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The same place but different: How neighborhood context differentially affects homogeneity in networks of different social groups

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ABSTRACT
In this paper, we explore how the neighborhood composition and individual choice relate to the network composition of different social groups. We predict that groups that engage more with the neighborhood, and those who control more resources have networks that are more homogenous than expected given the neighborhood composition. We also explore how two types of biased association (i.e., attraction to similarity and rejection of dissimilarity) vary by neighborhood composition. Analyzing neighborhood register data and the Survey of the Social Networks of the Dutch (2014), we find that networks of neighbors vary in their degree of homogeneity depending on the social group. Both groups that control more resources, and those who engaged more with the neighborhood had networks that were more homogeneous than expected given the neighborhood composition. Individual choice (i.e., attraction to similarity and rejection of dissimilarity) varied depending on both the neighborhood composition and group membership. Our findings show that neighborhood mixing with the aim to create intergroup ties might be effective for certain groups (i.e., middle aged, married), but it might backfire for others (i.e., retired individuals). Urban policies might be more effective when tailored to the needs of different social groups.

Introduction

Networks of neighbors tend to be homogenous with regard to a range of social dimensions, such as ethnicity or social class (Hipp & Perrin, 2009; Huckfeldt, 1983). The tendency to form homogeneous networks can be a challenge to social cohesion: social ties are an important predictor of cohesion (Hipp & Perrin, 2006), but if social ties are formed primarily between in-group members, then support and solidarity might become confined within the networks of similar neighbors (Hipp & Perrin, 2009).

Common explanations for network homogeneity are that individuals have a preference for similarity and that social contexts are segregated such that meeting opportunities are biased toward similarity (Blau & Schwartz, 1982; McPherson & Smith-Lovin, 1987). To the extent that network composition resembles the contextual composition, network homogeneity is interpreted as occurring by chance. The extent to which networks are more homogenous than would be expected by chance is interpreted as the result of individual choice, guided by preferences for similarity (McPherson & Smith-Lovin, 1987; Skvoretz, 1983).

When explaining homogeneity in networks, studies on neighborhood networks generally find a positive relationship between neighborhood composition and network composition (e.g., Hipp &

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Perrin, 2009). However, these studies assume uniform effects across social groups, and they are unclear about the specific mechanisms—other than contextual composition and preferences for similarity—that might produce homogeneity in networks of neighbors.

In this article, we consider conditional neighborhood effects. Firstly, neighborhood composition might affect social groups differently, because certain social groups spend more time in the neighborhood (Miltenburg, 2017; Mollenhorst, Volker, & Schutjens, 2009) or because they are more attractive targets for social association (Lin, 2000). Secondly, homogeneity in network of neighbors could be driven not only by preferences for similar others but also by preferences to avoid associating with dissimilar others (Atkinson, 2006; Skvoretz, 2013). Individuals not only select similar alters, but they also forgo possibilities to associate with dissimilar others (Huckfeldt, 1983). Therefore, in our contribution, we consider not only attraction to similarity but also rejection of dissimilarity. We combine neighborhood register data from Statistics Netherlands (2013) with the *Survey of the Social Networks of the Dutch* (SSND; Volker, Schutjens, & Mollenhorst, 2014), which contains comprehensive ego networks data for 1,069 respondents in 161 neighborhoods in the Netherlands.

Opportunity structure: Neighborhood composition

Neighborhoods are an opportunity structure from which social ties are selected (McPherson & Smith-Lovin, 1987; Verbrugge, 1977). Though people may have preferences for certain others, the social reality is that they can only act on their preferences to the extent to which their preferred others are available (Blau & Schwartz, 1982). Social contexts can thus be considered to constrain individual choice. However, they can also induce network homogeneity, because people associate with similar others due to mere availability (McPherson & Smith-Lovin, 1987). Neighborhoods in the Western industrialized world tend to be homogeneous with regard to ethnicity and socioeconomic status (Musterd, 2005), meaning that most residents are at an increased exposure of neighbors who are like them.

