to sustain creativity over one's career.

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TABLES AND FIGURES

TABLE 1
Doctor Who Content Categories

Category	Description	Number of sub-categories
1. Type of story	Describes whether the episode is about an historical event or has a sci-fi plot.	3 (1=historic, 2=pseudo-historic, 3=sci-fi)
2. Type of setting	Describes were the episode is mostly set in terms of location.	3 (1= Earth, 2= alien planet, 3= spaceship)
3. Type of alien	Describes the type of alien the Doctor is facing as foe in the focal episode.	23
4. Doctor	Describes which incarnation of the Doctor is the protagonist of the episode	12 (one per incarnation of the Doctor)

TABLE 2
Mean, Standard Deviations, and Correlations for the Cross-sectional Dataset [a]

Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1. Max Role Creativity	4.053	1.018								
2. Max Episode Creativity	4.043	1.003	.913							
3. N Highly Creative Contributions	1.210	2.559	.416	.402						
4. N Highly Creative Episodes	1.360	2.654	.431	.448	.938					
5. Network Openness	0.316	0.292	.540	.552	.505	.572				
6. Content Heterogeneity	0.502	0.175	.519	.543	.519	.593	.917			
7. Network Stability	0.546	0.148	.308	.314	.324	.340	.269	.489		
8. Expertise	4.330	6.594	.355	.359	.809	.882	.658	.679	.345	
9. Outside Experience	10.415	10.801	.063	.026	.080	.054	.067	.116	.122	.036

[a]: All correlations higher than |.26| significant at $p < .01$

TABLE 3
OLS and Poisson Models Predicting Creativity – Cross-sectional Dataset [a]

Variables	**Model 1** Max role creativity	**Model 2** Max role creativity	**Model 3** Max episode creativity	**Model 4** Max episode creativity	**Model 5** N creative contributions	**Model 6** N creative contributions	**Model 7** N creative episodes	**Model 8** N creative episodes
Network Openness		2.064** (0.730)		1.783* (0.728)		2.518** (0.886)		1.530 (0.861)
Content heterogeneity		- 0.691 (1.315)		0.022 (1.285)		- 0.962 (1.388)		1.324 (1.330)
Average network stability		1.532* (0.618)		1.335* (0.553)		3.820** (0.953)		3.078** (0.832)
Expertise (N episodes)	0.051** (0.013)	- 0.004 (0.008)	0.050** (0.016)	- 0.007 (0.007)	0.079** (0.011)	0.038** (0.007)	0.078** (0.010)	0.036** (0.008)
Outside experience	0.002 (0.007)	- 0.001 (0.006)	- 0.001 (0.007)	- 0.005 (0.005)	0.015 (0.008)	0.004 (0.007)	0.012 (0.008)	- 0.000 (0.007)
Ego role dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.187	0.358	0.179	0.366	0.393	0.468	0.408	0.500

[a]: Unstandardized coefficients. Huber–White robust standard errors are in parentheses.
Models 1-4 are OLS regressions. Models 5-8 are Poisson regressions, with the pseudo R-squared reported.
** p < .01
* p < .05

TABLE 4
Mean, Standard Deviations, and Correlations for the Panel Dataset [a]

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9
1. Creativity	3.659	1.015									
2. Network openness	0.217	0.266	-.059								
3. Content heterogeneity	0.468	0.307	-.016	.355							
4. Network stability	0.623	0.220	.061	-.007	.371						
5. Previous creativity	2.949	1.709	.077	.362	.771	.515					
6. Previous collaborations	0.684	0.967	-.063	.132	.130	-.056	.075				
7. Outside ties	1.114	2.484	-.053	-.230	-.037	-.076	-.102	.067			
8. Expertise	7.661	9.592	-.021	.530	.442	.227	.350	.067	-.181		
9. Input non-redundancy	0.510	0.344	-.024	-.529	-.675	-.395	-.691	-.042	-.179	-.628	
10. Outside experience	0.868	1.021	.002	-.305	-.117	-.078	-.135	.080	.418	-.172	.140

[a]: All correlations greater than |.10| are significant at $p < .01$

TABLE 5
Panel Regression Predicting Creativity [a]

