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Is having an educationally diverse social network good for health?

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Abstract

While network research often focuses on social integration as a predictor of health, a less-explored idea is that connections to dissimilar others may benefit well-being. As such, this study investigates whether network diversity is associated with changes in four health outcomes over a 3-year period of time in the U.S.A. Specifically, we focus on how an underexplored measure of network diversity—educational attainment assortativity—is associated with common self-reported outcomes: propensity to exercise, body-mass index, mental health, and physical health. We extend prior research by conducting multilevel analyses using this measure of diversity while adjusting for a range of socio-demographic and network confounders. Data are drawn from a longitudinal probability sample of U.S. adults ($n = 10,679$) in which respondents reported information about themselves and eight possible alters during three yearly surveys (2013–2015). We find, first, that higher educational attainment is associated with more educationally insular networks, while less-educated adults have more educationally diverse networks. Results further suggest that having educationally similar networks is associated with higher body-mass index among the less educated. Further exploration of the relationship between ego network diversity, tie strength, and health is warranted.

Keywords: egocentric networks; health; network diversity; assortativity

1. Introduction

Despite a strong tendency for people to affiliate with people who are similar to themselves (Lazarsfeld & Merton, 1954; Marsden, 1988; McPherson et al., 2001; Smith et al., 2014), being socially connected to different types of people appears to be an important factor in a range of domains, including community-level economic development (Eagle et al., 2010), higher-order cognitive processing (Molesworth et al., 2015), and pro-social communication with others (Alshamsi et al., 2016).

Social relationships—often theorized as a form of social capital (Bourdieu, [1986] 2018; Coleman, 1990; Lin, 2001; Putnam, 2001)—have been shown to be strongly implicated in health behaviors and health status through a range of pathways (Berkman & Krishna, 2014), and much research on social capital and health has been conducted in an egocentric research framework (Perry et al., 2018). An egocentric perspective on one's relationships provides a glimpse of the social contours of the range of social confidants who may provide social support, access to resources, opportunities for social influence, channels for disease spread, and who may help individuals to buffer against stress.

Although a great deal of research has focused on the benefits of social relationships—and specifically, integration and network size—as predictors of lower rates of morbidity and mortality (Holt-Lunstad et al., 2010), a less-frequently explored idea is that network composition, and more specifically, network diversity—a form of social capital that serves as a relational asset (Lin, 1999)—may possibly serve as a social determinant of health. In many realms of network life, birds of a feather do flock together, and connections to those who are *similar* on some dimensions may provide for increased social support and buffer one from ill health. Yet having connections to people who are *dissimilar* in some way may facilitate access to new information about appropriate health behaviors, provide a range of models for appropriate behavior, and serve as channels for social influence.

In this study, we review prior research on network diversity and health and find that, on balance, network diversity appears to benefit modifiable health behaviors, mental health, physical/cognitive function, and overall mortality. However, several conspicuous gaps merit further investigation. To a great extent, much of this foundational work has evaluated hypotheses related to heterogeneity of network roles (based upon measures of relationship type—or role—diversity). While role diversity has been established as a reliable measure and it has important properties, we argue that encountering other forms of attribute-based diversity in one's everyday experience—for instance, diversity in socioeconomic status (SES)—may also be important to health. Second, much of the existing research on network diversity relies upon individually based measures of diversity that do not explicitly measure ties *between* socially connected alters. Third, the majority of research in this area tends to be based on cross-sectional designs, and so movement toward understanding mechanisms through which network diversity may be shaping health has been understandably restricted.

In this paper, we aim to expand existing efforts in these areas by turning toward a unique longitudinal and nationally representative dataset of more than 10,000 Americans surveyed about their personal networks and health between 2013 and 2015. We pose the following questions: (1) *To what extent is the educational diversity in one's personal network associated with having better or worse health?* and (2) *Whose health benefits the most from having social ties to those with diverse educational attainment?*

2. Background

2.1 Why should network diversity be good or bad for one's health?

It is not a foregone conclusion that any given structural dimension of one's network—whether density, cohesion, diversity, or number of social ties—should necessarily be a benefit to one's health. As Lin (1999) explained in elaborating network dimensions of social capital, there can be a relational advantage in having cohesive networks for maintaining one's resources, while having structurally different alters that bridge across locations in the network may be more important for obtaining new resources. From one perspective, having large and diverse networks increases the number and range of types of individuals that an individual must maintain contact with, which may come at the expense of cognitive burdens, role conflict, and stress (Burt, 2004; Cornwell, 2009; Dunbar, 2018; Goldman & Cornwell, 2015). Indeed, having more ties can be stressful and be associated with poor mental health, especially for women (Kawachi & Berkman, 2001). Yet in terms of health, it is also reasonable to think that being connected with different kinds of people may confer health benefits—as a form of network health externality that emerges above and beyond one's own resources (Smith & Christakis, 2008; VanderWeele & Christakis, 2019).

Overall, research in this area suggests that network diversity—generally defined as being socially connected with people of different backgrounds—is indeed associated with better health, including better overall self-rated health (Cattell, 2001), less susceptibility to upper respiratory infections (Cohen et al., 1997), lower risk of heart disease (Barefoot et al., 2005), and indications

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of improved mental health indicators such as lower depression levels (Erickson, 2003). Although during the past two decades there has been sporadic attention to the topic of network diversity in health in an egocentric framework, this field of inquiry has rapidly expanded since Moore and colleagues (2009) showed in a cross-sectional study that greater network diversity (as part of a greater multi-measure construct of network social capital) was associated with lower risk of excess adiposity. More recently, findings from a longitudinal investigation in the same cohort largely comported with the earlier cross-sectional findings (Wu et al., 2018).

Cross-sectionally, greater network diversity has been associated with better mental health in the case of homeless California adults and depression (Rice et al., 2012), in lower incidence of post-traumatic stress disorder among U.S. adults (Platt et al., 2014), and greater dispositional optimism in U.S. adults (Andersson, 2012). Yet a study of Canadian adults and depression found that greater geographic diversity of alters was associated with more depressive symptoms (Bassett & Moore, 2013).

Egocentric studies of modifiable health behaviors have shown that greater network diversity is associated with more salubrious levels of physical activity among Canadian adults (Legh-Jones & Moore, 2012) and U.S.-based older adults (Shiovitz-Ezra & Litwin, 2012), and with lower odds of smoking in Canadian adults (Moore et al., 2014) and among adolescents in multiple countries (Choi & Smith, 2013). Yet interestingly, in a longitudinal study, Child et al. (2017) found that having a greater range of occupations in one's personal network (greater network extensity) was associated with higher incidence of binge drinking (a poor health behavior).

Last, research among older adults has shown that greater network diversity is associated with an absence of disability (Escobar-Bravo et al., 2012), and that higher proportions of family-based ties in respondents' networks (i.e., less diversity) are associated with higher levels of disability (Cornwell & Laumann, 2015). Greater network diversity was associated with higher white matter integrity in the brain and neuronal myelination processes among middle-aged U.S. adults (Molesworth et al., 2015). Among older Dutch adults, having more diverse networks was associated with less cognitive decline concurrently, and over time (Ellwardt et al., 2015). Finally, across a multi-national sample of approximately 14,000 older adults in several developing countries, having less diverse and integrated networks (i.e., networks with few friends or community contacts and restricted to family) was associated with earlier mortality (Santini et al., 2015).

2.2 How network diversity is conceptualized and measured in studies of health

A substantial majority of studies of network diversity and health status/behavior have operationalized the concept of *role diversity* (Barefoot et al., 2005; Cornwell & Laumann, 2015; Ellwardt et al., 2015; Escobar-Bravo et al., 2012; Kelly et al., 2014; Legh-Jones & Moore, 2012; Molesworth et al., 2015; Moore et al., 2014; Rice et al., 2012; Song et al., 2017; Viruell-Fuentes et al., 2013; Zhang et al., 2012). This concept is often measured using a form of a network position generator (Lin & Dumin, 1986) that seeks to enumerate characteristics of an individual's ties to a set of alters with different social roles (e.g., as family members, church members, friends, and neighbors). The most common instrument used in this context has been Cohen's Social Network Index (SNI), which evaluates ego's access to 12 different roles; a recent example is Mowbray et al. (2014). Usually, network size (i.e., number of alters within each role) and range (difference between the highest- and lowest-status alters in terms of their occupational prestige) are also measured (Molesworth et al., 2015; Moore et al., 2014).

Of course, the high prevalence of Cohen's Social Network Index is a reflection of an individual-level/egocentric analytic bias of this literature, which reflects data-collection norms in the public health domain where ties between socially connected alters were not explicitly taken into account during the period of the scale development. There are exceptions, however. For example, Choi & Smith (2013) depart from this egocentric tendency by doing a meta-analysis of the role of nodes' network position (as isolates, members, or liaisons) and their association with smoking behaviors

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in the context of eight different adolescent friendship networks. It would appear, then, to be a worthwhile endeavor to build upon these efforts by more carefully accounting for the structure of respondents' personal networks and incorporating information on the social connections between ego's alters.