In this article, we focus on neighborhood composition in terms of the social characteristics of a neighborhood's residents but, of course, we acknowledge the importance of other aspects of neighborhood segregation. For instance, turnover rates and moving histories, gentrification processes, and urban renewal programs could all play a role in network formation (Kleit, 2008). Where possible, we control for these important neighborhood characteristics in our analyses. We do not discuss them in detail because despite their potential for explaining several aspects of neighborhood networks, they are not as central to our understanding of the specific network characteristics that we are interested in in this article. We instead focus our theoretical and empirical contribution on the role of neighborhood composition, because we believe that it is the most important aspect of neighborhood segregation for our understanding of network homogeneity.

Neighborhood compositions are not randomly generated, but they are the result of dynamic processes attracting specific groups to specific neighborhoods (Bader & Warkentien, 2016). Socioeconomic background and preferences for specific ethnic/racial neighbors seem to guide individual selection into neighborhoods (Sampson & Sharkey, 2008). Even though we acknowledge that selection into neighborhoods is an important mechanism, in this article we are interested in the processes that occur once residents have already settled into their neighborhoods.

Once individuals have settled into a neighborhood, the neighborhood composition can directly induce network composition. But depending on the social group, the neighborhood composition has different meanings. The majority group is likely to meet an increased number of neighbors who resemble them. For the majority group, encounters with similar others are likely to be induced. For the minority group, however, the neighborhood does not offer many random encounters with fellow minority members; if they want to fulfill their desire for homogenous networks, they have to act on their preferences. Thus, though the neighborhood composition structures network composition, the same neighborhood composition constrains the individual choice of different groups differently.

Choice: Group-specific mechanisms

Above and beyond the neighborhood composition, tie formation depends on mechanisms that pertain to choice rather than chance. We consider group-specific mechanisms based on three theoretical sources: conditional neighborhood effects (Guest & Wierzbicki, 1999; Miltenburg, 2017), social capital theory (Flap & Volker, 2004; Lin, 2001; Lin & Erickson, 2008), and biased net theory (Skvoretz, 1983, 2013).

Conditional neighborhood effects

Conditional neighborhood effects refers to the notion that despite living in a neighborhood of the same composition, in practice, residents might meet a very different set of neighbors. Groups differ in the extent to which they spend time in the neighborhood and in the degree to which neighborhood ties are relevant to them. Groups that are less mobile, that spend more time in the neighborhood, and whose activities are more locally grounded are more strongly affected by the neighborhood (Miltenburg, 2017; Mollenhorst et al., 2009). Working people compared to nonworking people might be less likely to spend time in the neighborhood, because their jobs might require them to commute and spend time outside of the neighborhood. The elderly might rely on their immediate surroundings more so than younger people who are relatively mobile and physically fit to spend their leisure time outside of the neighborhood. Married individuals—especially those with young children—might be more engaged with others in their neighborhood, because they are involved in their children's kindergarten, spend time on local playgrounds, or are generally motivated to create a safe environment for their children (Volker, 2017). Members of groups that are more likely to spend time in the neighborhood thus have a disproportionately larger chance of meeting and forming ties with each other. These considerations lead us to the following hypothesis:

H1: Members of groups that engage more with the neighborhood (i.e., older, married, and unemployed people) have more homogenous networks.

Social capital theory

Social capital refers to resources that are available to individuals via their social ties. Resources that are accessible to people through their personal networks (i.e., wealth or knowledge) are crucial to improving life conditions (Flap & Volker, 2004). Given the benefits of social capital, individuals are (consciously or subconsciously) motivated to form ties with those who can offer more resources (Lin, 2000).

Such resources are distributed unequally across groups. White, male, and higher educated people are among the most privileged groups (Twine & Gardener, 2013). Men were shown to receive more opportunities for professional achievement than women, because men are embedded in networks of men who grant access to information on vacancies (McPherson & Smith-Lovin, 1987). Similarly, networks of ethno-racial minorities tend to be smaller and more restricted to kin (Lin, 2000), which negatively affects their labor market opportunities (Lancee, 2012). Given the benefits of personal networks, there might be an incentive to form ties with those who can offer access resources.

