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Positive Emotions, Instrumental Resources, and Organizational Network Evolution: Theorizing via Simulation Research

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ABSTRACT

In the workplace, people seek positive emotional experiences as well as instrumental resources while doing their work. Yet we know little about how affective micro-dynamics drive the evolution of organizational networks, influence network trajectories, and determine macro outcomes such as collective affect and overall network structure. Given the lack of theory on affective micro-dynamics and network evolution, we propose a model that includes both affective and instrumental micro-mechanisms and use simulation methods to explore evolutionary dynamics and develop new theory. The core of our model is the empirically observed tendency for people to forego the acquisition of instrumental resources to avoid a decrease in positive emotion when choosing interaction partners. We conduct "experiments" with the simulation, considering the effects of the tradeoff, dispositional affect, resource inequality, and ingroup favoritism. The results show that dispositional affect and the tradeoff have considerable effects on network trajectories, collective affect, and resource transfer. We provide new theoretical propositions about affect in organizations.

Introduction

Affect suffuses social and organizational networks. The analysis of emotions and sentiments in organizations has roots in classical sociology, psychology, and management theory; but in the last 30 years or so, an "affective revolution" has taken place in organizational behavior (Barsade et al., 2003; Barsade and Gibson 2007). Yet we know little about how affective micro-dynamics drive the evolution of organizational networks, influence network trajectories, and determine macro outcomes such as overall network structure and collective affect. Analyzing the genesis and dynamics of organizational networks is important for many reasons, such as understanding the distribution of network outcomes, the role of agency, and the institutional and governance benefits of networks (Ahuja et al., 2012). While organizations have both instrumental and affective networks (e.g., Lincoln and Miller 1979), most studies of organizational network evolution focus on *instrumental* micro-mechanisms—where unemotional "goal-directedness" is assumed to drive micro-dynamics and network trajectories (Kilduff and Tsai 2003)—and underplay or ignore *affective* micro-mechanisms (although researchers are beginning to reveal more about these mechanisms: see Casciaro and Lobo, 2015; Sasovova et al., 2010 or Troester et al., 2019). Here, we propose a model that includes both affective and instrumental micro-mechanisms. This model offers a more complete account of intraorganizational network dynamics by considering both types. The interactions and tradeoffs of these two micro-mechanisms provide opportunities to develop new theory about micro-dynamics, the evolution of organizational networks, and organizational outcomes.

Our model helps to solve the puzzle of how networks within many organizations evolve in ways such that actors acquire sufficient resources and also have primarily positive relationships while performing the work of the organization. One reason this is puzzling is the empirical observation (e.g., Baker et al., 2003; Cross et al., 2003; Casciaro and Lobo 2008; Collins, 2004) that people will avoid interacting with those whom they think will drain their positive affect even if it means losing some of the instrumental resources they need to do their work. Given this tendency, organizations might use formal authority or other means to force people to interact. We explore this possibility and find that, even if it were possible to force resources to flow, the likely result would be a dysfunctional organizational network. In fact, we find that allowing people to avoid those toward whom they feel negative affect increases the chances that organizations will evolve networks in which resources

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flow sufficiently and people obtain the instrumental resources, positive emotions, and positive relationships they need to do their work.

In brief, our model incorporates the affective micro-mechanism of *relational attributions* with the instrumental micro-mechanism of *purposive resource-seeking*. Relational attributions are beliefs ascribed to another person with regards to how positively a person tends to feel when he or she interacts with that person (e.g., Casciaro & Lobo 2008; Owens et al., 2016). They are beliefs about how we think we are likely to feel around specific people, and not the feelings themselves. People in a relationship make attributions about each other, and these attributions are what scholars capture in subjective surveys about social networks that examine trust, liking, or relational energy (e.g., Sparrowe and Liden, 2005; Owens et al., 2016). However, it is also possible for people to make attributions about others they are aware of but with whom they do not have relationships. Positive emotions, in contrast, are the feelings themselves. Emotions, along with moods and dispositions, are a type of affect that varies in how targeted and enduring they are (e.g., George and Dane, 2016). Affect is a psychological experience characterized by physiological activation and subjective appraisal. Dispositions are enduring tendencies to feel more or less positively; moods are temporary but longer-lasting, undirected feelings of positivity or negativity; and emotions are usually short experiences that emerge in reaction to specific events, people, ideas, or objects. Emotions are positive when the bodily physiological activation and subjective appraisal that make up the experience are pleasant. Generally speaking, people seek to maintain or increase the positive emotions they feel, and one of the most common ways in which people seek to do this is through social interaction (Baker, 2019; Collins 1993; Lawler & Yoon, 1996). Thus, in the absence of other considerations, a positive emotion seeker will search for and interact with the actors he or she perceives to be most likely to maintain or increase their positive emotions, or in other words, the people towards whom the actor has attributed a positive relationship.

The second mechanism—purposive resource-seeking—denotes that actors in an organization need instrumental resources (e.g., information, materials, tools, advice, money) to accomplish their goals. Instrumental resources can be obtained from impersonal sources (e.g., knowledge databases, files, Internet searches) without interacting with others, and from personal sources that require interactions with people who possess or control these resources. Here, we focus exclusively on instrumental resources obtained via interpersonal interactions. Thus, purposive resource-seeking occurs when one actor seeks out and interacts with another actor who is a source of instrumental resources that are helpful or useful for getting work done. In the absence of other factors, a resource-seeker will search for the best personal source of instrumental resources.

Both micro-mechanisms operate in an organization: actors seek instrumental resources *and* positive emotion. Both are obtained when a seeker interacts with a person who has the instrumental resources *and* who the seeker believes will increase his or her positive emotion. But what happens when a seeker believes that the actor with the resources will diminish the seeker's positive emotion? As we discuss, theory and research indicate that actors will trade off positive emotion and instrumental resources, willing to forego resources to avoid decreases in positive emotion. However, there is little theory or research that guides expectations about how tradeoff micro-dynamics influence the trajectory of an organizational network and macro-level outcomes such as overall network structure, "collective affect" (Barsade and Gibson 2007), and the diffusion of resources.

Our goal is to develop theory about the interplay of affective and instrumental micro-mechanisms, network evolution, and macro organizational outcomes. We use simulation methods because they are well-suited for theory development when (1) basic concepts and processes are established in prior work but their interactions are complex and vaguely understood, (2) the theoretical focus is longitudinal and dynamics may be nonlinear, and (3) fundamental tradeoffs are involved (Davis et al., 2007). Prior work provides concepts and processes, but the interactions of affective and instrumental micro-mechanisms and their influence on the evolution of organizational networks are vaguely understood. Network evolution is, by definition, longitudinal. And, our affective-instrumental mechanisms present a fundamental tension and tradeoff between resource seeking and positive relationships. We use agent-based modeling—a computational modeling procedure that simulates the behavior of individual actors under a variety of assumptions about social processes and actor preferences (Axelrod 1997). Agent-based modeling is useful for examining how macro-level patterns emerge from the micro-level interactions of individual actors (Miller and Page 2007).

As an approach for theory development, a simulation study does not begin with hypotheses but with theoretically and empirically informed assumptions; it then proceeds to model construction, and ends with theoretical predictions or propositions (Harrison et al., 2007:1233). We develop a set of assumptions about the dynamics of affective and instrumental micro-mechanisms, drawing upon and synthesizing prior theoretical and empirical work on affect in organizations. These assumptions provide the basis for designing our model. We use the simulation model to examine dynamics, track evolutionary network trajectories, and observe collective outcomes. We compare these outcomes with results from empirical networks. We conduct "experiments" with the simulations by varying inputs, altering parameter values, and adding simple features to the simulation model. The results provide new and novel theoretical insights into the role of affect in network evolution, which we summarize in three theoretical propositions.