2.3 Mechanisms linking educational diversity to health

What mechanisms might explain the observed relationships between health and network diversity? It is quite likely that across different health measures, different mechanisms link social ties with health (Thoits, 2011).

2.3.1 Similarity

Given that individuals with similar attributes tend to form ties with one another (McPherson et al., 2001), and also that network diversity has been associated with largely positive health outcomes, for individuals without access to health care, information, or other resources, *similarity by socioeconomic status to trusted confidants, as well as their ties to one another* may contribute to the reproduction of health inequalities via insulating them from health-based opportunities and by inhibiting forms of social support. In addition, how those trusted others are connected to one another is likely to matter as well. In a word, similarity along key attributes can significantly impede the flow of new resources and information. For instance, Schaefer et al. (2011) report that marginalized individuals such as depressed teenagers tend to befriend other marginalized and depressed individuals. In that context, mentally unhealthy (healthy) individuals, and their friends, are unlikely (likely) to have the resources to assist their likewise mentally unhealthy (healthy) friends in times of need. Similarity thus acts as a possible mechanism for the reproduction of health disparities between individuals.

2.3.2 Tie strength

To obtain resource benefits from social contacts, one must not just have a relationship with others but also be able to mobilize those resources—which implies that *tie strength* is also consequential (Granovetter, 1973). Greater closeness between two people is associated with a greater likelihood of similarity between them (Cornwell, 2009), and this may be associated with a less diverse network. There is evidence suggesting that individuals in poor health tend to have weaker friendships (Haas et al., 2010), which will further amplify the effects of similarity on the reproduction of health inequalities mentioned above. In short, if healthier individuals are indeed more likely to have both access to resources through their ties to similarly healthier others *and* to be able to actively mobilize such resources through their relatively strong connections, then it is easy to see how tie strength could be considered an important mechanism connecting network diversity and health.

2.3.3 Cohesion

Having a cohesive network may allow greater access to health-related social support if one is trying to maintain one's health (Lin, 1999). There could be a "differential access" mechanism wherein individuals having different levels of education access social capital through different network pathways (Moore et al., 2009). For instance, in research on the psychological well-being of Canadian adults, Moore and colleagues found that individuals with less education tend to rely upon friends and family (i.e., strong ties)—who tend to have similar SES—for resources, whereas individuals with more education rely on acquaintances (i.e., weak ties). The authors suggested that those who are less educated may have less educationally diverse networks. And indeed, in comparing the 1985 and 2004 General Social Survey samples, Smith et al. (2014) found higher levels of education homophily between egos and their close confidants at the lower end of the education distribution.

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2.3.4 Subjective social status

Last, the *perception of one's position in society* may be a relevant mechanism linking social capital and health outcomes. In examining the relationship between a social capital scale and psychological distress, Song (2011) finds a significant mediating role for subjective social status—i.e., one's perception of status relative to others. This is important because there is evidence suggesting that ego's subjective social status (e.g., perceptions of relative class identification) is in itself dependent on the SES of their social contacts, above and beyond ego's SES (Hodge & Treiman, 1968). In that context, assortative ego networks with relatively high (low) levels of education might increase (reduce) ego's subjective social status, which in turn might positively (negatively) affect their health.

Given the state of research on network diversity and homophily, we hypothesize that social networks of less-educated individuals are likely to have less educationally diverse (more assortative) personal networks than those of more-educated individuals (H1). Testing this hypothesis is both a necessary first step to then evaluating the relationship between network diversity and health and also novel in that prior studies have focused on education homo-/heterogeneity at the individual/egocentric level (e.g., ego's level of education), rather than network measures of assortativity. Based on prior research grounded in studies of role diversity, we hypothesize that, in general, less education assortativity (i.e., having social contacts with a more diverse range of educational attainment) will be associated with better general physical and mental health, more physical activity, and lower body-mass index (BMI) (Hypothesis 2).

Last, we also predict (Hypothesis 3a) that it is more likely that the health of individuals in a less-educated tier (who are more likely to have a health resource deficit due to their low-SES status) may benefit from access to more-educated others (greater network diversity). Yet maintaining educational diversity within one's network may also be more burdensome, particularly for low status egos (for whom educational diversity necessarily means keeping ties with higher status alters). Thus, a competing hypothesis (Hypothesis 3b) could also be that network educational diversity is more likely to lead to poorer health and/or less health-promoting behaviors among low-SES individuals.

3. Data and Methods

To test these propositions, we utilize three yearly waves of longitudinal egocentric survey data obtained through an online survey administered by the Gallup organization between 2013 and 2015 as part of its ongoing, longitudinal, probability-based panel of American households. The Gallup Panel (Gallup, 2014) contacts U.S. households at random via random-digit-dialing of landline telephones and cellphones or address-based sampling. This is an online panel, which the polling firm acknowledges only includes individuals with internet access (80% of the U.S. population). The social network instruments used here queried who respondents spent free time with and discussed important matters with, and we describe further details about the enumeration process below. These questions were adapted from the GSS and National Social Life and Health Survey and piloted in a smaller sample (O'Malley et al., 2012). The present sample was drawn from an enumeration of 20,373 respondents (Year 1), 27,829 (Year 2), and 24,087 (Year 3). Nearly half of this sample ($n = 10,679$) provided a response at all three waves, allowing for models to adjust for changes in network composition. There were no covariate-based exclusion criteria for this study.

We chose health outcomes that have been commonly examined in prior studies of network diversity—these include generalized measures of physical and mental health, as well as a common health behavior (exercise/physical activity) and BMI, which is an indicator of cardiometabolic risk. Information on health outcomes includes self-rated physical health (SRPH) ("How would you describe your own physical health at this time?") with ordinal responses being Poor, Fair, Good, and Excellent. This measure was then dichotomized into "Excellent vs. Other" to examine the contrast between the best health possible and other categories. A similar question was asked of self-rated mental health (SRMH) ("How would you describe your own mental health or emotional wellbeing at this time?"), with the same response categories and dichotomization. Self-reported height and weight were used to generate a continuous BMI score (height/weight^2), and outliers below 15 and over 60 were coded as missing. A weight-related behavior question was asked of the form "Please indicate whether or not you have done any of the following to try and improve your health in the past three months—exercised regularly (at least 3 times per week)."

Socio-demographic covariates include individual characteristics such as continuous age, sex (male/female), race (White/Black/Asian/Native Hawaiian and American Indian/Other, which was re-coded into White/Black/Asian/other/multi-racial), ethnicity (Hispanic/non-Hispanic), education (<HS/HS/some college/college/postgraduate, coded 1–5), income (ordinal tiers, coded as categorical 0–8), and household assets (ordinal tiers, coded as categorical 0–7). An adapted form of the original MacArthur network subjective social status ladder (Adler et al., 2000) asked respondents "Please imagine a ladder with steps numbered from zero at the bottom to ten at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you place yourself?" (coded as continuous 1–10), employment status (employed full-time/part-time but not a full-time student/full-time student/retired/homemaker/not employed, which was re-coded into employed full-time/part-time/other), region (Northeast/Midwest/South/West), and marital status (single/married/separated/divorced/widowed /never married/living with a partner, which was then re-coded into "married or living with a partner" vs. "other").

3.1 Egocentric network measures

For the key independent variable, education assortativity, we relied on (a) ego's nomination of up to eight alters, (b) information about whether the alters were connected to one another ("Please select the option that best describes the current connection between [alter x's name prompted by what the respondent wrote in on (a)] and [alter y's name, prompted by what the respondent wrote in on (a)]."), and (c) ego-reported educational attainment of alters ("As far as you know, what is the highest level of education ([alter's name]) has completed?").[1]

3.1.1 Assortativity coefficient

Much prior research relies on adapting a position-generator method to measure network diversity, and such research is able to reach outside the stronger ties that name generators typically enumerate. Yet given a wealth of research that family and friends (typically strong ties) are consequential to health (Christakis & Fowler, 2007; Yang et al., 2016), the richness of information on between-alter ties available to us from name generators, we instead opt to use the assortativity coefficient (Newman, 2003) to indicate the extent to which a given ego network is segregated along the exogenous attribute of education as a key predictor. Assortative (disassortative) mixing is a dyadic process where ties tend to emerge between nodes within (outside) the same categorical attribute (Goodreau et al., 2009). A low assortativity coefficient is indicative of a diverse/desegregated network, while a high assortativity coefficient indicates the presence of a non-diverse/segregated network (Bojanowski & Corten, 2014).