Given that men, natives, older people, married people, and working people are most likely to control valuable resources, we expect them to be the most attractive associational targets. If everyone prefers associating with members of these groups, they will receive most friendship nominations. On the one hand, this might lead to these groups having wider and more diverse networks. On the other hand, tie formation is a mutual process where both sender and receiver need to nominate one another to create a tie. Based on the rational choice framework that underlies social capital theory, it is unlikely that members of resourceful groups associate with members of less resourceful groups. Combining this with the argument that people try to maximize resources, one can expect that people associate with others who have similar resources (see also Laumann, 1966, the status hypothesis, and the "like me" hypotheses on tie formation).

To summarize, even though groups that control resources might receive many requests from out-group members, we theorize that those who control valuable resources are more likely to reciprocate ties with in-group members who also have a lot of resources than with out-group members.

H2: Members of groups that have more resources (i.e., men, older people, natives, and working people) have networks that consist of more in-group members.

Arguments based on conditional neighborhood effects and social capital theory produce hypotheses that are partly competing because they assume different underlying mechanisms. In the case of contradicting predictions, we expect conditional neighborhood effects to be the working mechanism (H1). This is because only if residents are sufficiently involved with the neighborhood can the preferences posited by social capital theory (H2) express themselves. For example, employed residents control more resources and might prefer associating primarily with other employed residents who also control valuable resources (H2); however, if it is true that they rarely spend time in the neighborhood (H1), then they cannot fully act on these preferences.

Biased association: Attraction and rejection

Though conditional neighborhood effects and social capital theory predict which groups are more likely to have homogenous networks net of neighborhood composition, biased association accounts for variations in network homogeneity depending on variations in the neighborhood composition.

Biased association refers to two associational preferences: attraction to similarity and rejection of dissimilarity. For those groups who have networks that are more homogenous than expected based on the neighborhood composition (see hypotheses H1 and H2), the deviation can be measured in terms of a bias toward similarity and a bias toward dissimilarity. Variations in these biases can be measured and described as the result of variations in the neighborhood composition.

Attraction to similarity and rejection of dissimilarity are not merely two sides of the same coin (Skvoretz, 2013). Though attraction to similarity is based on favoring one's own group, rejection of dissimilarity is grounded in discrimination against otherness (J. Feld, Salamanca, & Hamermesh, 2016). To explain attraction to similarity, previous research has focused on interactions with similar others being experienced as more rewarding (Newcomb, 1956). Because people with similar socio-demographic characteristics tend to share knowledge (Carley, 1991), language, and cultural tastes (Marks, 1994), communication is easier than it is with dissimilar people. In initial encounters, attitudes are not directly visible, which is why people deduce them from apparent sociodemographic characteristics (Harrison, Price, & Bell, 1998).

Rejection of dissimilarity fits with arguments on intergroup conflict. Conflict theory (Sherif, Harvey, White, Hood, & Sherif, 1961) assumes that groups are in a continuous struggle to secure scarce resources. Such competition produces stereotypes and discriminatory behaviors. Prejudice and discrimination can arise as the result of perceived, rather than realistic, conflict (Tajfel & Turner, 2001).

Attraction to similarity and rejection of dissimilarity can be formally modeled as the result of random and nonrandom events (e.g., Skvoretz, 2013). To the extent that personal network composition is determined by the opportunity structure, personal networks are considered the result of a random draw of alters from the opportunity pool. Attraction to similarity and rejection of dissimilarity are considered a bias or deviation from what we would expect to occur by chance. Attraction to similarity is modeled as a nonrandom event that leads similar alters to be overrepresented in personal networks compared to the opportunity structure (Skvoretz, 2013). Rejection of dissimilarity is modeled as a nonrandom event that leads dissimilar alters to be underrepresented (Huckfeldt, 1983).

