Homophily and Segregation in Cooperative Networks[1]

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Social networks affect individuals' ability to solve conflicts between individual and collective interests. Indeed, the ability to seek out cooperative others is a key explanation for the high levels of cooperation observed in social life. In contrast to existing research on cooperation and networks, sorting in the real world is typically driven by homophily, or similarity on socially significant attributes like ethnicity or religion. Here the authors develop and test an argument about how homophily alters network dynamics and cooperation using a large web-based experiment and an agent-based model. They find that homophily promotes cooperation, net of key determinants of cooperation. Further, homophily drives the selection of new ties, increasing clustering in dynamic networks. The authors also demonstrate the consequences of in-group preferences for between-group segregation. Their results therefore shed light on how cooperation can evolve in networks and how this process contributes to network-level segregation.

Much of social life is characterized by tension or conflicts between what is good for collectives and the individuals that comprise them. These situations

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are called "social dilemmas," and they are both fundamental to—and ubiquitous in—social life. At the microlevel, social dilemmas occur in dyadic collaborations in households and the workplace, where each party to an interaction benefits most (e.g., in time or money) if she allows her partner to take on the burden of the work or costs. But if each does so, both would be worse off than if they had both "cooperated" by putting forth more effort. Beyond dyads, communities and organizations face social dilemmas in managing scarce community resources (Ostrom 1990) and mobilizing social movements (Marwell, Oliver, and Prahl 1988). And some of the most pressing global issues, from nuclear arms races (Plous 1985; Komorita and Parks 1996) to climate change (Milinski et al. 2008; Bisaro and Hinkel 2016), result from conflicts between what is in the short-term interest of members of individual nations and what is best for humanity as a whole. As Kollock (1998, p. 183) put it, "Many of the most challenging problems we face, from the interpersonal to the international, are at their core social dilemmas."

As early as Hobbes ([1651] 1996), scholars have asked how groups and communities overcome social dilemmas and thus how social order is possible. Hobbes was pessimistic, pointing to an omnipotent state as the only viable solution. In the absence of such a "Leviathan," Hobbes predicted infamously that life would be "solitary, poor, nasty, brutish and short." Fortunately, cooperation is common outside the purview of all-powerful states, suggesting that social order is possible even when not imposed from the top down.

Early sociological solutions to the "Hobbesian problem of order," most notably Parsons (1937), explained cooperation and other prosocial behaviors via the internalization of norms, whereby collective interests and values are internalized into individuals' value systems. But as Wrong (1961) persuasively argued, while Hobbes's solution is "undersocialized" in its failure to recognize the social mechanisms that push people to act prosocially, Parsonian solutions are "oversocialized," going too far in the other direction. These latter solutions assume the problem of order away and predict more cooperation than is typically observed in the absence of close monitoring and enforcement.

A middle ground emerged out of economic sociology (Granovetter 1985; Raub and Weesie 1990; see Krippner and Alvarez [2007] for a review of the various approaches to embeddedness and their development within

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economic sociology) and the integration of social network approaches with evolutionary game theory (Macy 1991; Raub, Voss, and Weesie 1992; Nee and Ingram 1998; Nowak 2006; Burger and Buskens 2009). These approaches account for the embeddedness of people and organizations in broader social networks as core determinants of the patterns of cooperation and prosocial behavior we observe in the real world.[2] As Granovetter anticipated, these "embeddedness" explanations improve on undersocialized conceptions by specifying how embedded social relations incentivize cooperation. They also improve on oversocialized models that predict near total cooperation since "networks of social relations penetrate irregularly and in differing degrees in different sections of economic life, thus allowing for what we already know: distrust, opportunism, and disorder are by no means absent" (Granovetter 1985, p. 491).

Recent work on networks and cooperation has focused particularly on the role of network dynamics in shaping network topology and cooperative interactions. This work consistently shows that dynamic networks, where individuals can sever ties to interaction partners and form new ties, promote cooperation to a greater extent than static networks, where ties are stable and cannot be altered (Fehl, van der Post, and Semmann 2011; Rand, Arbesman, and Christakis 2011; Bravo, Squazzoni, and Boero 2012; Wang, Suri, and Watts 2012; Melamed, Harrell, and Simpson 2018). Yet, with some important exceptions (Eguíluz et al. 2005; Corten and Cook 2009; for a review, see Simpson and Willer 2015), most of this recent work has emerged outside of sociology and, perhaps as a consequence, neglects the bases on which people actually form social relations and the implications of those bases for behavior (Coleman 1990; Portes 1998; McPherson, Smith-Lovin, and Cook 2001). Instead, existing work focuses on whether cooperative "types"—defined as those with relatively stable preferences for cooperation (Van Lange et al. 1997; Kurzban and Houser 2005; Simpson and Willer 2008)—can "find" and selectively form ties with each other in dynamic networks (Rand et al. 2011; Wang et al. 2012; Melamed, Simpson, and Harrell 2017).

But in the real world, there is limited evidence that human relationships are characterized by a tendency for cooperative types to be tied to one another at levels greater than chance (Simpson et al. 2014). There is, however, strong evidence, documented in decades of sociological research (Ibarra 1992; McPherson et al. 2001; Ruef, Aldrich, and Carter 2003; Kossinets and Watts 2009; Centola 2011; Smith, McPherson, and Smith-Lovin 2014),

[2] More generally, existing sociological work imagines a middle ground, where "rules, reputations and relations" (Simpson and Willer 2015, p. 45) lead to outcomes that are neither the "war of all against all" that Hobbes imagined nor as cut through with cooperation as Parsons's solution predicts. Recent examples include Baldassarri (2015), Kuwabara (2015), Mark (2018), and Simpson et al. (2018).

that humans form relationships via *choice-based homophily*, or the tendency to preferentially associate with those who share category memberships based on ethnicity, religion, social class, or other identities. Thus, our current understanding of how network dynamics shape widespread cooperation is at odds with how humans form social ties to one another in the real world. We argue that bringing in fundamental sociological insights on homophily processes will yield clearer understandings of how and when cooperative relationships form and the implications for network topology and overall cooperation. In this vein, we show how homophily shapes cooperation and network dynamics and, in turn, how these processes shape aggregate network-level outcomes.

The next section outlines our arguments about how choice-based homophily affects network dynamics and cooperation in networks. We argue that homophilous interactions will increase cooperation net of other powerful predictors of cooperation and that homophilous sorting will increase clustering in networks, that is, yield small groups within the networks that are densely tied. Further, given homophily-based sorting, we expect the emergence of segregated ties between individuals with membership in distinct social categories (Henry, Prałat, and Zhang 2011). Thus, the tendency to be more cooperative with in-group members leads to increasing segregation between groups, as well as inequalities between homophilous and heterophilous communities in the rewards from social cooperation.

COOPERATION IN DIFFERENTIATED NETWORKS

Early research on networks and cooperation focused on static networks, where ties cannot be altered (Rand and Nowak 2013; see also Trivers 1971). This work focused on how opportunities to repeatedly interact with others on the basis of geography (Hauert and Doebeli 2004) or social network structure (Nakamaru, Matsuda, and Iwasa 1997; Rand et al. 2014) increase the likelihood of cooperation between neighbors. For instance, clustered networks (i.e., those containing densely tied subgroups) yield higher rates of cooperation than networks where ties are formed at random (Assenza, Gómez-Gardeñes, and Latora 2008; Melamed et al. 2018).

But research on static networks fails to capture a fundamental feature of human social networks—they emerge, persist, and change via the individual and joint choices of those embedded in them. Additional research has focused on dynamic networks where relations can change through time. This work consistently demonstrates that dynamic networks yield higher rates of cooperation than static networks (Pacheco, Traulsen, and Nowak 2006; Santos, Pacheco, and Lenaerts 2006; Fehl et al. 2011; Rand et al. 2011; Wang et al. 2012). This may happen for several reasons: (i) cooperators "punish" noncooperators by severing ties to them, and the threat of isolation can increase the incentive to cooperate, and (ii) those who are more cooperative can "find" and selectively sort with one another on the basis of reputational information (Fu et al. 2008; Wang et al. 2012) or the ability to signal and read "telltale signs of character" and form relations on those bases (Frank 1988; Macy and Skvoretz 1998).

Finding cooperative others via reputational information is much less straightforward in the real world, where both the connection between prior behaviors and reputation and the predictive power of reputation for future behaviors can be tenuous. Existing work on networks and cooperation solves the problem of linking prior behaviors to reputations by giving participants objective "reputation scores" based on the proportion of times the person cooperated in the past. But reputations, particularly those of people to whom we are not connected, are rarely, if ever, this clear-cut. First, some individuals in networks attract a disproportionate amount of attention, which has important consequences for how—or whether—reputations are linked to previous behaviors. For example, Anderson and Shirako (2008) found that only the reputations of those who were centrally connected in a group were linked to their previous behaviors. Second, a number of factors create a tenuous connection between previous behaviors and reputations, from strategic impression management by those seeking to establish or reclaim a reputation as a cooperative or trustworthy person (Gambetta and Przepiorka 2014) to inaccurate gossip or sabotage by competitors or previous partners who feel (justly or not) wronged by the target (Vaidyanathan, Khalsa, and Ecklund 2016). For these reasons, reputation is not always a straightforward selection mechanism to identify cooperative partners or a good indicator of past behavior.

More generally, knowledge of the extent to which prospective partners are cooperative may shape network formation in controlled network experiments where reputations are based explicitly on past behavior and where interactants have no access to other cues or information on which to form ties. But in the real world, there is limited evidence that cooperative dispositions shape network formation. Across multiple studies, Simpson and colleagues (2014) found no evidence that those with more cooperative dispositions were more likely to be friends with each other than would be expected by chance. Indeed, participants in their studies who were paid to predict how cooperative or egoistic their friends were did no better than chance.

Although there is no evidence that cooperative "types" are more likely to sort with one another in real world relations, there is abundant evidence of homophily along many other dimensions (Ibarra 1992; McPherson et al. 2001; Ruef et al. 2003; Kossinets and Watts 2009; Centola 2011; Smith et al. 2014). Individuals form homophilous ties for a variety of reasons, including an increased propensity to trust similar others (Brewer 1999; Newton, Stolle, and Zmerli 2018) and presumed ease of interaction (Carley 1991). Homophily is known to promote interaction across a wide range of issues and contexts (McPherson et al. 2001), facilitating coordination and communication (Wimmer and Lewis 2010). Part of the reason that homophily has these effects is that it is a basis of social balance (Davis 1963; Moody 2001). If two individuals are similar along one dimension, they are more likely to have a similar orientation toward another individual, issue, or action (Heider 1946; Cartwright and Harary 1956; Rawlings and Friedkin 2017).