THEORETICAL BACKGROUND AND ASSUMPTIONS

Network evolution is defined generally as a temporal process that involves a series of "events that create, sustain, and dissolve social structures" (Doreian and Stokman 1997:3). Actors are assumed to be purposive, and network structure enables and constrains their actions. Actors and network structures change over time, co-evolving as a result of prior sequences of events. For example, consider structural balance theory—one of the few theories of affect and network evolution. This theory is not typically applied to work organizations, but it illustrates how affective micro-mechanisms influence network evolution (see, e.g., the special issues of *Social Networks* edited by Doreian and Snijders 2010 and Doreian and Everett 2012). It assumes that actors are motivated to maintain ties that are psychologically "comfortable" and change those that are "uncomfortable." For example, ties are uncomfortable when *A* likes *B* but *B* dislikes *A*, or when *A* likes both *B* and *C* but *B* and *C* dislike one another. Micro-mechanisms such as "reciprocity" and "transitivity" are assumed to evolve into networks with more comfortable ties and fewer uncomfortable ties.[1]

By saying that actors are purposive, we are not implying that they are rational in the economic sense of having perfect information. Nor are we saying that people necessarily maintain work relationships independent of the roles they occupy or the geographical location in which they work. Rather, we argue that actors have at least two driving social motivations when they work within a given location and within a given set of roles that occasionally require varying degrees of interdependent work. One motivation is to talk to someone who can give them the resources they need to get their work done. The second motivation—usually less

[1] "Reciprocity" occurs in a dyad. For example, if *A* and *B* like one another, the dyad is stable (balanced) and likely to persist over time. If *A* likes B and *B* dislikes *A*, then the dyad is unbalanced and *A* or *B* is likely to withdraw from the dyad. "Transitivity" occurs in a triad. For example, if *A*, *B*, and *C* all like one another, then the triad is balanced and likely to persist over time. If *A* likes both *B* and *C* but *B* and *C* are neutral, then B and C will tend to develop mutual liking. If *A* likes both *B* and *C* but *B* and *C* dislike one another, then the triad is unbalanced and the positive tie between *A* and *B* or *A* and *C* will tend to dissolve over time.

explicit but often more powerful—is to avoid talking to anyone who might drain their positive emotion (Casciaro and Lobo, 2008; Cross et al., 2003).

Specifying underlying mechanisms is a key to a theory of network evolution (Doreian and Krackhardt 2001). Interaction ritual chain theory (Collins, 1981, 1993, 2004) provides a specific affective micro-mechanism centered on positive emotion. In this theory, positive emotions increase in social interactions and events in which “participants develop a mutual focus of attention and become entrained in each other’s bodily micro-rhythms and emotions” (Collins, 2004), and positive emotions decrease when people attempt and fail to achieve such focus and entrainment or in interactions in which others compel them to do things they do not wish to do (Collins, 1990). Interactions that achieve high focus and entrainment may be highly scripted events such as religious services or organized sports, but even everyday social encounters and interactions have ritualistic elements and can raise or lower positive emotion (Collins, 2004). Elevation of positive emotions increases participants’ motivation for their work and induces them to seek out similar social experiences in the future (Marks 1977; Quinn et al., 2012; Zajonc 1980).

The positive emotions that people feel in the interactions that achieve focus and entrainment lead to relational attributions about the partners with whom they interact, causing them to expect to feel similar emotions in the future when interacting with the same partners (e.g., Casciaro and Lobo 2008; Owens et al. 2016). And, interacting with these partners increases a person’s positive emotions (e.g., Baker, 2019). Relational attributions and Collins’ (2004) theory suggest the first two assumptions for our model of network evolution:

ASSUMPTION 1.—A key motivation that actors have for interacting with one another is to increase their positive emotions.

ASSUMPTION 2.—Positive emotions acquired through interaction enhance people’s motivation for their work and for subsequent interactions with the same others.

Interaction ritual chain theory and relational attributions assume that individuals within groups come to share the same or similar emotions through processes such as “emotional contagion” (Hatfield et al., 1994; Kelly and Barsade, 2001). Emotional contagion, and other forms of affective convergence, have been documented in dyads, groups, organizations, and large-scale networks (e.g, Barsade 2002; Barsade and Gibson 2007;Sy et al., 2005 Totterdell et al., 2004; Fowler and Christakis 2008). Affective convergence may occur through automatic processes such as mimicry and feedback or a “more cognitively effortful set of processes” such as social comparison, empathy, and perspective taking (Barsade 2002:648), often within productive interactions (Lawler, 2001; Lawler and Thye, 1999). Research on affective convergence is nuanced but has not addressed our core concerns: how the pursuit of positive emotion (Assumption 1) influences evolutionary network trajectories and macro outcomes such as network structure. For example, do particular initial conditions predict when an organization will likely take an evolutionary path that yields positive or negative structures and positive or negative collective affect? These questions have yet to be addressed. Therefore, we assume that positive emotion is contagious, that actors mutually influence one another, and that each actor’s positive emotions can go up, down, or stay the same. We use the simulation to observe the influence of affective convergence on network trajectories and macro-level outcomes.

Of course, the positive emotion an actor experiences in a social interaction might be influenced by additional factors. For example, the positive emotions people feel tend to be a function of their beliefs about their competence and autonomy as well as their beliefs about their relatedness (Ryan and Deci, 2000). Given this observation, we might expect people who receive an increase in instrumental resources to believe they are more competent and consequently experience an increase in positive emotion. Though resource acquisition sometimes increases positive emotion (Quinn et al., 2012), the causal relationship may be more complicated when resource transfer occurs during social interaction. For example, Lawler and colleagues (Lawler and Yoon, 1993; Lawler et al., 2000) find repeatedly that positive emotion (measured as excitement and interest) increases as participants in negotiations agree with each other more frequently, independent of the level of benefit generated by those agreements. In contrast, power (which comes from control over resources (e.g., Pfeffer and Salancik 1979), had no effect on positive emotion in the negotiations (Lawler and Yoon, 1993), and predictability (which depends on having the resource of information) did not enhance relational cohesion between negotiation partners (Lawler et al., 2000). The correlation between predictability and positive emotion was not presented. Even though power did not increase positive emotion and predictability did not increase cohesion, the frequency with which partners agree with each other increased positive emotion. Results like these suggest that resources transferred in social interaction may not always increase positive emotion.

Social network research raises further questions about if and when resources influence positive emotion in social interaction independent of affective considerations. For example, Casciaro and Lobo (2015) found that participants’ tendencies to go to a work colleague for resources at time t had no impact on the participants’ positive emotions at time t + 1, but that colleagues’ positive emotions at time t did affect participants’ positive emotions at time t + 1, which further questions whether resources transferred in social interaction influence positive emotion. Participants’ perceptions of colleagues’ competence at time t also influenced participants’ positive emotions at time t + 1, but Casciaro and Lobo acknowledged that there were concerns with how they had measured others’ perceived competence, so it is not entirely clear what their measurement of perceived competence was capturing. Also, in earlier studies, Casciaro and Lobo (2008) and others (Cross et al., 2003) find that people will, if possible, avoid those whom they believe will decrease their positive emotions, and will even forego the acquisition of needed resources to avoid such people.

This tradeoff suggests that people expect, based on previous experiences, for the affective dimension of their social interactions to override the instrumental benefit they anticipate from such an interaction, even if they had acquired resources they needed in previous interactions. This behavior is puzzling only if we assume that people are driven solely by rational optimization and will acquire instrumental resources to optimize performance regardless of the impact of an interaction on their emotions. However, psychologists who study emotions have shown that the need for attachment (belonging) may be more fundamental than other emotions (Fredrickson, 2013; Lewis et al., 2000). Even Collins’ observation—that people are trying to optimize the positive emotion they feel from participating in ritual social interactions rather than instrumental considerations (Collins, 1993)—can be understood as people trying to meet their need to belong. Given these findings and arguments, we do not assume that the acquisition of instrumental resources in social interactions will increase positive emotion. Rather, we assume that positive emotions will increase or decrease based on the experience people have when they interact with others, and that this experience, in turn, will depend on the attributions and emotions that partners bring to an interaction. In our sensitivity tests, we allowed the acquisition of instrumental resources to influence positive emotion, but doing so always generated unrealistic outcomes, which strengthens the validity of our assumption that resource acquisition itself does not influence emotions. Rather, consistent with theorizing about affective convergence, participants in a social interaction are influenced strongly by one another’s emotions, and each participant’s level of positive emotion after an interaction is a function of the emotion the person had at the beginning of an interaction and what happens during the interaction. We formalize these ideas in the next two assumptions:

ASSUMPTION 3.—When two actors interact, one actor’s positive emotion influences the other’s positive emotion and vice versa.

ASSUMPTION 4.—Actors bring and express varying levels of positive emotion to their interactions with others.