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Previous creativity	- 0.110** (0.030)	- 0.180** (0.043)	- 0.224** (0.042)	- 0.260** (0.056)	- 0.289** (0.052)
Previous collaborations	0.015 (0.045)	0.028 (0.050)	0.036 (0.050)	0.038 (0.049)	0.043 (0.049)
Outside ties	- 0.010 (0.020)	- 0.014 (0.017)	- 0.016 (0.017)	- 0.020 (0.016)	- 0.020 (0.016)
Expertise (N episodes)	- 0.014† (0.007)	- 0.017* (0.008)	- 0.018* (0.008)	- 0.018* (0.008)	- 0.018* (0.008)
Input non-redundancy	- 0.234 (0.216)	- 0.066 (0.231)	- 0.051 (0.233)	0.036 (0.230)	0.040 (0.233)
Outside Experience	- 0.024 (0.062)	- 0.014 (0.061)	- 0.013 (0.060)	- 0.022 (0.063)	- 0.020 (0.062)
Network openness		- 0.225 (0.240)	0.989* (0.464)	- 0.306 (0.245)	0.703 (0.467)
Content heterogeneity		0.558* (0.242)	0.613** (0.228)	2.195** (0.562)	2.092** (0.561)
Network stability		0.267 (0.209)	0.816** (0.255)	1.641** (0.466)	1.969** (0.441)
Openness*Stability			-1.899** (0.593)		- 1.567** (0.591)
Heterogeneity*Stability				-2.465** (0.678)	- 2.241** (0.694)
Ego role	Yes	Yes	Yes	Yes	Yes
Cohort	Yes	Yes	Yes	Yes	Yes

[a] Unstandardized coefficients. Huber–White robust standard errors are in parentheses.
** p < .01, * p < .05, † p < .10