Similarity is especially important under conditions of risk and uncertainty (Coleman 1990). A large body of prior research shows that we tend to trust and cooperate with others who share our social identities to a greater extent than strangers or members of other categories (Kramer and Brewer 1984; Brewer and Kramer 1986; Kollock 1997; Chen and Li 2009; Foddy and Yamagishi 2009; Romano et al. 2017; see Balliet, Wu, and De Dreu 2014 for a meta-analysis). These effects have been observed not only for ethnicity (Simpson, McGrimmon, and Irwin 2007), political party (Koopmans and Rebers 2009), and nationality (Romano et al. 2017) but also, as in the "minimal groups paradigm," for completely arbitrary categories (such as a tendency to under- or overestimate dots on a screen or a preference for the paintings of Klee vs. Kandinsky; Tajfel et al. 1971; Yamagishi, Jin, and Kiyonari 1999; Yamagishi and Kiyonari 2000; Aksoy 2015, 2019). This is because, as Brewer (1999, p. 433) notes, shared categories create "bounded communities of mutual trust and obligation that delimit mutual interdependence and cooperation." Combined, this work suggests that, when individuals are distinguished by recognized social categories or social identities, they will cooperate with in-group members at a higher rate.

Hypothesis 1.—*Homophily on social categories promotes cooperation.*

Hypothesis 1 predicts higher levels of cooperation within homophilous ties than within ties that are heterophilous or when identity information is unknown. Thus, we expect homophily to play a role in both static networks, where network structure is imposed exogenously (such as when organizations dictate work groups), and dynamic networks, where network structures emerge from the aggregation of individual choices about forming and maintaining ties (such as friendship networks). As noted above, hypothesis 1 is informed by prior work. But here we are interested in the consequences of such in-group cooperation. Accordingly, we also argue that identities will play a critical role in shaping ties and, as a result, the structure of social networks. Specifically, in dynamic networks, we expect that people will preferentially initiate new ties to fellow category members, even net of reputations, that is, information about past cooperative behavior (Aksoy 2015). This is because reputations, at least how they are typically theorized and investigated, are indicators about how a prospective alter treats people in general. Identities, however, carry prescriptions about how the particular other is likely to treat people like me (Yamagishi and Kiyonari 2000). As a consequence, as noted above, we tend to trust fellow category members under conditions of risk and uncertainty (Brewer 1999; Buchan, Croson, and Dawes 2002; Simpson et al. 2007; Romano et al. 2017). Again, previous research shows these effects across a wide range of different real world and manipulated identities (see Balliet et al. [2014] for a review). This expectation of more benign treatment by fellow in-group members should lead to preferential tie formation with fellow category members.

For reasons outlined above, we expect that a preference for sorting with similar others will be particularly strong under conditions of risk and uncertainty, like many social and economic exchanges (Coleman 1990; DiMaggio and Louch 1998; Molm 2010). But the broader homophily literature suggests additional mechanisms that push network relations toward homophily, beyond expectations of more favorable treatment from in-group members. For instance, in-group members are assumed to be more similar than out-group members (Tajfel and Turner 1979; Turner 1991), and similarity drives attraction and affiliation (Heider 1946; Cartwright and Harary 1956). As such, when given the opportunity to form new relationships, we expect individuals to disproportionately initiate homophilous ties.

Hypothesis 2.—*New ties will be more likely to be homophilous.*

Assuming hypothesis 2 holds, as has been demonstrated many times in the social networks literature (see McPherson et al. 2001 for a review), over time the ties of category members will become more homophilous. One relational consequence of increasing homophily is that there will be more within-group ties, resulting in an increase in network clustering. As Goodreau, Kitts, and Morris (2009, p. 107) put it, clustering will increase “since increasing the likelihood of within category ties enhances the opportunity for completed triangles within categories.” Given this, a corollary to hypothesis 2 is as follows:

Corollary 1.—*Increases in homophilous ties will increase clustering.*

Relatedly, assuming hypothesis 2 holds, relationships in the network will become increasingly segregated over time. That is, the process of selecting alters who one expects will be most cooperative will lead to segregation. As such, we distinguish between homophilous ties and network segregation—one result of homophily at above chance rates is the segregation of ties within the network. Thus, a second corollary to hypothesis 2 that can be stated at the network level is as follows:[3]

[3] It is possible for either corollary to be true, while the other is false. For example, in large networks, homophily may increase tie segregation but not clustering. Conversely, clustering can increase without corresponding increases in tie segregation if the clusters are composed of agents from different groups.

COROLLARY 2.—*Increases in homophily will result in tie segregation between groups.*

While hypothesis 2 itself is a straightforward prediction, our corollaries 1 and 2 offer novel insights into how these basic social psychological and network processes shape aggregate patterns, and the consequences of those patterns for segregation and group outcomes.

Finally, given a tendency to cooperate more with in-group members versus out-group members, we expect more homophilous communities—whether imposed exogenously in static networks or formed endogenously via tie alteration in dynamic networks—to be characterized by higher levels of cooperation. And because cooperation results in the best collective outcome, over time such heightened cooperation will lead to higher levels of benefits for those embedded in identity-based communities. Therefore, we expect the following result:

HYPOTHESIS 3.—*Those in more homophilous communities will receive more benefits from cooperation, compared to those in less homophilous communities.*

Note that literature on the "dark side" of social capital (Baker and Faulkner 2004; Yenkey 2018; see also Portes 1998) suggests compelling counter-hypotheses to those advanced above. Specifically, identity-based communities may perform worse than those that emerge based solely on sorting by cooperative behaviors. From this perspective, while we are more apt to trust fellow category members, this trust opens the door to exploitation by opportunistic category members. Indeed, misplaced trust in category members is the basis for well-known cases of "affinity fraud," such as Bernie Madoff's abuse of trust of fellow Jewish Americans, who represented a disproportionate number of his investors. But our arguments suggest that such cases are exceptions that prove the rule: affinity fraud works because choice-based homophily typically results in high levels of trust and social cooperation. Consistent with our argument, we show that homophilous communities are characterized by higher levels of cooperation than other communities. Additionally, we provide evidence for the theoretical process underlying the formation of these communities.

ANALYTIC STRATEGY

To test our hypotheses, we first conducted an experiment with participants embedded in networks. Interactions, like many social and economic exchanges, were characterized by risk and uncertainty. Following related work (Fehl et al. 2011; Rand et al. 2011; Jordan et al. 2013; Aksoy 2015; Melamed et al. 2017, 2018), we structured the interaction between participants as a prisoner's dilemma, the standard approach to capturing the conflict between individual and collective interest inherent in a wide range of social exchanges and social interactions (Bonacich and Light 1978; Axelrod 1984; Heckathorn 1988, 1996; Raub and Weesie 1990; Macy 1991; Kollock 1998; Macy and Skvoretz 1998; Lawler, Thye, and Yoon 2000). In its most basic form, and in our experiment, each individual simultaneously chooses to "cooperate" or "defect," although in the experiment we avoid the use of these loaded terms. Mutual cooperation is more beneficial than mutual defection; at the same time, short-term self-interest is maximized by defecting regardless of what the other person does. Social scientists have relied on the prisoner's dilemma to model not only cooperation in networks but also a variety of other real world conflicts and interactions, including the production of public goods (Hardin 1982), effort in the workplace (Petersen 1992), investment in joint ventures (Lawler et al. 2000), trench warfare (Axelrod 1984), and, as noted above, the various microinteractions that produce macro social order.

In our networks, participants made decisions to cooperate or defect independently with each of the others to whom they were tied. Note that much past work on cooperation in networks has instead forced participants to make a single decision to cooperate or defect with all of the others to whom they are connected (Rand et al. 2011; Wang et al. 2012; Shirado et al. 2013). But in real world interactions, we are typically able to cooperate in some of our relationships, including, most relevant here, our homophilous relations, while behaving less cooperatively in others (Melamed et al. 2018). As a result, we allow participants to make decisions to cooperate or defect with each other person to whom they are connected in the network (Fehl et al. 2011; Melamed et al. 2018).

To manipulate social identity, we conducted our experiment with participants from two universities interacting with one another in real time. In half of our networks, university affiliations were displayed, enabling participants to distinguish between those with whom they shared or did not share category membership. Note that, as described above, much past sociological work on homophily processes has instead centered on homophily in sociodemographic characteristics, including gender, race, age, religion, and social class (Ibarra 1992; McPherson et al. 2001; Ruef et al. 2003; Kossinets and Watts 2009; Wimmer and Lewis 2010; Centola 2011; Smith et al. 2014; Leszczensky and Pink 2019). But these demographic characteristics, unlike university affiliation, also commonly entail cultural notions of expected cooperation, whether accurate or stereotypical (e.g., "women tend to be more cooperative"; Sell and Kuipers 2009). These preexisting perceptions of who is more likely to cooperate could also yield homophilous clusters, but they are due to shared perceptions of who is more cooperative and thus preferred as a partner in general rather than preferences for associating with similar others. To conduct a more carefully controlled test of the role that preferential associations with similar others plays in promoting cooperation, we follow past work that uses shared university affiliation as the basis for group categorization (Mackie, Worth, and Asuncion 1990; Foddy and Yamagishi 2009; Steffens, Haslam, and Reicher 2014).

The next section outlines the behavioral experiment designed to test our hypotheses. The experiment also allows us to test the first corollary to hypothesis 2 (increased clustering). Thereafter we use the experimental data to train agents in a simulation of the longer-term consequences of individual decisions for network structure. This enables us to investigate the macrolevel consequence of in-group preferences on the segregation of social relationships (corollary 2).

THE EXPERIMENT

Participants and Design

Participants were recruited from the general student populations of two universities. The students responded to the opportunity to take part in a study for course credit and earned a monetary bonus based on the number of points they accrued from their own and others' decisions over the course of the study. Experimental sessions were scheduled so that students from both universities would participate simultaneously. We required a total of at least 11 students, with no fewer than two students from each university, in order to start the session.[4] In total, 646 participants, embedded in 40 networks, completed the study. Total network sizes ranged from 11 to 25, with a range of 5–14 students from university 1 and 2–14 students from university 2 (average network size = 16.2). Figure 1 presents a histogram of the number of participants per network.