We measure assortative mixing along categorical node-level attributes of alters. Since we are modeling self-reported relationships between a given ego and their alters, all ties are considered to be symmetric. This means that the personal networks here are always undirected. Following the notation of Newman (2003), and using a binary education attribute (i.e., high school graduate vs. college graduate) as an example, we define the assortative mixing coefficient as:

$$r = \frac{\sum_i e_{ii} - \sum_i a_i b_i}{1 - \sum_i a_i b_i} \tag{1}$$

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where $\sum_i e_{ii}$ is the sum of the fraction of within-category ties among all pairs (e.g., sum of the fraction of college-to-college ties and of the fraction of high school (HS)-to-HS ties), a_i is the sum of the fraction of within-category ties of nodes type j (e.g., HS-to-HS ties) plus the fraction of outside-category ties of nodes type j to nodes type k (e.g., HS-to-college ties) and b_i is the sum of the fraction of within-category ties of nodes type j (e.g., HS-to-HS ties) times the fraction of outside-category ties of nodes type k to nodes type j (e.g., college-to-HS ties). Since all ties under analysis are undirected, the fraction of outside-category ties is, by definition, the same irrespective of the node type (e.g., fraction of college-to-HS ties = fraction of HS-to-college ties).

Assortative mixing is often interpreted by some network theorists as a “preference” (Newman, 2003: 208701-1) of nodes to attach to other within-category (e.g., same-race or same-education level) nodes, as well as exposure to opportunities to interact or shared foci of activity (Feld, 1981, 1982). Decades of research suggest that, at the individual level, and assuming permeability of institutional barriers (McPherson & Smith-Lovin, 1987), nodes’ *preferences* to form connections to similar others—that is, *choice* homophily—are a ubiquitous force behind the formation of ties (Blau & Schwartz, 1984; McPherson et al., 2001; Centola, 2015). In this context, the assortativity coefficient is a summary measure designed to compare the pattern of within- vs. outside-category ties in a given (ego) network. Thus, it is an important tool to shed light on the prevalence of social processes like choice homophily by measuring assortative mixing.[2]

3.1.2 Network controls

Covariates were also included to adjust for the size of an ego’s personal network, as well as the density of one’s personal network given as the proportion of existing ties out of all possible ties of that network size. The correlation between these two covariates was low and did not pose a threat to model estimation. Due to the pervasiveness of (homophily-based) selection and social influence in social networks, some factors may systematically reduce the probability of observing a diverse network. More precisely, high frequency of contact or closeness with contact members will be important in this regard since these two factors are known to increase the likelihood that alters could be similar to each other (Cornwell, 2009). Thus, adjusting for average strength of “close” and “liking” ties among alters (two different indicators of strong ties here) serve as important controls. Closeness was measured using “How close do you feel to (display alter’s name, as appropriate)?” (1 = “Not close at all” and 10 = “Extremely close/closer than any other person I know”). Liking was measured with, “How much do you like (display alter’s name, as appropriate)?” (1 = “Do not like at all” and 10 = “Like a lot/Like more than any other person I know.”).

3.2 Analytic approach

We employ a multilevel modeling strategy (2-level panel data), wherein egos (level 2) are nested in time (level 1) (Perry et al., 2018). This framework has the advantage of accounting for an ego’s dependence with its prior observations. A random coefficient for education assortativity, included after testing a null random intercept model, allows change in assortativity to vary across egos. Conceptually, across all model frameworks, we theorize network diversity as part of the experiential social context—and thus a characteristic—of the ego. The appropriate form of each model was determined by the outcome variable specification, namely multilevel logistic regression for dichotomized exercise, SRPH, SRMH, and multilevel linear OLS for continuous BMI.

Covariate missingness

At baseline, 10,679 individuals were present at all three panels. All four dependent variables were missing at a low level, approximately $<5.0\%$ of respondents. Education assortativity could only

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be calculated for 85% of egos ($n = 9, 108$) for two main reasons. First, to calculate assortativity requires at least two alters (see footnote 2); those with less than two alters for whom an assortativity value was not calculable for this reason comprised 14.7% ($n = 1, 507$) of the baseline sample. Second, if an alter was nominated by ego but was missing an education value, we dropped that observation (<1%).

Analyses relied on complete-case analysis rather than partial imputation of individual-level covariate values because of our skepticism at imputing information on covariates without also imputing network ties as well. Although some recent work has offered promising steps in imputing edge information in sociocentric datasets (Huisman, 2014; Smith et al., 2017; Wang et al., 2016), this branch of the field of network science, and especially in egocentric settings, is at present relatively underdeveloped. At baseline, other covariate information was also missing on dependent variables (exercise regularly, 4.7%; BMI, 2.4%; SRPH, 0.8%; and SRMH, 1.4%) and socio-demographic covariates (household assets, 13.5%; income, 8.1%; marital status, 6.4%; employment status, 5.4%; subjective social status, 1.8%; ethnicity, 1.7%; race, 0.9%; and region of country, 0.2%). Of special note is the unusual completeness on respondent education; only 2 of the 10,679 respondents were missing this information.

Observations without complete covariate information across any two waves were dropped from multilevel models (analyses were missing ~15% of participants from the full sample). Those retained in the multilevel model sample have higher average income, household assets, subjective social status, and are slightly more educated. Because of known difficulties in using population weights in multilevel settings, we do not use these weights and spend additional time in the discussion section speculating on how the patterns of missing covariate data may bias the observed results. Because these data were deidentified to investigators, a human subjects approval waiver was granted by University of Massachusetts, Amherst. Data management, cleaning, and analyses were conducted using Stata 13 (StataCorp, 2013) and the R programming language (R Core Team, 2018).

4. Results

Figure 1 illustrates that education assortativity is approximately normally distributed ($\mu = -0.21$, SD = 0.23) though with a higher frequency of participants at the fully assortative end of the scale. Still, in general, there are very few individuals whose educational attainment networks are fully disassortative (more diverse) or fully assortative (more homogeneous), though there is overall a slight tendency toward assortativity. Bivariate associations describe a largely linear relationship between education assortativity and network size (where having a larger network is associated with greater alter educational homogeneity), and no relationship between assortativity and average alter closeness, average alter liking, or graph density.

Table 1 further describes the baseline analysis sample, and that on average, respondents report four alters (of a possible eight), that networks are relatively dense ($\mu = 0.87$), and that they like their nominated alters ($\mu = 8.65$) slightly more than they feel close to them ($\mu = 8.24$), though it bears keeping in mind these are likely to be largely strong ties. Roughly twice as many individuals report regular exercise as not, and although only 21% report being in excellent SRPH, twice that amount report excellent SRMH. The sample skews slightly male, with a strong majority who are non-Hispanic White, and the mean age of respondents is in their late 50s. Socioeconomically, the sample skews toward middle-to-upper class. Roughly half are employed full-time, average income is 5.8 (where 5 = \$75 − <100K/year and 6 = \$100 − <150K), and the modal category of educational attainment is postgraduate (39.8%), household assets average 3.9 (where 3 = \$100 − <\$250K and 4 = \$250 − <500K), and self-perception of subjective social status is 7.3 of a possible 10.

Figure 2 illustrates the variation in education assortativity by dependent variables (SRPH, SRMH, exercise, and BMI), as well as by respondents' educational attainment, household income,

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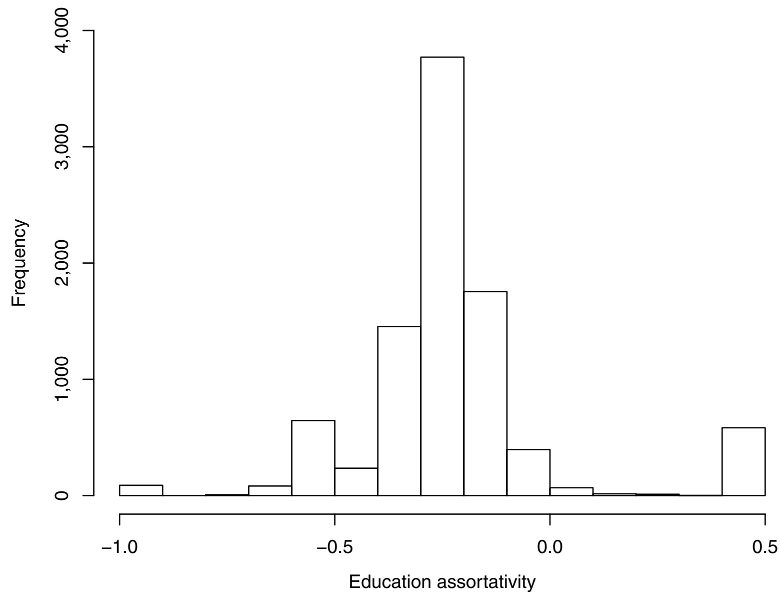

Figure 1. Egocentric education assortativity distribution. Note that lower values correspond with more dissortativity (greater attribute diversity), and higher values correspond with more assortativity (lower attribute diversity).