FIGURE 1
***Doctor Who* Collaboration Network**

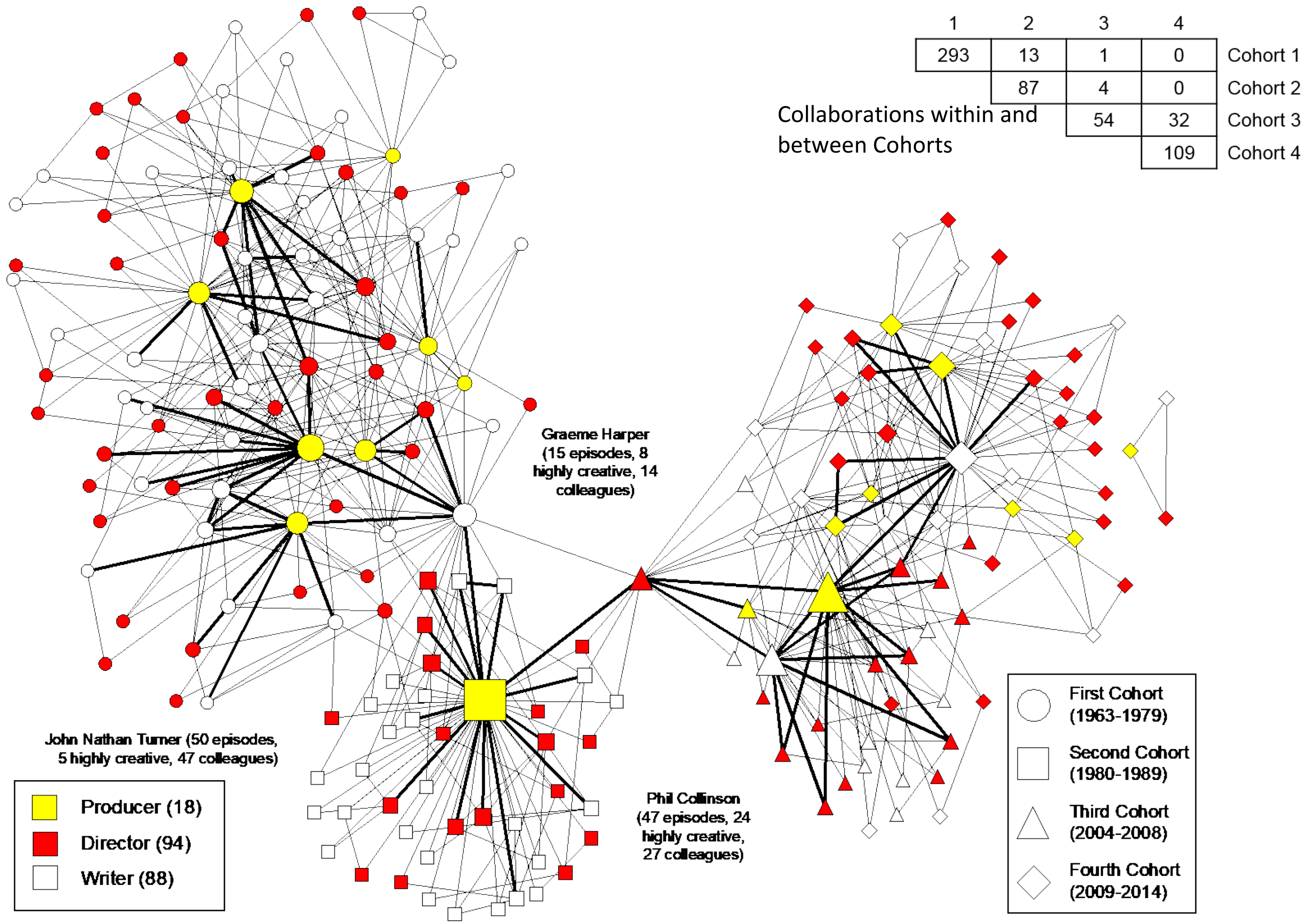


FIGURE 2
Association Between Network Constraint and Creativity – Cross-sectional Dataset