The attraction and rejection mechanisms can be written in the following equations:
Attraction mechanism:

$$Fij = \tau\mathrm{ij} + (1 - \tau\mathrm{ij})Sj. \tag{1}$$

Rejection mechanism:

$$Fij = \frac{Sj}{1 - \eta ij(1 - Sj)}, \tag{2}$$

where Fij is the propensity of member of group i in context j to form ties with other members of group i; Sj is the proportion of in-group members in neighborhood j; $(1 - Sj)$ is the proportion of out-group members in neighborhood j; τij is the attraction bias, the probability that a member of group i in neighborhood j seeks out encounters with members of group i; and ηij is the rejection bias, the probability that a member of group i in neighborhood j rejects associations with non-members of group i upon having encountered them.

Equation 1 describes the attraction mechanism as the process of tie formation of a member of group i with other members of group i in neighborhood j. Suppose that group i refers to women. Then, Fij is the propensity of a woman to form ties with other women in her neighborhood. The attraction mechanism depicts the following process: a woman can actively seek out encounters with other women in her neighborhood, and when she encounters them, she forms a tie. This occurs with probability τij (the attraction bias). To some extent, she does *not* actively seek out other women, which occurs with probability $1 - \tau ij$. In this case, encounters are unbiased, tie formation occurs randomly, and alters in her network are representative of the gender composition in her neighborhood (Sj). According to the attraction mechanism, homogeneity in personal networks is partly the result of attraction to similarity (τij) and partly the result of mere availability ($(1 - \tau ij)Sj$).

Equation 2 shows the process of tie formation via the rejection mechanism. Different from the attraction mechanism, the rejection mechanism assumes that people encounter a representative proportion of in-group members (Sj) and out-group members ($1 - Sj$). When they encounter an in-group member, they form a tie, but when they encounter an out-group member, they reject tie formation with a certain probability, which is represented by the rejection bias (ηij). To illustrate, when a woman randomly encounters another woman in her neighborhood (this occurs with probability Sj), she forms a tie with this woman. However, when she encounters a man in her neighborhood (this occurs with probability $1 - Sij$), she may or may not form a tie with that man. The extent to which she rejects forming a tie with this man is given by the rejection bias ηij.

Because attraction and rejection biases are contingent on the opportunity structure, we can test how these biases vary as the neighborhood composition changes. Contact theory and conflict theory, two prominent and contrasting theories, guide our predictions. The conflict hypothesis suggests that out-group threat may become more salient when people are confronted with more out-group members. Individuals may therefore become more motivated to distance themselves from out-group members and forgo ties with them. Simultaneously, an increased out-group threat might bind in-group members together because they are motivated to strengthen the relationships with the few in-group members available. This reasoning results in the following hypothesis:

H3a: As neighborhoods contain more out-group members, both the attraction bias and the rejection bias increase.

Contact theory opposes this prediction by claiming that intergroup contact is an efficient way of diminishing prejudice and fostering intergroup ties (Pettigrew & Tropp, 2006). Being exposed to out-group members in the neighborhood might create more favorable attitudes toward out-group members and thereby increase the likelihood of association. Predictions formulated based on conflict and contact theories refer specifically to the effect of out-group contact; however, previous research also points to the possibility that in-group contact might facilitate in-group favoritism (Balliet, Wu, & De Dreu, 2014; J. Feld et al., 2016). A meta-analysis reviewing 212 studies (Balliet et al., 2014) revealed that in-group favoritism is a primary motivator in social interactions. Rather than discriminating against out-group members, people seem to be motivated to strengthen their in-group. Consequently, we expect to find variations in attraction biases that are not driven by the prevalence of out-group members but rather by the prevalence of in-group members in the neighborhood.

This leads to the following hypothesis, which counters H3a:

H3b: As the neighborhood contains more out-group members the rejection bias will decrease, and as they contain more in-group members the attraction bias will increase.

To sum up, we expect individuals to build up homogeneous networks via different pathways that can occur in parallel. Specifically, individuals are more likely to form homogenous networks as they engage more with their neighborhoods (H1) and have more resources (H2). We also formulated competing predictions for the relationship between neighborhood composition and attraction to similarity versus rejection of dissimilarity (H3a–b), which is an additional explanation for why groups differ with regard to network homogeneity.