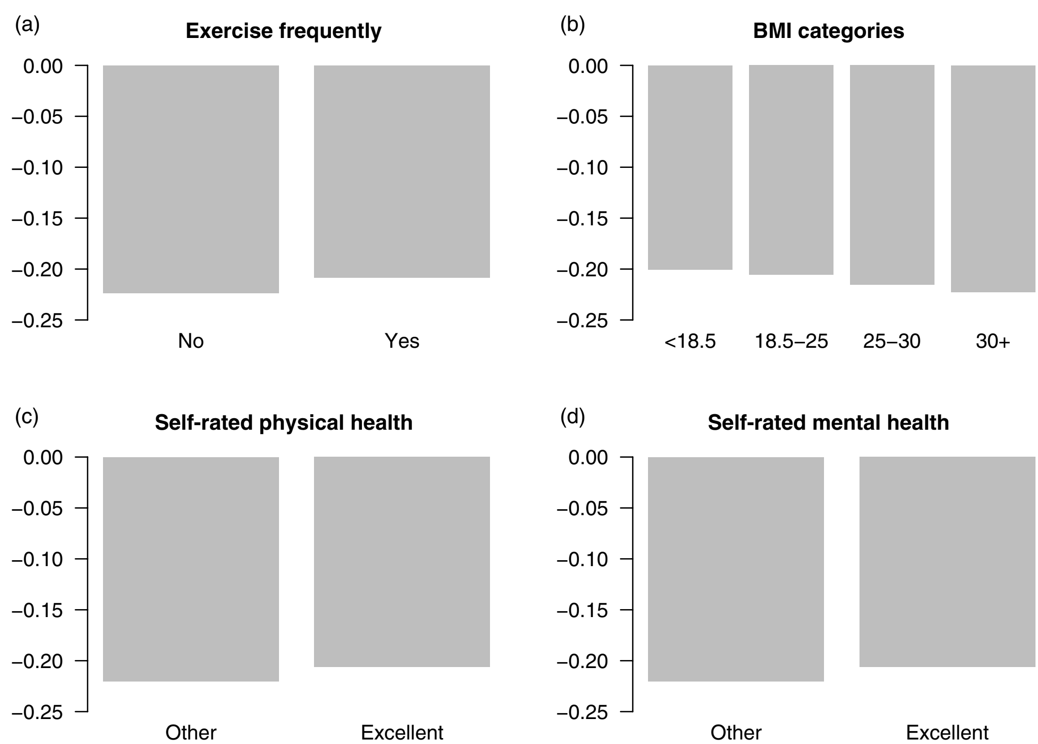

Figure 2. Mean egocentric network education assortativity, variation by participant characteristics. The assortativity scale is from −1.0 (most disassortative/maximally diverse education among alters) to 0.5 (most assortative/maximally homogeneous education among alters). There is a tendency for those who report frequent exercise, lower BMI, excellent self-rated physical health and mental health to have more educationally assortative egocentric networks.

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Table 1. Sample characteristics (baseline, Year 1)

Characteristics	*n*	Cat %/ mean (SD)	Range	Characteristics	*n*	Cat %/ mean (SD)	Range
Network covariates				(Socio-demographic covars., cont'd)			
Education assortativity	9,108	−0.21 (0.23)	−1.0 to 0.5	Race			
Number of alters	10,679	4.1 (1.89)	0 to 8	White	9,423	88.2%	
Personal network density	9,108	0.87 (0.16)	0.22 to 1.0	Black	437	4.1%	
Average closeness to alters	9,695	8.24 (1.12)	1 to 10	Asian	99	0.9%	
Average liking of alters	9,696	8.65 (0.96)	1 to 10	Other	158	1.5%	
Health covariates				Multiple	471	4.4%	
Body-mass index	10,177	27.8 (5.6)	15.3 to 59.6	NA (not available)	91	0.9%	
Exercised regularly				Ethnicity			
No	3,962	37.1%		Not Hispanic	9,896	92.7%	
Yes	6,464	60.5%		Hispanic	602	5.6%	
NA (not available)	253	2.4%		NA (not available)	181	1.7%	
Physical health				Employment status			
Poor	221	2.1%		Employed full-time	5,076	47.50%	
Fair	1,740	16.3%		Employed part-time	1,027	9.60%	
Good	6,364	59.6%		Other status	3,998	37.40%	
Excellent	2,269	21.3%		NA (not available)	578	5.40%	
NA (not available)	85	0.8%		Education			
Mental health				<HS	98	0.9%	
Poor	114	1.1%		High school	946	8.9%	
Fair	1,011	9.5%		Some college	2,471	23.1%	
Good	4,820	45.1%		College	2,916	27.3%	
Excellent	4,583	42.9%		Postgraduate	4,246	39.8%	
NA (not available)	151	1.4%		NA (not available)	2	0.02%	
Socio-demographic covariates				Income	9,816	5.8 (1.8)	1 to 9
Gender				Household assets	9,241	3.9 (2.0)	1 to 8
Male	5,588	0.52		Subjective social status	10,491	7.3 (1.6)	0 to 10
Female	5,091	0.48		Region			
Age	10,679	58.1 (13.5)	18 to 95	Northeast	1,589	14.9%	
Marital status				Midwest	2,838	26.6%	
Married/living with a partner	7,602	71.2%		South	3,474	32.5%	
Other status	2,496	22.4%		West	2,756	25.8%	
NA (not available)	581	6.4%		NA (not available)	22	0.2%	

wealth, and subjective social status. *P*-values for significance are reported across levels for a given covariate. Those respondents who regularly exercise, have lower BMI, and report excellent SRPH and SRMH tend toward more educationally assortative (more educationally homogeneous) networks. Figure 3 illustrates variation in education assortativity by different measures of SES. At the extremes of each measure, there is more assortativity at higher SES tiers, and lower assortativity at lower SES tiers, with a somewhat monotonic trend in the middle categories.

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Table 2. Associations with education network assortativity

	Year 1 OLS coeff.	Years 1–3 MLM coeff.
Key independent variables		
Educational attainment (ref: college)		
<HS	−0.067*	−0.012
	(−0.128, −0.006)	(−0.030, 0.006)
HS	−0.001	−0.015*
	(−0.024, 0.021)	(−0.028, −0.001)
Some college	−0.033***	−0.006
	(−0.047, −0.018)	(−0.017, 0.004)
Postgraduate	0.016*	0.023***
	(0.004, 0.029)	(0.011, 0.035)
Network covariates		
Number of alters	0.032***	0.033***
	(0.028, 0.036)	(0.031, 0.035)
Personal network density	0.055**	0.040***
	(0.018, 0.092)	(0.018, 0.062)
Average closeness to alters	0.008	0.005
	(−0.001, 0.018)	(−0.000, 0.011)
Average liking of alters	−0.007	0.000
	(−0.018, 0.004)	(−0.007, 0.006)
Socio-demographic covariates		
Male (ref: female)	0.005	0.005
	(−0.005, 0.016)	(−0.003, 0.013)
Age	0.000	−0.001***
	(−0.001, 0.000)	(−0.001, −0.000)
Race (ref: White)		
Black	−0.017	−0.014
	(−0.044, 0.010)	(−0.033, 0.006)
Asian	0.013	0.022
	(−0.043, 0.069)	(−0.018, 0.062)
Other race	−0.003	0.008
	(−0.046, 0.041)	(−0.024, 0.039)
Multiracial	−0.006	0.001
	(−0.032, 0.020)	(−0.018, 0.020)
Hispanic	−0.018	−0.023**
	(−0.043, 0.006)	(−0.041, −0.006)
Subjective social status	0.001	0.001
	(−0.003, 0.004)	(−0.001, 0.003)
N (observations)	–	21,795
N groups (egos)	7,308	9,090
AIC	−1,218.1	−4,418.1
BIC	−956.0	−4,074.6

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
Note: Both models adjust for covariates shown above, as well as categorical measures for region, marital status, household asset tiers, income tiers, and employment status. Multilevel model includes a continuous time measure.

