Bachelor Thesis

Collaborative Networks in Creative Industries: The Case of Tatort

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Abstract

This thesis examines network structural factors that explain why some creative teams are able to evince ingenuity resulting in acclaimed innovative cultural products. By adopting a retrospective, multilevel perspective on social networks of creatives, knowledge on the interplay of brokerage and cohesion is driven forward and recommendations on the formation of successful teams are derived. Specifically, it is first hypothesized that open networks, formed by aggregated individual brokerage positions, only benefit group performance up to a certain point, where too much contradictory brokered influences create frictions inside the team, leading to a loss of cohesion necessary to produce innovative outputs. Second, concerning the intricacies of complementation in groups, it is theorized that both current and previous experiences shaped in age-diverse teams favor creative achievement. These assumptions are tested, and for the most part confirmed, in a study on the collaborative networks of artists who worked on the TV series *Tatort* in the last 50 years.

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I hereby declare that:

1. I have written this Bachelor thesis myself, independently and without the aid of unfair or unauthorized resources. Whenever content has been taken directly or indirectly from other sources, this has been indicated and the source referenced.

2. This Bachelor Thesis has not been previously presented as an examination paper in this or any other form in Austria or abroad.

3. This Bachelor Thesis is identical with the thesis assessed by the examiner.

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Contents

List of Figures

List of Tables

1 Introduction

The innovative strength of collaborative undertakings, just as their resulting success, are contingent on a multitude of factors [48]. While uniquely gifted, imaginative individuals might be promising elements of creative teams [41], they do not necessarily guarantee novel results. Achieving such results can be facilitated by putting together teams exhibiting functional diversity, but also a diversity of previous experiences [49]. As Schumpeter put it: Innovation emerges by combining and recombining knowledge elements [80]. The role of social networks in passing on these knowledge elements has been examined in economic sociology for the past two decades, adding to our understanding of the roots of creativity and success in teams [24, 75]. In this context, research emphasizes the importance of social structural factors [77, 70]. In line with increasing project volumes and complexity in most industries [97, 101], teams have grown in size [43] and interdisciplinary expertise [28] over the last decades. This development has also led to a shift from hierarchy to network, when it comes to the inner workings of organizations, adding to the importance of comprehending social networks of creative collaboration [87, 60].

Determinants of creativity and performance boosting structural conditions in innovative teams can be examined on three distinct levels: Early research looked at (1) individuals as drivers of innovation [76, 46], a perspective that has soon been expanded to the social network of the individual, resulting in an (2) intra-team viewpoint [73, 6]. Influential in this regard have been Granovetter's ideas on "social embeddedness", where structures of social relations influence the behaviour (including creativity) of team members [42]. Once again increasing the scope of contributing factors, research has (3) opened up collaborative efforts by considering external influences [22].

Holistic approaches comprising these three levels of observation utilize network analysis to uncover structural factors in the collaboration networks of creative teams that promote innovation and success [34]. Just as with most socioeconomic realities, many of these factors exhibit effects contrasting each other, making it desirable to detect "sweet-spots", where intra-team composition and inter-team positioning allow for an empowering idea-creation setting.

Two central concepts on how the "production" of ideas and their realization can be facilitated are cohesion and diversity. Teams in creative fields lacking diverse ideas are said to be unable to execute re-combinations of existing ideas that are needed for a successful performance [40, 91]. This diversity is reasoned through brokerage ties of connectivity outside the team [51]. Even if sources of novel approaches are recognized, groups need to have the means to implement them - "good ideas" [24] alone are not enough, they have to be effectively implemented to ensure success [70]. There is widespread consensus that implementation requires cohesion, which promotes trust and mutual understanding, thereby stimulating coordination within a team [77]. Less confident are scholars concerning the optimal balance of network openness (associated with diversity) and closure (associated with cohesion) [19].

This thesis draws on work researching social networks of creative teams, deploying network analytical methods to further our understanding on the interplay of openness and closure. Specifically, two measures representing the (1) inter-team and (2) intra-team perspective of collaboration networks are applied: (1) Burt's concept of structural holes, suggesting that the manner in which an individual is embedded in a social structure can be of advantage or disadvantage for its own and its group's performance accordingly [24]. (2) Newman's concept of mixing patterns in networks, describing the preference of nodes in a network to connect with other nodes that are somehow alike (or unlike) them [69]. In line with Bizzi's [14] investigation of structural holes, the present work elaborates a retrospective inter-team theory of structural holes and explores how individual brokerage positions aggregated at the team level influence the innovative strength of a creative unit. This approach is intended to point out the possibly naive attitude of common research on structural holes, assuming that brokering is always of advantage to all parties concerned. Furthermore, interest is taken in the opposing aspect of the openness/closure balance by studying mixing patterns of demographic characteristics inside and outside cohesive teams.

I attempt to determine reliable reference points for the formation of successful creative teams by looking at collaboration networks formed by creators of the hit TV series *Tatort*[1] (German for "Crime scene"), airing in German-speaking regions since 1970. It is postulated, that patterns of previous interactions as well as patterns of current interactions between directors, screenwriters, producers, etc., are predictive of their creativity and success. Based on staff-data originating from nearly 1200 Episodes, I map collaboration networks encoding these interaction patterns and relate their structure to outcomes, measured in terms of critical and award-winning achievements.

The remainder of this thesis is structured as follows. I begin by giving an overview of relevant literature on creativity in teams, structural holes and demographic assortative mixing in section 2, ending with the development of hypotheses. Subsequently, section 3 describes the empirical setting, the

[1] https://www.daserste.de/unterhaltung/krimi/tatort/index.html, accessed 03-29-2022

data and noteworthy characteristics thereof. The regression models, together with their variables, is established in section 4. Presenting the results of the analysis takes place in section 5, their discussion in section 6. Section 6 also includes theoretical and practical implications, as well as limitations of the study and future research areas. I finish in section 7 by drawing conclusions following the main implications of this thesis.

2 Theory and Hypotheses

Social network analysis is an interdisciplinary tool bringing together computational methods of graph theory and research from sociology, in the present case. Contributing to the expanding field of computational social science, one must not be distracted by technicalities, but rather be devoted to adhering to sociological theory and practices. The following discusses both, the sociological background and technological resources.

2.1 Creativity-Driven Innovation in Collaborative Ventures

Before exploring the intricacies of network structural implications, let us take a step back and look at the fundamental workings of creativity and innovation in teams. Generally speaking, creativity is considered a function of social interaction [2], it occurs when a person deviates from its prior thinking, based on individual or social motives. However, it has been challenging for sociologists to agree on an integrated definition and assessment of creativity. Commonly accepted conceptualizations involve the intrinsic properties of novelty and appropriateness [13, 88], properties that are not firmly associated with an object but rather are determined within "the bounds of social, cultural, and historical precedents of the field" [74]. Hence, in order to conduct empirical research, creativity is often assessed based on consensus - qualified observers independently agree on the novelty and value of creative outputs [7]. In 1999, Csikszentmihályi adds to this notion by stating that creativity, in fact, is not "the product of single individuals, but social systems making judgments about individuals' products" [31]. The last decade has seen a shift from a rather individual-based take on creativity to a more social perspective. Termed the "sociocultural approach" [79], today Csikszentmihalyi and others specifically take into account interpersonal factors, reaching the conjecture that a team's creativity climaxes when it is neither too uniform nor too divided [32]. Teams are innovative, when they are able to implement their creative ideas and introduce change into a stable system while producing value in one way or another.

The recurring theme of the growing importance of collaborative efforts in form of innovative teams is reflected in the number of publications on this topic. Many of which define Teams according to Alderfer's three-pillar model of context, identity and teamwork: Teams are understood as social system of three or more individuals, embedded in an superordinate organization (context), whose members consider themselves as such and are viewed as members by third parties (identity), and who cooperate on a joint task (teamwork) [5]. Research on innovation in such teams can be classified into two viewpoints, the team climate perspective (team perceptions shared by team members) and the knowledge integration perspective (combining individual knowledge). Combining both perspectives, Van Knippenberg locates a lack of knowledge on the aforementioned transition from creativity to true innovation [95]. Conceptualizations of this transition can include four phases: idea generation, idea elaboration, idea championing, and idea implementation [73], all of which are influenced by the social system of the participating team members as well as their position therein [8, 18].

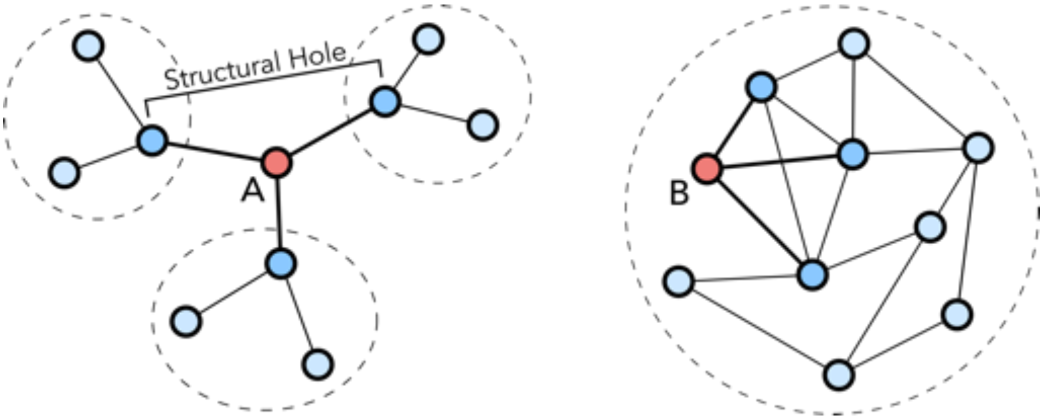
2.2 The Social Embeddedness of Creative Teams

In theory, Burt [21] admits, social networks are not imperative to creativity. Teams are creative when they come up with new and practical ideas, while only after these ideas and their implementation have been judged, their creative value is known, and only after these judgements are circulated, the creative minds behind the innovation are associated with creativity. With this in mind, regardless of a person's proclivity for creativity, in practice, the social system around them will most certainly influence the creativity expressed. Research in the field of computational social science [56] has shown that network structure (who you talk to) and network content (what you are exposed to) are enablers of non-redundant perspectives, and individuals are are more likely to generate creative ideas if they are embedded in an empowering social system [39, 26]. This embeddedness also translates from individuals to teams. In the same way as conceptualizing the individual level as the network of each team member, one can view the team level as an aggregated structure of team members' networks [50]. Non-redundant perspectives, both on the individual- and team-level, may develop by being in a network exhibiting a lot of so-called *structural holes*, connecting social groupings that else would merely exist separate to each other [24, 23], or they develop by being in a network providing access to diverse, heterogeneous knowledge allowing for effective recombination [9, 102].