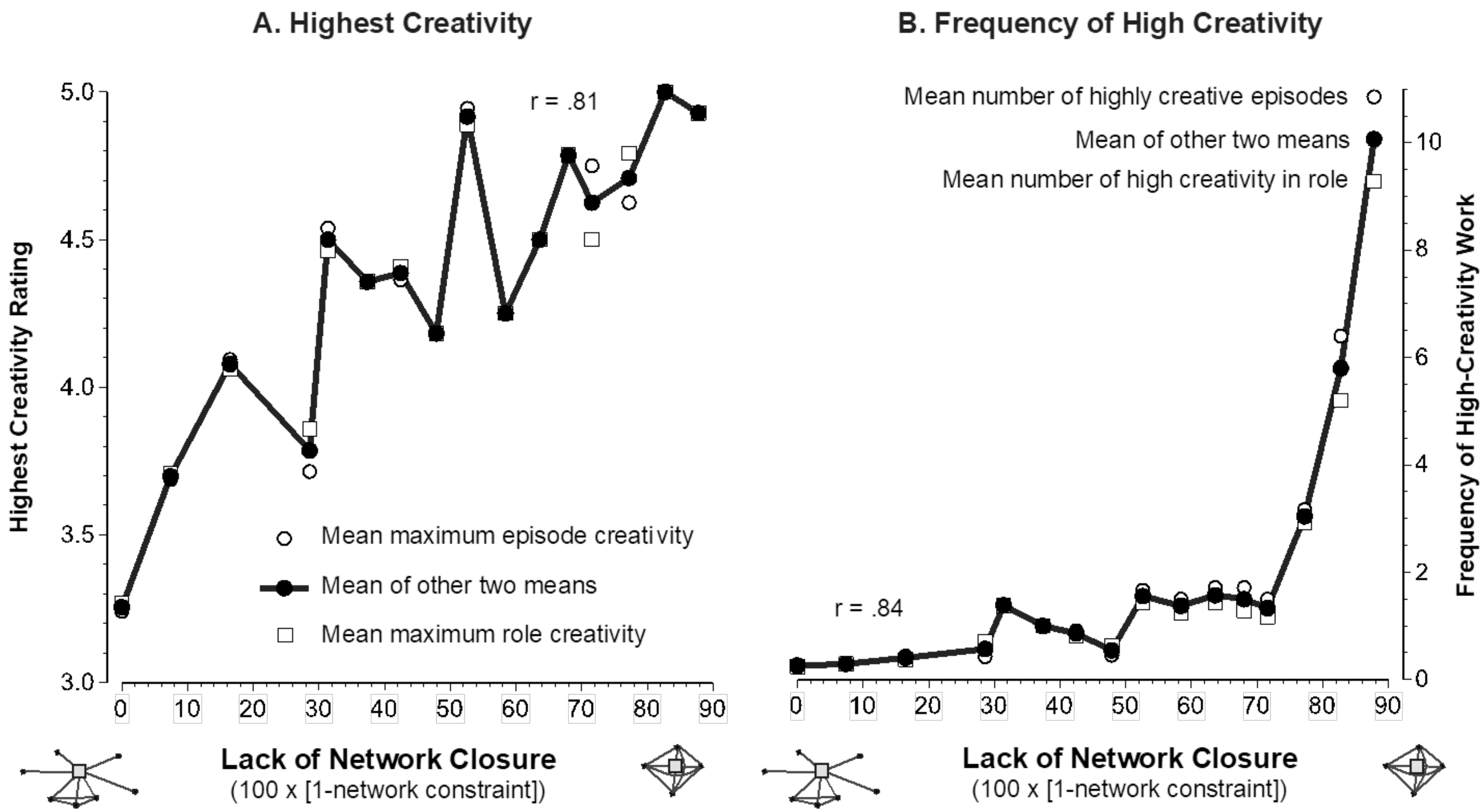
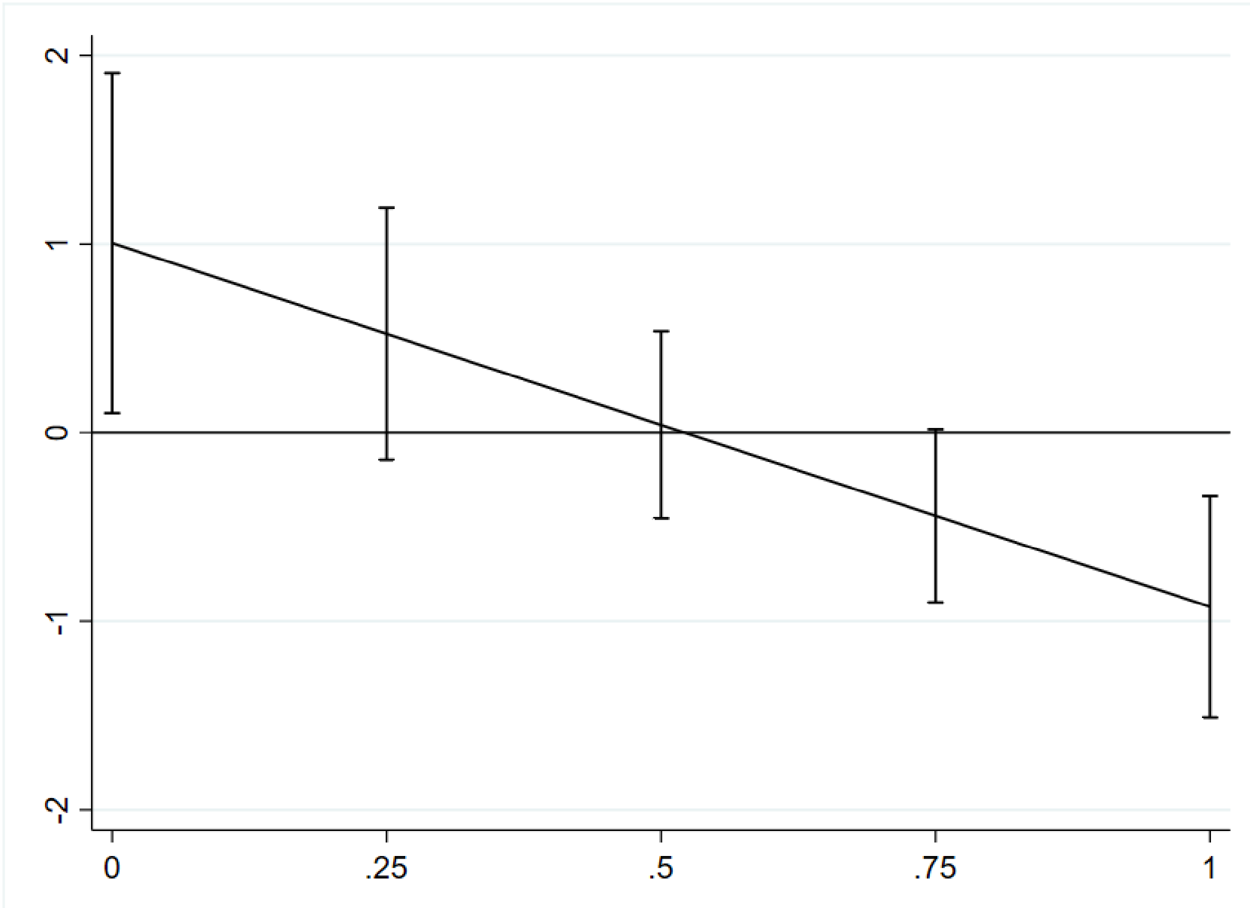