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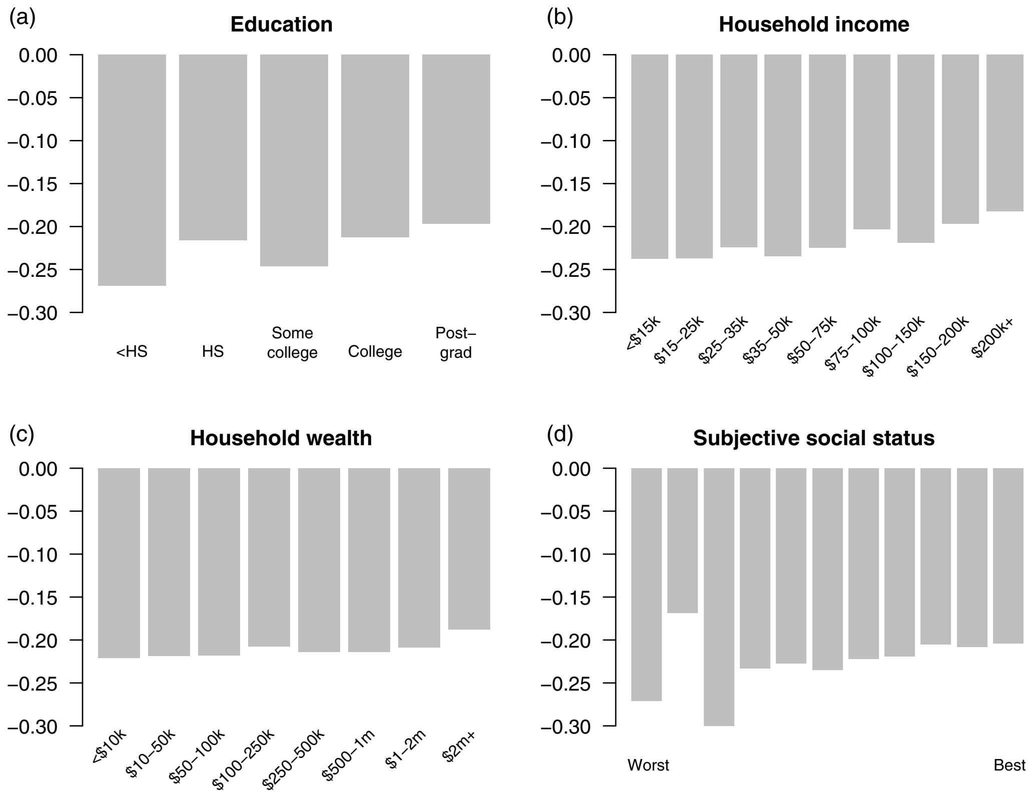

Figure 3. Mean egocentric network education assortativity, variation by socioeconomic status. The assortativity scale ranges from -1.0 (most disassortative/maximally diverse alter education) to 0.5 (most assortative alter education). These measures suggest a nearly linear gradient between those with lower SES having more educationally diverse networks, and those with higher SES having more educationally homogenous networks (the fewer number of responses in <high school and HS education categories suggest that if these categories were pooled, the pattern would be more linear; the same is the case with the three lowest subjective status categories).

4.1 Association of network and socio-demographic covariates with education assortativity

Table 2 reports on network and socio-demographic characteristics associated with education assortativity. Models include an OLS regression (Year 1 only) and a multilevel regression (Years 1–3). The question asked here is: to what extent does one's educational attainment predict one's network assortativity on education, net of socioeconomic, and structural network characteristics? Estimates in both model specifications reveal that relative to college-aged respondents, having a higher level of education is associated with greater assortativity (less diversity in one's network), while having less education is as sociated with more educational diversity in one's personal network. We also observe that having more alters and a denser network is associated with greater assortativity (more homogeneity), but there is no association between the two measures of tie strength (alter closeness and alter liking) and assortativity.

4.2 Multilevel regression estimates of education assortativity and health

Having documented evidence of a relationship between educational attainment and education assortativity, we next turn to evaluating relationships between educational assortativity and our suite of health indicators (Table 3). Three stepwise models are reported. The best-fitting model

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Table 3. Network education assortativity and health (random-coefficient multilevel models)

	Exercise regularly			BMI		
	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort
	OR	OR	OR	coeff.	coeff.	coeff.
Key independent variable						
Educational attainment (ref: college)						
<HS	0.348***	0.411***	0.449***	0.230*	0.128	0.237
	(0.254, 0.475)	(0.299, 0.564)	(0.297, 0.678)	(0.023, 0.437)	(−0.082, 0.339)	(−0.033, 0.507)
HS	0.557***	0.637***	0.762	0.137	0.061	0.229*
	(0.445, 0.698)	(0.507, 0.801)	(0.564, 1.029)	(−0.000, 0.274)	(−0.079, 0.201)	(0.045, 0.414)
Some college	0.789**	0.842*	0.934	0.124**	0.088	0.124
	(0.665, 0.936)	(0.709, 1.000)	(0.735, 1.186)	(0.036, 0.212)	(−0.001, 0.177)	(−0.004, 0.252)
Postgraduate	1.439***	1.454***	1.632***	−0.775***	−0.773***	−0.703***
	(1.167, 1.774)	(1.179, 1.794)	(1.252, 2.128)	(−1.020, −0.530)	(−1.019, −0.528)	(−0.967, −0.439)
Education assortativity	1.283*	1.260*	0.760	0.012	0.009	−0.303
	(1.020, 1.615)	(1.002, 1.585)	(0.387, 1.490)	(−0.141, 0.165)	(−0.143, 0.162)	(−0.702, 0.095)
Interactions (ref: college)						
Education assortativity × <HS	–	–	1.491	–	–	0.421
			(0.479, 4.642)			(−0.286, 1.128)
Education assortativity × HS	–	–	2.191	–	–	0.691**
			(0.931, 5.159)			(0.182, 1.199)
Education assortativity × some college	–	–	1.624	–	–	0.173
			(1.000, 1.000)			(−0.245, 0.592)
Education assortativity × postgraduate	–	–	1.709	–	–	0.304
			(0.804, 3.634)			(−0.151, 0.760)
Subjective social status	1.445***	1.407***	1.407***	−0.153***	−0.149***	−0.149***
	(1.386, 1.506)	(1.349, 1.467)	(1.349, 1.467)	(−0.182, −0.124)	(−0.178, −0.120)	(−0.178, −0.120)

Table 3. Continued

	Exercise regularly			BMI		
	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort
	OR	OR	OR	coeff.	coeff.	coeff.
Network covariates						
Number of alters	1.023	1.023	1.023	−0.009	−0.009	−0.009
	(0.983, 1.065)	(0.983, 1.065)	(0.983, 1.065)	(−0.032, 0.014)	(−0.033, 0.014)	(−0.033, 0.014)
Personal network density	0.551**	0.549**	0.547**	0.204	0.213	0.210
	(0.377, 0.805)	(0.376, 0.802)	(0.375, 0.799)	(−0.016, 0.425)	(−0.008, 0.433)	(−0.010, 0.431)
Average closeness to alters	0.945	0.944	0.945	−0.020	−0.018	−0.017
	(0.859, 1.040)	(0.858, 1.038)	(0.859, 1.040)	(−0.075, 0.036)	(−0.074, 0.037)	(−0.072, 0.039)
Average liking of alters	1.03	1.036	1.034	0.000	−0.001	−0.002
	(0.926, 1.147)	(0.931, 1.152)	(0.929, 1.151)	(−0.061, 0.062)	(−0.062, 0.060)	(−0.064, 0.059)
Socio-demographic covariates						
Male (ref: female)	1.149	1.147	1.147	−0.996***	−0.986***	−0.987***
	(0.995, 1.328)	(0.992, 1.327)	(0.992, 1.327)	(−1.224, −0.767)	(−1.214, −0.758)	(−1.215, −0.758)
Age	1.01	1.000	1.000	0.000	0.000	0.000
	(1.000, 1.011)	(0.994, 1.006)	(0.994, 1.006)	(−0.011, 0.006)	(−0.008, 0.009)	(−0.008, 0.009)

Table 3. Continued

	Exercise regularly			BMI		
	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort
	OR	OR	OR	coeff.	coeff.	coeff.
Race (ref: White)						
Black	0.957	1.031	1.031	1.159***	1.119***	1.119***
	(0.666, 1.374)	(0.718, 1.480)	(0.718, 1.479)	(0.583, 1.735)	(0.544, 1.694)	(0.544, 1.694)
Asian	2.379*	2.290*	2.292*	−3.679***	−3.651***	−3.648***
	(1.085, 5.215)	(1.044, 5.023)	(1.044, 5.029)	(−4.870, −2.488)	(−4.840, −2.463)	(−4.836, −2.460)
Other race	1.144	1.129	1.127	0.859	0.859	0.857
	(0.629, 2.082)	(0.622, 2.049)	(0.621, 2.047)	(−0.091, 1.810)	(−0.089, 1.807)	(−0.091, 1.805)
Multiracial	1.580*	1.656**	1.656**	1.144***	1.117***	1.116***
	(1.110, 2.250)	(1.164, 2.355)	(1.164, 2.355)	(0.578, 1.709)	(0.553, 1.681)	(0.552, 1.680)
Hispanic	1.281	1.293	1.294	0.395	0.393	0.393
	(0.918, 1.787)	(0.928, 1.801)	(0.929, 1.803)	(−0.129, 0.919)	(−0.130, 0.916)	(−0.130, 0.915)
N (observations)	21,525	21,525	21,525	21,199	21,199	21,199
N groups (egos)	9,056	9,056	9,056	8,967	8,967	8,967
AIC	24,104.7	24,073.7	24,078.35	105,676.9	105,663	105,662.5
BIC	24,296.1	24,416.7	24,453.27	105,883.9	106,021.3	106,052.6

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Notes: Model 1 adjusts for covariates shown, as well as region (categorical), marital status (categorical), and time (continuous). This model is arguably the best-fitting, with the lowest BIC across the four health models. Model 2 adds additional SES measures to prior model: household asset tiers (categorical), income tiers (categorical), employment status (categorical). Model 3 adds interaction between education attainment categories and education assortativity.

