NETWORK AMPLIFICATION

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Introduction

Social networks play a key role in shaping our tendency towards adopting beneficial behaviors, or avoiding risky ones, as well as our success in achieving desirable outcomes. Social scientists routinely document how having friends who excel at school (Sacerdote 2011), or those with well-paying jobs (Lin 1999; Rivera 2016), bring us closer to reaching similar results. Researchers also show how social relationships to people with healthy habits (Centola 2010) and emotional states (Fowler & Christakis 2008), or those on sensible financial tracks (Duflo and Saez 2002), make us more likely to choose similar behaviors.

Social networks can help diffuse behaviors or enable outcomes that improve our well-being. But, on the flip side, social networks can also concentrate such behaviors and outcomes in certain segments of the population and amplify differences between groups. The reason is simple. Our social relationships do not come about at random, but rather follow certain patterns. We tend to be-friend people who resemble us, for instance, in socio-economic status (Marsden 1987), race (Moody 2001), and immigrant background (Smith et al. 2016), and thus, display a bias towards 'homophily' (McPherson, Smith-Lovin and Cook 2001). We also live in societies where different characteristics, like income and race in the United States, are highly correlated. Under such 'consolidation' (Blau 1977; Blau and Schwartz 1984), our friendships become segregated along many characteristics, even if we do not consider each and every characteristic in establishing our social ties (Moody 2001; Zhao and Garip forthcoming).

Research shows that social networks can amplify inter-group inequalities in the adoption of beneficial practices under conditions of homophily and consolidation. DiMaggio and Garip (2011) use a computational model to simulate the network-based diffusion of a practice. The higher the bias towards homophily in network formation, the authors find, the greater the divergence in the adoption paths of groups defined on the basis of income, education, and race. Zhao and Garip (forthcoming) use a slightly different modeling strategy to show that network amplification of inter-group differences depends not just on homophily, but also on consolidation. The more correlated the relevant attributes in a population are, the higher the inequality in adoption across groups.

In each of these examples, homophily or consolidation (or both) lead to social ties that are segregated along key attributes (like income or education), and this segregated structure enables the amplification of existing differences in behaviors and outcomes across groups in society. This process, however, only works if the behaviors or outcomes in question are more likely among the advantaged groups initially (e.g., the rich and educated), and if the behaviors and outcomes are subject to 'network effects', that is, if they are easier to undertake or achieve when others around us are also doing them.

Recent work focuses on clarifying what 'network effects' mean and suggests different mechanisms through which our alters can influence us. This development is crucial to improve our understanding of network-based inequality. In particular, we argue, research to date has focused almost exclusively on the mechanisms for network formation (such as homophily bias) in connecting networks to inequality. Network formation is an important process to unpack in understanding network-driven differences in the distribution of behaviors and outcomes in a population. But it does not exhaust the mechanisms through which our alters shape our choices and, more generally, the extent to which networks can amplify existing differences or outcomes. Different kinds of network effects, in other words, can create different trajectories of behavior or outcome differentiation across groups that cannot be simply reduced to network formation (DiMaggio and Garip 2012).

In what follows, we first review the research on network formation, focusing particularly on work that considers homophily and consolidation as mechanisms that segregate networks along individual attributes. We then briefly discuss empirical research that suggests 'network effects' in behaviors and outcomes, and provide examples of studies that connect network processes to inter-group differences in behaviors and outcomes. We then take a decidedly analytical-sociological turn, and review the theoretical work laying out the mechanisms underlying network effects. Such a mechanistic approach, we argue in our concluding section, opens up a new path to understanding network amplification, and its consequences for inequality.

Network formation: A precursor to network amplification

Network amplification of inter-group differences depends on particular patterning of network connections. One such patterning comes from the higher likelihood of individuals to associate with those who occupy proximate social positions (Blau 1977). Our tendency to connect with people who resemble us, also known as homophily bias, implies that our experiences, activities and relationships to different social contexts (e.g. clubs, workplaces, voluntary organizations) might show strong correlations to our personal attributes (Feld 1981; McPherson & Ranger-Moore 1991; Marsden 1987; McPherson, Smith-Lovin & Cook 2001).