People use their attributions of others to decide whether to engage in interactions (Casciaro and Lobo 2008; Cross et al., 2003). Generally, people are motivated to seek and repeat interactions that they believe will increase positive emotion and avoid interactions that they believe will decrease positive emotion. Because actors in organizations pursue positive emotion through their interactions (Assumption 1), positive emotion is contagious (Assumption 3), and positive emotion varies from person to person (Assumption 4), actors seek interactions with those who they think will not decrease positive emotion and avoid interactions with those who they think will decrease it. In other words, actors' attributions about others' tendencies to diminish their positive emotions influence the choices they make about the people with whom they will interact. We acknowledge that some people may be more willing to tolerate interactions with those who may diminish their positive emotions if they have high positive dispositional affect themselves or if they think the people will have a minimal effect on their emotion. However, as long as people have a choice, they are more likely to choose to avoid interacting with those who might decrease their positive emotions.

Sometimes task interdependence compels people to interact with other people whom they have attributed a tendency to diminish their positive emotions. By task interdependence, we mean that people in organizations may have to get resources from others to perform their work. Left to their own devices, people generally choose to interact only with those who energize them, but interdependent work might constrain their choice of interaction partners. These arguments suggest our next two assumptions:

ASSUMPTION 5.—Actors use relational attributions to guide their choices of who to interact with such that they try to avoid those with negative relational attributions and prefer those with positive attributions.

ASSUMPTION 6.—Task interdependence may limit the extent to which actors can use relational attributions to guide their choices of interaction partners.

Positive emotion generated from interpersonal interactions enables people to accomplish their tasks and achieve their objectives (Assumption 2). However, actors need instrumental resources as well as positive emotions to get work done. Purposive resource-seeking is the means by which people obtain such instrumental resources (e.g., Morrison 1993). In organizations, these resources are available from impersonal sources (files, databases, Internet search, etc.) and interpersonal sources—social networks (Nohria and Eccles 1992; Kilduff and Tsai 2003). Obtaining resources via social networks depends on the structural properties of networks (e.g., Monge and Contractor 2001; Borgatti and Cross 2003; Burt 2004) and on cognitive factors, such as whether those who need resources know, or can find out, who has resources and are willing to share them (Cross and Borgatti 2004; Cross and Sproull 2004; Labianca and Brass 2006). The transfer of instrumental resources through social networks has significant effects on organizational learning (Reagans et al., 2005), the spread of best practices (Szulanski 1996), innovation (Obstfeld 2005), and performance (Hansen 1999). The instrumental value of resources and the purposive use of social networks to obtain them suggest our seventh assumption:

ASSUMPTION 7.—Actors in an organization interact with one another to obtain instrumental resources to get their work done.

Assumptions 5 and 7 create a tension: Actors need both positive emotions and instrumental resources to get their work done, but sometimes actors perceive potential sources of resources as likely to decrease the positive emotions they feel. Actors have to decide between a potential loss of positive emotion versus not acquiring resources. In other words, an actor must choose between the perceived instrumental value and affective value of work relationships. Instrumental value is "a subjective evaluation of a relationship's contribution to accomplishing assigned tasks" and affective value is "a feeling of positive affect from interacting with a colleague" (Casciaro and Lobo (2015:373). Casciaro and Lobo (2015) hypothesize that affective value supersedes instrumental value and influences the perception of instrumental value and the selection of task-related ties. Using longitudinal network data on affective and instrumental ties in a work setting, they find support for their hypothesis of "affective primacy" for high-activation positive affect (e.g., positive emotion) but not for low-to-neutral activation positive affect (e.g., pleasantness). Qualitative and quantitative evidence from network studies of diverse organizations revealed a common tendency to trade off resources for positive emotion (Baker et al., 2003; Cross et al., 2003; Cross and Parker 2004). "People rely on their networks for resources to get their work done, and they are much more likely to seek resources and learn from energizers than from de-energizers" (Cross et al., 2003:52). Based on theory and evidence, we assume affective primacy, noting that task interdependence may restrict its operation (Assumption 6).

ASSUMPTION 8.—Actors tend to trade off affective and instrumental values in their choice of interaction partners, sometimes foregoing resource acquisition to avoid a decrease in positive emotion.

A change in emotion resulting from an interaction is temporary and "ebbs away" over time (Collins, 2004:45). Generally, in the absence of additional interactions, an actor's emotion tends to return to a set point—an average or typical level (Collins, 1993). This change can go in two directions. After an interaction that raises an actor's positive emotion above the actor's dispositional set point, positive emotion will tend to decline; after an interaction that lowers an actor's positive emotion below the actor's set point, positive emotion will tend to rise. The ebb and flow of emotion after interaction is consistent with the observation that emotions are short-lived with varying durations (Verduyn and Lavrijsen 2015). Therefore, we assume:

ASSUMPTION 9.—An actor's increase or decrease in positive emotion that resulted from an interaction tends to return to an average or typical level.

Similarly, we expect relational attributions to fade in the absence of interaction. Relational attributions are more enduring than emotion, but even so, people tend to forget cognitions over time, or remember less accurately (e.g., Feeney and Cassidy 2003). There are socio-temporal, cognitive, and affective limits on the number of ties a person can sustain (McCarty et al., 2001). Over time, relationships tend to weaken and disappear—what Burt (2000) calls relationship "decay." Negative relational attributions are less easily forgotten than positive ones. Generally, negative events have an asymmetric effect on people's cognitions (Taylor 1991), particularly with regard to relationships (Labianca and Brass 2006). People tend to remember negative relational attributions to avoid future interactions that decrease positive emotion (Assumption 5). Hence, we assume:

ASSUMPTION 10.—Positive relational attributions that result from an interaction tend to fade over time.

ASSUMPTION 11.—Positive relational attributions fade more slowly than positive emotion, and negative relational attributions fade more slowly than positive relational attributions.

Assumptions 1 – 11 are the micro-foundations of our model and work together to create aggregate outcomes in an organizational network. Collins, 2004:141-182) uses the metaphor of a "market" for interaction rituals and emotion to conceptualize the micro-macro link. This "interpersonal market" is composed of a population of actors who have variable amounts of positive emotion (Assumption 4 above) and who seek and obtain positive emotion from one another (Assumptions 1, 3). Actors choose interactions with higher positive emotion "payoffs" and avoid interactions with lower positive emotion "payoffs" (Assumption 5). Interactions are sequential, forming interaction chains (Collins, 1981). These chains form networks that evolve over time, shaped by the structure of opportunities for and constraints on interaction, and produce "collective affect" (e.g., Barsade and Gibson 1998, 2007). A related concept is organizational "productive energy" (Cole et al., 2012). Group-level affect influences performance, the level of conflict and cooperation in a group, absenteeism, decision making, and prosocial behavior (e.g., George 1990; Barsade 2002; Gibson 2003; Barsade and Gibson 2012). Similarly, organizational energy predicts commitment to unit and organizational goals as well as firm performance (Cole et al., 2012).

Collins is vague about the specifics of the micro-to-macro aggregation process, but our simulation model enables us to specify the process. We assume a "bottom-up" aggregation process in "which individual level affective characteristics combine, often through emotional contagion, to form group level emotion or mood" (Barsade and Gibson 2007:38; Barsade and Gibson 2012). This affective-compositional process interacts with purposive resource-seeking (Assumption 7), the tradeoff of affective and instrumental values (Assumption 8), the tendency for positive emotion to ebb and flow (Assumption 9), and the tendency to forget relational attributions (Assumptions 10-11). Together, affective and instrumental processes drive network trajectories and produce collective outcomes.

These eleven assumptions, grounded in evidence and theory, provide the basis for designing our simulation. The simulation allows us to examine the dynamics of affective and instrumental micro-mechanisms over time, track evolutionary network trajectories, observe collective outcomes, and compare these outcomes with results from empirical networks. Conducting experiments with simulations is useful for theory development (Davis et al., 2007). We do so by varying inputs, altering parameter values, and adding simple features to the basic simulation model. The results provide novel theoretical insights into the role of affect in network evolution that can guide future empirical research and inform organizational and management theory.