As described in more detail below, we manipulated three factors: (1) whether the network was dynamic or static, (2) whether identity information about one's own and others' university affiliation was shown, and (3) whether reputation information about one's own and others' past cooperation was shown. Whether the network was dynamic or static was manipulated within subjects: all groups completed both a dynamic network phase and a static network phase, in random order.[5] Whether identity information

[4] We intended to have networks no smaller than 12, but on one occasion, we ran a session with 11 participants.

[5] Participants also completed a third phase in which their individual ties were randomly assigned to be either static or dynamic. This third condition was completed for a separate project that used only the no-identity-information conditions to examine how the presence of dynamic ties in networks promotes cooperation (Harrell, Melamed, and Simpson 2018), and we do not make explicit predictions about these networks here. As a result, this condition is omitted from analyses. Where relevant, we include statistical controls for the sequence of phases and for whether the participant completed a phase first, second, or third.

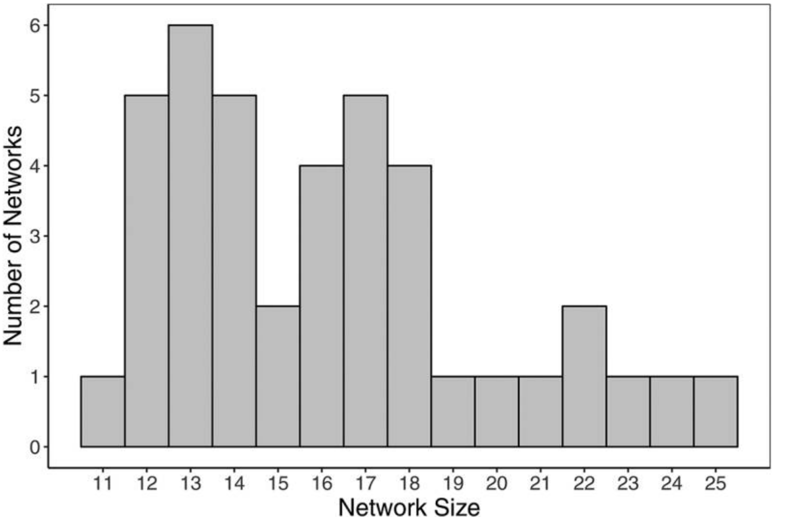

FIG. 1.—Histogram of the number of participants per network.

and reputation information were shown was manipulated between subjects. Crossing these two between-subjects factors yielded a four-condition experiment; we collected data on 10 networks in each condition.

Procedure

As participants arrived to the laboratory at each university, they were seated at an isolated computer station. Before starting the study, participants read a consent form detailing the study procedures, length of the study, and their expected payment for participating. Thereafter, a custom web app displayed the instructions (see screen shots in online app. B). A number of comprehension check items, with feedback, were included in the instructions. Following the instructions and comprehension check questions, the web app assigned each participant an identifying letter and a position within a randomly generated network (average density = .21, corresponding to an average of 3.4 ties per participant). Then it recorded their behaviors as they interacted with other participants located at their own and the other university.

As noted above, the basic task was a prisoner's dilemma decision with each of the participant's alters in each round of interactions. Participants began each phase with 1,000 monetary units (MUs). In each round of the phase, they made the decision to cooperate or defect independently with each of the alters to whom they were tied. Following related work (Rand et al. 2011; Melamed et al. 2018), cooperation (referred to in the study instructions as "giving") entailed paying 50 MUs, which resulted in the alter gaining 100 MUs. Defection ("keeping") entailed paying nothing and generating no benefits for the alter. As a result, if both the participant and alter cooperated, they both received 50 MUs (−50 MUs + 100 MUs each). If both defected, their earnings did not change. If one cooperated and one defected, the partner choosing cooperation lost 50 MUs while the defector earned 100 MUs. Participants were told in advance that the MUs they earned throughout the study would be translated into dollars as their bonus for participating.

In the dynamic network phase, after every three rounds, participants could choose whether they wanted to sever a tie and initiate a tie to a new alter.[6] Specifically, after viewing the outcome of the decision with each of their ties (i.e., whether the alter cooperated or defected and the resulting earnings from that tie), participants viewed a list of their ties sorted by their alters' identifying letter. They could choose whether to sever a tie to one alter or to sever no ties. If they chose to sever a tie, they selected which tie to sever. They then proceeded to a new screen displaying a list of potential new alters and were asked to choose one new alter with whom to initiate a new tie. Prospective alters were all those not currently tied to the participant, including those the participant had dropped in prior rounds. Participants who chose not to shed a tie to an alter could not initiate a new tie. Thus, choosing to drop a tie did not lead to a greater number of ties. Rather, dropping one tie created an opportunity to replace that tie.

Those to whom new ties were initiated were allowed to approve or decline the initiated tie. That is, while ties could be dropped unilaterally, new ties could only form bilaterally if both partners agreed (Wang et al. 2012; Melamed et al. 2018). Ties were not replaced for participants who were dropped (Rand et al. 2011; Shirado et al. 2013; Melamed and Simpson 2016; Melamed et al. 2017). Any participant who lost all of her ties became an isolate and was excluded from both the network and the tie selection process for the remainder of the phase.

In the static network phase, participants remained tied to the same alters over the course of the phase. Each phase lasted 12 rounds, although participants were not told how many rounds to expect. Nor were participants in the dynamic networks phase told exactly how often tie-dropping rounds would occur, only that they would happen "periodically" (Wang et al.

[6] Shirado and colleagues (2013) demonstrate that there is a "Goldilocks effect" of the tie alteration rate in dynamic networks: when the rate is too high, cooperators cannot avoid defectors; when it is too low, cooperators cannot selectively form ties with fellow cooperators. As a result, as in past work (Wang et al. 2012; Melamed et al. 2018), we allow tie altering opportunities every several rounds, rather than every round.

2012). After completing the first phase (either static or dynamic, chosen at random), participants completed instructions for the other phase, were randomly assigned a new position in a new random network, and were given a new randomly generated identifying letter and a new 1,000 MUs.

There were two between-subjects conditions: whether identity information was available and whether reputation information was available. We manipulated the presence of identity information by either revealing participants' university affiliations or not (Mackie et al. 1990; Steffens et al. 2014). Specifically, as noted above, all networks included students from two universities (here, called university 1 and university 2; in the actual experiment, the universities were referred to by their names and initials). Only in the identity information condition were these affiliations revealed, via labels attached to participants' identifying letters. For example, those in the identity information condition saw "U1-A" if they were tied to participant A and participant A was at university 1. In the no-identity-information condition, they only saw the alter's identifying letter (i.e., A). Labels were displayed both when making decisions in the prisoner's dilemma and, in the dynamic condition, when making the decision to sever ties and select and approve new ties.

Following related work, we manipulated reputational information by either displaying reputations or not when participants initiated and approved new ties in the dynamic network phase. Specifically, reputation was operationalized as the proportion of times participants had cooperated in previous rounds within the current phase (Wang et al. 2012; Melamed et al. 2018). To clearly distinguish between identity-based sorting and reputation-based sorting, reputations were "global," that is, not specific to one's own versus the other category. That is, an alter with a reputation of 50% had cooperated with 50% of her ties in the previous rounds of the current phase. After completing all phases of the study, participants were paid on the basis of the number of MUs they had accumulated over the course of the study and dismissed. There was no deception.

RESULTS

Cooperation

Figure 2 shows the proportion of cooperation by round. In the dynamic networks (fig. 2*A*), there is a steplike increase in cooperation after each opportunity to alter ties (i.e., after every three rounds), generally followed by a slow decrease in cooperation until the subsequent opportunity to change ties. Cooperation in the static networks (fig. 2*B*) trails off slowly and much more smoothly than in the dynamic networks. These findings are consistent with prior work (Rand et al. 2011; Shirado et al. 2013; Melamed et al. 2018).

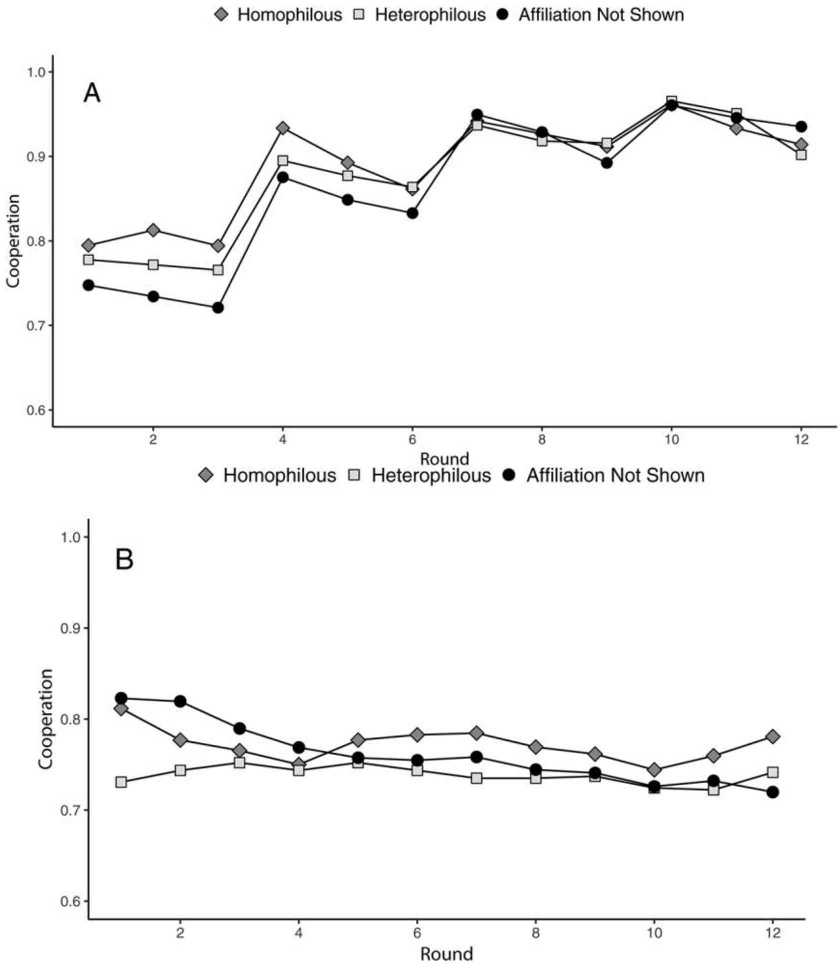

FIG. 2.—Average cooperation by round in dynamic (*A*) and static (*B*) networks with affiliations not shown, with homophilous others, and with heterophilous others.