The sources of homophily are much contested in the literature. A big debate is on whether existing social groups (e.g., based on a shared attribute or a social setting) enable formation of network ties or whether network ties eventually give rise to social groups. A useful conceptual break in thinking about social groups and social networks comes from differentiating 'induced homophily' from 'choice homophily' (McPherson & Smith-Lovin 1987).

Under induced homophily, existing social groups, and their particular composition, explain similarity of connected nodes. For example, an elite school might exclusively recruit students of high-income families, and social ties within the school might inadvertently be homophilous with respect to income. Under choice homophily, friendship ties result from a deliberate preference for similarity, or avoidance of dissimilarity[1], one that cannot be attributed to composition of the social setting alone. For example, students might select friends sharing their ethnic background even in a diverse classroom with ample opportunities to interact with other ethnic groups

[1] Skvoretz (2013) considers both social attraction and social repulsion as sources of homophily, suggesting that "repulsion is the driver of intergroup relations when the dimension type is ascribed like ethnicity/race and religion, while attraction is the driver of intergroup relations when the dimension type is achieved, like educational attainment" (p. 501).

(Smith et al. 2016). To underline the distinction between induced and choice homophily, some researchers refer to the former as 'homogeneity' and reserve the term 'homophily' for cases of preferential association only (DiMaggio and Garip 2011; Wimmer & Lewis 2010).

Previous research finds that induced and choice homophily do not exist in isolation. Rather, observed ties between similar people result from a combination of structural constraints and individual preferences (McPherson & Smith-Lovin 1987). Kossinets and Watts (2009) use data on electronic communications, for example, to show how induced and choice homophily work in tandem to reinforce the tendency for similar individuals to interact. As a social network evolves, similar but structurally distant individuals are brought closer together, creating a dynamic that produces strong homophily even when there is weak preference for homophilous relationships (see also Wimmer & Lewis 2010).

Homophily in network formation is important for diffusion processes because of its potential to segregate social relationships. When network ties are homophilous with respect to socio-demographic (or other) attributes, social contagion might remain stuck in certain parts of the network rather than spreading globally. Under homophily, one might observe strong empirical correlations between sociodemographic attributes and various attitudes, opinions, and behaviors, which are in fact an artifact of the network structure (DellaPosta, Shi and Macy 2015). To see that, consider a setting where support for gun control is high among the educated, and where network ties are homophilous with respect to education (McPherson 2004). The observed correlation between education and gun-control views in this case might be due less to a direct effect of the former on the latter, and more to the ease with which the educated individuals can share common spaces, and exchange ideas, with similar others, thus reinforcing their own biases. Boutyline and Willer (2017), for example, show a positive correlation between political homophily and political extremism, suggesting that the clustering of the latter in certain segments of society may be less about inter-personal influence and more about preferential attachment among like-minded individuals. Consistent with this idea, Macy et al (2019) find that political opinions depend far more on the initial conditions under which social influence takes off than on core values or ideological divisions.

Individuals who share attributes also often share multiple social spaces. Contact between different groups depends on the extent to which different social spaces overlap, and thus, bring together individuals with different attributes. Blau (1977) argued that inter-group contact, or social integration, would be low in societies with low diversity (where one group dominates others), and in societies with high consolidation of individual attributes. Consolidation makes one attribute highly predictive of the other ones, severely affecting formation of cross-cutting social circles (Blau and Schwartz 1984). Say, income and ethnicity are highly correlated so that high-income individuals are generally white and low-income individuals are generally Latino/a. Then, it will be a rare event for a low-income white and a high-income Latino/a to meet, let alone share ideas and influence one another's behavior.

Low homophily and low consolidation, then, should facilitate diffusion of ideas because individuals located in different parts of the network, and with access to unique information, can still connect, and share that information, with dissimilar others. This idea, put forth by Blau (1977) and Blau and Schwartz (1984), is also reinforced by strength-of-weak-ties hypothesis (Granovetter 1974; Burt 1992) and the small-world models (Watts and Strogatz 1998).