Other takes on explaining the implications of network structure on creativeness include Uzzi & Spiro's *small world* approach [91], taking up the concept going back to Milgram's landmark study of 1967 [66]. Unlike most systemic-level network structures, small worlds comprise both a short path length and high local clustering, two features normally opposing another [99]. They have been found to organize numerous real-life systems and their effect on creative success is inversely-u shaped, which indicates that the best conditions for creative accomplishment occur when a network encompasses neither too much nor too little small worldliness. Another approach of network analysis introduces a core/periphery perspective on creative performance, theorizing that an individuals/a teams position between the core and the periphery of their social system is predictive of its creative results. Cattani & Ferrani [27] examined cinematic achievements in the Hollywood film industry in this vein and were able to, again, identify an inverted u-shape relation between an actors position relative to the core and creative performance - actors in the network are most likely to be highly creative if they take on a intermediary position between core and periphery, bridging the cohesive inner circle with the imaginative outer rim. Studies by Juhász & colleagues [51] suggest that both core and peripheral actors benefit from forming connections. Worth adding to the core/periphery perspective is the fact that over time, network participants get closer and closer to the core, resulting in a decrease of the actors creative capability [74].

Coming back to the diversity of perspective and knowledge in creative networks, it has been shown that greater separation of individuals in a network results in a more heterogeneous cognitive distribution, raising the chance of creating manifestations of novelty out of differing opinions and behaviours [58, 45]. For three decades now, the centerpiece on this idea of bringing new knowledge into a coherent system has been Burt's theory on structural holes, suggesting that the unique ties of brokers (an actor occupying the sole intermediate position between otherwise closed groups [39]) allow for mediation and control of the flow of ideas in the network, that brokers can use for their own benefit [53]. In a more unbarred orientation, brokers are seen as enablers of linking previously unconnected actors/groups [22]. The most adopted and well proven measure of structural holes is constraint, designed to express how many non-redundant others (adjacent nodes without a connection) an individual has access to [36]. Anytime a possible tie between an actor's neighbor's is not closed, there is opportunity for brokerage - for bringing together the efforts and knowledge of individuals in a way that benefits them, the broker, and others concerned. Figure 1 displays the dichotomy of structural holes and constraint in collaboration networks. Node A takes a brokerage position between three distinct groups that would have no ties to

Figure 1. Structural Holes vs. Constraint



Note: Node A bridges structural holes; B is faced with constraint

one another if A did not bridge the structural holes - A does not experience much constraint. Node B, on the other hand, is not in the position to act as broker - it is faced with constraint as all of its neighbors are fully connected.

The fact that brokers can exploit their position between individuals for their own advantage raises the question if this is also true on the team-level [67]. Is it beneficial for a team to bridge unconnected teams? The scarce research on this issue detects a "dark side of structural holes" - teams exhibiting multiple brokers might suffer from arising frictions and other problems. Bizzi's [14] multilevel view on structural hole positions poses an antithetical stance to the multitude of previous works investigating brokerage by means of single-level models, deducing positive effects of diminishing constraint on creative performance [40]. One might argue that an approach spanning the individual and team level is closer to reality and more fruitful in situations where collaborative work between strong individuals is prevalent. Truth is, brokers exert control over the most lucrative opportunities and gain an advantage by not allowing others to make use of them [20, 37]. Burt's structural holes theory builds on the rationale of the tertius gaudens (the third who rejoices), assuming independence among actors [70]. This implies that bridged alters follow the rules of the game and do not presume that a broker joins them or acts amicably towards them [55]. While the competitive and self-centered logic of brokers may benefit single actors, it creates friction when it comes to individuals who are not independent among each other as they are linked in the same group. The competitive nature of open networks, constituted by structural holes, intensifies rivalry, reducing the possibility of achieving common goals [3]. In contrast, closed networks, featuring a high constraint, foster a sense of community that makes achieving common goals easier.

2.3 Assortative Mixing of Demographic Diversity in Cohesive Teams

Having consolidated the views on bringing new perspectives and knowledge into a creative team by utilizing brokers, let us now look at the other predominant aspect of facilitating innovation in collaborative undertakings. As noted, in order to successfully implement novel ideas - which have possibly been stimulated by brokerage - cohesion within the team is required [92]. In a cohesive social structure, most actors have dense and overlapping ties to one another. Actor B in Figure 1 is embedded in such a cohesive network. The constraint he is faced with is reflected in the tight connections between his neighbors, the lack of bridges to different groups emphasizes the closure of the network. Studies arguing that this closure is often conflated with knowledge and content homogeneity, which hinder creativity [62], are assuming that structure represents content - leading to closure reflecting homogeneity. This assumption has recently been called into question, with scholars disconnecting the dimensions of structure and content and identifying independent qualities with distinct effects of the otherwise deeply interconnected dimensions [9]. On another note, high closure entails highly mutually interconnected specialists, sharing trust, routines and meanings [39]. Individuals in this setting are drawn together by their likeness of beliefs and actions, a likeness that keeps increasing with time [52], similar to the increasing coreness of actors in the core/periphery perspective on social network structures [15]. Collaborative network connections serve as conduits of cultural norms, interpretations, and perceptions [50].

In this context, the social phenomenon of homophily - where similarity proliferates connection - exerts influence on successful teamwork [78]. Looking at a team's demographic diversity for example, it is hardly surprising that individuals with the same age, gender or education tend to share similar values, experiences and conversation topics [10]. Even though this overlapping of interests creates redundancies, some researchers remark that the new social knowledge generated from the enhanced contact between like-minded individuals helps creating innovation. In some cases, cohesive social networks have been found to outperform the creativity displayed in open networks with structural holes [70]. In general, diversity in teams either enhances or disrupts performance, heavily depending on team composition and the context of the task at hand [94]. While it is desirable for creative groups to consist of members that contribute to a diverse repertoire of skills [89], many groups - especially if they congregated organically - are formed by homogeneous members. This tendency of individuals to associate and bond with similar others is known as assortative mixing (or assortativity) in network research. Formally defined by Newman [68], assortative mixing based on categorical or scalar node characteristics is mainly associated with social networks, but can also be observed in other types of networks (e.g. biochemical networks in the cell [63]). Particularly well studied is mixing according to vertex degree - the proclivity of high-degree nodes to connect with other high-degree nodes (analogous with low-degree nodes) [11]. To my knowledge, the effect of assortativity of demographic traits on innovative team performance has not been studied yet.

2.4 Hypotheses

In light of the discussed previous works, this thesis sets out to enrich our understanding of little researched aspects of the brokerage/cohesion trade-off. First of all, I share the scepticism of Bizzi [14] in regard to the unwavering benefits of structural holes in social networks of strong individuals. In a multi-level perspective, the existence of individual brokerage positions aggregated at the team level appear to be stirring up conflict between the members, hindering the collective capacity of creating innovative outputs [3]. Furthermore, it is recognized that the research setting, discussed in section 3.1, comprises unstable collaboration networks. According to Soda et al. [86], network stability influences the relationship of structural holes and creativity. In networks with low stability, brokerage and heterogeneous content do have a more positive effect on creativity than in stable ones. It is therefore expected that unstable open networks, enriched by structural holes, benefit the creation of successful, creative results. This effect is valid until a tipping-point is reached, where too much contradictory brokered influences create frictions inside the team, leading to a loss of cohesion necessary to produce innovative outputs. I theorize:

> **Hypothesis 1.** *There is a significant, curvilinear (inverse U-shaped) effect of network openness - assessed in average constraint per team - on a team's creative success.*

The second research goal of this thesis is studying the implications of mixing patterns of demographic characteristics in cohesive teams and in previous collaborations of members. The diverse dispersion of demographic features such as age, gender or education in groups can be an enrichment, by constituting an informational resource, or a liability, by causing inter-group biases and interpersonal tension, to group performance [93]. The short-lived project teams that are inherent to this setting can in particular profit from cognitive diversity [65]. I focus on investigating assortativity in age demographics, as the impact of seniority on cognitive feats has been well studied [44] and the data at hand allows for its instrumentalization. The essential nature of assortative mixing patterns of actors based on age is reflected in the fact that Newman [68] has used them to describe his original conceptualization of assortativity. I look at age-assortativity to measure diversity in a team - diversity that is believed to be mainly of advantage for creativity, as the lack of long lasting ties between actors in the investigated collaboration networks does not allow for an intensification of possible conflicts [71]. The conjecture:

> **Hypothesis 2.** *Short-lived creative teams display greater innovative power and are significantly more successful when there is lower assortative mixing by age in the group.*

This viewpoint may be valid in the intra-team perspective, though it is also desired to address the retrospective view of previous interactions of the team members, engraved in the team-ego networks presented in section 3.3. While I believe - much like in the intra-team perspective - that the advantages of cognitive diversity, provided by a diversity of seniority, outweigh the disadvantages, the reasoning differs slightly. Teams benefit from cohesive diversity because the team members are able to combine their inherent differences. This direct causation is different to the holistic perspective of also incorporating extrinsic experiences, a perspective that is very much appropriate in this context. Therefore:

> **Hypothesis 3.** *Creative teams, embedded in their previous-interaction networks, are significantly more successful when there is lower assortative mixing by age in the aggregated, retrospective collaboration networks of the members.*