SIMULATING AFFECTIVE-INSTRUMENTAL NETWORK EVOLUTION

Stokman and Doreian (1997:245-248) articulated six general principles for modeling the evolution of networks and we follow them here. Principle 1.—Network ties should be useful for actors to obtain instrumental resources and affective motivation.[2] Our Assumptions 1 and 7 address Principle 1. Principle 2.—Actors make decisions based on limited resources. In our model, actors have incomplete resources. Principle 3.—Actors act in "parallel." That is, they act separately but not completely independently, simultaneously attempting to achieve their objectives without being able to anticipate the actions of all other actors. Ideally, an actor (ego) requests an interaction with another actor (alter), who either accepts or rejects it. In practice, most models of network evolution have followed this principle implicitly but not explicitly (Snijders and Doreian 2010:2). Here, we explicitly model choices involving requests for interactions. Because our focus is the decision between instrumental and affective values, we keep our model simple by assuming that, if an interaction is requested, it is accepted and alter transfers resources to ego and each actor's positive emotion goes up, down, or stays the same . Principle 4.—Models of network evolution should be "simple" to begin with, and complexity added "stepwise." Before conducting the experiment that we present here, we examined a simple model with no additional features, and then conducted multiple sensitivity tests of the model to make sure it was robust and that we understood the basics of how it works. Then, we conducted the experiment as a way of both generating realistic results and exhibiting the key outcomes the model generates. To be thorough, as we examined more complex models, we ran millions of simulations using hundreds of input values to examine complex interactions and conduct sensitivity tests of the model. Principle 5.—Models should have "sufficient empirical references." We use findings from empirical research to guide us in building the model. Principle 6.—Model "fit" should be evaluated. We compare simulated network structures with the structural characteristics of several empirical networks composed of affective ties, as well as with empirical observations and theoretical claims from other research. We identify conditions that are sufficient to explain these patterns. Equations used in our simulation are presented in the Appendix.

Overview of Model

The goal of our model is to identify minimally sufficient conditions for realistic organizational networks to emerge, given the assumption that people tend to trade off instrumental resources for positive emotion. Each simulated organization is populated with $N = 50$ actors, which is the average number of actors observed in our empirical organizational networks (look ahead to Table 2). We create a simple structure by dividing an organization of 50 actors into two units of equal size (Unit 1 and Unit 2). We assume these units are horizontally differentiated and approximately at the same level in the organization. Actors may seek instrumental resources from their own unit or from the other unit, and they may have ingroup/outgroup biases for interaction. Empirical examples include the classic division of sales and marketing (e.g., Kotler et al., 2006), "creatives" and "accounts people" in advertising agencies (e.g., Snell et al., 2011), and management consulting practices that have specialists with "hard" skills (information technology, data science) and specialists with "soft" skills (organizational behavior, strategy) (e.g., Cross et al., 2007).[3]

Each simulation run proceeds in sequential timesteps. In each timestep, one actor encounters a problem that requires resources and makes choices about whom to approach for the resources, taking the expected emotional valence of the interaction into account. Timesteps are sequential, but in real organizations people experience time as continuous and multiple interactions can occur in the same period of time. In agent-based models, continuous time is approximated by treating each timestep as a "micro" segment of time and designating a number of timesteps as a meaningful period of time (Huberman and Glance, 1993)). Because each timestep involves the potential interaction of two actors, a meaningful period of time in our model is 25 steps (N/2). We run each simulation for 20,000 uninterrupted timesteps. These runs evolved into stable patterns well before they reached 20,000. In real organizations, endogenous changes (e.g., personnel turnover, new role assignments, re-locations) and exogenous impacts (e.g., shifts in market demand, legal-regulatory changes, changes in macro-economic conditions) could interrupt the evolutionary process and alter the trajectory of organizational networks and collective outcomes.

Each actor in a typical simulation run begins with a set point for dispositional affect that varies between 0 and 1. Each actor also begins with relational attributions about ten randomly selected actors. We chose ten to capture the idea that people generally have at least some expectations about how positive or negative others will be (e.g., Golden-Biddle et al., 2007). Actors typically begin the simulation with mostly positive relational attributions and a small number of negative attributions, consistent with empirical observations about organizational

[2] Stokman and Doreian (1997:245) use the term "instrumental value" instead of "useful" but their discussion makes it clear that their term is broad and includes both affective and instrumental values. We describe network ties as "useful" because it conveys their meaning but avoids confusion with our distinction between affective value (e.g., positive emotion) and instrumental value (e.g., information).

[3] We ran sensitivity tests with larger organizational sizes and found that larger organizations typically show the same evolutionary patterns as 50-person organizations, but just take longer to converge. We also explored varying the relative sizes of units. For example, we considered a 10/40 split and required those in the larger unit to often seek information from the smaller one. This design mimics a hierarchy, where the 40 "employees" must seek information from the 10 "managers." Design changes like this one influence outcomes, but these outcomes still align with the findings reported here. For theoretical reasons, we decided to focus on simulated organizations with two units of equal size. Our theoretical assumptions center on the tradeoff of instrumental resources for positive emotion, not the effects of different organizational designs, such as more units or units of different sizes. Future research would consider the analysis of more complex organization designs.

networks (Labianca and Brass, 2006). During a simulation run, an actor's relational attributions toward another actor can fluctuate between a minimum of -1.0 (interactions are expected to be highly negative) and a maximum of 1.0 (interactions are expected to be highly positive). We ran numerous sensitivity tests, such as varying the number of attributions actors make at the outset of the simulation, the mean value of these attributions, and the ranges of these initial values. Small variations yield similar results. Extreme variations yield unrealistic organizational networks. Our goal was to find minimally sufficient conditions for explaining how realistic networks emerge when people trade off resources for positive emotion. Our experiment presents input and output values consistent with previous research, but also examines small changes from typical observations to see what results those deviations produce.

Once starting values are set, a typical simulation run operates as follows:

1 —In each timestep, an actor (ego) randomly chosen from a uniform distribution encounters a need for instrumental resources. Following Cohen et al., 1972), we assume that the need for resources comes as "problems" that "enter" the organization and "attach" to particular actors more or less randomly. In reality, of course, problems do not enter and attach randomly. A "problem" is a label that people apply to situations that require the action response of "solving" the problem (Smith 1988). We can model "problems" as entering and attaching because this is often how people experience problems, and the simplification generates realistic outcomes (Cohen et al., 1972).

2 —Ego identifies a subset of alters who have potentially valuable instrumental resources. This subset includes three alters randomly selected from a uniform distribution. The value of the resources each alter has varies from 0.0 (no value) to 1.0 (the most valuable resources) (see Equation 1 in the appendix). Three alters is an arbitrary number. Sensitivity tests revealed that the number of alters does not make a material difference on network trajectories or outcomes.

3 —Ego approaches and acquires instrumental resources from the alter who has the most valuable resources and who does not decrease ego's positive emotion. Ego uses relational attributions as a guide when making this decision. If ego does not have negative attributions toward the alter with the most valuable resources (in other words, if the attribution of alter is positive or neutral), then ego seeks and obtains resources from this alter. If ego has negative attributions toward the alter with the most valuable resources, then ego considers the alter with the next most relevant resources instead. Ego considers alters until ego obtains resources or has no alters with valuable resources left. We examined various alternatives, such as actors who would suffer small decrements in positive emotion, or actors who would occasionally interact with people toward whom they have made negative attributions. Small differences from the rule we use made no material difference in outcomes; large differences generated results significantly different from empirical networks.

4 —If ego and one of the three alters interacted in the third step, the simulation updates the positive emotion and relational attributions of the actors that interacted (Equations 2 and 3 in the appendix). We used the research literature and extensive sensitivity tests to determine the most plausible range of values to represent change in emotions and relational attributions. We use values from this range for the coefficients in the updating equations when we conduct experiments with the model.

5 —For any actor who has not interacted with at least one other actor in a meaningful period of time ($N/2 = 25$ timesteps), the actor's emotion ebbs, returning to a set point—an average or typical level. We ran sensitivity tests for different values of the ebbing rate. A high rate of ebbing causes actors to interact at their set points without variation most of the time; a low rate of ebbing causes actors to operate most of their time at extremely low or high levels of positive emotion. To have a realistic, plausible influence on ego's positive affect, ebbing must occur at a moderate rate. Therefore, we set the ebbing rate at 0.2, meaning that an actor whose positive emotion is below (above) the actor's set point will experience an increase (decrease) of 0.2, or will return to the set point if the difference from the set point is less than 0.2.

6 —If any two actors have not interacted in a meaningful period of time (25 timesteps), then the two actors tend to forget their relational attributions. Forgetting means that an actor who has a positive attribution toward another actor will feel a little less positive about that actor, while an actor who has a negative attribution toward another will feel a little less negatively about that actor. The range of values we examine for forgetting attributions is always lower than the ebbing rate for positive emotions because emotions ebb more quickly than attributions decay. Moreover, the rate of forgetting negative attributions is slower than the rate of forgetting positive attributions because negative events have stronger effects on people's cognition than positive events do (Baumeister et al., 2001). We ran sensitivity tests for the ebbing and forgetting parameters. We found that, when the theoretical inequalities hold (ebbing rate of positive emotion > forgetting rate of positive attributions > forgetting rate of negative attributions), and the differences in these inequalities are about an order of magnitude different from each other, plausible outcomes tend to occur (i.e., outcomes resemble empirical networks).[4] Here, we hold the rates of ebbing and forgetting as follows: ebbing rate of emotion = 0.2; forgetting rate of positive relational attributions = 0.01; forgetting rate of negative relational attributions = 0.001.