Yet, overlapping ties in cohesive groups (as one would observe under high homophily and high consolidation) also provide advantages in diffusion, such as more bandwidth for information sharing due to heightened social pressure and common social expectations (Aral & Van Alstyne 2011). Using computational experiments, for example, Centola (2015) explores emergent network topologies, and diffusion outcomes, under different combinations of homophily and consolidation. Contrary to Blau and Schwartz's (1984) idea that low homophily and low consolidation lead to higher diffusion (and more social integration), Centola finds that moderate-to-high levels of homophily and consolidation facilitate the diffusion of norms that require reinforcement from multiple individuals, and thus, follow what Centola and Macy (2007) call a 'complex contagion' process. Diffusion, in the Centola model, is facilitated by dense neighborhoods that provide exposure to multiple 'infected' individuals, and by 'wide bridges' that connect diverse clusters of individuals. In support of this idea, Centola (2010) sets up an online experiment, and shows that adoption of health-promoting behaviors is faster, and reaches a greater proportion of the population, when individuals are assigned a position in cluster-lattice networks (with dense and overlapping local connections) than in random networks (with little local structure). Other researchers have found either mixed support for complex contagion, for example, in diffusion of exercise behaviors (Aral and Nicolaides 2017), or showed with a combination of computational models and empirical data that the theory needs to consider heterogeneous involvement of actors in the diffusion of complex technologies (Manzo et al. 2018). In particular, when early adopters that are centrally located in the network are not heavily involved in the person-to-person learning process, wide bridges can actually slow down the diffusion process by spreading uncertainty about the technology.

Research to date is, thus, unequivocal on the importance of network formation (shaped by homophily and consolidation, as well as other population parameters) for diffusion outcomes. The next step is to understand how network ties, once formed, give rise to differential diffusion trajectories across groups in a population. Before we delve into this question, we take a detour into the broader literature on network effects, and briefly discuss their potential implications for inequality.

Network effects on behaviors and outcomes: A necessary condition for network amplification

There is a vast empirical literature on 'network effects' where characteristics or behaviors of network alters are seen as critical to individual outcomes. Our goal here is not to offer a comprehensive account of this sprawling field, but rather to review some canonical examples and consider their implications for network-driven inequality.

Research identifies network effects in many domains, including education (Sacerdote 2011), work (Marsden and Gorman 2001), health (Pampel, Kruger and Denney 2010; Smith and Christakis 2008) and political participation (Campbell 2013). Empirical findings suggest positive effects of network peers on school performance (Calvó-Armengol, Patacchini & Zenou 2009), finding a job (Peterson et al. 2000), healthy behaviors (Centola 2010; Christakis and Fowler 2013; Aral and Nicolaides 2017), adoption of new technologies (Manzo et al. 2018; Keating et al. 2020), and civic participation (Lewis, MacGregor and Putnam 2013).

The extent of network effects depends on the characteristics of alters and ego. Let's focus on labor market outcomes. Individuals with ties to high-status individuals access better resources that lead to prestigious jobs (Lin, Ensel and Vaughn 1981) and promotions at work (Burt 1998). Individuals who are high-status themselves often reap higher returns from their social ties. Those with high socio-economic status, for instance, are more likely to rely on their networks in findings a job compared to their lower-status counterparts (Smith 2007), and also to land higher-quality jobs by doing so (Lin 1999). Similarly, whites benefit more from their networks in obtaining desirable labor-market outcomes compared to African-Americans in the United States (Korenman and Turner 1996; Smith 2005), and men more than women (Burt 1998; Ensel 1979). (For a more detailed description of how different individuals come to reap differential returns over time, see Freda Lynn's chapter on cumulative advantage in this volume.)

These findings have clear implications for network amplification of inequality. If characteristics of alters matter in the magnitude of network effects, we can conjecture, any process that differentially distributes social ties will influence inter-group differences in outcomes. We have already reviewed one such process – homophily bias. If high-status individuals are likely to be connected among themselves, for example, the advantages of having high-status alters will be concentrated among the already-advantaged (high-status) individuals, leaving those lacking status farther behind. Similarly, regardless of the degree of homophily, if high-status individuals reap greater benefits from their ties, the presence of network effects in an outcome will serve to amplify existing status inequalities in that outcome.