Table 3. Network education assortativity and health (random-coefficient multilevel models)

	Excellent self-reported physical health			Excellent self-reported mental health		
	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort
	OR	OR	OR	OR	OR	OR
Key independent variable						
Educational attainment (ref: college)						
<HS	0.501**	0.607*	0.377**	1.049	1.159	1.218
	(0.314, 0.798)	(0.378, 0.973)	(0.191, 0.745)	(0.768, 1.433)	(0.843, 1.594)	(0.795, 1.866)
HS	0.718*	0.821	0.732	1.046	1.131	1.077
	(0.524, 0.985)	(0.595, 1.133)	(0.478, 1.121)	(0.834, 1.312)	(0.899, 1.425)	(0.792, 1.464)
Some college	0.962	1.031	0.816	1.016	1.059	1.184
	(0.762, 1.216)	(0.814, 1.305)	(0.590, 1.130)	(0.854, 1.209)	(0.888, 1.263)	(0.928, 1.511)
Postgraduate	1.775***	1.721***	1.355	0.963	0.978	0.953
	(1.342, 2.349)	(1.299, 2.280)	(0.956, 1.920)	(0.785, 1.181)	(0.796, 1.201)	(0.734, 1.238)
Education assortativity	1.068	1.053	2.903*	1.155	1.152	1.096
	(0.783, 1.456)	(0.772, 1.437)	(1.146, 7.357)	(0.918, 1.452)	(0.916, 1.450)	(0.548, 2.192)
Interactions (ref: college)						
Education assortativity × < HS	–	–	0.128*	–	–	1.24
			(0.019, 0.877)			(0.375, 4.102)
Education assortativity × HS	–	–	0.529	–	–	0.831
			(0.151, 1.860)			(0.341, 2.028)
Education assortativity × some college	–	–	0.324*	–	–	1.643
			(0.112, 0.941)			(0.750, 3.597)
Education assortativity × postgraduate	–	–	0.310*	–	–	0.883
			(0.112, 0.862)			(0.410, 1.902)
Subjective social status	2.892***	2.819***	2.821***	2.997***	2.959***	2.959***
	(2.672, 3.131)	(2.604, 3.053)	(2.605, 3.055)	(2.837, 3.165)	(2.800, 3.126)	(2.800, 3.127)

Table 3. Continued

	Excellent self-reported physical health			Excellent self-reported mental health		
	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort
	OR	OR	OR	OR	OR	OR
Network covariates						
Number of alters	0.987	0.988	0.987	1.065**	1.065**	1.064**
	(0.934, 1.043)	(0.935, 1.044)	(0.934, 1.043)	(1.023, 1.109)	(1.023, 1.109)	(1.022, 1.108)
Personal network density	0.908	0.927	0.925	1.332	1.32	1.331
	(0.538, 1.533)	(0.548, 1.566)	(0.547, 1.563)	(0.908, 1.954)	(0.899, 1.938)	(0.906, 1.955)
Average closeness to alters	0.872*	0.866*	0.865*	1.021	1.022	1.021
	(0.762, 0.998)	(0.757, 0.991)	(0.756, 0.990)	(0.925, 1.128)	(0.925, 1.128)	(0.924, 1.127)
Average liking of alters	1.258**	1.268**	1.274**	1.242***	1.246***	1.245***
	(1.081, 1.464)	(1.089, 1.477)	(1.094, 1.483)	(1.111, 1.388)	(1.114, 1.393)	(1.113, 1.393)
Socio-demographic covariates						
Male (ref: female)	1.506***	1.511***	1.511***	0.669***	0.667***	0.668***
	(1.240, 1.830)	(1.241, 1.840)	(1.241, 1.841)	(0.582, 0.768)	(0.579, 0.768)	(0.580, 0.769)
Age	0.978***	0.977***	0.977***	1.020***	1.017***	1.018***
	(0.971, 0.985)	(0.969, 0.985)	(0.969, 0.985)	(1.015, 1.025)	(1.011, 1.023)	(1.012, 1.024)

Table 3. Continued

	Excellent self-reported physical health			Excellent self-reported mental health		
	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort	(1) Baseline	(2) +Inc, Wealth	(3) +Ed × EdAssort
	OR	OR	OR	OR	OR	OR
Race (ref: White)						
Black	0.338***	0.369***	0.368***	1.229	1.261	1.259
	(0.199, 0.576)	(0.217, 0.628)	(0.216, 0.627)	(0.870, 1.737)	(0.891, 1.784)	(0.889, 1.782)
Asian	1.909	1.788	1.795	0.945	0.925	0.92
	(0.728, 5.006)	(0.682, 4.687)	(0.684, 4.711)	(0.459, 1.946)	(0.448, 1.909)	(0.446, 1.901)
Other race	0.598	0.594	0.597	0.881	0.885	0.886
	(0.262, 1.366)	(0.260, 1.356)	(0.261, 1.365)	(0.498, 1.558)	(0.500, 1.568)	(0.500, 1.571)
Multiracial	0.449**	0.472**	0.472**	1.477*	1.507*	1.504*
	(0.268, 0.753)	(0.281, 0.792)	(0.281, 0.792)	(1.051, 2.076)	(1.071, 2.121)	(1.069, 2.118)
Hispanic	1.001	1.021	1.016	1.138	1.137	1.138
	(0.642, 1.560)	(0.654, 1.593)	(0.651, 1.585)	(0.830, 1.560)	(0.828, 1.561)	(0.829, 1.562)
N (observations)	21,701	21,701	21,701	21,600	21,600	21,600
N groups (egos)	9,191	9,191	9,191	9,065	9,065	9,065
AIC	16,330.6	16,300.4	16,301.1	22,243.1	22,258.3	22,260.2
BIC	16,522.3	16,643.8	16,676.4	22,434.6	22,601.4	22,635.3

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Notes: Model 1 adjusts for covariates shown, as well as region (categorical), marital status (categorical), and time (continuous). This model is arguably the best-fitting, with the lowest BIC across the four health models. Model 2 adds additional SES measures to prior model: household asset tiers (categorical), income tiers (categorical), employment status (categorical). Model 3 adds interaction between education attainment categories and education assortativity.

series (according to BIC minima) includes main effects of education assortativity and education attainment, and subjective social status, though a more expansive series can be found in the Supplementary Information Appendix. This model also includes four network attributes (number of alters, personal network density, average alter closeness, and average alter liking), a vector of confounders (gender, age, race, ethnicity, region, and marital status), and a continuous panel measure.

Across all health outcomes, and contrary to our expectations, education assortativity (more homogeneity) is positively and significantly associated with propensity to regularly exercise ($\text{OR} = 1.28$, $\text{CI} = 1.02 - 1.61$, $p = 0.03$). Network characteristics vary in their associations across outcomes; network density is negatively associated with propensity to exercise regularly, for instance ($\text{OR} = 0.55$, $\text{CI} = 0.38 - 0.81$, $p = 0.002$). Greater average liking of alters is associated with being in excellent SRPH ($\text{OR} = 1.26$, $\text{CI} = 1.08 - 1.46$, $p = 0.003$) and SRMH ($\text{OR} = 1.25$, $\text{CI} = 1.11 - 1.39$, $p < 0.001$), while greater average alter closeness is negatively associated with excellent SRPH ($\text{OR} = 0.87$, $\text{CI} = 0.76 - 1.00$, $p = 0.046$). Educational attainment is as expected—positively associated with propensity to exercise, negatively associated with BMI, and positively associated with SRPH. Subjective social status is consistently associated in expected directions with all four outcomes.

The second series adds additional SES variables to models, including household asset tiers (categorical), income tiers (categorical), and employment status (categorical). Across all models, higher levels of education assortativity (less diversity) remain significantly associated with greater propensity to regularly exercise. The associations between network characteristics and the outcome variables reported above are consistent between the first and the second series of models. In other words, the association between average liking and being in excellent SRPH and SRMH, as well as the association between average alter closeness and excellent SRPH are all statistically significant and remain the same direction.