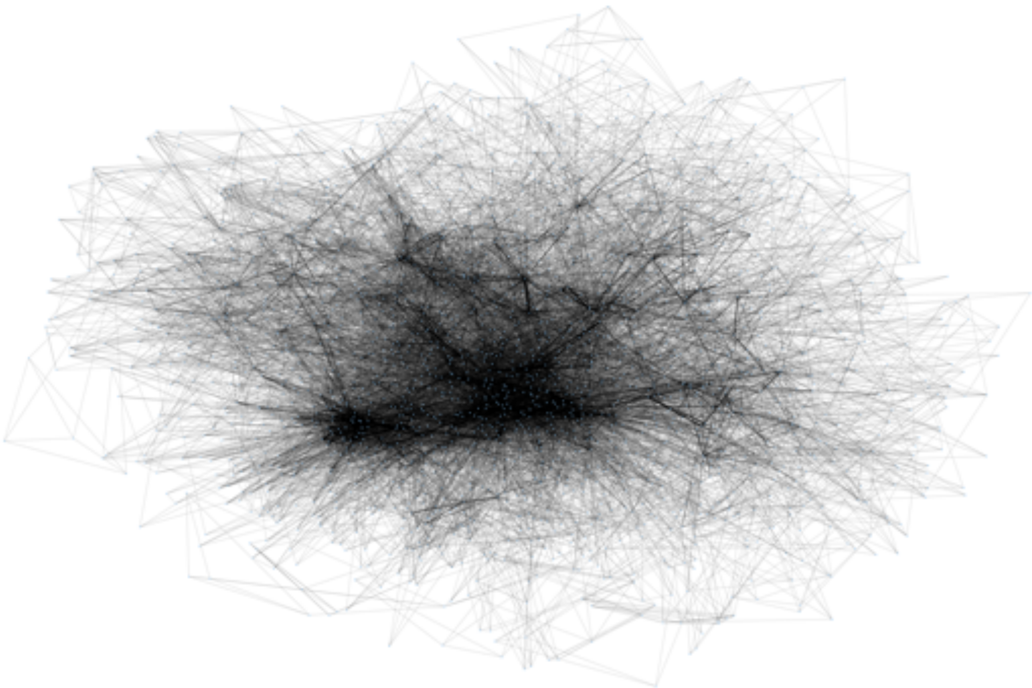
3 Methods

Testing the proposed hypotheses about diminishing returns of structural holes and benefits of age-diverse collaboration takes place in the creative industries. The following outlines the empirical setting, underlying data and noteworthy properties of the resulting social networks.

3.1 Empirical Setting

Putting the assumptions of this thesis to the test required an empirical setting evincing creative individuals repeatedly participating in short-term endeavours producing innovative outcomes. Meeting these requirements, the collaboration networks formed by creators of *Tatort* are of utmost suitability. *Tatort* (German for "Crime scene") is a German police crime drama series [90] that has been on-air since 1970, making it one of the longest-running television shows in the world. The continuous popularity - over 1200 episodes have been produced to date - is reasoned in the show's ability to keep up with the times and address genuinely socially relevant topics [82]. *Tatort* has become a cultural phenomenon in German-speaking regions [64]. More than 50 years after its inception - with a contentual formula that has hardly changed - many families still gather around the TV, or people meet in bars, to watch the premiering of new episodes on Sunday evenings. Achieving a cult status like that requires a disposition to innovation, that might be supported by the decentralized production system of the show. Not one, but eleven TV stations are working on *Tatort*, nine German regional TV channels (forming the ARD), and Austria's ORF as well as Switzerland's SRF each produce their own episodes. This allows for incorporation of local peculiarities (best expressed with the German term "lokalkolorit"), creating longer episodes of around 90 minutes, and alternating the main characters (the inspectors) to cater for variety [47]. With its sustained, decentralized and innovative production style, *Tatort* provides an ideal context to explore collaboration networks relevant to this study. The series constitutes a single cultural product realized for an extended period of time within identical organizational structures. This results in a controlled environment for creativity and allows ruling out product-specific factors that may influence innovation [27, 62].

Figure 2. One Mode Projection of the Entire Population



Note: Graph comprises 2106 distinct nodes connected by 17052 edges

3.2 Data and Sample

The unique and comprehensive dataset compiled for this thesis describes patterns of previous and current collaboration between creatives and consists of the entire population of TV-creators that worked on Tatort in any episode between 11-29-1970 (the first episode) and 04-18-2022 (episode 1198). While it has to be recognized that creating a single episode is the accomplishment of dozens of specialists, a widespread practice in empirical creative network research is to focus on "core" artists - individual creators that hold critical positions in the production process [72, 85]. This simplification is transposed by selecting five core roles, based on an assessment of importance by movie production experts [16, 98]. Included are the director, screenwriter, producer, cinematographer and editor, all of which there can be multiple of in a team. A number of sources were used for compiling the data. Information on staff and background information on episodes was drawn from the Internet Movie Database[2], Wikipedia[3], and a fan-based website[4].

[2]https://www.imdb.com/title/tt0806910/?ref_=ttep_ep_tt, accessed 04-22-2022.
[3]https://de.wikipedia.org/wiki/Liste_der_Tatort-Folgen, accessed 04-23-2022.
[4]https://tatort-fans.de/, accessed 04-22-2022.

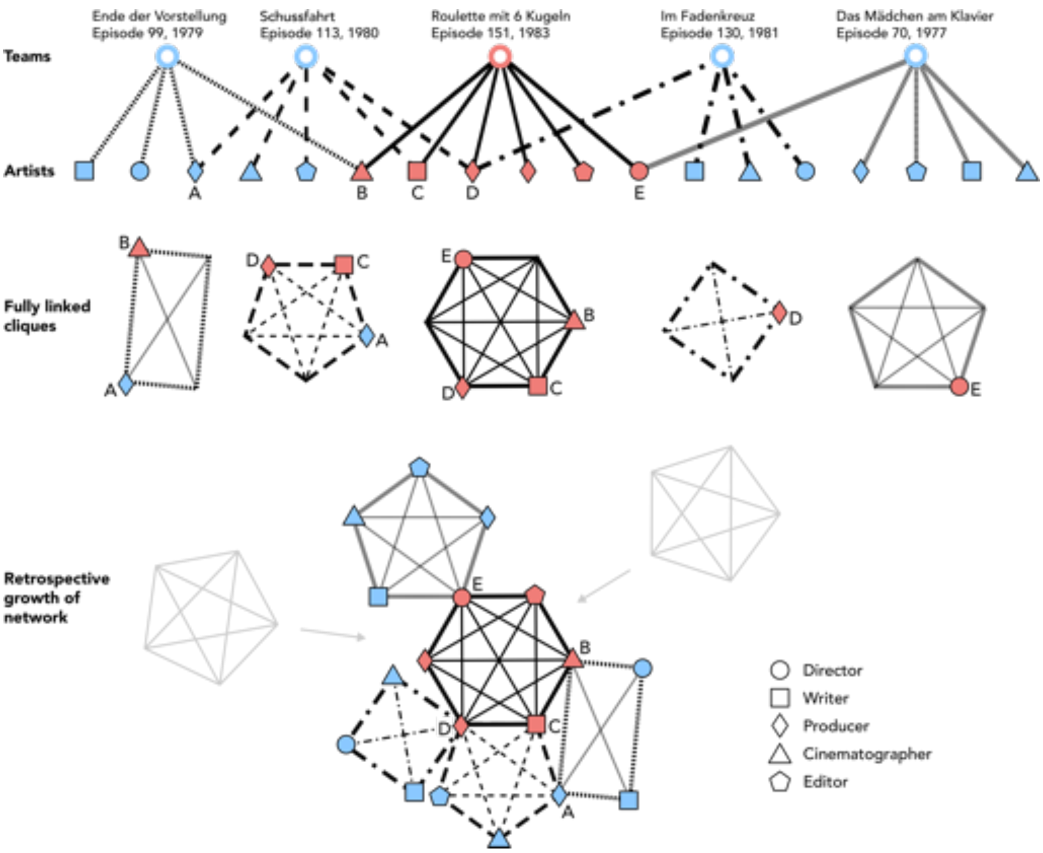
The staffing data contains the name, age and role of team members. Episode background information includes, among others, the title, date of airing, broadcaster, investigating inspector and location. The various sources were merged to ensure a depiction of relations that is as accurate and complete as possible. Figure 2 portrays the entire sample of 2106 individual creators with 17052 ties connecting them to a cohesive cluster. Data on consumer ratings and awards, quantifying the success of a production, has been collected from IMDb[5], a fan-based website[6] and another fan-based site[7]. The utilization of these diverse data points is outlined in section 4, all program code, including scripts for web-scraping, data cleaning, network creation, metrics calculation and model fitting, will be made available on github.com.

3.3 Collaboration Network Characteristics

Development of the retrospective inter-team approach on assessing team-performance related implications of aggregated structural holes is built on collaboration networks of core team members. The assembly of these networks in our context is depicted in figure 3. Starting point of the applied perspective are the production teams working on each episode, or rather just a single focal team (creators of episode 151 in example) at one point in time (the year 1983). Artists that have come together for the focal episode might have previously been involved in the production of a different episode with different colleagues - accordingly, the concerned team is appended to the focal team by connecting to the artist present in both teams. This artist can be regarded as a broker, introducing knowledge and experiences from his previous engagements into the focal system. These relations are represented in a bipartite structure at the top row of figure 3, where the red nodes represent the focal team. Bipartite networks are a type of complex networks in which the nodes are part of either of two groups, episode or artist, and only connections between nodes in different groups are allowed (an actor is connected to one or more episodes, never to another artist) [11]. They are usually compressed using one-mode projection to directly illustrate the relation structure among a certain type of nodes [29]. Inherent to compression techniques is the loss of information, in one-mode projections this entails that repeated collaboration is not recorded. Commonly used to compensate for that is weighting the ties between actors according to the number of previous cooperations [104].

[5] https://www.imdb.com/title/tt0806910/awards/?ref_=tt_awd, accessed 04-27-2022.
[6] https://www.tatort-fundus.de/web/rangliste.html, accessed 04-25-2022.
[7] https://www.wiewardertatort.de/, accessed 05-02-2022.

Figure 3. Retrospective Collaborations of Tatort Creators



Note: Figure is illustrative but based on actual data. A = Jürgen Sehmisch, B = Hermann Reichmann, C = Peter Hemmer, D = Peter Hoheisel, E = Lutz Büscher. Top row displays the bipartite structure of actor-team-affiliation. Middle row shows teams as fully linked cliques with labelled brokers. Bottom row presents assembly of collaboration network.