Table 1 presents the results of a mixed-effects logistic regression predicting cooperation.[7] In addition to our manipulated factors, reputation information and identity information, model 1 controls for a variety of other factors. First, we include a term for direct reciprocity (i.e., whether the alter cooperated in the previous round), which is known to have a strong effect

[7] The convention in this literature is to use multilevel or mixed-effects models (Wang et al. 2012; Melamed et al. 2018) or to cluster by participant and session (Rand et al. 2011), with the former accounting for more residual variation. We use mixed-effects models to analyze our data. This accounts for nesting resulting from multiple decisions per round, multiple rounds per person, and multiple people per network.

TABLE 1
FOUR-LEVEL GENERALIZED LINEAR MIXED MODELS PREDICTING COOPERATION

	Model 1		Model 2	
	β	AME	β	AME
Affiliation shown (A, =1)	.22	.02	.21	.02
	(.20)	(.01)	(.20)	(.01)
Same school (S, =1)	−.03	−.00	−.03	−.00
	(.06)	(.00)	(.06)	(.00)
A × S	.21*	.02*	.21*	.02*
	(.09)	(.01)	(.09)	(.01)
Dynamic network (D, =1)	.64***	.05***	.65***	.05***
	(.07)	(.01)	(.07)	(.01)
Reputations shown (R, =1)	.50*	.04*	.51*	.04*
	(.20)	(.01)	(.20)	(.01)
D × R	.23*	.02*	.23*	.02*
	(.11)	(.01)	(.11)	(.01)
Alter cooperated on the previous round (=1)	3.72***	.42***	3.74***	.42***
	(.05)	(.01)	(.06)	(.01)
Dynamic network came first (=1)	.11	.01	.10	.01
	(.19)	(.01)	(.19)	(.01)
Second phase of the experiment (=1)	.84***	.07***	.83***	.07***
	(.12)	(.01)	(.12)	(.01)
Third phase of the experiment (=1)	1.50***	.11***	1.45***	.11***
	(.19)	(.02)	(.20)	(.02)
White (=1)			.16	.01
			(.16)	(.01)
Female (=1)			−.27	−.02
			(.15)	(.01)
Age			.01	.00
			(.03)	(.00)
Constant	−2.22***		−2.16**	
	(.29)		(.67)	
Variance component:				
Round	1.43		1.43	
	(.09)		(.09)	
Participant	2.34		2.34	
	(.19)		(.19)	
Network	.18		.18	
	(.09)		(.09)	
McFadden's Pseudo-R^2	.29		.29	

NOTE.—SEs are in parentheses. Coefficients for rounds 2–12 and 14–23 are excluded for brevity. N = 44,438 network participant round alters.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

on cooperation (Nowak 2006). Accordingly, the first round in each phase is excluded since alter's cooperation in the previous round is necessarily missing. Second, we include a dummy variable for whether the participant completed the dynamic network before the static network. Third, we include two additional dummy variables denoting phases in the experiment. Specifically, we included a dummy for the second and third phases, meaning that phase 1 is the reference category. This captures experience and timing of the experience. While parameter estimates are not reported in table 1, we also included a series of dummy variables for rounds 2–12 and 14–23. Dummies for rounds 1 and 13 are missing because of controls for decisions in the previous round of the phase (i.e., direct reciprocity). Round 24 was omitted as the reference category.

Controlling for all other factors, participants cooperated 87% of the time in dynamic networks and 76% of the time in static networks. This difference is significant ($\beta = .64$, $P < .001$) and consistent with previous work (Rand et al. 2011; Wang et al. 2012).

Turning to our key predictions, in support of hypothesis 1, we find that cooperation increases when interacting with an alter from the same university when identity information is present ($\beta = .21$, $P = .04$).[8] That is, participants were more likely to cooperate with homophilous others. Model 2 in table 1 includes individual-level controls for race category, gender, and age. These factors are not associated with cooperation and do not affect the relationship between homophily and cooperation, as can be seen by the fact that the average marginal effect (AME) for homophily is the same in both models in table 1.

Table 2 presents two more models of cooperation, showing that the homophily effect found in table 1 does not vary by whether the network was static or dynamic (fig. 2 and table 2, model 1) or whether reputation information was shown (model 2). Reputations have an impact on cooperation (fig. 3) but do not alter the positive effect of shared university affiliation. The AMEs for the three-way interactions between affiliations being known, being from the same university, and dynamic networks or reputations are not significant. These findings are important as they show that the homophily effects are not moderated by the other primary determinants of cooperation in networks (i.e., dynamics and reputations). This points to the robustness of homophily effects across a wide range of conditions.

Network Dynamics

When given the opportunity, participants chose to sever a tie to an alter 27.8% of the time. There were multiple opportunities to alter ties nested in participants, who were nested in networks. Accordingly, we estimated

[8] The effect of homophily on cooperation does not vary by university. To assess this, we estimated the same model as model 1 in table 1, except we added a main effect for being at university 1 and interacted this term with whether identities were known, whether ties were homophilous, and their interaction. This three-way interaction was not significant ($\beta = .15$, SE $= .17$, $P = .40$). Furthermore, in a separate model we estimated just a main effect for university affiliation, to test for any baseline differences in cooperation by school. This term was not significant either ($\beta = .13$, SE $= .14$, $P = .34$).

TABLE 2
FOUR-LEVEL GENERALIZED LINEAR MIXED MODELS PREDICTING COOPERATION

	MODEL 1		MODEL 2	
	β	AME	β	AME
Affiliation shown (A, =1)	.40	.03	.18	.01
	(.21)	(.02)	(.28)	(.02)
Same school (S, =1)	.02	.00	−.11	−.01
	(.07)	(.01)	(.08)	(.01)
A × S	.12	.01	.25*	.02*
	(.11)	(.01)	(.11)	(.01)
Dynamic network (D, =1)	.85***	.06***	.63***	.05
	(.11)	(.01)	(.07)	(.01)
Reputations shown (R, =1)	.52**	.04**	.38	.03
	(.20)	(.01)	(.28)	(.02)
D × R	.21	.01	.24*	
	(.11)	(.01)	(.11)	
D × S	−.12	−.01		
	(.12)	(.01)		
D × A	−.42**	−.03**		
	(.14)	(.01)		
D × A × S	.22	.02		
	(.17)	(.01)		
R × S			.18	.01
			(.12)	(.01)
R × A			.09	.01
			(.40)	(.03)
R × A × S			−.08	−.01
			(.18)	(.01)
Alter cooperated on the previous round (=1)	3.72***	.42***	3.72***	.42***
	(.05)	(.01)	(.05)	(.01)
Dynamic network came first (=1)	.12	.01	.11	.00
	(.19)	(.01)	(.19)	(.01)
Second phase of the experiment (=1)	.96***	.08***	.84***	.07***
	(.13)	(.01)	(.12)	(.01)
Third phase of the experiment (=1)	1.70***	.13***	1.50***	.11***
	(.21)	(.02)	(.20)	(.02)
Constant	−2.48***		−2.16***	
	(.30)		(.32)	
Variance component:				
Round	1.43		1.43	
	(.09)		(.09)	
Participant	2.33		2.34	
	(.19)		(.19)	
Network	.18		.18	
	(.09)		(.09)	

NOTE.—SEs are in parentheses. Coefficients for rounds 2–11 and 14–23 are excluded for brevity. N = 44,438 network participant round alters.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

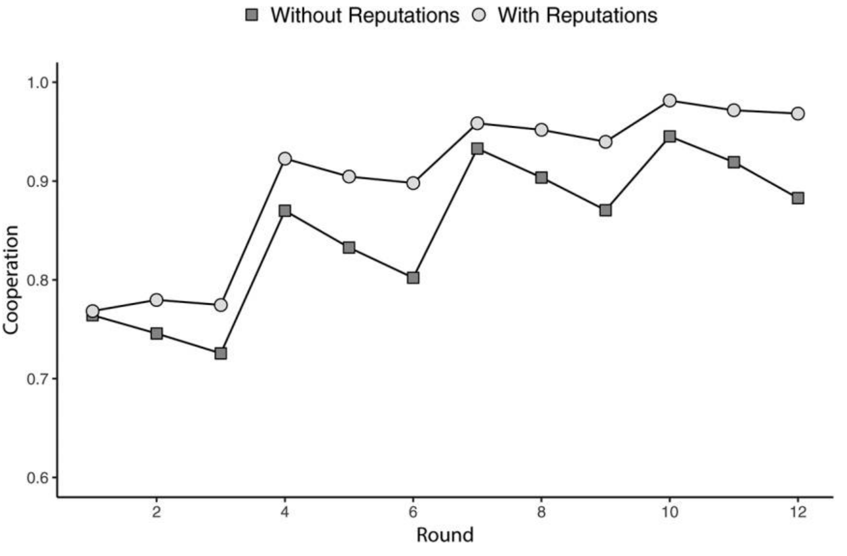

FIG. 3.—Average cooperation by round in dynamic networks with reputations and dynamic networks without reputations.

a generalized linear mixed model using a logistic link function. The results are reported in table 3. Participants were more likely to sever a tie to an alter earlier in the phase, indicating that network ties became more stable over time. Importantly, we find that participants were more likely to sever a tie as more of their alters defected ($\beta = 5.48$, $P < .001$).

Once participants decided to sever a tie to an alter, they indicated which alter they wanted to drop. We modeled this selection process as a conditional logistic regression with clustered standard errors for multiple decisions in participants. When participants selected which alter to drop, they were much more likely to drop a tie with an alter who defected ($\beta = 3.06$, $P <.001$), and identity information played no role in this process. That is, net of behavior, participants were not more likely to sever a tie to an out-group member.

After deciding whom to drop, participants selected a new alter. To model this selection process, we estimated another conditional logistic regression, with participants selecting one of the available alters. We adjusted standard errors for multiple opportunities within participants. Net of reputations, which are themselves significant, participants were more likely to select those from the same university when information about affiliation was available ($\beta = .49$, $P < .05$). To illustrate, this result suggests that if a participant given identity information about potential alters was selecting between one homophilous other and one nonhomophilous other, the probability the participant would choose the homophilous other is .62 (i.e., $\exp(.49)/$

TABLE 3
Three-Level Generalized Linear Mixed Model Predicting Whether Participants Decided to Drop an Alter

	Model 1
Affiliation shown (=1)	.17
	(.22)
Reputations shown (=1)	−.32
	(.22)
First opportunity to drop a tie[a]	1.26***
	(.19)
Second opportunity to drop a tie[a]	.78***
	(.19)
Third opportunity to drop a tie[a]	.26
	(.19)
Percentage of alters who defected on the previous round	5.48***
	(.37)
Constant	−2.87***
	(.26)
Variance component:	
Participant	2.03
	(.39)
Network	.18
	(.12)

Note.—SEs are in parentheses. $N = 2{,}395$ network participant rounds.