Turning toward the fully specified third model series which include an interaction between education assortativity and education tiers, we observe little evidence of moderation for exercise frequency, SRPH, or SRMH. However, there is evidence that the relationship between assortativity with BMI is modified somewhat by ego's education level as predicted by H3a. Relative to college-educated adults, education assortativity among HS-educated adults ($b = 0.69$, $p < 0.008$) appears associated with higher BMI (marginal effect is 0.62 kg/m^2 greater BMI). Thus, greater assortativity (less diversity) is associated with higher BMI among low-education individuals. This relationship is visualized in Figure 4 below.[3]

In addition to moderation of assortativity and health by ego education, we also tested for moderation of this relationship by tie strength.[4] Table 4 reports that although tie strength does not moderate the relationships between education assortativity and exercise frequency, BMI, or mental health, it does appear to moderate the relationship with physical health, and rather strongly. The most straightforward interpretation is that among people with very assortative (educationally similar) networks, having a higher average strength of ties (as measured by ego's liking of alters) significantly increases ego's odds of being in excellent health by a large order of magnitude. This comports with the position that being in a homophilous network may be linked with better health due to having less burden to maintain relationships.

5. Discussion and Conclusions

Although the field of egocentric network analysis has enjoyed several decades of development from its early roots (Fischer et al., 1977; Lauman & Pappi, 1973; Lin, 2001; Wellman, 1979), careful attention to measuring network diversity as part of inquiring how social capital shapes health has been a less-developed area. Recent efforts to renew conceptual and accompanying measurement attention to forms of network composition are encouraging (Bojanowski & Corten, 2014). While examination of role diversity and health has been a consistent focus in network studies cutting across population health and social science, there has been very little attention given to

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Table 4. Tie strength moderation of network education assortativity and health (random-coefficient multilevel models)

	Exercise regularly	BMI	Excellent self-reported physical health	Excellent self-reported mental health
	OR	coeff.	OR	OR
Education assortativity	1.445	−0.026	18.795*	1.062
	(0.282, 7.399)	(−1.069, 1.018)	(1.518, 232.7)	(0.171, 6.582)
Average liking of alters	1.032	0.000	1.181*	1.249***
	(0.918, 1.159)	(−0.069, 0.068)	(1.003, 1.391)	(1.104, 1.412)
Interaction				
Education assortativity × avg. alter liking	0.984	0.004	0.717*	1.009
	(0.815, 1.188)	(−0.116, 0.124)	(0.537, 0.956)	(0.819, 1.244)
Network covariates				
Number of alters	1.023	−0.009	0.989	1.065**
	(0.983, 1.065)	(−0.033, 0.014)	(0.936, 1.045)	(1.023, 1.109)
Personal network density	0.549**	0.213	0.928	1.32
	(0.376, 0.802)	(−0.008, 0.433)	(0.549, 1.569)	(0.899, 1.938)
Average closeness to alters	0.944	−0.018	0.866*	1.022
	(0.858, 1.038)	(−0.074, 0.037)	(0.757, 0.991)	(0.925, 1.128)
Socio-demographic covariates				
Male (ref: female)	1.147	−0.986***	1.510***	0.667***
	(0.992, 1.327)	(−1.214, −0.758)	(1.240, 1.840)	(0.579, 0.767)
Age	1.000	0.000	0.977***	1.017***
	(0.994, 1.006)	(−0.008, 0.009)	(0.969, 0.985)	(1.011, 1.023)
Race (ref: White)				
Black	1.031	1.119***	0.365***	1.261
	(0.718, 1.479)	(0.544, 1.694)	(0.215, 0.622)	(0.891, 1.784)
Asian	2.290*	−3.651***	1.776	0.925
	(1.044, 5.023)	(−4.840, −2.463)	(0.677, 4.660)	(0.448, 1.910)
Other race	1.129	0.859	0.596	0.885
	(0.622, 2.049)	(−0.089, 1.807)	(0.261, 1.361)	(0.500, 1.568)
Multiracial	1.655**	1.117***	0.473**	1.507*
	(1.164, 2.354)	(0.553, 1.681)	(0.282, 0.795)	(1.070, 2.121)
Hispanic	1.293	0.393	1.017	1.137
	(0.928, 1.801)	(−0.130, 0.916)	(0.652, 1.587)	(0.828, 1.561)
Educational attainment (ref: college)				
<HS	0.411***	0.128	0.610*	1.159
	(0.299, 0.564)	(−0.083, 0.339)	(0.380, 0.978)	(0.843, 1.594)
HS	0.637***	0.061	0.823	1.131
	(0.507, 0.801)	(−0.079, 0.201)	(0.596, 1.135)	(0.899, 1.425)
Some college	0.842*	0.088	1.031	1.059
	(0.709, 1.000)	(−0.001, 0.177)	(0.814, 1.305)	(0.888, 1.263)
Postgraduate	1.454***	−0.773***	1.726***	0.978
	(1.179, 1.794)	(−1.019, −0.528)	(1.302, 2.287)	(0.796, 1.201)

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Table 4. Continued

	Exercise regularly	BMI	Excellent self-reported physical health	Excellent self-reported mental health
	OR	coeff.	OR	OR
Subjective social status	1.407***	−0.149***	2.820***	2.959***
	(1.349, 1.467)	(−0.178, −0.120)	(2.605, 3.054)	(2.800, 3.126)
N (observations)	21,525	21,199	21,600	21,701
N groups (egos)	9,056	8,967	9,065	9,191
AIC	24,075.64	105,665.0	16,297.5	22,260.3
BIC	24,426.62	106,031.2	16,648.8	22,611.4

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
Notes: Models adjust for income tiers, household asset tiers, region, employment status, marital status (all categorical), and time. Independent covariance structure specified.

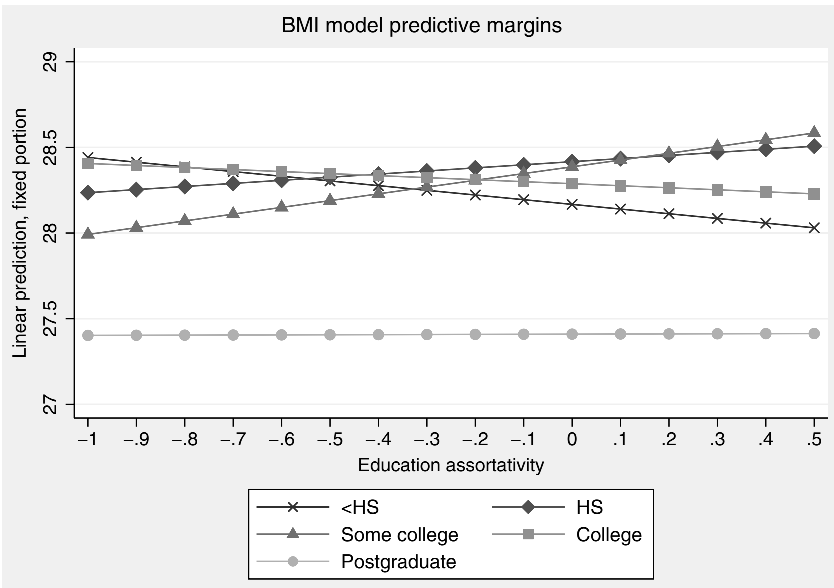

Figure 4. BMI model predictive margins from multilevel model (Table 3), showing that greater assortativity (lower network education diversity) is associated with higher BMI among individuals with a high school degree or some college.

attribute-based diversity and health in network settings. A novel aspect of the present study is that our analyses prospectively test relationships between education assortativity and multiple health indicators. In so doing, we hope to spur additional interest in examining attribute-based diversity in studies of health.

The present research finds that, contra to our expectations for Hypothesis 1, social networks of less-educated individuals are less assortative—that is, they are more, not less, educationally diverse than networks of more-educated individuals, whose network members tend to be more similar to their own education levels. This is not consistent with recent findings in the GSS that suggest greater education homophily at the lower end of the SES spectrum than the higher end (Smith et al., 2014). Yet the present measure of homophily is also quite a different measure than a simple tie homophily measure, in that assortativity takes into account educational homophily between alters and the structure of an ego's network.[5]

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We had also hypothesized (Hypothesis 2) that less education assortativity (i.e., having social contacts with a more diverse range of educational attainment) would be associated with better general physical and mental health, more physical activity, and lower BMI. Though we saw support in bivariate models, in multilevel multivariable specifications, we see no evidence to support this claim. In fact, we find the opposite in terms of physical activity, where less diversity (greater assortativity) is associated with propensity to exercise regularly. These findings stand in contrast to recent findings of a protective effect on BMI for network diversity in a 5-year longitudinal setting (Wu et al., 2018). This may be attributable to measurement differences of network diversity between these studies and differences in measurement period (3 years in the present study vs. 5 years in the prior study). Though we do not wish to overinterpret what are essentially null associations between education assortativity and separate models of BMI, SRPH, and SRMH, a conservative interpretation would be that measuring personal network assortativity reveals a different story than prior research that has found evidence of a diversity benefit to health using a role diversity measure.