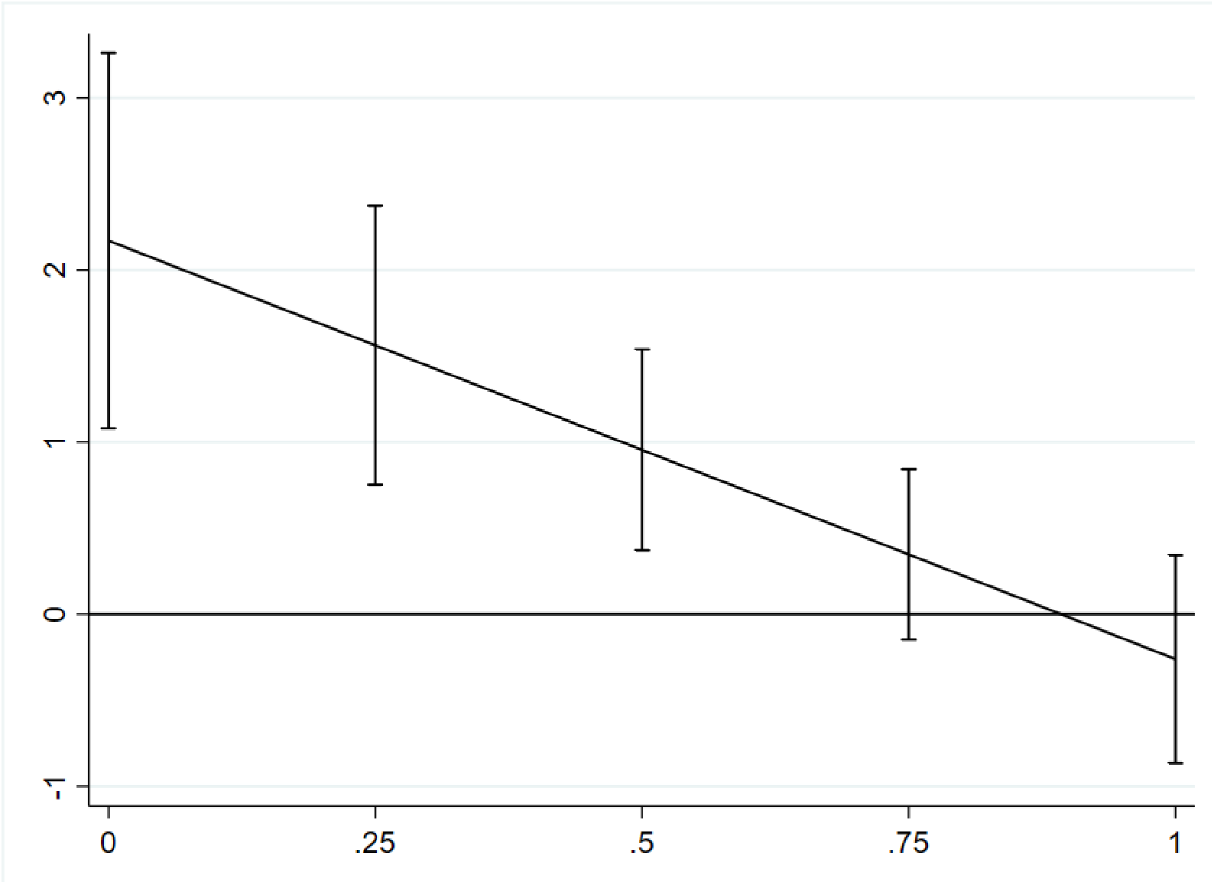
FIGURE 3
Marginal Effects of Network Brokerage on Individual Creativity at Different Levels of Network Stability – Panel Dataset [a]



Network Stability

[a]: 95% confidence intervals

FIGURE 4
Marginal Effects of Content Heterogeneity on Individual Creativity at Different Levels of Network Stability – Panel Dataset [a]



Network Stability

[a]: 95% confidence intervals

FIGURE 5A
Distribution of Creativity Ratings Across Combinations of Network Openness and Network Stability – Panel Dataset