[a] Reference category is fourth opportunity to drop a tie.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

$(1 + \exp(.49)) = .62)$. In this way, homophily shaped the formation of new relations, as predicted in hypothesis 2.

The foregoing results show that participants severed ties to alters on the basis of whether those alters defected and initiated ties to new alters who shared their identity, net of their reputation. Figure 4*A* shows the average proportion of homophilous alters (from ego's perspective) for each university affiliation by round. Participants from university 1 began with a higher level of homophily, due simply to a larger proportion of the network, on average, coming from university 1. We modeled homophilous others using linear mixed models, with multiple proportions nested in participants, nested in networks. Table 4 presents our results. As expected, the proportion of homophilous ties increased over time. Given the specification, the main effect of round refers to linear increases in homophily for those affiliated with university 2. The main effect of university 1 refers to the difference in homophily between university 1 and university 2 at the beginning of the experiment. The interaction between round and university 1 refers to the linear

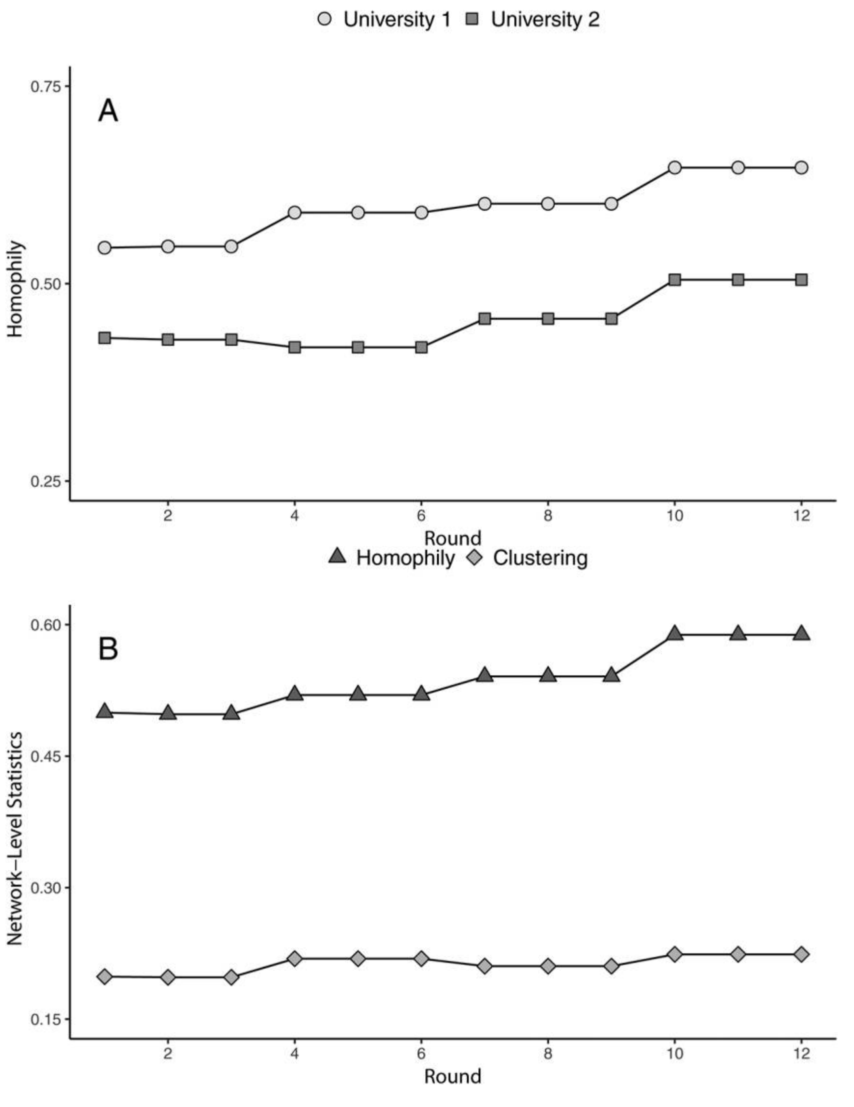

FIG. 4.—Average proportion of homophilous alters for university 1 and university 2 (*A*) and average network-level homophily and clustering by round in the dynamic networks with university information (*B*).

increases in homophily above and beyond those observed in university 2. Thus, for each tie change opportunity, those from university 2 experienced a .02 unit increase in homophily, while those from university 1 experienced a .03 (i.e., .02 + .01) unit increase in homophily. This means that in round 1, ties for university 1 were 54.5% homophilous and became 17.6% more homophilous by the end of the phase. Similarly, ties for university 2 were

TABLE 4
Three-Level Linear Mixed Model Predicting Proportion of Homophilous Alters

	Model 1
Round (R)	.02**
	(.01)
University 1 (U, =1)	.09***
	(.03)
R × U	.01*
	(.01)
Number of ties	.00
	(.00)
Dynamic network came first (=1)	.01
	(.06)
Second phase of the experiment (=1)	.02
	(.05)
Third phase of the experiment (=1)	−.05
	(.07)
White (=1)	−.02
	(.03)
Female (=1)	−.04
	(.03)
Age	.00
	(.01)
Constant	.44***
	(.12)
Variance component:	
Participant	.07
	(.01)
Network	.01
	(.00)

Note.—SEs are in parentheses. Estimated on rounds in which dynamics occurred (3, 6, 9, and 12). $N = 2{,}382$ network participant rounds.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

43.1% homophilous and became 11.1% more homophilous by the end of the phase. These results are net of a variety of controls, as noted in table 4.

For each dynamic network, we computed initial clustering (asymptotically equivalent to the density in random networks) and the clustering coefficient for the network following each opportunity to drop a tie. We modeled network-level clustering with linear mixed models, with multiple rounds nested in networks. These results are reported in table 5. As predicted by corollary 1, the increases in homophily noted above translate into increased clustering. Specifically, model 1 shows that as the proportion of homophilous alters increases, so does clustering. Model 2 in table 5 shows that the presence of reputation information does not moderate the relationship between homophily and clustering. Figure 4B illustrates this pattern by showing trends

TABLE 5
Two-Level Linear Mixed Models Predicting Network-Level Clustering

	Model 1	Model 2
Round	−.00	−.00
	(.00)	(.00)
Average proportion of homophilous alters (H)	.35*	.38*
	(.14)	(.16)
Network size	−.01	−.01
	(.01)	(.01)
University 1 size	.00	.00
	(.01)	(.01)
Reputations shown (R, =1)	.01	.07
	(.04)	(.14)
H × R		−.12
		(.25)
Constant	.16	.15
	(.11)	(.12)
Variance component:		
Network	.01	.01
	(.00)	(.00)

Note.—SEs are in parentheses. N = 80 network rounds.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

in network-level homophily (percentage of same-university ties) and network-level clustering. Indeed, individual decisions to form homophilous relations result in clustering at the network level, as anticipated.

Earnings

The increase in identity-based clustering is important, as prior work has shown that clustering of cooperators in static networks promotes cooperation and, thus, a wealth advantage for cooperators (Rand et al. 2011; Melamed et al. 2018). We tested whether the endogenous emergence of identity-based clusters resulted in increased within-community earnings. To do so, we computed the community structure of each network, which assigns each node to a single dense community or subsection of the network. Specifically, we optimized the modularity function (Newman and Girvan 2004) using all possible partitions of the network (Brandes et al. 2008). Our networks had, on average, 3.44 communities per network (see fig. 5). We then modeled earnings with a linear mixed model, with rounds nested in participants and participants nested in networks. Specifically, we examined the effects of being embedded in homophilous communities (i.e., dense subnetworks; Newman and Girvan 2004).

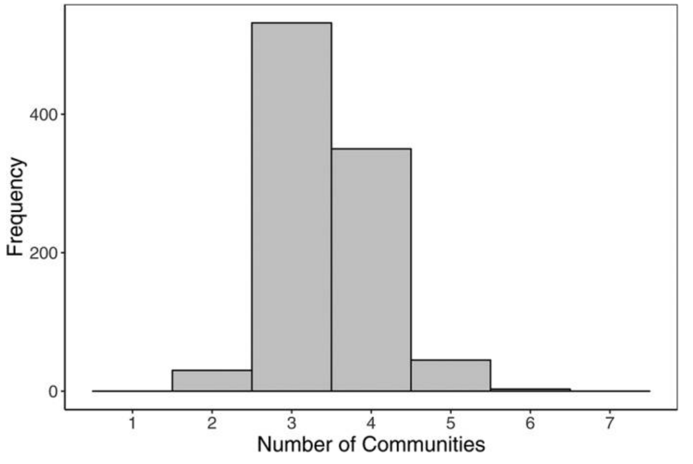

FIG. 5.—Histogram of the number of communities per network.

Table 6 shows three models of earnings. Model 1 shows that when university affiliations were known, as the proportion of homophilous others within the community increased, so did earnings ($\beta = 37.29$, $P < .01$). This supports hypothesis 3. Participants in dynamic networks earned more ($\beta = 16.10$, $P = .04$), as did those in the second and third phases of the study (β's $= 28.30$ and 33.84, $P < .01$ and $P < .001$, respectively). Model 2 shows that the effect of homophilous communities does not vary by whether the networks were dynamic—even those in static networks benefited from exogenously imposed ties to homophilous others. Finally, model 3 shows that the relationship between homophilous communities and earnings is not driven by local clustering or transitivity within each participants' ego network, although this does have a main effect on earnings ($\beta = 150.60$, $P < .001$).

Discussion of Experiment and Motivation for the Agent-Based Model

Summarizing the results from our network experiment, we find that homophily promotes cooperation, net of two other key determinants of cooperation—dynamics and reputations (Rand and Nowak 2013; Cuesta et al. 2015). Further, homophily drives the selection of new alters and thus increases clustering in dynamic networks. In turn, those in homophilous clusters earn more. Homophily thus promotes both cooperation and endogenous clustering. These results have important implications for our understanding of how networks shape cooperation and how cooperation, in turn, shapes networks.