The projected structure of a cohesive team, such as our focal team of episode 151, is a fully linked clique, as can be seen in the middle row of figure 3. Connecting these cliques via shared nodes leads to retrospective growth of mapped collaborations, this construction is equivalent to an *affiliation network* - a network of nodes linked by common group affiliation. Study of such networks in comparable settings to the present has been conducted e.g. by Uzzi & Spiro with Broadway artists [91], or Soda & colleagues with creators of Doctor Who[8] [86].

[8]https://www.bbc.co.uk/programmes/b006q2x0, accessed 13.05.2022

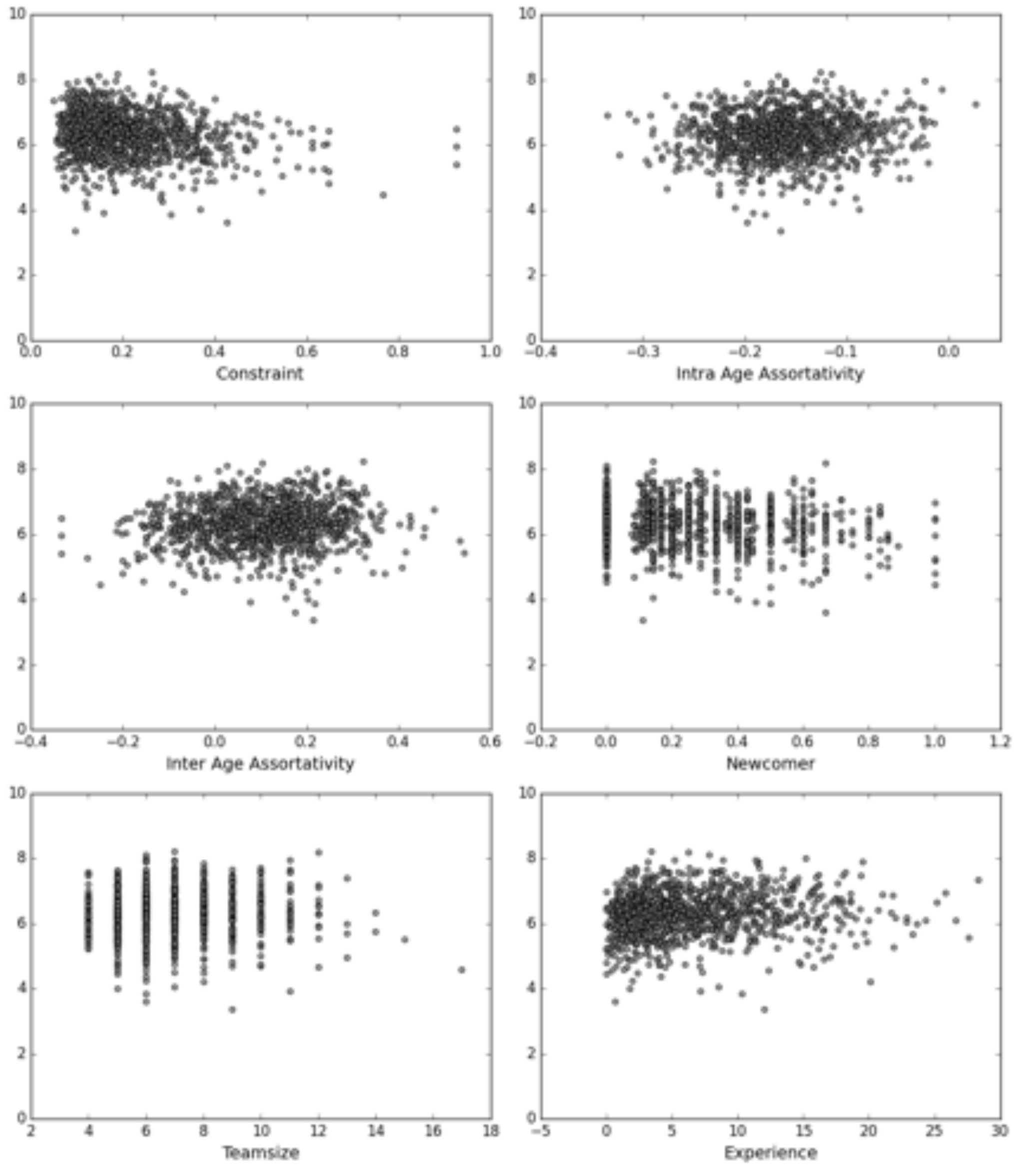
While these studies deal with affiliation networks structured by quintessential *latent organizations*, *Tatort* collaboration do not entirely match this definition. According to Starkey and colleagues [87], latent organizations are "groupings of individuals and teams of individuals that persist through time and are periodically drawn together for recurrent projects by network brokers [...]". Because of the decentralized production system and high incidence of newcomers in the creation of the show, the "periodical" aspect of this conception is not given that frequent, relations pertaining to *Tatort* are less stable. Nevertheless, general latent organization-traits are valid in this setting - including the fact that the vast majority of collaborations occur within the confines of a project [87]. As a result, the affiliation network of an episode does not include engagements of creators outside the scope of *Tatort*.

To recap, social system of consideration are the ties between a team of five core creator roles of a *Tatort* episode and their links to previous teams they have cooperated with within the *Tatort*-sphere, modeled as an affiliation network with weighted edges indicating repeated collaboration. As every team member of a focal episode has its own "past" - or lack thereof, in case the artist did not previously work on *Tatort* - these social systems (illustrated in the bottom row of figure 3) can also be seen as an aggregation of ego-networks. An ego-network is a fraction of a network formed by a central individual (the ego) and all actors (the alters) directly connected to it through social relationships [35]. Limiting the duration of such a relationship between individuals is not only true to live (as the saying goes: "long absent, soon forgotten.") [96], but also necessary to avoid inflating network connectedness and skewing statistics by including ties to inactive actors. Commonly used to counter these implications in network research are decay periods of around seven years, which is taken up in this analysis too [91, 27]. Consequently, only links that formed up to seven years before airing are considered in the affiliation network of an episode. This also means that productions of the first seven years are excluded, the period 1970 through 1977 is utilized for establishing a network structure that permits brokerage and cohesion. Tests conducted with alternative windows of three, five, ten or 15 years did not yield substantially different results. In compliance with the above specifications for nodes, ties, and decay, intra- and inter-team perspectives of each episode's collaboration network are associated with project success in order to eventually derive insight as to how innovative strength can be facilitated in creative teams.

4 Variable Construction and Model Specification

This section gives an overview on variables quantifying creative success, predicting it and controlling for other contributing factors. Figure 4 familiarizes with the six independent variables in relation to the primary dependent variable (episode ratings).

Figure 4. Independent Variables on Success



4.1 Success Quantification

The notion of successful creativity in this thesis is based on creative *outcome*, instead of trying to appraise the creative *process* of creating a *Tatort* episode [7]. While critique by specials of a field - either professional film critics or fellow industry participants - is the standard method of quantifying creative outcome [84], it is argued that valuation by non-specialist, such as the average *Tatort* viewer, are of similar informative value [38]. The fact that layman attach importance to different aspects than critics do makes it worthwhile to include their viewpoint on outcome quality, especially since *Tatort* is a product of public service broadcasting that has the remit of entertaining and gratifying the public [54]. In addition to the perspectives of critics and ordinary viewers, stand-alone reviews published on a *Tatort*-enthusiast website are considered as a performance variable, to control for preferences of "hardcore"-fans. It is proposed that the three disparate measures of creative outcome - ratings, awards and reviews - are all dependent on a production team's access to structural holes and age assortativity.

Table 1. Correlations of Dependent Variables.

		1	2	3	4	5	6
1	Weighted Rating	1.00					
2	IMDb Rating	0.92	1.00				
3	Fundus Rating	0.97	0.80	1.00			
4	WWDT Review	0.63	0.66	0.57	1.00		
5	Overall Awards	0.29	0.28	0.27	0.29	1.00	
6	Creator Awards	0.22	0.22	0.20	0.28	0.66	1.00

Note: All correlations significant at $p < 0.05$

Ratings. As a measure of creative success on the consumer level, ratings are widely used in research evaluating project outcome [61, 33]. The two most popular platforms for viewer ratings on Tatort are IMDb[9] and tatort-fundus.de[10], each with around 200 unique ratings per episode. Table 1 shows that these sources comprise highly correlated values, as should be expected. To boost explanatory power, the two individual ratings are combined using a *true Bayesian estimator* resulting in a weighted rating, WR, with the formula

[9]https://www.imdb.com/title/tt0806910/episodes?year=2022, accessed 04-25-2022
[10]tatort-fundus.de, accessed 04-25-2022

$$WR = \frac{v}{v+m} \cdot R + \frac{m}{v+m} \cdot C \quad (1)$$

With v being the number of votes for the movie, m - the minimum votes to be considered, R - average rating for the episode from zero to ten, and C - the mean vote across all episodes. This decision rule minimizes the posterior expected value of a loss function and is also used in IMDb's ranking-lists. Hereafter, this continuous weighted rating will be used as main variable indicating an episodes success.

Awards. Representing achievements on the expert level, this captures the dichotomy of episodes that either won an award and episodes that did not receive this honor. I include nominations for an award according to Simonton [84], arguing that nomination in itself is already a recognition of success. As awards and ratings value different qualities, they are not all that correlated. While the investigated social networks are formed by creatives behind the camera, awards are often focused on actors in front of it. To distinguish the technical aspects of film-making from the acting performance, the set of non-actor awards (commending efforts of directors, cinematographers, etc.) was detached from the all-embracing awards. Prominent awards that *Tatort* won or was nominated for are, among others, the German Television Awards, Golden Camera or Austria's Romy Gala. Both creator- and overall-award variables are included as binary dependent variables in separate models.

Reviews. To even further expand the variety of success quantifications, I look at reviews from wiewardertatort.de[11]. This *Tatort*-enthusiast blog contains reviews mainly on recent episodes (605 episodes are covered), that are condensed into a grading scale from from one to ten. Including this view on the quality of an episode makes it possible to test predictors on rather opinionated values, though no significant results are expected.