Sample, methods, and measurements

Data

We combined the third wave of the SSND (Volker et al., 2014) with neighborhood register data from Statistics Netherlands (2013). The SSND contains comprehensive data on ego networks of 1,069 respondents in 161 neighborhoods in the Netherlands. For the first wave of the SSND, a stratified random sample of 40 was drawn from approximately 500 municipalities in the Netherlands, accounting for the degree of urbanization and number of residents. Within each municipality, a random sample of four neighborhoods was drawn, and 25 addresses within those neighborhoods were randomly selected. Interviews were conducted at eight of these addresses with the occupant whose birthday was next. For every additional wave of the SSND panel data, a refreshment sample was added to account for attrition.

Neighborhood composition

The SSND provides respondents' four-digit postal codes, which enables linking respondent data to neighborhood data by Statistics Netherlands (2013). According to the definition of Statistics Netherlands (2013), neighborhoods are administrative units that are separated by natural boundaries, such as large streets, canals, or changes in types of housing. Neighborhoods have a mean surface of 1.60 km^2 (SD = 2.72 km^2) and an average of 4,341 residents (SD = 3,930). We know each respondent's neighborhood composition, such as percentage of women, age groups, immigrants, marital status, and work status, as well as the neighborhood degree of urbanization and neighborhood size. Degree of urbanization is measured categorically as the average address density per square kilometer (<500 addresses/km^2 = not urban, 500–1,000 addresses/km^2 = somewhat urban, 1,000–1,500 addresses/km^2 = moderately urban, 1,500–2,500 addresses/km^2 = strongly urban, >2,500 addresses/km^2 = very strongly urban). Descriptive statistics of all relevant neighborhood characteristics can be found in Table 1.

Personal networks

Network information was collected in two steps: first, names and functions of network members were obtained using several name generator questions; for instance, "When you have a problem,

Table 1. Descriptive statistics of neighborhoods.

	N	Mean	*SD*	Min	Max
Gender					
Female	1,061	0.50	0.02	0.38	0.72
Age					
15–24	1,059	0.13	0.05	0.03	0.47
25–44	1,059	0.26	0.07	0.02	0.51
45–64	1,059	0.28	0.05	0.08	0.41
65 +	1,059	0.17	0.08	0.02	0.86
Migration background					
Native	1,059	0.73	0.25	0.05	0.99
Work status					
Employed	1,055	0.71	0.07	0.20	0.95
Unemployed	920	0.15	0.09	0	0.61
Retired	924	0.15	0.06	0	0.31
Marital status					
Married	1,059	0.39	0.10	0.08	0.56
Count of inhabitants	1,061	4,340.88	3,929.53	35	22,920
Degree of urbanization					
Not urban	226	0.21			
Somewhat urban	170	0.16			
Moderately urban	119	0.11			
Strongly urban	203	0.19			
Very strongly urban	343	0.32			
Total	1,061	1			

from whom do you ask advice?" or "From whom do you ask help when you are sick?" Second, follow-up questions were asked to obtain relational information. We included alters as neighbors if they met one of two criteria: either respondents themselves indicated that the respective alter was a neighbor in response to the question, "What is your relationship with this person?" or respondents reported that the alter lived less than 1 km away from them. This distance is in line with neighborhood delineations by Statistics Netherlands (2013). We excluded alters who were reported to be kin or (ex-)partners.

Respondents answered a series of follow-up questions about each alter's sociodemographic characteristics. We recoded these alter characteristics such that they matched the categorical neighborhood measurements of Statistics Netherlands (2013). These were gender (male, female), age (15–24, 25–44, 45–64 and 65+ years), migration background (native born, migrant), marital status (single, married), and work status (working, retired, not working). Descriptive statistics of respondents and alters are shown in Table 2.

In our analyses of personal networks, we consider one social dimension at a time. This is for two reasons. First, we aim to dissect which social dimensions are most affected by the neighborhood composition. Second, at the neighborhood level, we do not have information on intersecting group memberships. If social dimensions intersect, then network homogeneity in one dimension might produce network homogeneity in another dimension as a by-product. To address this, Table 3 presents correlations of all ego characteristics under study. Though many of the correlations emerge as statistically significant, they are very small in magnitude ($r < 0.10$). The exception is the intersection between age and work status, which is mostly driven by young people being in education and old people being retired. We therefore conclude that the issue of intersecting group memberships is unlikely to affect our main conclusions.