For the third hypothesis, we predicted that it would be more likely that the health of individuals in a lower SES tier would benefit from access to higher-SES others. The finding that network education diversity is associated with higher BMI status for low-education egos provides limited evidence for Hypothesis 3a, consistent with an explanation that relationships with educationally similar alters were deleterious to the weight status of lower-SES participants. There was no evidence to support Hypothesis 3b, that maintaining education diversity in one's network was burdensome in a way that was associated with poorer health.

Prior literature has suggested several different mechanisms that might link (ego) network diversity and health outcomes. In that context, we discussed, and tested, moderation through three additional mechanisms: tie strength, differential access to social capital by ego's educational level, and subjective social status. Our results suggest that tie strength does moderate the association between assortativity and health, where higher average strength of ties reduces ego's odds of being in excellent health. We thus strongly believe that fully incorporating tie strength into future analyses by using a weighted assortativity coefficient is a highly desirable next step in the study of ego network diversity and health. Also worthy of note and further exploration is that of the multiple covariates used to indicate SES, subjective social status tended to be more predictive of the health outcomes being scrutinized than more objective measures (e.g., household assets, income, and educational attainment), a finding that comports with earlier work (Singh-Manoux et al., 2005; Tan et al., 2018) and is increasingly recognized as an important social determinant of health.

It is also important to note how demographic patterns of structural advantage and disadvantage affect network selection. Namely, not all respondents have the same underlying probability of *access* to diverse networks. On average, people of color ["collective blacks," in the words of Bonilla-Silva (2004)] living in the U.S.A. are systematically at a disadvantage. We know, for instance, that blacks, Hispanics/Latinos, and Native Americans are at a greater risk of being incarcerated (e.g., Kim, Losen & Hewitt, 2010; Hirschfield, 2018; Alexander, 2010; Roberts, 2004). Given this fact, these individuals should be, in all likelihood, less able to have access to educationally heterogeneous networks. Therefore, it can be expected that a person of color may have less diversity in their networks when compared to an average White individual whose neighbors, parents, friends, and other close social contacts are much less likely to be forcefully removed (e.g., incarcerated, deported, and killed) from their network.

With these important structural limitations in mind, this is believed to be the first study to investigate educational assortativity (and among the first to investigate a form of SES diversity) and its relationship with several different commonly investigated indicators of health. This form of attribute-based diversity measures a different dimension of lived experience than the role-based measure more often used. Importantly, the investigation of this new dimension revealed results that were not hypothesized based upon prior research based upon measures of role-based relationship type diversity. A particular strength of this study is its large size and national scope; the Gallup network panel represents one of the largest longitudinal egocentric network datasets currently

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available to investigators. Although other currently available datasets such as the National Social Life Health and Aging Project (Cornwell & Laumann, 2015) and the UC Berkeley Social Networks Study (Offer & Fischer, 2018) offer more depth of focus on health-related traits, both have fewer, smaller panels.

Other possible considerations that may affect interpretation of results are measurement-related. First, network diversity as measured by a "name generator" is less likely to reach the same range as may be found using a position generator (Lin, 1999; Lin & Dumin, 1986). It is worth noting that this study does not include perfectly isolated people (egos with no ties) and those who are highly isolated (egos with one tie only) because of demands in calculating assortativity. Yet given this, we suspect that observing the associations we do even with a relatively blunt instrument such as a name generator to calculate education assortativity suggests that we may be underestimating the strength of a relationship between network diversity and health. Additionally, there may be measurement error in that ego report of alter traits (such as educational attainment) may not be as accurate as if those alters reported upon their traits directly. To this point, Marsden (1990) reviewed research on reports of alter attributes and found ego-proxied alter attributes to be largely similar to alter direct report. Next, although research on personal network composition has been long presumed that the egocentric network reflects only the closest of ties, recent research suggests that especially around major life transitions, individuals reach out to more peripheral social contacts for emotional support (Small, 2017). Thus, although models adjust for network density, incorporating additional information about tie strength beyond simple measures of average alter closeness and alter liking to weighted measures of assortativity could be revealing.

While controls of network size and density are important structural measures, consideration of the consistency of these networks—specifically, identification of which specific alters were dropped and which were newly added—was beyond the scope of this research. Last, those in the sample tended to be of higher SES, women, not Hispanic, with more homogeneous types of relationships with others, and larger and more sparse networks. Given this overrepresentation of high-SES individuals, it is possible that our findings underestimate the strength of a mechanism linking low-SES educational assortativity with health. Additionally, though population weights were available, we opted not to include them because of known difficulties in using population weights in multilevel models.

In sum, the pursuit of social diversity in everyday life—of thought, of experience, and in interpersonal relationships—is a noble idea, and arguably fundamental in some sense to the human experience, even mirrored at a biological level in the role of genetic diversity in human evolution. However, research which focuses on how diversity matters in everyday life reminds us that investigating different forms of diversity in one's interpersonal life is critical to obtaining a more comprehensive picture of how social context shapes health.

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Notes

1 To elicit alter names, a first name generator question asked, "Looking back over the past 12 months, think of up to four adults (ages 16 and over) with whom you spend the most free time. By free time, we mean time spent for your enjoyment after work or school or on the weekend. These adults could be members of your household, friends from work or school or elsewhere, family members or relatives, or others. Please enter the first names (or initials, nicknames) of these adults." A next name generator asked, "From time to time, most people discuss important matters with others. Looking back over the past 12 months, think of up to four adults (ages 16 and over) with whom you most often discussed important matters. These adults could be members of your household, friends from work or school or elsewhere, family members or relatives, or others. Please enter the first names (or initials, nicknames) of these adults." Then respondents were instructed, "Please review the full list of names you just provided. If any people appear twice on the list, click the box next to the name to REMOVE duplicate names so that each person will only appear once on the list below." A series of follow-up questions were then asked about characteristics of each of the confirmed alters.

2 As suggested by Bojanowski & Corten (2014), the assortativity coefficient can be interpreted as an index that represents the (proportional) weight of the main diagonal of the cross-tabulation of within- and outside-category ties of a given (ego) network. If all ties happen to be within-group ties (i.e., if all ties are located in the main diagonal) that indicates perfect assortative mixing in the ego's personal network. The assortativity coefficient ranges from complete disassortativity (indicating greater diversity or heterogeneity) to complete assortativity (indicating a lack of diversity or homogeneity) in the mixing pattern of the observed ties within and across a given exogenous category (e.g., education level) [see technical details in Newman (2003)]. Because the algorithm calculates an infinite value in the case of perfect assortativity (see details below), we assigned a value of 0.5 to "fully assortative" ego networks as just outside the maximum observed value (0.49). Alternative analyses not reported here were conducted that modified this by changing the upper bound to 1.0. Findings were robust to this measurement change. Following Equation (1), a_i is the sum of the fraction of *existing* within-category ties of nodes type *j* plus the fraction of *existing* outside-category ties of nodes type *j* to nodes type *k*, and b_i is the sum of the fraction of *existing* within-category ties of nodes type *j*. In that context, the denominator in Equation (1) will necessarily reduce to 0 when there is only one alter or when all ties are within-category ties since in those scenarios the available alter(s) will represent the entirety (i.e., a proportion of 1) of the *existing* (within- and outside-category) ties in the ego network, thus reducing the denominator in Equation (1) to $0(1-1=0)$. Once the denominator of Equation (1) becomes 0, the assortativity coefficient becomes undefined. Relatedly, since a_i, b_i, and e_{ii} are all a function of the pattern of *existing* ties, adding isolates (i.e., non-contacts) does not affect the pattern of existing ties at all and, for that matter, the assortativity coefficient. For a technical explanation of this property, called intransitivity to adding isolates, see Bojanowski & Corten (2014).

3 In the model predicting self-reported physical health, we do find some crossover effects of education assortativity by educational attainment on SRPH wherein among college-educated adults, being in a highly educationally assortative (similar) personal network is associated with marginally better self-reported health, but the mean difference (0.04) on a scale of 0.0–1.0 suggests statistical significance, but little practical significance.

4 Additionally, we tested for moderation by subjective social status and observed no association (not presented here, though available from authors).

5 As a sensitivity analysis, following (Smith et al., 2014) we constructed a measure of average categorical education distance between ego and their nominated alters in order to compare how our assortativity measure comports with their dyadic measure. We then examined how educational attainment and network characteristics are associated with education distance in a multi-level model that adjusts for the full range of socio-demographic characteristics (available from authors). Briefly, we find that less-educated individuals (<HS) and the most-educated individuals (postgraduate) have the least education homophily (see Supplementary Information Appendix). Though a more thorough comparison and interpretation of measures is beyond the scope of this study, future work may productively interrogate this direction.

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