Network amplification of group differences, although implicit in the examples above, is hard to show with data. Identification of network effects is already challenging methodologically, given the difficulties around specifying peer influences (Manski 1993, 2000; Shalizi and Thomas 2011), and separating them from the process of peer selection (Aral, Muchnik and Sundararajan 2009; Durlauf and Ioannides 2010; Mouw 2003). Ignoring these different pieces that contribute to the explanation of diffusion can have severe consequences for the estimation of network effects. For instance, Aral et al. (2009) study the adoption of a new technology and show that two empirical patterns often claimed to be evidence of peer influence (assortative mixing and temporal clustering) can be substantially explained by homophily. Indeed, when homophily is not accounted for, the authors find, social contagion can be overestimated by up to 700%.

If we add to these difficulties of inference the dearth of longitudinal data on networks and behaviors required to trace group-specific trajectories, we end up with a tall order to fill, indeed. This is why existing work repeatedly turns to computational models to demonstrate network-driven inequality, as we describe below.

Networks amplification of inter-group differences: Evidence from computational models

Empirical findings on network effects carry clear implications for social inequality. If different groups have ties to different kinds of individuals, or benefit from their ties in different ways, it is not a big leap to think that network ties will have consequences for inter-group differences. But, to understand this process systematically, it helps to study it as a unified causal chain that takes us all the way from (i) how social ties form to (ii) how those ties shape our choices and (iii) how those choices then aggregate into broader patterns of social inequality.

DiMaggio and Garip (2011) consider this causal chain to understand the sources of the racial divide in Internet service subscription in the United States. Their argument draws upon a number of stylized facts. Social networks in the United States display a high degree of homophily by education and race (Marsden 1987), and play a key role in the adoption of Internet service, which, like other communication technologies, becomes more valuable to us as more of our social ties use it (Fischer 1992). The adoption of Internet service is driven in part by personal resources, such as income and education, and, in the United States, African-Americans have lower levels of education and income, on average, compared to the whites.

These stylized facts suggest a possible explanation for the racial divide in Internet adoption. First, given their higher income and education, whites are likely to be over-represented among the early adopters of Internet in the United States. Second, given racial homophily in social ties, whites are also likely to experience stronger network effects (or what DiMaggio and Garip call ‘network externalities’) in adoption, that is, they are likely to benefit disproportionately from their social ties. These two factors together – initial differences in adoption and differential network effects – are sufficient to give rise to an enduring racial gap in Internet adoption.

To illustrate and generalize this argument, DiMaggio and Garip rely on an agent-based model, where aggregate patterns emerge from the interactions of agents following simple rules (Bruch and Atwell 2015). Instead of relying on synthetic agents, however, the authors use the respondents to the 2002 General Social Survey (GSS), and thus capture empirical distributions of (and correlations among) income, education, race, and network degree in the United States.

Their model starts by generating a network of ties among agents. Depending on the degree of homophily bias, each agent establishes a share of its target ties to socially proximate agents (in terms of race, income and education), and the remainder of its ties randomly. Each agent has a reservation price (a price it is willing to pay for the Internet service) which is an increasing function of income, education and share of its social contacts who have already adopted. The price of the Internet service is a declining function of the total number of adopters, reflecting economies of scale.

In this set-up, an agent can adopt the Internet because its reservation price has increased with more adoptions in the agent’s network, or because the price of the service has dropped due to more adoptions in the population. The model runs until it reaches equilibrium by determining adopters in each time period (whose reservation price exceeds the price of the service), and updating reservation prices and the price of the service given the new adoptions.

The results from the model allow for a comparison of diffusion levels in the population, and across different income, education and race groups, under different degrees of homophily, and confirm the authors' initial intuition. As homophily increases in the network, the level of adoption in the population drops. The practice (Internet service) remains concentrated among the more advantaged (the rich, educated, and white), and fails to spread to less advantaged groups (the poor, less educated, and African-American). The higher the homophily, the higher the inequality in adoption.