Neighborhood engagement and resources

To assess which social groups are more likely to engage with the neighborhood (see Hypothesis 1) and which groups have access to more resources (see Hypothesis 2), we provide the following measures: With regard to neighborhood engagement, we assessed positive contact with direct

Table 2. Descriptive statistics of respondents and alters.

	Respondents			Alters		
	N	Mean	Missing	*N*	Mean	Missing
Gender						
Male	535	0.50		1,874	0.62	
Female	534	0.50		1,166	0.38	
Age (years)						
15–24	10	0.09		53	0.03	
25–44	152	0.14		671	0.25	
45–64	451	0.42		1,315	0.39	
65 +	452	0.42		888	0.20	
Migration background						
Native born	931	0.87		2,793	0.93	
Migrant	136	0.13		226	0.07	
Work status						
Employed	425	0.42		1,613	0.55	
Not employed	139	0.14		1,353	0.45	
Retired	452	0.44				
Marital status						
Married	691	0.65		2,160	0.72	
One child or more	589	0.86				
No children	97	0.14				
Single	378	0.36		849	0.28	
One child or more	133	0.37				
No children	223	0.63				

Note. We included having children by marital status to support an earlier claim that married individuals tend to have children. Information on children was available only for respondents, and not for alters, which is why we are unable to construct network homogeneity measures with regard to having children.

Table 3. Correlation matrix of ego characteristics.

	Female	Age 15–24	Age 25–44	Age 45–64	Age 65 +	Nonmigrant	Employed	Not employed	Retired
Female									
Age 15–24	0.00								
Age 25–44	0.06*	−0.04							
Age 45–64	0.03	−0.08**	−0.35***						
Age 65 +	−0.07*	−0.08**	−0.35***	−0.74***					
Nonmigrant	−0.01	−0.01	0.06*	−0.02	−0.02				
Employed	0.02	−0.04	0.23***	0.61***	−0.76***	−0.08*			
Not employed	0.06*	0.18***	0.18***	0.20***	−0.36***	0.10**	−0.34***		
Retired	−0.06*	−0.08**	−0.36***	−0.75***	1***	0.01	−0.76***	−0.36***	
Married	−0.02***	−0.09**	0.01	0.13***	−0.12***	−0.09**	0.19***	−0.10**	−0.12***

Note: **p* < .05. ***p* < .01. ****p* < .001.

neighbors, namely, whether respondents occasionally drink coffee with their direct neighbors (yes, no) and whether they occasionally have barbeques with their direct neighbors (yes, no). We also captured willingness to contribute to the neighborhood as a whole, which was an instrument consisting of 10 hypothetical scenarios that would disrupt safety or comfort in the neighborhood; for example, "The municipality wants to remove benches in a nearby square" or "Teenagers are spraying graffiti." For every scenario, respondents indicated on a 5-point scale (5 = *absolutely*, 1 = *absolutely not*) to what extent they would intervene if this happened in their neighborhood. We averaged responses across the 10 items to construct one measure of willingness to contribute to the neighborhood.

To measure access to resources, we used three indicators measuring financial, cultural, and social capital. We operationalized financial resources as the net monthly income, measured in steps of €250, ranging from an income of up to €250 at the low end to €4,000 or more at the high end. We used highest completed education as proxy for cultural resources ("primary education to lower vocational education," "general secondary education to pre-university education," "intermediate vocational education to higher vocational training," and "university degree"). Social capital was measured with the position generator, which captures access to socioeconomic and cultural resources via social ties that occupy different positions in the social hierarchy (Lin & Dumin, 1986). Respondents were presented with a list of 30 occupations that are typical in the Netherlands and were asked whether any of their social ties occupied these jobs. Scores range from 0 to 30, and higher scores indicated more resources that are accessible via social ties. Table 4 summarizes our measures of neighborhood engagement and resources by social groups.