4.2 Creativity Predictors

The hypotheses presented in section 2.4 relate the above quantified creative success with the two determinants of interest in this thesis - network openness (H1) and age diversity (H2 & H3). These are operationalized in the following with Burt's network constraint measure [22] and Newman's attribute assortativity coefficient [68], respectively. Both characteristics are calculated from the seven-year collaboration networks of creatives producing an episode.

[11] https://www.wiewardertatort.de/, accessed 04-27-2022

Constraint. Measuring a team's aggregated access of creatives to structural holes is commonly implemented by calculating network constraint. Constraint does not literally describe openness of a social network, in fact it delineates closure [22]. Ranging between 0 and 1, it depends on three network characteristics: size, density, and hierarchy. Constraint is low when an individual has many connections (size), those connections are hardly or not at all directly connected to one another (density), and hardly indirectly connected through their contacts to a third party (hierarchy). This situation of low constraint is exemplified in figure 5, top graph on the next page, by means of actual data on an episodes social network. One can clearly make out that the team (red nodes) exhibits multiple opportunities for brokerage (size), connecting to lots of previous peers (density), that are not exceedingly connected to other brokers (hierarchy). The counter-example is the network on the bottom, showcasing the production team facing the highest constraint, reasoned in the circumstance that none of the participants has previously worked on *Tatort*, and consequently only has access to the redundant ties of current colleagues. In regard to these two extremes, I control for both team size and newcomers (section 4.3). For the sake of completeness, the network in between depicts median constraint.

Formally defined, the overall constraint of a network builds on dyadic constraint, c_{ij}, which is the extent to which actor j constrains actor i:

$$c_{ij} = \left(p_{ij} + \sum_{q \in N(i)-j} p_{iq} p_{qi} \right)^2 , \tag{2}$$

where p_{ij} is the amount of energy actor i invests in actor j [36]. Conformed to the requirements of aggregated constraint constructed in this thesis, I follow Burt's implementation of overall constraint, c_i - the sum over all j in i's neighborhood,

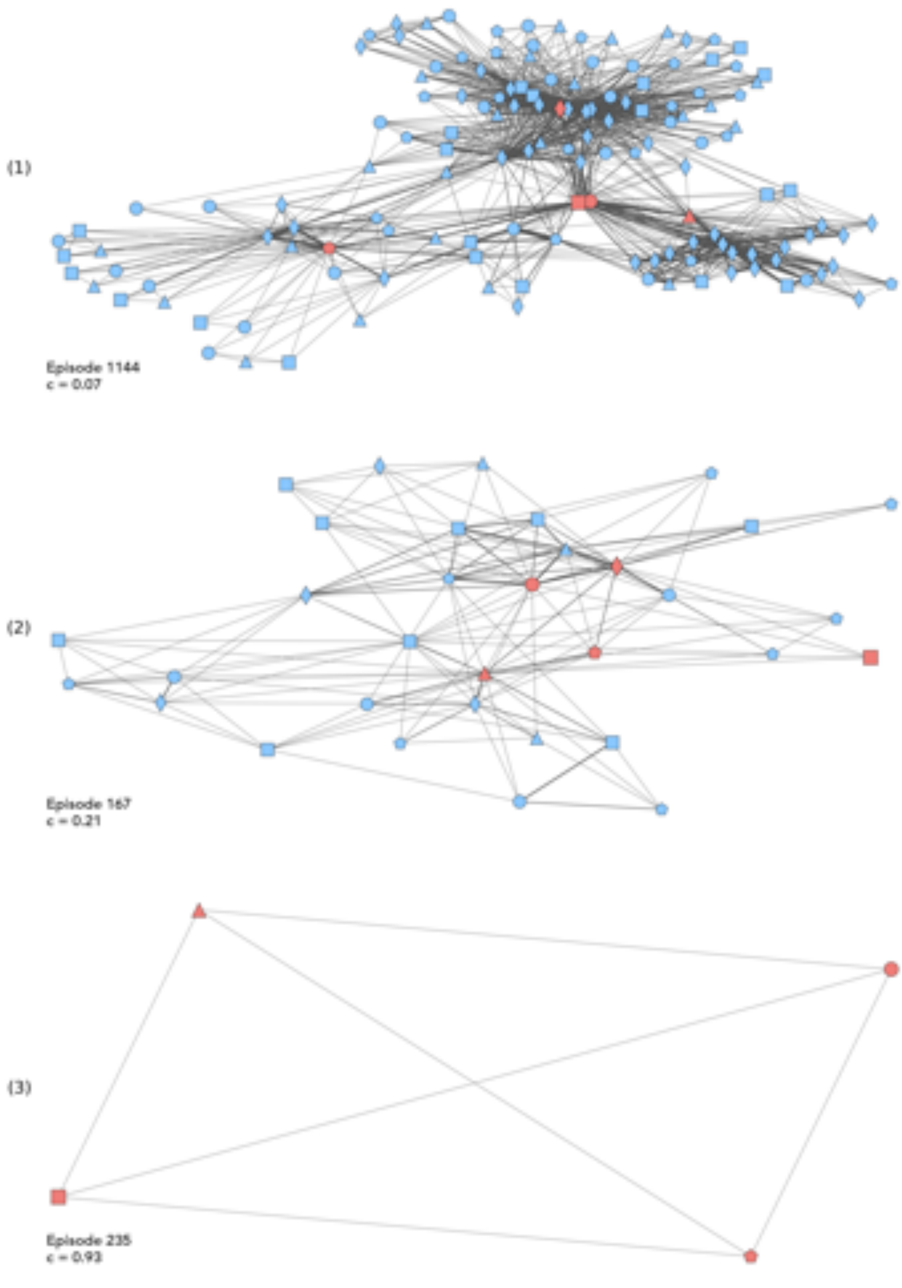
$$c_i = \sum_{j \in N(i) \setminus \{i\}} c_{ij}, \tag{3}$$

where $N(i)$ denotes the subset of neighbors of i that are either predecessors or successors of i. Subsequent, the aggregated and team-size adjusted constraint of core-members, c_{core}, is

$$c_{core} = \frac{1}{n} \sum_{i=1}^{n} c_i, \tag{4}$$

with n being the number of team members. Looking at this team constraint measure, one can deduce that low values constitute openness and high values reflect closure.

Figure 5. Minimum, Median & Maximum Constraint in Team



Note: Constraint-values are computed for the core-nodes (in red).

Intra-Team Age Assortativity. Quantifying the age diversity inside the core team is put into practice by computing the assortativity coefficient of the actors' age attribute. In the exceptional case that all team members are of the exact same age, this value will be 1 (perfect assortativity). If the team comprises young and old creators, the coefficient will be closer to -1, indicating disassortativity. Newman [68] operationalized this assortative mixing by scalar properties by defining a quantity e_{xy} - the fraction of all network edges that connect vertices with age-values x and y - that satisfies the sum rules

$$\sum_{xy} e_{xy} = 1, \quad \sum_{y} e_{xy} = a_x, \quad \sum_{x} e_{xy} = b_y, \tag{5}$$

where a_x and b_y are the proportion of ties that start and end at nodes with values x and y. Assortative mixing can then be measured by computing the the standard Pearson correlation coefficient:

$$r = \frac{\sum_{xy} xy(e_{xy} - a_x b_y)}{\sigma_a \sigma_b}, \tag{6}$$

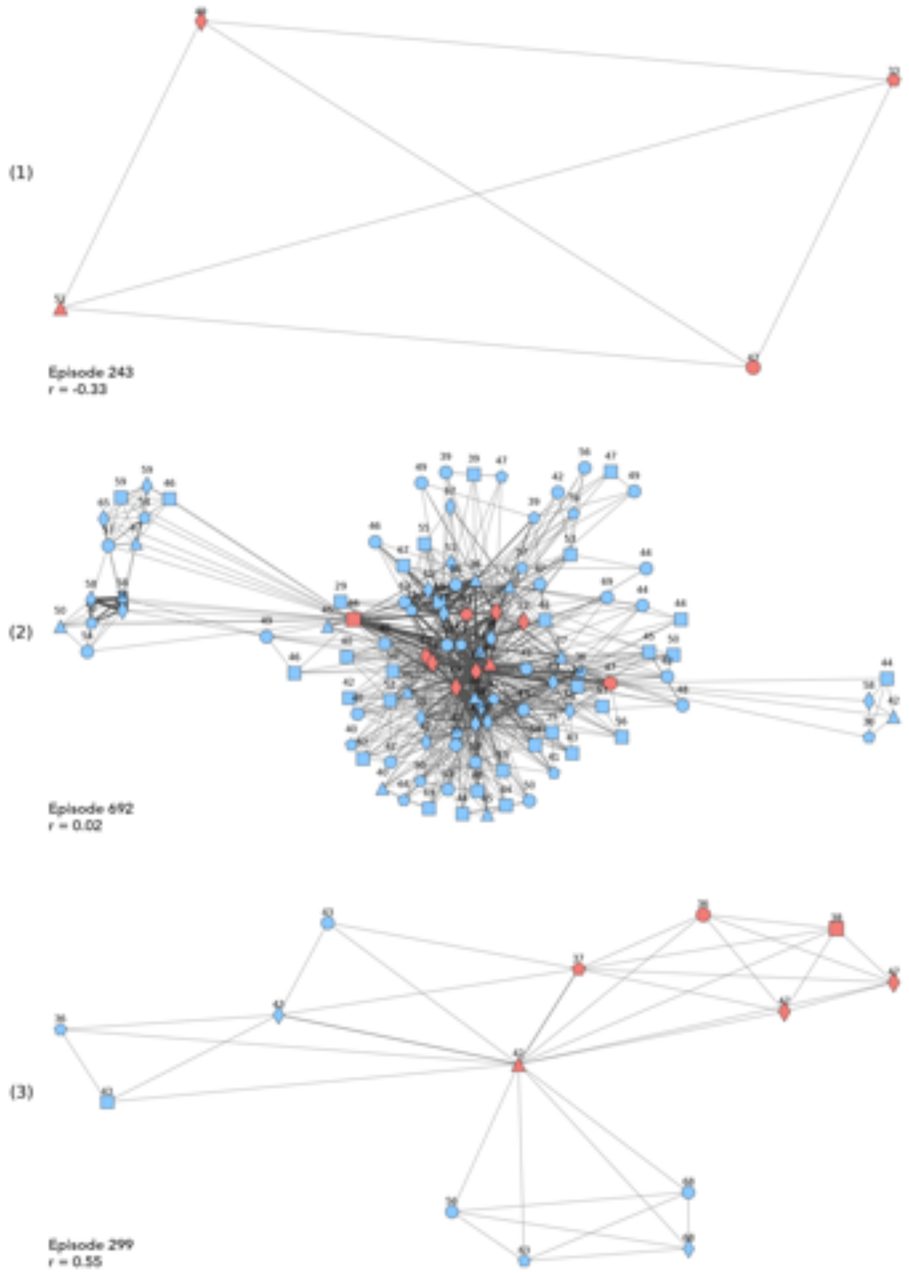
with σ_a and σ_b as standard deviations of the distributions ax and by. Just as any Pearson's r, the resulting values are in the range $-1 \leq r \leq 1$. In contrast to the examples in figure 6, that show the global age assortativity in an episodes collaboration network, the r-value of intra-team age assortativity denotes diversity of age exclusively between core team members (illustrations on the intra-team view can be found in appendix A).