Once a timestep concludes and all values are updated, the next timestep is simulated. This process continues until it reaches the maximum number of timesteps. The organizational network evolves as the simulation proceeds from timestep to timestep, terminating at 20,000 timesteps. When a simulation run terminates, each actor has some level of positive emotion and an egocentric network, which we use to calculate individual-level measures (emotion), and an egocentric network measure, specifically, indegree centrality. We use indegree centrality because empirical studies show that indegree centrality for positive affective ties predicts job performance (Baker et al., 2003). In our context, a tie is a relational attribution from alter to ego. It varies from -1 to +1. We calculate indegree centrality for positive ties (> 0) and for negative ties (< 0). Thus, ego's positive (negative) indegree centrality is a count of the number of alters whose relational attributions about ego are greater (less) than 0.

The evolutionary process generates three macro-level outcomes: network structure, the amount of instrumental resources transferred, and collective affect. We use indegree graph centralization to represent network structure. It varies between 0 and 1, where 0 is a highly decentralized network (e.g., a fully connected network) and 1 is a highly centralized network dominated by one or a few actors (e.g., a hub-and-spoke network). This measure can be expressed as a percentage. We calculate resources transferred as a percentage of the total amount of resources available. Collective affect is "affective homogeneity" (Barsade and Gibson 2012:120) or what George (1990) called "affective tone," calculated as the average level of positive emotion experienced by the members of a "work group"—a set of "individuals who see themselves and who are seen by others as a social entity, who are interdependent because of the tasks they perform as members of a group, who are embedded in one or more larger social systems (e.g., community, organization), and who perform tasks that affect others such as customers or coworkers" (Guzzo and Dickson 1996: 308-309). Empirical research shows that these work groups can be large (Baker et al., 2003).

[4] From a simulation perspective, both ebbing and forgetting are forms of negative feedback, which is necessary for systems to be sustainable (Sterman 2000). Negative feedback prevents an endless (and unrealistic) upward spiral.

Collective affect varies between 0 and 1 and can be expressed as a percentage.

Experimental Design

Our experimental design includes four factors: the tradeoff of instrumental resources for positive emotions, dispositional affect, relational attributions, and instrumental resource inequality. To explore the full range of our model, we include all possible combinations of these factors.

Tradeoff

We compare results when actors trade off instrumental resources for positive emotion versus results when actors who do not. We manipulate the tradeoff by switching it on or off. Our sensitivity tests considered degrees of tradeoff between on and off, such as what happens when actors are only occasionally forced to interact with others. At high levels of forced interaction, the results were similar to those when every interaction was completely forced, but if the rate of forced interaction was not high, then occasional forced interactions did not make a material difference on network trajectories or outcomes.

Dispositional Affect

Each actor begins a simulation run with a set point for dispositional affect that varies between 0 and 1. If the average set point for all 50 actors is greater than 0.5, our model reflects the practice of selecting and hiring people with high positive dispositional affect (e.g., Burlingham 2005; Carvin 2005; Gittell 2003). Colloquially, this practice is called “hiring for attitude.” Hiring for attitude can strengthen organizational social capital, improve the flow of resources, and promote prosocial behavior (Baker and Dutton 2007; Cohen and Prusak 2001; George and Brief 1992). We created three conditions: high, medium, and low average dispositional affect, with set points drawn from normal distributions with means of 0.6, 0.5, and 0.4, and ranges of [0.2, 1.0], [0.1, 0.9], and [0.0, 0.8], respectively.

Relational Attributions

The two-unit formal structure enables us to manipulate relational attributions in a way that reflects a common affective dimension of organizational life: ingroup favoritism. Ingroup favoritism or bias is a pattern of positive regard or preference for one’s own group over other groups (Brewer 1979). It can lead to intergroup competition and conflict, impede the flow of resources between groups (e.g., Argote and Ingram 2000; Morrison 1993), and reduce the ability to respond to crisis (e.g., Krackhardt and Stern 1988). We examine two conditions: moderate ingroup favoritism versus low ingroup favoritism. We create ingroup favoritism by assigning actors higher levels of initial relational attributions for actors in their own unit and lower levels for actors in the other unit. If positive attributions are higher within than between units, then actors are more likely to interact with members of their own unit than with members of the other. Specifically, moderate ingroup favoritism occurs when initial values of relational attributions are drawn from a normal distribution with a mean of 0.3 and a range of [0, 0.6] for actors in their own unit, and a mean of 0.0 and a range of [-0.3, 0.3] for actors in the other unit. The initial values for weak ingroup favoritism are drawn from a distribution with a mean of 0.3 and a range of [0, 0.6] for actors in their own unit, and a mean of 0.1 and a range of [-0.2, 0.4] for actors in the other unit. The values for weak ingroup favoritism create initial conditions in which 92 – 98 percent of attributions are positive, and 2 to 8 percent of attributions are negative.

Resource Inequality

In organizations, actors may depend more on some groups for resources than on other groups. Here, resource inequality means that one unit has more resources than the other unit. We specify the probability that the actors with instrumental resources are in Unit 1 or Unit 2 and, when resources are distributed unequally, Unit 1 has more resources than Unit 2 and actors in Unit 2 are more likely to seek resources from actors in Unit 1 than from their own unit. We create three conditions: resource equality (equal distribution of resources between units), low resource inequality (an actor has a 60 percent probability of finding resources in Unit 1 and a 40 percent probability of finding resources in Unit 2), and high resource inequality (80 percent probability of finding resources in Unit 1 and a 20 percent probability of finding resources in Unit 2).

The four factors create a 2 × 3 X 2 × 3 full factorial design (36 conditions). We conducted 100 simulation runs for each condition. We use multiple regression with dummy coding to analyze main effects and interaction effects. We emphasize that we are *not* using multiple regression to test hypotheses; simulations are used to *generate* hypotheses or propositions, not to test hypotheses. We use multiple regression as a systematic way to identify major effects and eliminate minor effects or those due to chance. With this approach, we identify the (few) key effects on which we base our theoretical propositions.

RESULTS

Evolutionary network trajectories diverged early during the course of the simulations. To illustrate, Fig. 1 depicts the temporal evolution of collective affect—one of our macro outcomes—over 20,000 timesteps for 100 simulated organizations. These organizations took three distinct trajectories, producing high, medium, or low collective affect. Every simulation run produced temporal variations, but patterns like Fig. 1 were common. Our experimental results help us understand why networks followed evolutionary trajectories such as these, and also why results varied within trajectories.

Key Effects of Experimental Factors on Macro-Outcomes

We regressed macro-level outcomes on the tradeoff, dispositional affect, ingroup favoritism, and resource inequality, and their two-way, three-way, and four-way interactions. Table 1 presents main effects and two-way interactions. We suppressed three-way and four-way interactions because they do not significantly influence outcomes.

Collective Affect

Recall that collective affect varies from 0 to 1 and can be expressed as a percentage. The constant in Model 1 indicates that, on average, collective affect is 80.6 percent of its maximum when actors do not trade off resources for positive emotion, ingroup favoritism is low, average dispositional affect is medium, and resource inequality is low. The main effects for the tradeoff, low dispositional affect, and high disposition affect are significant, but the main effects for favoritism and inequality are not. The largest main effect is low dispositional affect, depressing collective affect by 53.5 percentage points to only 27.1 percent (assuming that actors do not trade off, ingroup favoritism is low, resource inequality is low, and other factors are held constant). When actors trade off resources for positive emotions, collective affect increases by 5.3 percentage points, controlling for other factors. By itself, this is a modest increase, but the tradeoff also exerts influence by its interaction with low dispositional affect. If the simulation begins with low average dispositional affect and the tradeoff operates, then collective affect is 48.1 percent, holding constant other factors. Low affect also interacts with high inequality (increasing collective affect) and favoritism (decreasing collective affect).

Model 1 enables us to identify the various combinations of factors that influence which evolutionary path organizations take. Like the organizations in Fig. 1 that evolved on a path that produced high levels of collective affect, Model 1 suggests that organizations will yield a high level of collective affect (mean = .859) if we assume that actors begin the simulation with medium average dispositional affect and they trade off instrumental and affective values, holding constant other factors.