Manzo (2013) similarly applies an agent-based model to investigate the sources of inequality in educational attainment in France. The model follows from the reasonable assumption that agents make educational choices based on their ability, expected payoffs, and choices of others in their own socio-economic group. Strikingly, the results show that the observed educational stratification in France cannot be closely reproduced in silico unless the model features group-specific network effects.

In Manzo's analysis, network effects on inequality depend both on homophily (because educational payoffs increase with the number of individuals with similar social background) and on consolidation (because ability and payoffs are positively correlated with parental education). His modeling approach also implies that increasing inter-group contact creates a zero-sum game for the individuals with different social backgrounds. That is, when groups intermingle, the low-status group benefits at the expense of the high-status group, which ends up losing its competitive advantage, or more specifically, the 'wide bridges' that enable the diffusion of better educational outcomes within this group. The results from this model, when combined, suggest that educational differentiation in France plausibly results from social influences in individual choices combined with homophily and consolidation in social ties by socio-economic status.

The studies posit similar conditions for the network amplification of inequality. To the extent that our social networks matter in adopting behaviors or achieving outcomes that help us get ahead (such as subscribing to the Internet or obtaining education) and to the extent that those networks are selective with respect to attributes that also matter in our choices, social networks will amplify existing inequalities between groups. In both cases, we see that the higher the homophily in the population, and the more segregated the networks (or social groups), the more divergent the trajectories of adoption across groups.

Zhao and Garip (forthcoming) qualify these findings using a slightly different modeling strategy that varies not just homophily, but also consolidation (the correlation among different attributes) in the population. The effect of homophily on the extent of network amplification, the authors argue, is contingent on the level consolidation. Their logic becomes clear if we consider two extreme cases. In the first case of full consolidation (where attributes are perfectly correlated), there is a single axis of differentiation. Knowing an individual's income, for instance, allows us to accurately predict her education, ethnicity, and so on. In the opposite case of no consolidation (where attributes are randomly distributed), there are multiple axes of differentiation. Knowing one attribute does not give us any information on the other attributes.

Zhao and Garip argue that the implications of homophily for network amplification will vary across these two extremes. Under full consolidation, even small degrees of homophily will be enough to concentrate adoption among those with the initial advantage (for example, the rich, educated and white in the Internet adoption case). A slight preference for similar alters in one dimension (e.g., income) will end up reinforcing homophily along other status dimensions (such as education). Under no consolidation, by contrast, high degrees of homophily will be necessary to divert advantages to groups with the initial advantage. In this case, a preference for, say, high-earning alters will not automatically yield highly-educated alters, as income and education are not correlated. Put differently, the adoption advantage that comes from one's status in different dimensions (income and education, in this example) will not be consolidated.

To illustrate these ideas, Zhao and Garip use an agent-based model, introducing status differentiation into a set-up used earlier by Centola (2015). Similar to DiMaggio and Garip (2011), their results suggest that status-based homophily can exacerbate inter-group inequality in adoption of a beneficial practice (like the Internet) when initial adopters are high-status individuals, and when adoption is subject to network effects. But different from earlier work, Zhao and Garip show that homophily drives inequality only when consolidation is moderate to high, that is, when social dimensions are correlated to a degree that the practice remains trapped in parts of the network where high-status actors cluster. Surprisingly, homophily actually alleviates inequality when consolidation is low, that is, when social dimensions are too weakly related to generate a network with overlapping ties, or 'wide bridges,' across which the practice can diffuse (Centola and Macy 2007).

In sum, these computational models allow researchers to trace network-driven inequality to mechanisms of network formation (such as homophily and consolidation). We now turn to an alternative direction for investigating the evolution of network-based differences: identifying the mechanisms through which networks enable the transmission of behaviors and outcomes.

Mechanisms for network effects: The missing link between networks and inequality

As mentioned above, we define 'network effect' simply as the effect of an alters' behavior (or outcome) on ego's choices. Network amplification of social inequality is predicated on the presence of network effects, or 'social interactions' as economists typically refer to them (Manski 2000; Durlauf and Ioannides 2010). Network effects are not only difficult to identify empirically, but also hard to demarcate conceptually.