Inter-Team Age Assortativity Expanding the scope of the intra-team perspective, assortative mixing by age might also exists in the retrospective connections of the core creators. Figure 6 lines up three episodes with increasing assortative mixing from top to bottom. Actors are labeled with their respective age at time of publication of the episode, core team members are highlighted red. Graph (1) demonstrates disassortativity of age, relatively many ties are joining creators with disparate age, graph (3) exemplifies an episode with connections between similarly aged individuals.

4.3 Controls

I include control variables to compensate for factors that possibly influence the characteristics of an episodes collaboration network structure or that might distort the validity of the dependent variables. Six alternative explanations for creative success are examined: Newcomer, experience, team size, inspector, city and period.

Figure 6. Minimum, Median & Maximum Inter-Team Age Assortativity



Note: Age assortativity is computed including all nodes in the network. Labels indicate ages of creatives at time of episode airing.

Newcomer. Creators that have not worked on *Tatort* in the past cannot reach back to prior experiences and connections. They are also unbiased in their methods [57] and might be favoured by award decisions because of the attention they are met with [103]. By calculating the proportion of team members that have never worked on an episode before, taking on values between zero (all members have at least worked on one episode prior) to one (no member worked on *Tatort* before), I control for the influence of these newcomers.

Experience. The adeptness of teams whose members accumulated experience working on previous productions might be impacting success of the production. *Experience* denotes the average number of preceding episodes per creator in the team.

Teamsize. Counting the individuals involved in creating a television film does control for variation in the dependent variables that is brought about by to a simple increase in the number of human resources. It can be argued that having more members leads to better performance, regardless of how diverse or cohesive the team is.

Inspector dummy. As each regional broadcaster of *Tatort* produces its own episodes with unique main characters, the audience might be drawn to some more than to others. The actor playing the inspector could be well known and a public favourite, skewing ratings as the non-expert viewers value the engagement of certain actors more than overall episode-quality. This is also true for the situation that *Tatort*-fans do not appreciate the appearance of a specific inspector, as was the case with episodes featuring inspector "Nick Tschiller" - played by Til Schweiger - receiving famously low ratings[12] from both average viewers and critics. A dummy for each inspector will be used to factor in such preferences.

City dummy. Similar to the inspector, the place of filming is manipulating subjective assessments. Well known cities such as Berlin or Vienna speak to more people, the fact that the shooting location is prominently displayed in *Tatort* episodes increases the emphasis on the city. Again, each city is coded with a dummy.

Semidecade dummy. While there is no expectation about the presence of a time trend over the study period, unobserved factors (e.g., changes in audience taste, viewing habits and other factors that might affect the *Tatort* franchise) are captured by including a dummy for every 5 years (semi-decade) since the first episode in 1970.

[12] https://www.imdb.com/title/tt4651460/, accessed 05-15-2022

4.4 Regression Models

In accordance with the three dependent variables - rating, award and review - and their respective data - continuous, binary and discrete - I deploy three different types of regression for testing the hypotheses. In this analysis, Ordinary least squares (OLS) regression predicts ratings, and is considered the main tool to explain differences in creative success, because the present data-situation allows more confidence in the rating variable than in award or review, as it is the most complete and informative quantifier of success [83]. In addition, probit regression focuses on the awards, and proportional odds logistic regression deals with the categories of the review variable. Predictors and controls used in these regression models were checked for the existence of multicollinearity by computing the variance inflation factors (VIF), with all values under 5.0, no problem in this regard was found.

5 Results

The descriptive statistics, correlations and regression results reported in the following are based on seven-year-window collaboration networks of five key roles in *Tatort* production, exceptions describing other time-frames are pointed out. After omitting the first 7 years of production (see section 3.2), 1118 episodes enter the analysis, whereby it was managed to compute the full set of variables for each episode[13].

Table 2. Descriptive Statistics.

	N	Mean	SD	Min	Max
Constraint	1118	0.24	0.12	0.07	0.93
Intra Age Assort.	1118	−0.19	0.06	−0.33	−0.06
Inter Age Assort.	1118	0.03	0.11	−0.33	0.55
Newcomer	1118	0.25	0.22	0.00	1.00
Experience	1118	6.44	4.98	0.00	28.29
Teamsize	1118	6.86	1.84	4.00	17.00

[13] An exception is the availability of review data, where only 599 observations are recorded

Table 2 summarizes the characteristics of the variables in question. As expected, network openness is generally high in the unstable conditions of the setting. Some outliers with high constraint, also visible in figure 4, can be found in teams comprising predominantly newcomers. Intra-team age mixing is rather disassortative, whereas its inter-team equivalent is inclined to cautious assortativity. Quite often, newcomers are part of a team, whose sizes vary from four to 17, with most core-teams comprising six or seven professionals. Those professionals have on average slightly more that six episodes under their belt.

The correlation matrix in table 3 shows that the correlation for some variable pairs exceed 0.60. Many of which relate to constraint, which is not surprising as for example teams with many newcomers, or few experience, face increased constraint. The pair of intra-team age assortativity and team size is correlated 0.93 is, amongst others, due to imputed information that will be discussed later.

5.1 Main Analysis

Investigating the main dependent variable - *rating* - table 4 gives indications on the three hypotheses. All five OLS regression models incorporate the dummy variables *inspector*, *city*, and *semidecade*, as well as the controls *teamsize*, and *experience*. It has to be noted that *inspector* alone explains half of the variance of *rating*, *city* also has a lot of explanatory power. A time-trend measured with *semidecade* was not found in any of the analyses, neither was an impact of *teamsize* on team success.

In my first hypothesis, H1, I posited that the effect of an open team-ego network on team performance is inversely U-shaped - ratings are highest when the aggregated constraint is neither too high nor too low. To this effect, a variable containing the squared values of *constraint* is introduced. By examining the sign and significance of both the linear and the squared constraint, this relation can be scrutinized. A negative and significant coefficient for the linear term coupled with a positive and significant coefficient for the squared term would support a U-shaped curvilinear effect [30]. Indeed, indications of this effect can be picked out across all models, albeit with varying significance. Concerning H2 and H3, a significant negative coefficient for both *intra age assortativity* and *inter age assortativity* is anticipated. Regression shows, although the signs of the diversity-related variables were in the expected direction, they differ in substantiality. While *inter age assortativity* is significant at $p < .05$ in all regression models, *intra age assortativity* does not seem to be equally relevant for innovative team performance.

Table 3. Pearson Correlation Coefficients.

		1	2	3	4	5	6	7	8	9
1	Rating	1.00								
2	Award	0.22	1.00							
3	Review	0.63	0.28	1.00						
4	Constraint	−0.20	0.00	−0.04	1.00					
5	Inter Age Assort.	0.03	0.02	−0.03	−0.33	1.00				
6	Intra Age Assort.	0.08	0.04	−0.02	−0.51	0.22	1.00			
7	Newcomer	−0.15	0.02	−0.05	0.67	−0.14	−0.00	1.00		
8	Experience	0.10	−0.05	−0.05	−0.62	0.12	0.15	−0.53	1.00	
9	Teamsize	0.06	0.04	−0.02	−0.48	0.20	0.93	−0.02	0.14	1.00

Note: All correlations higher than $|.06|$ significant at $p < 0.05$

Table 4. OLS Models Predicting Rating.

	(1)	(2)	(3)	(4)	(5)
Constraint		-1.63^{*}	-2.08^{***}	-2.05^{***}	-1.56^{*}
		(0.84)	(0.70)	(0.69)	(0.84)
Constraint^2		1.49^{*}	1.71^{**}	1.49^{*}	1.12
		(0.82)	(0.78)	(0.77)	(0.84)
Inter Age Assort.	-0.45^{**}			-0.50^{**}	-0.50^{**}
	(0.19)			(0.20)	(0.20)
Intra Age Assort.	-0.22		-0.79		-0.52
	(1.01)		(1.04)		(1.06)
Newcomer	-0.33^{***}	-0.15			-0.13
	(0.10)	(0.14)			(0.14)
Experience	-0.01^{*}	-0.02^{**}	-0.02^{***}	-0.02^{***}	-0.02^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Teamsize	0.01	-0.01	0.00	-0.02	0.00
	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)
Intercept	6.02^{***}	6.48^{***}	6.29^{***}	6.60^{***}	6.31^{***}
	(0.44)	(0.31)	(0.49)	(0.29)	(0.49)
Inspector Dummy	Yes	Yes	Yes	Yes	Yes
City Dummy	Yes	Yes	Yes	Yes	Yes
Semidecade Dummy	Yes	Yes	Yes	Yes	Yes
R^2	0.385	0.384	0.383	0.387	0.388
Adj. R^2	0.301	0.299	0.298	0.303	0.302
Observations	1118	1118	1118	1118	1118

Note: Standard errors in parentheses $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Looking closer at each model specification in table 4, it can be seen that model 1 encompasses *inter- and intra age assortativity*, *newcomer*, and the baseline variables. Bearing in mind the relation of *newcomer* and *constraint* - newcomers face high constraint - this model does neither include linear nor squared *constraint*, resulting in the *newcomer* variable being most significant in model 1. Model 2 excludes the cohesion perspective but includes *constraint* as a inverse measure of network openness. Bringing down the significance of both *constraint* and *newcomer*, the interaction of those two features also appears uninfluenced in the full model (5). Splitting H2 & H3, models 3 &

4 exclude *newcomer* to focus on *constraint*, which is significant at $p < .01$. With the ceased *newcomer*, these models also have significant coefficients for the squared term of *constraint*, with evidence of $p < .05$ and $p < .1$ against the null-hypotheses, respectively. Model 5 combines the full set of variables in this study. Just like in most models, *experience* influences *rating* negatively and is significantly different from zero. Also like ascertained before, *inter age assortativity* is significant at $p < .05$, but *intra age assortativity* is not. And finally, while the curvilinear relationship of constraint and creative success does not provide the strongest evidence, a tendency towards a U-shape can be detected. These findings are returned when considering collaboration networks that decay after seven years of no further contact between creatives. Using a 15 year time-span as basis of calculation, coefficients across the board become less significant, whereby tendencies remain the same (see table 7 in appendix for details). The five-year case basically shows significances going the other way, *inter age assortativity* becomes significant at $p < .01$ (appendix table 8).