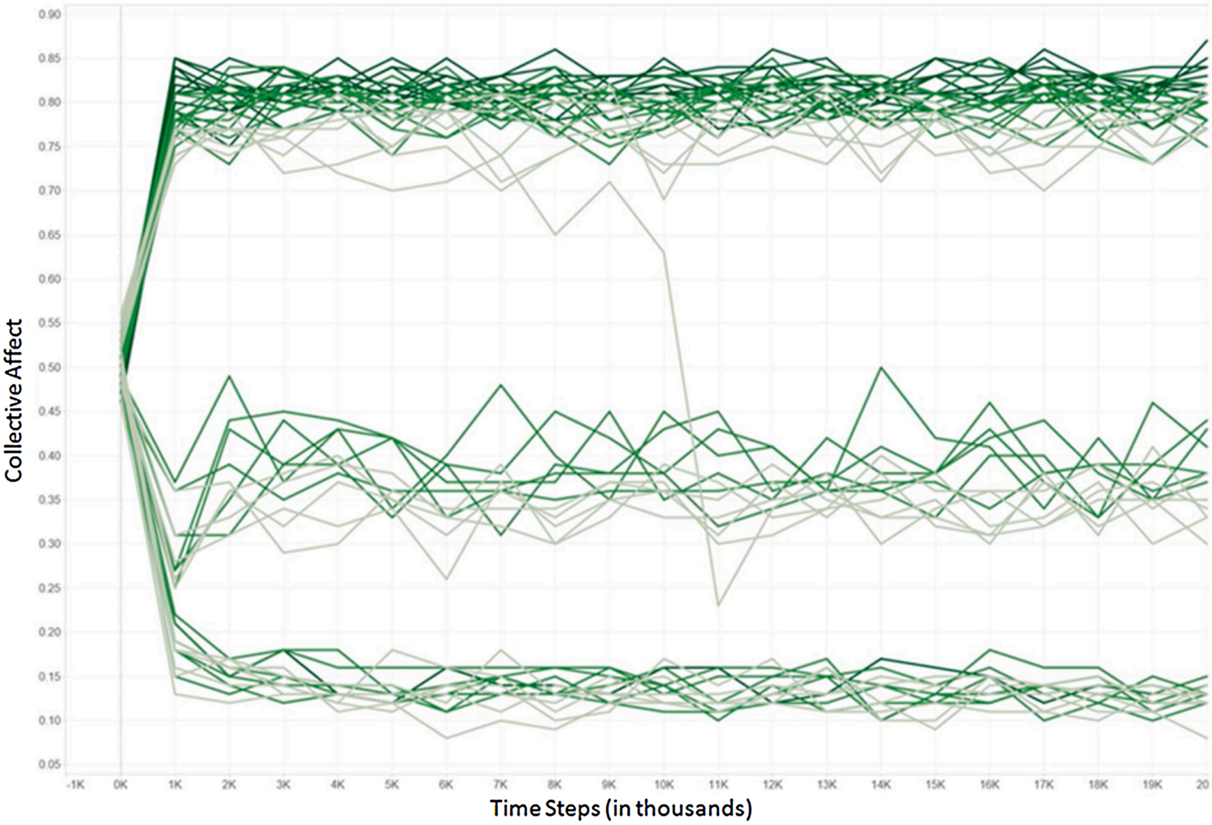

Fig. 1. Network Trajectories for Simulated Organizations: Collective Affect by Time.

Model 1 produces a medium level of collective affect (mean = .424) if we assume low average dispositional affect, the tradeoff, and moderate ingroup favoritism, controlling for other factors. Finally, the combination of factors in Model 1 that can produce low collective affect (mean = .205) includes low average dispositional affect and moderate ingroup favoritism, holding constant other factors.

Resources Transferred

Resources transferred varies from 0 to 1 and can be expressed as a percentage. The constant in Model 2 indicates that all instrumental resources are transferred when actors do not trade off resources for positive emotion, assuming that average dispositional affect is medium, ingroup favoritism is low, resource inequality is low, and other factors are held constant. This is unsurprising because not trading off means that actors are forced to acquire resources from the alters who have the most valuable resources—regardless of the emotional impact of the interactions. Allowing actors to trade off decreases resources transferred only by 4.1 percentage points. The biggest impact of the tradeoff occurs when average dispositional affect is low at the start of the simulation. The interaction of low affect and the tradeoff cuts resources transferred by more than half . In this scenario, resource seekers frequently encounter alters who, if the seekers interacted with them, would depress their positive emotions; hence, by trading off, they preserve their positive emotions at the considerable cost of losing valuable resources. The interaction of the tradeoff with high dispositional affect is significant and positive (but small). Generally, Model 3 indicates that the tradeoff has almost no effect on resource transfer when organizations hire people with high average dispositional affect because negative attributions become so rare as to be negligible in the tradeoff decision.

Networks

Models 3 and 5 indicate the effects of the tradeoff, dispositional affect, favoritism, and resource inequality on positive and negative ties, respectively. Recall that a tie is a relational attribution from alter to ego that varies between -1 and +1. The constant in Model 3 indicates that, on average, actors end the simulation with about 28 positive ties when actors do not trade off resources for positive emotion, average dispositional affect is medium, ingroup favoritism is low, resource inequality is low, and other factors are held constant. The constant in Model 5 indicates that they end up with about 5 negative ties under the same assumptions. The tradeoff does not have a statistically significant effect on positive or negative ties. The biggest main effect is low dispositional affect. It decreases the number of positive ties from 28 to 7 and increases the number of negative ties from 5 to about 38 (compared to the base of medium dispositional affect and holding constant other factors). Low affect also interacts with high inequality (increasing the number of positive ties and reducing the number of negative ones) and with ingroup favoritism (decreasing the number of positive ties and increasing the number of positive ones). High dispositional affect has a significant effect, though smaller in magnitude than the effect of low dispositional affect. It increases the number of positive ties from 28 to 31 and decreases the number of negative ties from 5 to almost zero.

Models 4 and 6 indicate the effects of the tradeoff, dispositional affect, favoritism, and resource inequality on the centralization of the network of positive ties and of negative ties, respectively. Recall that graph centralization varies between 0 (highly decentralized) and 1 (highly centralized) and can be interpreted as a percentage. Both networks are quite decentralized. The constant in Model 4 indicates that, on average, the centralization of the positive network is 16.6 percent of its theoretical maximum; the constant in Model 6 indicates that negative

Table 1
Parameter Estimates from Regression of Organizational Outcomes on Tradeoff, Dispositional Affect, Resource Inequality, and Ingroup Favoritism.