Note, however, that the experiment was limited in size and duration: our networks contained, on average, 16 participants, and phases lasted 12 rounds with four opportunities for participants to change their ties. To understand

TABLE 6
THREE-LEVEL LINEAR MIXED MODELS PREDICTING INDIVIDUAL EARNINGS

	Model 1	Model 2	Model 3
Proportion of homophilous ties within the community (H)	−.24	−8.08	−.79
	(9.66)	(22.07)	(9.63)
Affiliation shown (A, =1)	−19.39	−6.45	−19.56
	(10.51)	(20.28)	(10.38)
H × A	37.29**	4.36	37.42**
	(13.34)	(30.70)	(13.30)
Dynamic (D, =1)	16.10*	5.71	15.63*
	(7.73)	(17.28)	(7.58)
H × D		9.27	
		(24.53)	
A × D		−12.05	
		(24.19)	
H × A × D		40.85	
		(34.09)	
Local clustering			150.60***
			(23.49)
Reputations shown (=1)	−7.13	−7.69	−6.43
	(7.77)	(7.62)	(7.61)
Dynamic network came first (=1)	2.59	2.65	2.92
	(7.76)	(7.60)	(7.60)
Second phase of the experiment (=1)	28.30**	26.67**	27.52**
	(9.71)	(9.66)	(9.51)
Third phase of the experiment (=1)	33.84***	33.29***	33.86***
	(9.16)	(9.04)	(8.98)
Constant	101.63***	109.80***	96.29***
	(11.82)	(16.90)	(11.66)
Variance component:			
Participant	3,742.90	3,741.81	3,709.50
	(173.48)	(173.44)	(171.99)
Network	902.08	854.34	857.02
	(185.33)	(178.58)	(177.70)

NOTE.—SEs are in parentheses. Coefficients for rounds 2–12 and 14–23 are excluded for brevity. N = 14,760 network participant rounds.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

both the longer-term and macrolevel consequences of the processes we observed in the experiment, we use the parameter estimates from the experimental results to inform an agent-based model. This allows us to investigate the implications of the in-group biases demonstrated above on downstream segregation between larger groups.

THE AGENT-BASED SIMULATION

Recall that participants in the dynamic conditions of our experiment made four decisions: whether to cooperate with each alter, whether to drop a tie to an alter, which alter to drop, and which new alter to select. As expected, we found that homophily affects both cooperation and which new alter to select. And given its impact on cooperation, homophily also indirectly shapes who is dropped. Our agent-based model is informed by these results, such that agents' decisions are based on marginal probabilities from the models of the experimental data.

For the agent-based model, we simulated random networks with 1,000 nodes and a density of .0034, corresponding to the same number of ties, on average, that existed in the network experiment.[9] As in the experiment, ties represented interactions in a repeated prisoner's dilemma. After every two interactions with alters, agents had the opportunity to replace one tie.[10] Given this setup, the 1,000 agents made prisoner's dilemma decisions for each alter for 800 rounds and could alter their networks every other round (i.e., 400 times). For each condition, we replicated the simulation 100 times.

The simulation was a $2 \times 3 \times 2$ design. The first factor was the type of information available to agents beyond whether the alter cooperated on the previous round. Agents either knew the social identities of the other agents (and interacted with them accordingly), or they knew both the social identities and the reputations of the other agents. The second factor was the proportion of the population that each social identity category comprised. In our lab experiment, the categories were roughly equal in size. Our simulation varied this such that there was a 50/50, a 70/30, or a 90/10 split between the two categories. This allows us to assess how the baseline availability of similar or different alters shapes downstream segregation (Blau 1977*a*; Cheng and Xie 2013).

The final factor was the available pool of potential alters agents could select from when forming new relationships. In one condition, agents could select from all possible alters (i.e., all alters for whom a tie was not already present). This is similar to our lab experiment, except the population of possible alters is much larger. In light of the fact that the pool of possible alters is so much larger, and given that in the real world ties are more apt to form on the basis of shared ties (Wimmer and Lewis 2010; Bianconi et al. 2014; McFarland et al. 2014), we included an additional condition in which agents could select new alters only from their current alters' alters. This logic is consistent with the prevalence of triadic closure in real world social networks (Davidsen, Ebel, and Bornholdt 2002; Kossinets and Watts 2009). In

[9] To generate the networks, we used the erdos.renyi.game function in the igraph package for R.

[10] Dynamics occurred after every other interaction, as opposed to every third (as in our behavioral experiment) because the second interaction provides sufficient information for our factors to shape the probability of cooperation, but those probabilities are the same in any subsequent interaction.

light of this specification, we only assess increases in clustering when new ties were formed at random from the entire population.

Agents' cooperative decisions were based on marginal probabilities from models of our experimental data (table A1). Recall that we excluded new interactions from our analyses of the experimental data since direct reciprocity is, by definition, missing. No predictors were significant for new interactions in the experimental data. As such, agents with new partners cooperated with a probability of .83 in new interactions. For subsequent interactions, we again computed marginal probabilities using the model in table A1 and had agents cooperate using those probabilities. We modeled initial and subsequent interactions separately since direct reciprocity had such a strong effect on cooperation, as can be seen in the table 1 analyses. Agents probabilistically made decisions about whether to sever a tie to an alter on the basis of estimates in table 3 and, conditional on dropping an alter, which alter to drop on the basis of the estimates given in table A2. Agents selected new alters as a function of homophily in the identity information condition (using the model in table A4) and as a function of both reputation information and identity information in that condition (using the model in table A3). In the identity information condition, all ties were accepted; in the identity and reputation information condition, agents were less likely to accept a tie proposal as the prospective alter's reputation decreased (described in app. A).

Our key questions center on the extent to which relationships became segregated over time. To track tie segregation, we computed Newman's (2003) discrete assortative mixing coefficient at the beginning of the simulation and after each tie update. The assortative mixing coefficient is 0 when there is no assortative mixing, positive when there is more assortative mixing than expected by chance, and negative when there is less assortative mixing than expected by chance. One nice feature of this measure is that it adjusts for the baseline likelihood of two agents having a tie due to category size. For example, if there are two categories, but one of them comprises 90% of the population, we would expect to see more ties between members of the majority than between minority members (Blau 1977*a*). This assortative mixing coefficient adjusts for this baseline homophily effect. The agent-based model therefore allows us to examine the longer-term consequences of our experimental data among a larger population.

RESULTS

Figure 6 shows assortative mixing, or tie segregation, through time when the agents selected new alters from all possible alters.[11] Later, we turn to the

[11] We also tracked network-level clustering in the agent-based model. In all conditions, it increased at an almost uniform rate. Since the experimental results showed support for this argument, we do not present the clustering results for the agent-based model.

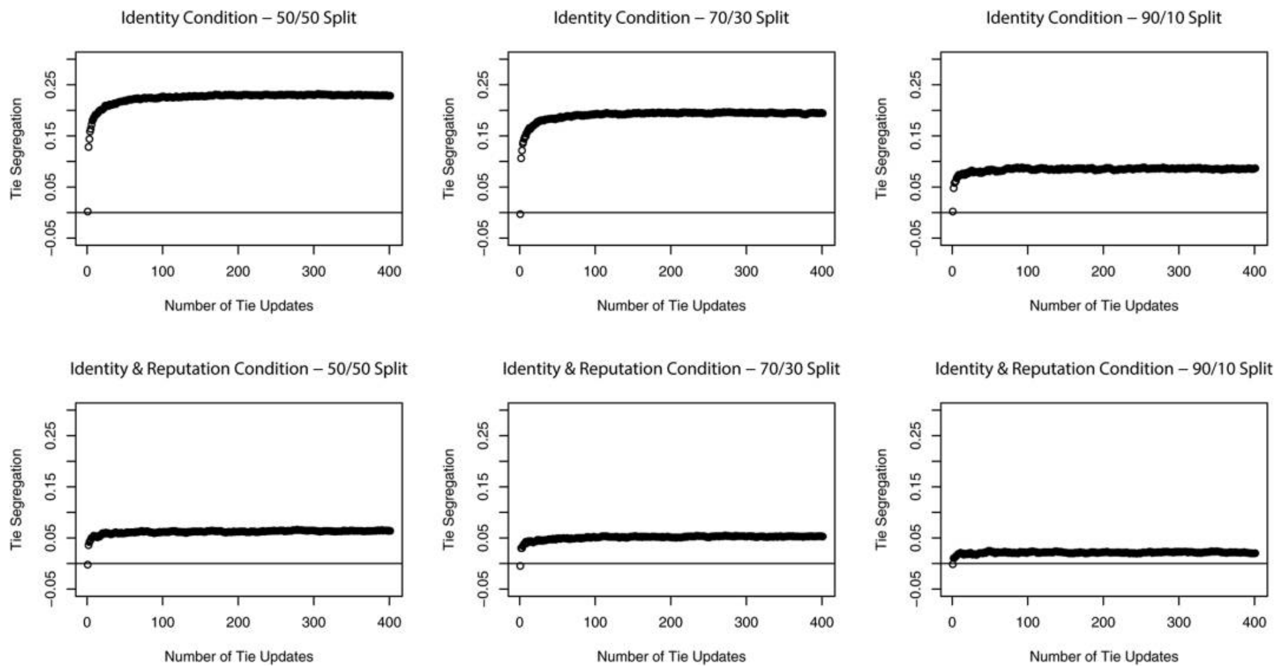

FIG. 6.—Assortative mixing in the agent-based model when all other agents in the simulation were available as potential alters. Rows correspond to whether only identity information was available (*top*) or both identity and reputation information was available (*bottom*). Columns correspond to the sizes of the groups.

condition where agents selected new alters locally, that is, from their alters' alters.

The horizontal line in each graph in figure 6 corresponds to no assortative mixing beyond chance. Thus, divergences from this line indicate tie segregation beyond what is expected based on the baseline likelihood of tie formation. The rows correspond to the information the agents could use in selecting new alters (identities only or identities and reputations), and the columns correspond to the relative sizes of the two categories. Much more segregation is observed when agents use only identities to form new ties than when they use identities and reputations. In the real world, however, social identities (based on race category, social class, religion, etc.) are often much more visible than reputations for cooperation.