5.2 Supplementary Analysis

In addition to the OLS regression on *rating*, the following looks at the other two dependents *award* and *review*. Table 5 presents probit regression models on the binary variable *award*, encompassing the same variables in the same composition as the OLS-models, with the exception that *inspector* and *city* dummies could not be included due to computational limitations. The utilized variant of *award* in this table does not contain awards for actors. Calculations including actor-awards did not produce significant results, due to the fact that predictors are targeted at behind-camera creators. All models in table 5 indicate weak evidence on the effect of *constraint* and *constraint*^{2}. Age-differences are not significant, but interestingly enough, the sign of *inter age assortativity* did switch to positive, indicating that in the shorter run, creative success might be fostered by an less age-diverse environment.

The last dependent variable of interest is the discrete variable *review*, denoting Tatort assessment on a scale from one to ten. Proportional odds logistic regression was deployed to uncover possible influencing factors, but did not yield significant results. Under the assumption that *review* is continuous [1], OLS regression was conducted instead, producing outputs very similar to the OLS models on *rating*. Table 6 displays these outputs.

Table 5. Probit Models Predicting Awards.

	(1)	(2)	(3)	(4)	(5)
Constraint		6.79*	5.82*	5.77*	6.82*
		(3.80)	(3.46)	(3.47)	(3.83)
Constraint^2		−8.99*	−8.40	−8.12	−8.89*
		(5.29)	(5.20)	(5.21)	(5.36)
Inter Age Assort.	0.51			0.41	0.44
	(0.62)			(0.63)	(0.63)
Intra Age Assort.	−0.42		−0.76		−0.48
	(3.31)		(3.29)		(3.43)
Newcomer	0.01	−0.30			−0.30
	(0.35)	(0.47)			(0.49)
Experience	−0.05***	−0.03	−0.03	−0.03	−0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Teamsize	−0.00	0.03	0.04	0.02	0.05
	(0.10)	(0.05)	(0.10)	(0.05)	(0.10)
Intercept	−6.27	−7.78	−7.94	−8.31	−8.17
	(2911.41)	(5271.87)	(8302.97)	(77525.24)	(10516.36)
Inspector Dummy	No	No	No	No	No
City Dummy	No	No	No	No	No
Semidecade Dummy	Yes	Yes	Yes	Yes	Yes
Observations	1118	1118	1118	1118	1118

Note: Standard errors in parentheses $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Table 6. OLS Models Predicting Reviews.

	(1)	(2)	(3)	(4)	(5)
Constraint		-8.70^{**}	-7.56^{**}	-8.05^{**}	-8.95^{**}
		(3.98)	(3.28)	(3.25)	(3.97)
Constraint^2		7.84^{*}	6.68	6.67	6.90
		(4.44)	(4.25)	(4.19)	(4.47)
Inter Age Assort.	-1.54^{*}			-1.84^{**}	-1.79^{*}
	(0.90)			(0.91)	(0.92)
Intra Age Assort.	-2.03		-3.55		-3.21
	(4.37)		(4.43)		(4.49)
Newcomer	-0.81^{*}	0.25			0.32
	(0.46)	(0.65)			(0.65)
Experience	-0.04^{*}	-0.07^{***}	-0.06^{***}	-0.07^{***}	-0.07^{***}
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Teamsize	0.03	-0.12^{*}	-0.02	-0.10^{*}	-0.04
	(0.12)	(0.06)	(0.12)	(0.05)	(0.12)
Intercept	5.25^{***}	7.63^{***}	6.35^{***}	7.65^{***}	6.84^{***}
	(1.46)	(0.91)	(1.62)	(0.81)	(1.64)
Inspector Dummy	Yes	Yes	Yes	Yes	Yes
City Dummy	Yes	Yes	Yes	Yes	Yes
Semidecade Dummy	Yes	Yes	Yes	Yes	Yes
R^2	0.349	0.351	0.352	0.356	0.357
Adj. R^2	0.243	0.245	0.246	0.251	0.249
Observations	599	599	599	599	599

Note: Standard errors in parentheses $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

6 Discussion

The creative success of collaborative ventures is in part dependent on patterns of current and previous interactions of involved individuals. Creative teams exhibit greatest ingenuity when they can benefit from both cohesion within the group, and brokering external influences. The present thesis investigated this balancing act between open- and closed networks, diverse- and homogeneous team compositions, arguing (1), too much brokerage might be similarly detrimental for creativity as too little, and (2), age-disassortativity promotes creativity by providing cognitive diversity.

Regarding (1), I elaborated a retrospective inter-team theory of structural holes, exploring how individual brokerage positions aggregated at the team level influence the innovative strength of a creative unit. Much like in Bizzi's work [14], it was proposed that there is an inverse U-shaped effect of network openness on a team's creative success. This was reasoned in the fact that while decreasing constraint on a group brings in new knowledge necessary for effective recombination, too little constraint - indicating an open network - means too much contradictory brokered input, which creates frictions inside the team, leading to a loss of cohesion that is vital in producing innovative outputs.

Concerning (2), my hypotheses were based on the benefits of diversity in creative teams [71]. First, an intra-team approach was taken to discern the effect of age-diverse teams on their performance. I theorized that age-based mixing patterns occurring in cohesive teams are influencing outcomes - disassortativity of age increases creativity because team members are able to combine their inherent differences and profit from synergies. Second, the inter-team approach incorporated retrospective age-assortativity by exploring mixing patterns in the affiliation networks of creators, again expecting disassortativity to boost creativity. This was based on the assumption that previous experiences in age-diverse teams positively effect current innovative strength.

I tested and largely found support for my conjectures by analyzing collaboration networks of 1118 creative teams working on the television show *Tatort*. An unambiguous trend towards the curvilinear nature of open networks - moderate values of constraint promote creativity best - was discernible, just as the negative effect of high inter-team age assortativity was significant. These findings contribute to research on creativity, diversity and social networks and add reference points for the formation of successful creative teams.

6.1 Theoretical Contributions

Most works investigating structural holes in the past have solely focused on the upside of brokerage [24, 59, 105], few looked at possible drawbacks of this network characteristic [14, 12]. Nonetheless, as Brass points out [17], new developments in social network research include holistic approaches, going onwards to multilevel views and adding cognition to the traditional structural analysis of social networks. New research directions that the present thesis adds circumstantial findings to.

Findings can be viewed in light of a recent concept, suggesting that network composition stability can have explanatory power on what type of network structure (closed or open) is beneficial for creative performance, and to what extent [75, 86]. Since *Tatort* collaboration networks exhibit low stability, openness - ensured by brokerage - is particularly instrumental for successful outcomes. This significance of constraint (as inverse openness metric) was found in the main regression models. Regular changes in the composition of creative networks, induced by the incorporation of newcomers, provoke "shocks" that demand flexibility and reconsideration of collaborative and cognitive structures from the longer-established team members. Open networks increase the likelihood that these shocks have a positive impact - instead of just being disruptive, they can promote creative recombination and reconfiguration processes. In this network structure perspective, the present work also supports views of Shirado & Christakis [81], saying that collective problem-solving is only benefitting from new ties when they are added to the core of the network. This is replicated in *Tatort* collaboration networks, where new members are compulsorily starting off in the latest team enabling them to influence the creative line of approach. Even if unstable networks require open social structures to produce truly innovative outcomes, the fruitfulness of such constellations is often limited by the human traits of being manipulative and selfish. Studies indicate that brokers keep their connections apart because in this way they are able to achieve or retain a position of supremacy, and not because they want to participate in collective group efforts in which they share their unique information [55, 3]. The aggregation of individual brokerage positions acted out in this thesis, and found in real-life collaborations, multiplies the effects of this egoistic attitude, leading to a lack of solidarity and an eradication of trust within the team. While the group theoretically has plentiful access to non-redundant information, the nature of brokers is to withhold crucial details - creating tensions instead of innovation.

A second field of contribution of my study concerns diversity in creative teams. This adds to the well-researched, but often inconsistent views on the effect of demographic diversity on group performance. The presented intra-team perspective was not able to make out significant benefits of age diverse teams. Much like in other works [89, 100], the negatives of lower cohesion and cultural differences counteract cognitive synergies within the group. By increasing the temporal sphere of influence of diversity - not just assessing current diversity but also previous - one can measure the impact of personal experience coming from working with different-aged colleagues. This experience coming from earlier engagements of creatives in age diverse teams seem to have a positive effect on creative success. Inter-team diversity might be more important than intra-team diversity in my setting, again, due to the instable conditions of considered collaboration networks. Individuals are able to contribute their incoherent knowledge, but do not know each other long and well enough to be able to combine their inherent qualities to create truly novel outputs. This situation is also expressed in the big picture of the *Tatort*-franchise. While the continued influx of new creators keeps a baseline of "sparks" that carry the series from episode to episode, it does not allow for a sustained creation of cohesive ties that potentially have the means to generate outstanding innovation. If *Tatort* was a car, newcomers would be short taps on the throttle briefly accelerating it - that might save fuel which makes the ride last longer, but the car will only really pick up speed by chance, in case there is a slope, other times it will not get to full speed.