							Positive Relationships						Negative Relationships					
							Model 3			Model 4			Model 5			Model 6		
	Model 1 Collective Affect			Model 2 Resources Transferred			Degree Centrality			Graph Centralization			Degree Centrality			Graph Centralization		
	Coeff.		Std. Err.	Coeff.		Std. Err.	Coeff.		Std. Err.	Coeff.		Std. Err.	Coeff.		Std. Err.	Coeff.		Std. Err.
Constant	0.806	*	0.015	0.999	*	0.011	0.561	*	0.013	0.166	*	0.005	0.107	*	0.020	0.035	*	0.002
Tradeoff	0.053	*	0.016	−0.041	*	0.012	0.032		0.014	0.017		0.005	−0.055		0.022	0.011	*	0.002
Favoritism	−0.005		0.016	0.013		0.012	−0.002		0.014	0.002		0.005	0.006		0.022	−0.003		0.002
Low Avg Dispositional Affect	−0.535	*	0.018	0.008		0.014	−0.418	*	0.016	−0.124	*	0.006	0.664	*	0.025	−0.027	*	0.002
High Avg Dispositional Affect	0.091	*	0.018	0.002		0.014	0.077	*	0.016	0.013		0.006	−0.104	*	0.025	−0.012	*	0.002
No Inequality	−0.016		0.018	−0.010		0.014	−0.006		0.016	−0.035	*	0.006	0.021		0.025	−0.003		0.002
High Inequality	−0.006		0.018	−0.014		0.014	−0.039		0.016	0.076	*	0.006	0.001		0.025	0.004		0.002
Low Affect X High Inequality	0.088	*	0.020	0.043		0.015	0.097	*	0.018	−0.023	*	0.006	−0.119	*	0.027	0.013	*	0.002
Low Affect X No Inequality	0.015		0.020	0.006		0.015	0.006		0.018	0.029	*	0.006	−0.017		0.027	0.003		0.002
High Affect X No Inequality	0.016		0.020	0.006		0.015	0.013		0.018	0.003		0.006	−0.020		0.027	0.002		0.002
High Affect X High Inequality	0.006		0.020	−0.004		0.015	−0.004		0.018	0.010		0.006	−0.002		0.027	−0.004		0.002
Low Affect X Favoritism	−0.062	*	0.016	−0.048	*	0.012	−0.060	*	0.014	−0.019	*	0.005	0.088	*	0.022	0.003		0.002
High Affect X Favoritism	0.005		0.016	−0.006		0.012	0.003		0.014	0.004		0.005	−0.007		0.022	0.003		0.002
No Inequality X Favoritism	0.005		0.016	0.013		0.012	0.008		0.014	−0.001		0.005	−0.011		0.022	−0.001		0.002
High Inequality X Favoritism	−0.016		0.016	0.001		0.012	−0.011		0.014	−0.014		0.005	0.019		0.022	−0.001		0.002
Low Affect X Tradeoff	0.156	*	0.016	−0.500	*	0.012	0.003		0.014	0.009		0.005	−0.083	*	0.022	0.067	*	0.002
High Affect X Tradeoff	−0.058	*	0.016	0.042	*	0.012	−0.033	*	0.014	−0.017	*	0.005	0.062		0.022	−0.014	*	0.002
No Inequality X Tradeoff	0.001		0.016	−0.004		0.012	−0.004		0.014	−0.003		0.005	0.004		0.022	0.000		0.002
High Inequality X Tradeoff	0.003		0.016	0.034		0.012	0.011		0.014	0.010		0.005	−0.021		0.022	0.006		0.002
Tradeoff X Favoritism	0.010		0.013	−0.026		0.010	0.000		0.012	0.002		0.004	−0.007		0.018	0.002		0.002
N	3600			3600			3600			3600			3600			3600		
Adjusted R Square	0.600			0.646			0.593			0.593			0.586			0.594		

Notes: *$p < .001$.

network is even more decentralized (3.5 percent of its maximum). The tradeoff is significantly associated with the centralization of negative networks, but not positive networks. When actors trade off resources for positive emotions, the network of negative ties becomes more centralized, meaning that negative relational attributions are concentrated on fewer actors. In effect, the tradeoff helps to isolate these actors. Low average dispositional affect tends to make each network more decentralized. However, for negative networks, low dispositional affect interacts with the tradeoff, tending to make the network somewhat more centralized, isolating negative actors even more. Resource inequality has a positive linear effect on the centralization of positive networks. Equality tends makes the network more decentralized, compared to the medium inequality, while high inequality tends to make it more centralized (holding constant other factors).

Comparing Model Results with Empirical Networks

We obtained secondary data on affective networks in five organizational settings: a management consulting firm, a manufacturer, a multifunctional task force in a large firm, a leadership team, and a professional (nonprofit) organization. Network surveys of these organizations included measures of "relational energy."[5] These network data enabled us to calculate indegree centrality and graph centralization for networks of positive and negative relational attributions. For comparisons, we chose the starting conditions in our model that were both realistic and produced results close to the structural features of these empirical networks. These conditions include the tradeoff of resources for positive emotions and medium average dispositional affect.

Table 2 presents indegree centrality and graph centralization for the empirical and simulated organizations. As noted above, we chose an organizational size of 50 to match the average size of these empirical

[5] The surveys of these empirical organizations collected data on "relational energy" (Owens et al., 2016), which is a measure of what we call relational attributions here. The single-item scales used in these surveys are similar to the single-item scales used in other network studies of relational energy (e.g., Baker et al., 2003) and to the items in the relational energy scale: "I feel invigorated when I interact with this person." "After interacting with this person, I feel more energy to do my work." "I feel increased vitality when I interact with this person." "I would go to this person when I need to be 'pepped up'." "After an exchange with this person I feel more stamina to do my work" (Owens et al. 2016).

Table 2
Descriptive Statistics for Empirical and Simulated Organizational Networks.

		Positive Affective Ties		Negative Affective Ties	
	Number of Actors	Indegree Centrality	Graph Centralization	Indegree Centrality	Graph Centralization
Empirical Organizations					
Management Consultants	125	24.6	.38	6.6	.20
Heavy Manufacturing	33	6.6	.59	.8	.10
Multi-Functional Task Force	30	7.3	.20	.03	.03
Industry Learning Team	45	9.0	.21	.4	.04
Non-Profit Organization	18	3.7	.39	.4	.10
Average	50.2	10.2	.35	1.7	.09
Simulated Organizations	50	27.5	.17	5.26	.05

Notes: The results for simulated organizations are estimates using the coefficients in Table 1 and the starting conditions of the tradeoff of resources for positive emotions and medium average dispositional affect (see text for details). Averages reflect rounding.

networks. Our model overestimates indegree centrality for positive affective ties but is close for negative affective ties, assuming the realistic starting conditions. The ratio of indegree centrality for positive to negative ties is quite similar: on average, about 6.2:1 for empirical networks, and about 5.2:1 for simulated organizations. Empirical positive networks are, on average, more centralized than our model estimate, though the estimate is close to the graph centralization for the multi-functional task force and industry learning team. Empirical negative networks are, on average, slightly more centralized than our model estimate, but the estimate is inside the observed range. Finally, the ratio of graph centralization for positive to negative networks is very similar: on average, about 3.77:1 for empirical networks, and about 3.53:1 for simulated organizations.

These network studies do not provide data on starting conditions, or on the macro outcomes of collective affect and resources transferred. However, in our simulated data, these two macro outcomes are highly correlated with measures of network structure. Note, too, that the realistic starting conditions are the same as the combination of factors that produced the high level of collective affect (estimated mean = .859) as illustrated by the upper path in Fig. 1. These conditions also generated high levels of resource transfer. We speculate, therefore, that these empirical organizations experienced, on average, similar levels of collective affect and resource transfer, and that these macro outcomes were the result of the tradeoff and medium average dispositional affect.

DISCUSSION

Our study brings together two separate domains of theory and research: the role of emotions in organizations and organizational network evolution. It connects the “affective revolution” in organizational behavior (Barsade et al., 2003; Barsade and Gibson 2007) with interest in the genesis and dynamics of organizational networks and their consequences (e.g., Ahuja et al., 2012; Doreian and Snijders 2012). Research on affect in organizations has shown the importance of affect for decision making, creativity, prosocial behavior, turnover, conflict resolution, engagement, and firm performance (Barsade and Gibson 2007; Cole et al., 2012; Owens et al., 2016). This line of research assumes that affect is transmitted from person to person via emotional contagion, but the micro-to-macro aggregation process is often vague or would benefit from greater specificity; hence, we lack an understanding of how affect influences network trajectories and produces variation in macro-level outcomes such as network structure, collective affect, and the distribution of resources. Research on the evolution of organizational networks says little about how affective mechanisms drive network trajectories and macro outcomes (Ahuja et al., 2012). Here, we developed a model that includes both affective and instrumental micro-mechanisms and used simulation methods to understand their effects on network trajectories and outcomes under a variety of conditions.

We made eleven assumptions about the dynamics of affective and instrumental micro-mechanisms, drawing upon and synthesizing prior work on positive emotion, positive relationships, affective primacy, emotional contagion, and collective affect. A core idea is that actors in organizations need both affective motivation and instrumental resources to get their work done, and they use their interpersonal networks to get them. When an actor gets positive emotion and resources from an interaction, the actor has the means to address a problem or perform a task plus the motivation to use those means. However, when an actor obtains resources from an interaction and suffers a reduction of positive emotion, the actor often experiences less motivation to put the resources to use. Prior theory and research indicate that, given a choice, actors will trade off affective and instrumental values, foregoing the acquisition of resources to avoid a loss of positive emotion. We focus our discussion on the dynamics that involve this tradeoff, deriving theoretical propositions from the patterns we observed. Note that these patterns emerged from uninterrupted simulation runs. In real organizations, endogenous changes (e.g., personnel turnover, new role assignments, re-locations) and exogenous impacts (e.g., shifts in market demand, legal-regulatory changes, changes in macro-economic conditions) could interrupt the evolutionary process and alter the trajectory of organizational networks and collective outcomes.