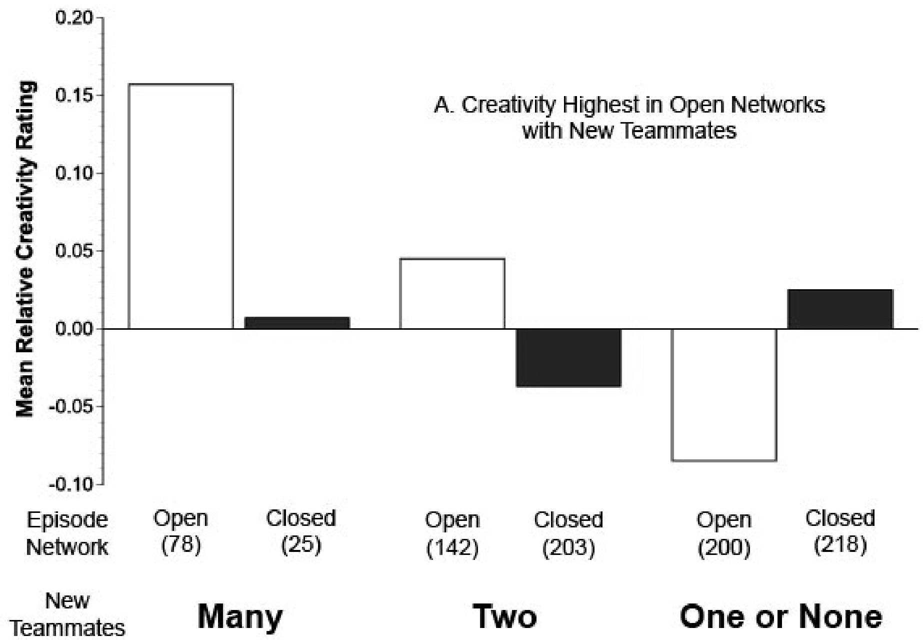
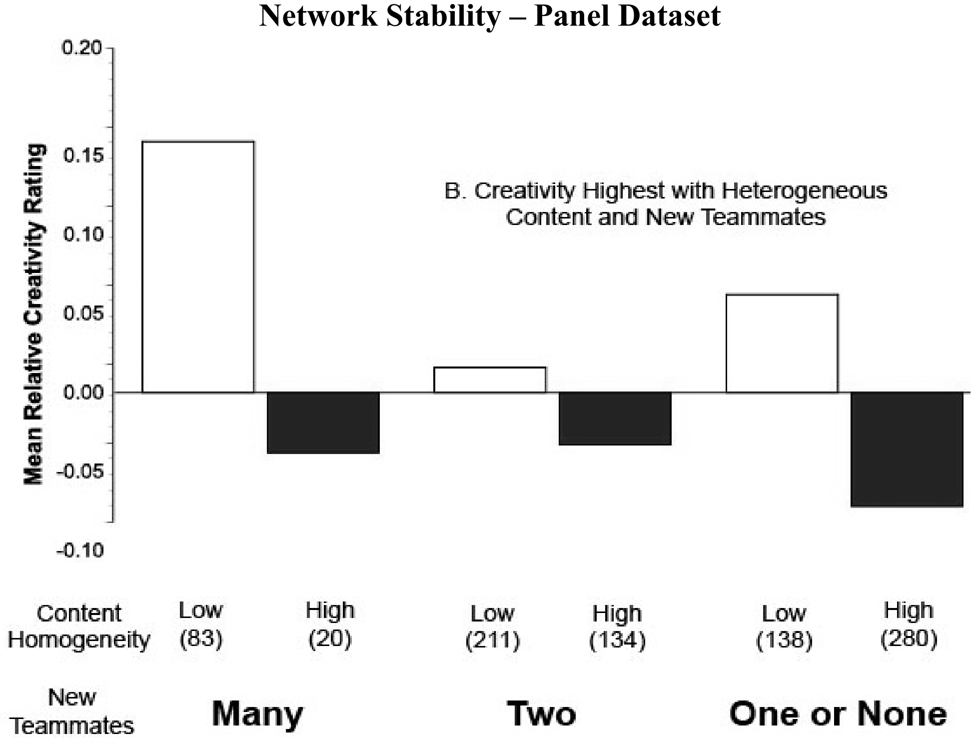


FIGURE 5B
Distribution of Creativity Ratings Across Combinations of Content Homogeneity and Network Stability – Panel Dataset



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