There are many mechanisms that can give rise to network effects. Indeed, researchers have come up with different typologies of mechanisms, and some have sought to characterize empirical 'footprints' of each mechanism (e.g., Young 2009). We cannot do justice to this complicated literature given space limitations. But, we can point out two general questions that animate most existing categorizations of network-effect mechanisms: (1) what is it about the alters that shape ego's behavior, and (2) what is it about the ego that shifts in response?

DiMaggio and Garip (2012), for instance, focus on the first question, and define four classes of mechanisms. Each mechanism is represented via a different functional form relating alters' behavior to ego's choices. In *social contagion*, ego adopts as soon as it is exposed to a single alter depicting a behavior. Under *social learning*, ego needs to observe a certain number of adopting alters, and that threshold of adoption varies according to the riskiness of the behavior. Under *normative influence*, ego faces pressure from adopting alters in proportion to their prevalence among its immediate ties. And, finally, under *network externalities*, ego draws more benefit from a behavior the more alters adopt it. In each of these cases, ego's adoption is a function of the number or proportion of adopting alters in its network.

A similar question of alter behavior underlies Young's (2009) distinction between *contagion* and *social influence* (where ego is compelled to conform once adopting alters increase in numbers), and Rossman, Chiu and Mol's (2008) definitions of *contagion*, *threshold models* (a version of social learning) and *network externalities*.

Hedström (2005) and Åberg and Hedström (2011), by contrast, focus on the second question, that is, on how the ego (or its environment) changes in response to alters' behavior. In their typology, network effects can work through ego's changing *desires* (D), *beliefs* (B), or *opportunities* (O) in relation to alters' choices (also known as the DBO theory of social interactions). Under *desire-based interactions*, ego's desires shift with alters' behavior. For example, an individual might wish to start exercising after seeing her friends criticize those who do not. Or, a person might choose to wear a mask during the COVID-19 pandemic after realizing that not doing so is stigmatized in her community. Under *belief-based interactions*, ego's beliefs about the efficacy of a behavior change after observing it among its alters. For example, an individual might take up exercising after seeing her friends improve their health by jogging regularly. Under *opportunity-based interactions*, ego's opportunities to adopt a behavior or achieve an outcome depend on the choices of its alters. For example, an individual might be more likely to find out about job opportunities on Silicon Valley if she has many friends already working there.

The DBO typology is similar to Manski's (2000) categorization of network effects. Manski identifies three channels for social interactions (economists' preferred terminology to refer to network effects: *preference interactions*, *expectation interactions*, and *constraint interactions*. These three channels correspond to the desire-based, belief-based, and opportunity-based interactions, respectively, in the Hedström classification.

The DBO and Manski classifications – although inspired by a slightly different question – also bear affinity to the categories in DiMaggio and Garip's (2012) or Young's (2009) typology. For example, *desire-based interactions* give rise to what DiMaggio and Garip call *normative* *influence*; while *belief-based* and *opportunity-based interactions* underlie *social learning* and *network externalities*.[2]

Regardless of the terminology and classification used, we argue, focusing on the mechanisms underlying network effects is crucial for unpacking the network amplification of inter-group differences. For example, empirically, we observe large inequalities by socio-economic status in health-improving behaviors, such as exercising, dieting, or quitting smoking, in the United States (Christakis and Fowler 2008; Pampel, Krueger and Denney 2010). We see relatively smaller gaps by socio-economic status in adoption of new technologies (DiMaggio and Garip 2011). The differences in relative magnitude in inequality might be connected to the differences in the mechanisms underlying network effects in the adoption of healthy habits or novel technologies.

Manzo et al. (2018) offer a perfect illustration of the importance of mechanisms in understanding variation in diffusion outcomes. Using data from Kenyan and Indian potters along with simulations, the authors find social learning to be a key mechanism for inter-group inequality in the adoption of new technologies. Specifically, presence of reinforcement from several early adopters activates 'wide bridges' for diffusion, while absence of such reinforcement inhibits any potential influence such network structure might have. In a similar vein, Barkoczi and Galesic (2016) argue that different social-learning strategies interact with network structure to affect group-level performance. When individuals rely on exploration and search as a strategy, for example, locally connected lattices ('inefficient networks') lead to more optimal group-level outcomes. Conversely, when individuals rely on exploitation and imitation of others as a strategy, fully-connected lattices ('efficient networks') produce better group-level performance.