Figure 6 also shows that as the size of the majority increases, the amount of "inbreeding homophily" (Blau 1977*a*), or homophily beyond what is expected at the baseline, decreases. This occurs for two reasons. First, inbreeding homophily becomes more difficult since the population distribution limits the availability of alters. For example, when the majority group makes up 90% of the population, inbreeding homophily would require that more than 90% of the ties of majority group members be with other members of the majority. Similarly, it becomes more difficult for minority group members to attach to one another when they represent a smaller proportion of the population. Second, and relatedly, cooperation decisions are probabilistic. As the number of in-group members increases, the likelihood that one of them will defect also increases, and defection has a strong effect on being dropped by one's alters. This, in turn, decreases ties to in-group members. This occurs at a higher rate than their replacement since the effect of defection on being dropped is stronger than the effect of selecting an in-group member.

A final point worth noting from figure 6 is that while segregation increases quickly, it does not reach its maximum until 258 tie update opportunities, on average, across the six panels in the figure (based on the derivative of the regression equations predicting segregation as a function of number of tie updates [N] and N^2; see app. A). That is, while our experimental results show significant effects of in-group category membership on tie formation, they cannot show the full or long-term consequences of such in-group preferences, given that the experiment consisted of "small" networks with 12 rounds per phase. Allowing our agent-based model to iterate for 800 rounds shows that it takes many interactions and changes to the network structure for the full consequences of in-group preferences to be observed.

The figure 6 results were based only on those conditions in which agents chose new alters from the global population. Figure 7 shows tie segregation for the conditions in which agents selected new alters locally, that is, from their alters' alters. Generally speaking, the results are similar to those of figure 6 with two notable exceptions. First, when agents only use identity information (*top*

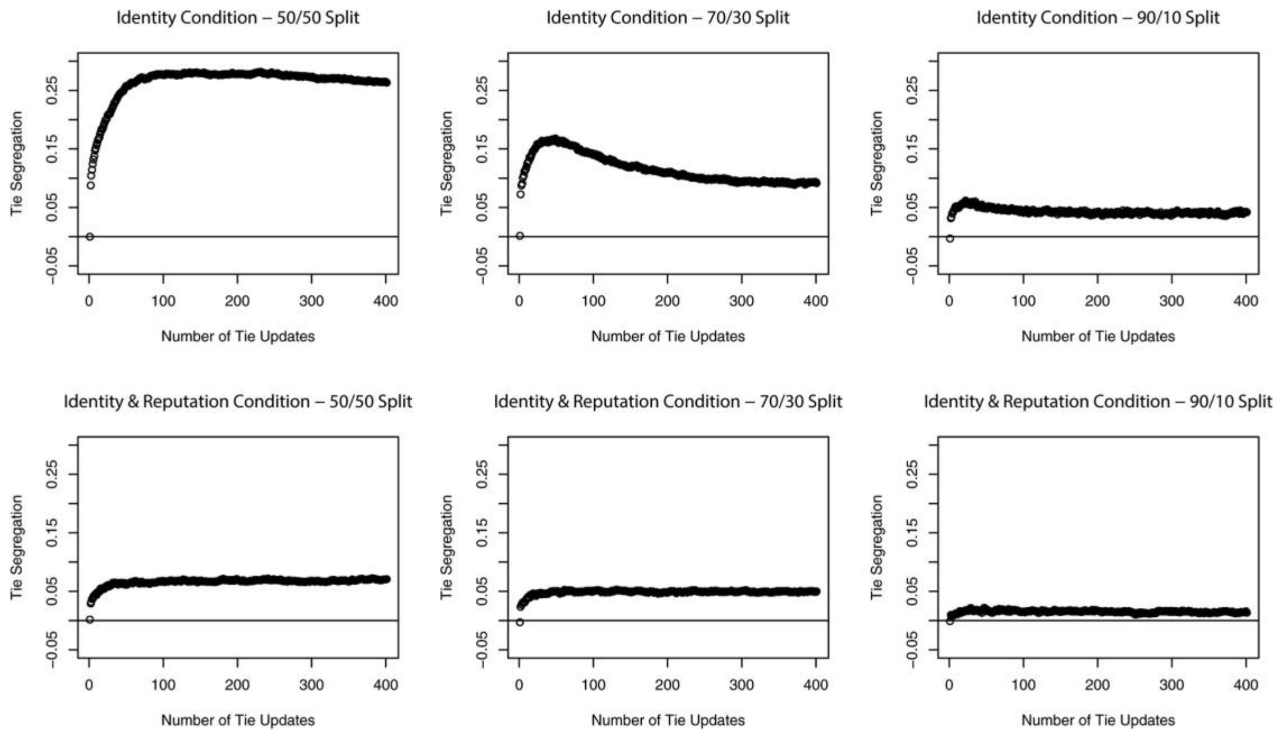

FIG. 7.—Assortative mixing in the agent-based model when only alters' alters were available as potential new alters. Rows correspond to whether only identity information was available (*top*) or both identity and reputation information was available (*bottom*). Columns correspond to the sizes of the groups.

row), there is greater segregation when the two groups are evenly divided, and less segregation when the groups are unevenly divided, as can be seen by comparing the top row in figures 6 and 7. As above, this is a consequence of tie availability: when the categories are equal in size, similar alters are readily available, while this becomes less so with increases in inequalities in category size.

Second, we find that maximum segregation is reached faster when new alters can only be selected from one's local network. With the exception of a single condition (corresponding to a 70/30 split when only identities are known), it takes fewer tie updates to reach maximum segregation for the triadic closure conditions, compared to conditions in which the formation of new ties is not restricted to one's local network. (Specifically, for these conditions, maximum segregation is reached by 231 tie updates, 27 fewer updates than observed for the fig. 6 networks.) The condition with the 70/30 split when only identities are known differs, however. As is evident from figure 7, a squared term for the number of tie updates is inappropriate. Here, segregation increases quickly, declines, and then levels off. Accordingly, there are two tangents with slopes of zero: one at the 55th tie update and one at the 326th tie update (see app. A). More generally, though, this finding is consistent with other results from conditions where ties form on the basis of triadic closure: maximum segregation occurs faster when ties form on the basis of triadic closure than when ties can be formed with anyone in the population (Cheng and Xie 2013).

Our second network-level corollary to hypothesis 2 predicts that preferential in-group assortment will result in between-group segregation. Our experimental data showed a preference for in-group members when forming new ties, but they could not show the long-term consequences of these effects. Using our results to train agents, the agent-based model shows the longer-term consequences of such in-group preferences. All conditions in figures 6 and 7 show tie segregation beyond the baseline likelihood of ties between members of different groups. The parameter estimates from the experiment, coupled with the results from the simulation, thus support this network-level corollary to hypothesis 2.

DISCUSSION

The recent proliferation of research on how networks shape cooperation has yielded a number of important insights. But we know far less about the role of social differentiation in this process (Perc and Szolnoki 2008; Di Stefano et al. 2015). This is a critical omission, as social differentiation is a hallmark of human social networks. In particular, the tendency for networks to be characterized by homophily (Lazarsfeld and Merton 1954; Blau 1977*b*) is one of the most robust findings in the social networks literature (McPherson et al. 2001). Here we bring fundamental sociological insights to bear on the puzzle of cooperation in networks to ask whether cooperation networks also tend toward homophily and, if so, whether homophily promotes or undermines the levels of cooperation typically observed in these networks.

These questions are critical to our understanding of when and why networks promote cooperation since a tendency toward choice-based homophily can be expected to moderate the effect of network dynamics on cooperation. One line of thinking on the dark side of social capital, or "affinity fraud," suggests that choice-based homophily will reduce the capacity for network dynamics to promote cooperation, as the expectation that fellow category members will act benevolently is often illusory. From this perspective, while we tend to put greater trust in similar others, this trust is prone to exploitation by opportunistic category members (Baker and Faulkner 2004; Yenkey 2018).

That participants in our study preferentially sorted with fellow in-group members provides clear evidence that they expected more cooperation from fellow category members. But we argued that we should observe not only higher in-group trust but also higher levels of cooperation within categories. And, as expected, we found that participants cooperated with fellow in-group members at higher rates than out-group members, as well as those whose identities were unknown. Importantly, then, even though participants were sorting on something other than baseline cooperative tendencies, the sorting process resulted in remarkably high levels of cooperation.

These results are particularly surprising given that our experiment employed a benign basis for category membership. That is, we used university affiliation to increase experimental control, since it is less likely that there are preexisting cultural beliefs about category members' cooperativeness. In the real world, homophily is often observed along demographic and other categorical distinctions that have implications for cooperation and other forms of prosocial behaviors, such as social class or gender. Furthermore, the consolidation of attributes in social space (Blau 1977*a*, 1977*b*) implies that dyads are often homophilous along several dimensions. Thus, our test of the effects of homophily on cooperation is very likely to be a conservative one. Despite this, identity effects occurred over and above two other manipulated factors, namely, static versus dynamic networks and the presence or absence of reputational information. This is important, as these are arguably the two most powerful predictors of cooperation in existing research (Rand and Nowak 2013; Cuesta et al. 2015).

The tendency for participants to preferentially sort with fellow group members and to cooperate at higher rates with fellow group members had important effects on the level of homophily observed in the networks over time. Participants were, all else equal, not more likely to cut ties to out-group members. But when they did cut ties, they were more likely to form new ties with fellow category members. That this effect held even when participants had knowledge of prospective partners' reputations is a testament to the importance of shared category membership in relationship formation. As a result of these processes, we observed clusters of homophilous communities, characterized by high levels of cooperation and, consequently, higher earnings.

Our ability to trace the emergence of particular network structures from particular conditions is a key advantage of studying these processes with experimental networks. With observational data, network structures are already in place, making inferences about how the structure shapes prosociality or how structures change over time challenging (Simpson et al. 2018). As a consequence, it is difficult to know whether structure precedes behavior or vice versa in many observational studies (cf. Steglich, Snijders, and Pearson 2010). Yet one potential downside to our approach is that our networks were randomly generated at the beginning of each session. Human networks are characterized by a host of structural factors, including clustering, differences in sociality, and so on. These features are lost when doing experimental work with random assignment. While this realism can be offset by gains in experimental control and causal inference (Webster and Sell 2014), it is important for future research to address the robustness of our conclusions when initial networks are structured differently from those we studied.

More generally, given both the homophily effects observed here and their ubiquity in real world networks, we hope that future work on network dynamics and cooperation will more explicitly take them into account. One important next step for understanding how homophily processes alter cooperation and network dynamics is to study within-category reputations, in addition to the global reputations we studied here. The global reputations we studied represent a conservative test of the choice homophily process. After all, defecting in relations with out-group members harmed participants' reputations and, theoretically, could have reduced the tendency to be selected by fellow in-group members seeking new ties, thereby dampening identity effects. And in the real world, reputations often depend primarily on treatment of fellow in-group members (Yamagishi and Kiyonari 2000; Bernhard, Fischbacher, and Fehr 2006). Indeed, cooperation with out-group members may be detrimental to one's in-group reputation. If we had instead allowed players to establish distinct reputations for their behaviors vis-à-vis in-group and out-group members, the processes we observed would have likely unfolded at a much higher rate.