6.2 Practical Implications

This research offers practical implications for all areas building on creative teamwork. First, I highlight the importance of ensuring non-redundant ties to outside influences. Brokerage is in particular important in iteratively re-assembling social structures, where the positive effects of cohesiveness do not have the opportunity to unfold in a timely manner. Leaders in creative teams are tasked with bringing in new members exhibiting complementary cognitive attributes and social embeddedness, while also safeguarding a certain cohesion within the team by consolidating trust and encouraging communication. Second, focusing on ensuring a diversity of age of the members is not generally recommended. Creative success in unstable social networks is much more dependent on a team-compilation that is reasoned in diverse previous experiences than on current group-diversity. While demographically diverse teams are certainly beneficial in many social structures, decision-makers facing high staff churn rates should rather focus on cognitive diversity.

6.3 Limitations and Directions for Future Research

Multiple restraints of this study present opportunities for further research. Beginning with the limitations imposed by the characteristics of the setting - the *Tatort* production world - emphasizing the relevance of creativity and project-based collaborative operation in the creative industry. This concentration on the functioning of highly qualified specialists who work together to achieve innovative results is presumably not applicable to an inherently different ambit, where individuals are less proficient, positions are more flexible, or creativity is not that decisive. That said, it has to be noted that working methods in many industries are getting closer to those in the creative sector, with more and more of the above listed characteristics being found in, e.g., production- or service-centered operations [4]. This increases the general validity of the presented findings, and also constitutes an invitation to study innovative social structures in other areas and conduct comparative research.

A more methodical constraint lies in the data forming the basis for this elaboration. It solely includes information on creatives within the scope of *Tatort*, none of their other engagements. Further work could look into creating an all-embracing database, exploring the interconnected landscape of German television-creators in a similar vein. While the data on Tatort was quite comprehensive, some dates of birth relevant for computing age assortativity could not be identified. Utilizing imputation methods [25], the few and random missing data points were added, which might have skewed the results in spite of precautionary measures.

Another limitation stems from the way that creative success is operationalized. Using ratings originating from online-platforms introduces bias into the quantification of success. They tend to over-represent the most extreme views of only a handful of inveterate *Tatort* enthusiasts that take the time to express their opinion on specialized websites. Therefore, the validity of this measure cannot be taken at face value unconditionally. Future research might measured creativity following, e.g., the consensual assessment technique [6], resulting in a more balanced performance criteria. The dependent variable *awards* used additionally in this analysis would also be an alternative, provided that data quality is rectified.

7 Conclusion

Facilitation of creative success in innovative teams remains a crucial field of study, I believe that the presented findings are of value to theorists and practitioners alike. By deploying social network analytical methods, this thesis explores collaborative structures of *Tatort* creators and derives recommendations for the formation of successful teams. A fresh, multilevel perspective on the implications of colluding brokerage positions as well as the importance of age diversity is given and offers the potential for further research. I am confident that composing teams in light of my observations and in all conscience results in better group performance.

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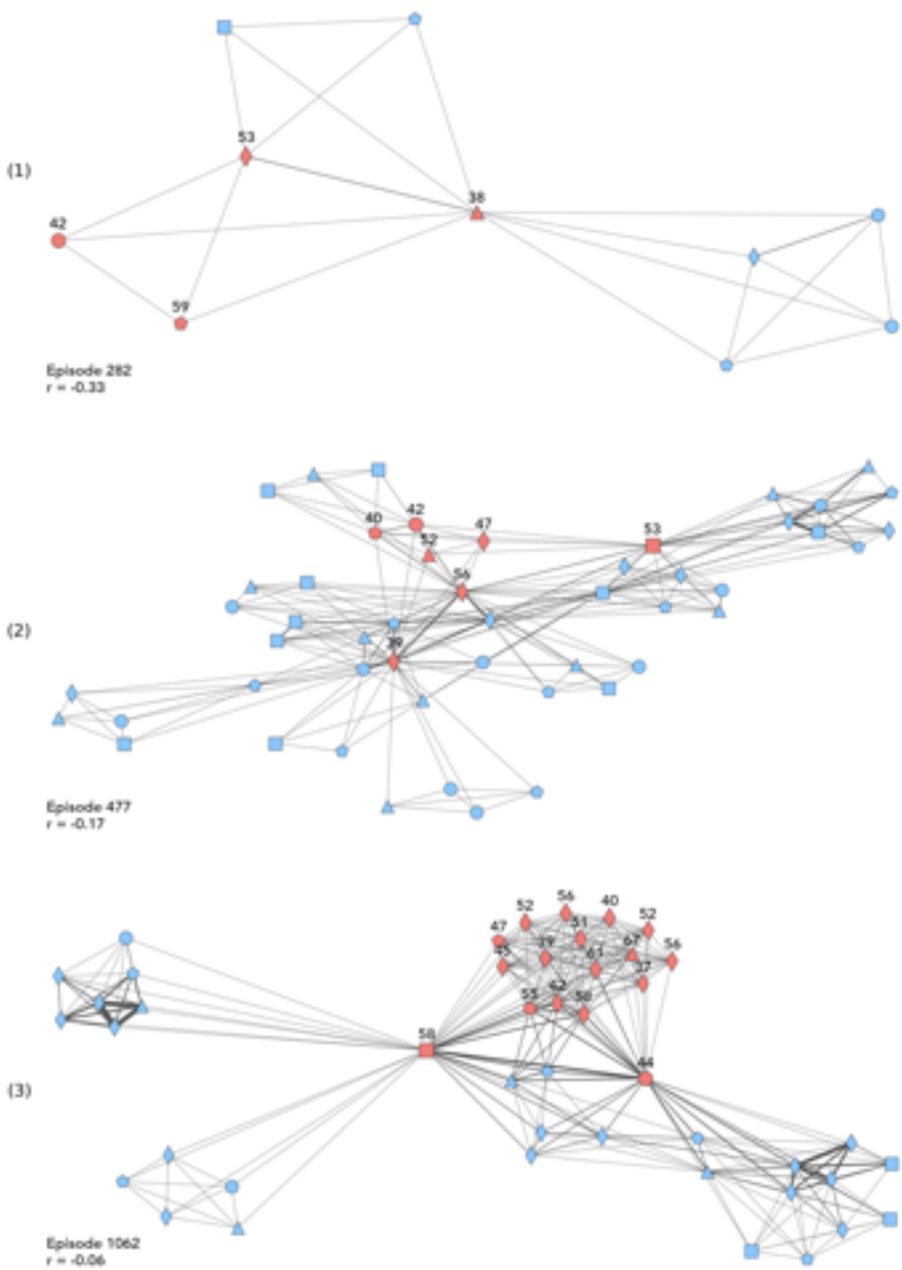
A Collaboration Networks

Figure 7. Minimum, Median & Maximum Intra-Team Age Assortativity



B Regression Tables

Table 7. OLS Models Predicting Rating, 15 year time window.

	(1)	(2)	(3)	(4)	(5)
Constraint		-0.63	-1.56^{**}	-1.54^{**}	-0.59
		(0.97)	(0.72)	(0.72)	(0.98)
Constraint^2		0.55	1.08	1.01	0.26
		(0.93)	(0.83)	(0.83)	(0.95)
Inter Age Assort.	-0.27			-0.31	-0.30
	(0.20)			(0.21)	(0.21)
Intra Age Assort.	-0.75		-1.29		-1.01
	(1.04)		(1.07)		(1.09)
Newcomer	-0.34^{***}	-0.26			-0.22
	(0.11)	(0.16)			(0.17)
Experience	-0.01^{*}	-0.01^{*}	-0.02^{**}	-0.02^{**}	-0.01^{*}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Teamsize	0.02	-0.00	0.02	-0.02	0.02
	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)
Intercept	5.74^{***}	6.14^{***}	5.88^{***}	6.34^{***}	5.81^{***}
	(0.40)	(0.27)	(0.45)	(0.24)	(0.45)
Inspector Dummy	Yes	Yes	Yes	Yes	Yes
City Dummy	Yes	Yes	Yes	Yes	Yes
Semidecade Dummy	Yes	Yes	Yes	Yes	Yes
R^2	0.362	0.360	0.359	0.360	0.362
Adj. R^2	0.288	0.287	0.286	0.287	0.288
Observations	1023	1023	1023	1023	1023

Note: Standard errors in parentheses $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Table 8. OLS Models Predicting Rating, 5 year time window.

	(1)	(2)	(3)	(4)	(5)
Constraint		-1.52^{*}	-1.97^{***}	-1.99^{***}	-1.53^{*}
		(0.80)	(0.70)	(0.69)	(0.79)
Constraint^2		1.38^{*}	1.59^{**}	1.36^{*}	1.02
		(0.79)	(0.77)	(0.75)	(0.80)
Inter Age Assort.	-0.49^{***}			-0.58^{***}	-0.57^{***}
	(0.17)			(0.18)	(0.18)
Intra Age Assort.	-0.24		-0.80		-0.58
	(1.00)		(1.03)		(1.04)
Newcomer	-0.32^{***}	-0.17			-0.13
	(0.10)	(0.13)			(0.13)
Experience	-0.01^{*}	-0.02^{**}	-0.02^{**}	-0.02^{***}	-0.02^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Teamsize	0.01	-0.01	0.00	-0.02	0.00
	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)
Intercept	5.91^{***}	6.39^{***}	6.20^{***}	6.53^{***}	6.22^{***}
	(0.43)	(0.29)	(0.48)	(0.28)	(0.48)
Inspector Dummy	Yes	Yes	Yes	Yes	Yes
City Dummy	Yes	Yes	Yes	Yes	Yes
Semidecade Dummy	Yes	Yes	Yes	Yes	Yes
R^2	0.392	0.389	0.388	0.394	0.395
Adj. R^2	0.309	0.306	0.305	0.312	0.311
Observations	1141	1141	1141	1141	1141

Note: Standard errors in parentheses $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.