Identifying the mechanisms underlying inter-personal influence, as these examples illustrate, allows us not only to understand the sources of network-driven differences in society, but also to design network-based interventions to alleviate those differences (An 2015; Kim et al. 2015).

Conclusion

Analytical sociologists have long argued for the importance of specifying the mechanisms, or micro-level elements, underlying key relationships in the social sciences (Gambetta 1998; Hedström 2005, Hedström and Bearman 2009, Manzo 2010). This insight has made little segue into the vast 'network effects' literature to date. This literature has amassed impressive empirical evidence on how social ties among individuals, and their particular patterning at the local and global levels, can be linked to various outcomes, such as educational attainment (Calvó-Armengol, Patacchini and Zenou 2009; Crosnoe, Cavanagh and Elder Jr. 2003), labor

[2] The so-called 'social influence network theory', which highlights how ego's susceptibility to be influenced is determined by social relations, can also be related to the existing categorizations (Friedkin 1998; Friedkin and Johnsen 2011). See Childress and Friedkin (2012) for an illutrative application of the theory.

market success (Granovetter 1974; Ioannides and Loury 2004; Petersen, Saporta and Seidel 2000), and health-improving behaviors (Christakis and Fowler 2013; Kreager and Haynie 2011). But the literature has little clarity on explaining how exactly networks matter in different instances, often reverting to a laundry list of potential mechanisms underlying alter influences on the ego.

In this review, we have argued that the recent efforts to clarify the mechanisms for network effects offer a crucial path forward for understanding how networks can amplify inter-group inequality. In particular, existing work on network-driven inequality has highlighted the importance of network structure, and how that structure comes to be through individual choices, like a bias toward homophily, or population-level factors, like consolidation of attributes. This literature has focused little, if at all, on how different kinds of alter effects can lead to different trajectories of behaviors or outcomes for different groups (DiMaggio and Garip 2012).

Recent attempts to develop typologies of network effects, for example, Hedström's (2005) desires-beliefs-opportunities (DBO) framework or DiMaggio and Garip's four-part categorization (social contagion, social learning, normative influence and network externalities), bring much-needed clarity to a cluttered literature. These typologies offer a natural starting point for investigating how different kinds of alter influences shape trajectories of behavioral adoption among different groups. For example, do we observe more or less inequality in healthy behaviors across socio-economic groups if those behaviors spread via peers changing our beliefs (e.g., in the benefits of exercising) or through peers changing our opportunities for adopting (e.g., by offering to exercise together)? Similarly, do we observe more or less inequality in the adoption of a technology (where peers increase its value to us by using it themselves), or in the adoption of societal norms, like vaccinating our children (where peers can actively offer rewards or sanctions)?

Future work can focus on the mechanisms underlying network effects (choosing a typology that best fits the purpose at hand) to understand how different mechanisms might drive the inequalities in the adoption of the same behavior (e.g., exercising), or to compare how different mechanisms might explain levels of inequality in the adoption of different practices (like technology and vaccination in the above example).

This direction, although fruitful, requires detailed data on individuals' behaviors and social ties over time. Furthermore, the identification of network effects, even with the requisite data, poses difficult methodological challenges. There is reason to believe that these difficulties are not insurmountable, however. Recent data sources (such as AddHealth, CILS4EU, or traces of online behaviors) offer unprecedented detailed information on the ties and choices of a large group of individuals. Similarly, recent advances dynamic network models (Snijders and Steglich 2015) or network matching (Aral, Muchnik and Sundararajan 2009) offer new solutions to the identification of network effects. For these data sources, and methodological developments to be of value to understanding network-driven inequality, however, we first need to hone in on the task of clearly specifying the mechanisms underlying network effects, and theorizing about their potential impact on patterns of inequality in our particular domains of interest. This task, we argue, is one that analytical sociologists are well-suited for given their orientations to sink to the micro-level to understand the macro-level phenomena, and given their particular toolkits for theory development (such as agent-based models).

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