A better understanding of the factors that moderate the identity-based clustering we reported here will not only yield clearer insights into the conditions that give rise to cooperation with in-group members. It could also help shed light on more detrimental consequences of this sorting, including the "echo chambers" that can result from choice-based homophily and sorting (e.g., DellaPosta, Shi, and Macy 2015; Boutyline and Willer 2017). That is, people's preferences for building cooperative relationships with similar others may also facilitate group polarization, reducing exposure to diverse others. Particularly when sorting results in contact with out-group members that is infrequent or superficial (Pettigrew et al. 2011), we might expect to find the low level of intergroup trust and cooperation that is, unfortunately, increasingly characteristic of contemporary political partisanship (Iyengar and Westwood 2015). These negative effects may be especially likely when the identities on which people sort themselves are based on "consolidated" (Blau 1977*a*) or "mega identities" (Mason 2018), that is, identities that assume a number of others, thereby limiting the number of crosscutting ties. An important goal for future research is therefore to understand how the positive effects of clustering we focus on here relate to the downsides documented in other streams of research.

It is also important for future work to investigate when and why affinity fraud might interrupt the processes observed here. For instance, it seems reasonable to assume that opportunistic exploitation of fellow in-group members' trust will be more likely to occur when the stakes are especially high, when the relations are not embedded in a dense cluster of fellow category members (Coleman 1988), or when there is larger variation in individuals' loyalties to a given identity. These issues could be addressed with relatively straightforward extensions of the work presented here.

In line with sociological accounts of between-group inequality (e.g., DiTomaso 2013), our simulations also point to downstream macrolevel consequences of in-group preferences. In particular, we observed a high level of tie segregation within categorical memberships. These did not arise out of malice toward out-group members, or threats from them, but rather through an anticipation that in-group members would behave in a trustworthy fashion. After all, attachment to one's in-group does not require hostility toward out-groups (Allport 1954; Brewer 1999; Perry et al. 2018). That said, a variety of contextual factors have been shown to shape tie segregation, but our simulations are necessarily based on a simplified model of how the agents form ties. While we varied group size, network researchers have shown that agents respond differently to different group compositions. For example, tie segregation peaks with moderate heterogeneity (Moody 2001), and small minorities tend to cluster together at rates beyond chance levels (Quillian and Campbell 2003). Furthermore, our participants did not know their alters personally and so there was very little to distinguish the strength of ties (Granovetter 1973) between interactants. Yet recent work suggests that core networks of strong ties are more segregated than extended networks (Hofstra et al. 2017). Subsequent work should address how humans respond to different group and tie compositions and the downstream consequences of this for network segregation and individual outcomes.

In summary, we provide evidence for the importance of homophily to the evolution of cooperation. Homophily promotes cooperation in both static and dynamic networks. In dynamic networks, homophily shapes the evolution of network topology that, in turn, promotes wealth accumulation. These behaviors have consequences for contact between groups, as tie segregation emerges as a downstream consequence of these processes. Our findings therefore shed new light on a critical puzzle: the literature on cooperative networks suggests that networks promote cooperation when cooperative types can "find" each other. But analysis of real world networks show that they are not characterized by "altruism homophily" (Simpson et al. 2014). Instead, humans form relationships based on categories orthogonal to altruism (McPherson et al. 2001). Our arguments and findings reveal how sociological insights contribute to the burgeoning literature on cooperation in networks and demonstrate how cooperation can thrive despite the tendency for humans to sort on characteristics that are independent of cooperative dispositions.

APPENDIX A

The Agent-Based Model

Probabilities for the Agent-Based Model

As noted above, participants made four key decisions that we implemented in our agent-based model: (1) whether to cooperate, (2) whether to drop an alter, (3) which alter to drop, and (4) which new alter to select. Agents also decided whether to accept a tie request. This was not discussed in the main text, but we provide the results here that were included in the agent-based model.

In order to generate predicted probabilities of cooperation for the agents in the simulation, we estimated a four-level logistic regression, with alters in rounds, rounds in participants, and participants in networks. A summary of this model is presented in table A1. From this model, we generated marginal predicted probabilities, given the condition of the agent-based model, and used those probabilities to determine whether our agents behaved cooperatively.

TABLE A1
Four-Level Generalized Linear Mixed Models
Predicting Cooperation

	Model 1
Affiliation shown (A, =1)	−.03
	(.06)
Same school (S, =1)	.19
	(.20)
A × S	.37*
	(.18)
Dynamic network (D, =1)	.71***
	(.05)
Reputations shown (R, =1)	.59**
	(.20)

TABLE A1 (*Continued*)

	Model 1
Alter cooperated on the previous round (=1)	3.74***
	(.05)
Constant	−1.47***
	(.18)
Variance component:	
Round	1.46
	(.09)
Participant	2.32
	(.19)
Network	.20
	(.09)

NOTE.—SEs are in parentheses. N = 44,438 network participant round alters.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

In terms of whether to drop an alter, we used predicted probabilities from the model reported in table 3. In terms of which alter the agent chose to drop, conditional on deciding to drop one, we used the conditional logistic regression reported in the main text, where each alter is eligible for selection, and multiple decisions are nested in participants. Table A2 presents a summary of this model. Predicted probabilities from this model were used to determine whom the agents selected as a potential new tie.

TABLE A2
CONDITIONAL LOGISTIC REGRESSION PREDICTING WHICH ALTER IS SELECTED TO BE DROPPED

	Model 1
Alter defected on the previous round (=1)	3.06***
	(.25)
Same school (=1)	−.21
	(.18)

NOTE.—SEs are in parentheses. N = 1,143 decisions to drop an alter in the dynamic condition with affiliations.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

In terms of tie formation, we used estimates in table A3 to generate probabilities that each alter was selected based on whether the alter was homophilous and his and her reputation. In the homophily-only condition, we estimated another conditional logistic regression, reported in table A4. Here we selected only those networks where university affiliation was known; as such, reputations were unknown in half the networks and hence are not significant in this model.

TABLE A3
Conditional Logistic Regressions Predicting Which Alter Is Selected When Forming a New Tie

	Model 1
Same school but not known	.21
	(.14)
Same school and known (homophily)	.49*
	(.22)
Alter reputation but not shown	−.10
	(.33)
Alter reputation shown	3.56***
	(.71)

Note.—SEs are in parentheses. $N = 5{,}492$ possible alters.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

TABLE A4
Conditional Logistic Regression Predicting Which Alter Is Selected in the Tie Formation Process

	Model 1
Homophilous Other (=1)	.67***
	(.17)
Alter's Reputation	.31
	(.40)

Note.—SEs are in parentheses. $N = 2{,}486$ decisions to select an alter in the dynamic condition with affiliations.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

Finally, in terms of rejecting tie requests (not discussed in the main text), the only significant predictor we identified was the reputation of an alter. Specifically, as alters' reputations increased, the likelihood of rejecting their tie request decreased ($\beta = 10.25$, SE $= .0434$, $P = .02$).

Determining Maximum Segregation in the Agent-Based Models

As is apparent in figures 6 and 7, in all but one panel of the figures, segregation increases quickly at the start of the simulation and then levels off. In order to determine at which point segregation reaches its maximum, we modeled segregation as a function of number of tie updates and number of tie updates squared using linear regression (we included a cubed term in the 70/30 split condition when ties formed based on triadic closure). In order to obtain the maximum predicted value on segregation, we took the first derivative of the regression equations and solved for x. This tells us at which point the function goes from increasing to decreasing (or conversely, from decreasing to increasing). Tables A5 and A6 report the estimated regression models, the first derivative of those models, and the solution for x, which corresponds to the point on the curves where segregation stops increasing and starts decreasing. This is not to say that segregation decreases (it does not; it reaches a ceiling given the probabilistic nature of the simulation), but the way it is modeled here, we can find the point where segregation reaches its maximum and determine exactly how long it took to do so. The results reported in the main text come from averaging the solutions to x in each of the tables.

TABLE A5
SEGREGATION WHEN AGENTS CHOSE ALTERS FROM THE ENTIRE POPULATION

	Segregation	Derivative	x
Homophily only:			
50/50	$.19 + .0003x - .00000061x^2$	$.0003 - .00000122x$	245.9
70/30	$.165 + .000268x - .000000529x^2$	$.000268 - .000001058x$	253.31
90/10	$.074 + .000103x - .000000202x^2$	$.000103 - .000000405x$	254.57
Homophily and reputations:			
50/50	$.543 + .0000738x - .000000133x^2$	$.0000738 - .00000267x$	276.82
70/30	$.0422 + .0000888x - .000000166x^2$	$.000088 - .0000003328x$	266.83
90/10	$.01876 + .00002772x - .0000000549x^2$	$.00002772 - .00000011x$	252.46

NOTE.—Regression models predicting segregation as a function of number of tie updates and number of tie updates squared for each condition when agents chose alters from the entire population. The first derivative of the model and the solution to x (i.e., the number of rounds with the maximum predicted segregation) are also reported.

TABLE A6
SEGREGATION WHEN AGENTS CHOSE ALTERS FROM THEIR ALTER'S ALTERS

	Segregation	Derivative	x
Homophily only:			
50/50	$.194 + .00081x - .0000017x^2$	$.00081 - .00000342x$	235.86
70/30	$.137 + .0003114x - .00000331x^2 + .0000000058x^3$	$.0003114 - .00000661x + .0000000174x^2$	55.08 and 325.68
90/10	$.05244 + .0000878x - .00000015x^2$	$.000878 - .0000003x$	292.67
Homophily and reputations:			
50/50	$.054 + .000123x - .000000231x^2$	$.000123 - .00000461x$	266.16
70/30	$.0422 + .0000724x - .00000015x^2$	$.0000724 - .0000003x$	241.11
90/10	$.0154 + .0154 + .00000729x - .0000000305x^3$	$.00000729 - .000000061x$	119.47

NOTE.—Regression models predicting segregation as a function of number of tie updates and number of tie updates squared for each condition when agents chose alters from their alter's alters. The first derivative of the model and the solution to x (i.e., the number of rounds with the maximum predicted segregation) are also reported.

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