Our simulations reveal that the main effects of this tradeoff are to reduce the amount of resources transferred, raise collective affect, and isolate actors who are perceived negatively, controlling for other factors. When actors do not trade off resources for positive emotion, they acquire 100 percent of the available resources but end up with lower levels of collective affect and more decentralized networks of negative ties (i.e., negative relational attributions are more “spread out” in the organization). The main effect of the tradeoff is significant, but modest in magnitude. By itself, the tradeoff reduces the transfer of resources by only a small amount. These patterns suggest our first proposition.

PROPOSITION 1.—As an organization evolves, the tradeoff of resources for positive emotion raises collective affect and sustains high levels of resource transfer, while not trading off resources for positive emotion maximizes resource flow and depresses collective affect (ceteris paribus).

Each simulation ran for 20,000 timesteps, but by 1,000 most organizations evolved along specific trajectories (e.g., Fig. 1). Recall that we defined a meaningful unit of time as 25 timesteps, which, in our basic model, gave actors an equal probability of interacting with one another. Thus, each actor typically had about 40 interactions by 1,000 timesteps, and this time was enough to determine which trajectory most organizations would take. These patterns imply that the interplay of affective and instrumental micro-mechanisms produces a path dependent process. Path dependence is a well-known and widely observed social process (e.g., David 1985; Sydow et al., 2009) in which a number of outcomes is possible at the start (multiple equilibria), patterns in the initial stages have large consequences in the long term, the timing and sequence of events is crucial, once a process is established it leads to a particular outcome (single equilibrium), and it is difficult to alter course (Pierson 2000) though it might not be impossible (e.g., Bruch and Vogel 2011).

Path dependence occurs through recursive influence. For example, an actor's relational attributions change as a result of interacting, and the actor's updated relational attributions, in turn, influence decisions about who to interact with in the future. Recursive influence occurs between positive emotion and relational attributions, each influencing the other through positive feedback. Our model also includes negative feedback: In the absence of interaction, an actor's positive emotion tends to return to its dispositional level and relational attributions fade. But it is positive feedback that drives path dependence, creating virtuous or vicious cycles (Sterman 2000), depending on the valence of early interactions.

In a virtuous cycle, early positive interactions establish a process that increases positive emotion and makes relational attributions more positive, and the organization evolves to a state of high collective affect with positive networks. Early positive interactions are likely when actors begin with high dispositional affect. Our results show that high dispositional affect raises collective affect, increases the number of positive ties, and decreases the number of negative ties. By itself, high dispositional affect does not influence the amount of resources transferred. Coupled with the tradeoff, however, high dispositional affect makes up for any loss in resources transferred when actors trade resources for positive emotion. The two-way interaction of high affect and the tradeoff cancels out the (modest) elevation of collective affect produced by main effect of the tradeoff, but collective affect remains high. With or without the tradeoff, starting with high average dispositional affect produces positive early interactions, yielding high levels of both collective affect and resource transfer. Hence, our next proposition:

PROPOSITION 2.—Whether or not organizational actors trade off resources for positive emotions, when early interactions are positive, the organization tends to evolve on path that maximizes the flow of resources and yields high collective affect; it also produces more positive ties and fewer negative ties (ceteris paribus).

Is Proposition 2 plausible? Are there real-world referents for high dispositional affect? Examples include Southwest Airlines (Gittell 2003), W. L. Gore and Associates (Manz et al., 2009), Valve Corporation (Felin and Powell, 2016; Purnam and Håkonsson 2015), and Zingerman's Community of Businesses (Burlingham 2005). These organizations are known for their positive workplace cultures and high levels of cooperation and resource sharing. They have in common human resource practices known colloquially as "hiring on attitude" or "hiring on values, " or what we would call hiring for high dispositional affect. Southwest, for example, "places a great deal of importance on the hiring process to identify people with relational competence" (Gittell 2003:86). This process emphasizes soft skills, especially having "the right attitude." As a Southwest employee put it, "One thing we cannot teach is attitudes toward peers…. You find an individual with an upbeat attitude—and you'll find that everything that needs to be done, will get done. It's very contagious" (Gittell 2003:86). Generally, "positive attitude" (high dispositional affect) is an important ingredient of a positive organizational climate (Cameron 2012:25; Staw and Barsade 1993).

A vicious cycle is created when early negative interactions depress positive emotions and turn relational attributions more negative; the organization evolves to a state of low collective affect with negative networks. Early negative interactions are likely when actors begin with low dispositional affect. But even with medium or high dispositional affect, if enough early interactions are negative, a vicious cycle could be created. The tradeoff micro-mechanism complicates the process. When it operates, it partly offsets the impact of low dispositional affect, as indicated by the two-way interaction of these two factors.[6] Low dispositional affect means that many actors will be perceived as drains on positive emotion. The tradeoff allows actors to avoid interacting with them and may isolate negative actors. But doing so comes at a steep cost: the amount of resources transferred is cut by at least half.

PROPOSITION 3a.—When early interactions are negative and organizational actors trade off resources for positive emotion, the organization tends to evolve on a path that severely reduces the flow of resources and yields low collective affect; but it also produces fewer and more concentrated negative ties (ceteris paribus).

PROPOSITION 3b.—When early interactions are negative and organizational members do not trade off resources for positive emotion, the organization tends to evolve on a path that maximizes the flow of resources but yields very low collective affect; the organization produces fewer, more concentrated positive ties, as well as more negative ties that are spread out in the organizational network (ceteris paribus).

Are there examples of organizations with low collective affect? Dysfunctional organizations with toxic cultures have been documented (e.g., Goldman 2006) that could be referents for Propositions 3a and 3b, but we are not aware of research that explicitly examines the social networks of such organizations. There is research on negative relationships in (mostly positive) social networks (e.g., Labianca and Brass 2006). It may be that organizations do not last long after becoming extremely dysfunctional, or that interventions are employed to stall or prevent the formation of highly dysfunctional networks. Propositions 3a and 3b may represent the theoretical lower bounds of possible empirical organizations.

A central tenet of our study is that people need both instrumental resources and positive emotions to accomplish their work, and, if possible, will trade resources for positive emotion. Allowing organizational members to choose their interaction partners and trade off instrumental and affective values would evolve networks that give actors the instrumental resources they need *and* the motivation to use them. But these outcomes depend on the valence of early interactions. Early negative interactions are likely when actors begin with low average dispositional affect and trade off. If so, then networks evolve on a path that yields neither the resources nor the collective affect actors need; if they cannot trade off, then they are left with an abundance of instrumental resources but little affective motivation to use them. Early positive interactions are likely if actors begin with high dispositional affect. But early positive interactions are also likely if actors begin with *medium* dispositional affect and are able to trade off resources for positive emotions. This appears to be the case in the five empirical organizations in Table 2 as well as prior empirical studies of affective networks in organizations (e.g., Baker et al., 2003; Casciaro and Lobo 2008). Our results suggest that, as long as actors can trade off, beginning with medium dispositional affect is enough to set organizations on a positive path and provide actors with both the instrumental resources and positive emotions they need.

CONCLUSION

Affect is an integral part of organizational life. In the workplace, people need both affective and instrumental resources to get their work done, and they use their interpersonal networks to acquire them.

[6] From Table 1, we note that low average dispositional affect also interacts with high inequality (e.g., increasing collective affect but not influencing resource transfer) and with ingroup favoritism (e.g., decreasing both collective affect and resource transfer). These interactions are not covered by the theoretical framing of this study, nor by the eleven assumptions. Therefore, in the absence of theoretical guidance and in the interest of parsimony, we refrain from offering theoretical propositions about these interactions.

Collective affect is produced in the process, which in return influences the interpersonal flow of affect and impacts both individual and organizational performance. However, the precise causal relationships between the micro and the macro have not been well understood. Research on affect in organizations has tended to focus on micro-dynamics, while research on organizational network evolution has largely neglected the role of affect. Our study connects these two separate streams of theory and research. We developed a formal model that includes both affective and instrumental micro-mechanisms. We used simulation research to understand micro-dynamics, network trajectories, and macro-level organizational outcomes such as collective affect, network structure, and resource diffusion. The model we propose here is only the beginning. We sought to find a simple explanation for how realistic organizational networks might evolve when we assume that people trade off resources for positive emotion, and we found that a handful of assumptions are sufficient for generating realistic outcomes. However, as we pointed out, there are many endogenous and exogenous factors which could also be added into the model, which also affect network evolution such as turnover or environmental shocks. Even so, our simulation findings yielded new theoretical propositions about affect in organizations. We hope that our study will stimulate future research on the role of affect in organizations and encourage evolutionary network theorists to include affect in their models.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.socnet.2020.08.007.

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