Descriptively, we observe that the three measures of neighborhood engagement converge such that those groups that tend to drink coffee with their direct neighbors also tend to have barbeques with them and show more willingness to contribute to the neighborhood. Though gender differences appear negligible, we do observe age differences, such that neighborhood engagement increases with increasing age, peaks at age 45–64, and drops again at age 65 or older. Differences can also be observed for migration background, work status, and marital status, such that nonmigrants, employed individuals, and married individuals show more neighborhood engagement than migrants, unemployed individuals, and single individuals. With regard to Hypothesis 1, we thus expect to find that those aged 45–64, nonmigrants, employed individuals, and married individuals have more homogenous networks after accounting for neighborhood composition.

With regard to resources, we also observe that our three measures converge such that those who have more financial capital also have more cultural and social capital. The groups that controlled most resources were men, those aged 45–64, nonmigrants, working people, and married individuals. With regard to Hypothesis 2, these are the groups that we expect to have more homogenous networks after accounting for neighborhood composition. Please note that groups that engage more with the neighborhood are almost identical to the groups that have access to more resources. This overlap hampers our ability to empirically distinguish between evidence for Hypotheses 1 and 2. The exception is men, who do have access to more resources but do not engage with the

Table 4. Neighborhood engagement and resources by social groups.

		Neighborhood engagement						Resources					
		Coffee with neighbors		Barbeque with neighbors		Contribute to neighborhood		Financial capital		Cultural capital		Social capital	
	N	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Gender													
Male (reference)	535	0.56	0.50	0.33	0.47	3.85	0.84	9.11	3.88	1.50	1.04	10.33	6.34
Female	534	0.55	0.50	0.30	0.46	3.80	0.82	6.03***	2.86	1.33**	0.96	9.67	5.88
Age													
15–24 (reference)	10	0.33	0.52	0.17	0.41	2.88	0.79	3.56	2.13	1.40	0.84	7.70	7.24
25–44	152	0.55	0.50	0.36	0.48	3.72**	0.95	6.38*	3.11	1.74	0.86	10.52	5.73
45–64	451	0.57	0.50	0.35	0.48	3.96***	0.73	8.05***	3.89	1.59	0.94	11.61*	6.22
65 +	452	0.55	0.50	0.26	0.44	3.74**	0.85	7.65**	3.69	1.13	1.04	8.33	5.64
Migration background													
Nonmigrant (reference)	931	0.57	0.50	0.32	0.47	3.90	0.76	7.75	3.78	1.48	0.98	10.49	5.98
Migrant	136	0.47	0.50	0.24	0.43	3.28***	1.10	6.32***	3.13	0.97***	1.05	6.81***	6.09
Work status													
Not employed (reference)	139	0.49	0.50	0.27	0.45	3.60	0.98	5.33	3.26	1.29	1.01	9.16	6.61
Employed	425	0.59***	0.49	0.38***	0.48	4.00***	0.69	8.29***	3.67	1.80***	0.82	12.41***	5.54
Retired	452	0.55	0.50	0.26	0.44	3.74	0.85	7.65***	3.69	1.13	1.04	8.33	5.64
Marital status													
Single (reference)	378	0.48	0.50	0.21	0.41	3.46	0.94	6.67	2.90	1.17	1.01	7.58	5.84
Married	691	0.60**	0.49	0.36***	0.48	4.02***	0.70	8.06***	4.02	1.55***	0.97	11.33***	5.86
Total	1,069	0.56	0.50	0.31	0.46	0.38	0.83	7.60	3.75	1.42	1.00	10.00	6.12

Note. **p* < .05. ***p* < .01. ****p* < .001. Asterisks denote whether the respective mean is statistically different from the mean of the reference category based on a 2-tailed *t* test.

neighborhood more than women. Therefore, we can leverage results with regard to gender to distinguish between the mechanisms underlying hypotheses 1 and 2.

Analytical strategy

Testing hypotheses 1 and 2, we first established whether personal networks of different groups are more homogenous than we would expect given the neighborhood composition. Based on the number of neighborhood ties and the neighborhood composition we calculated the expected number of similar neighborhood ties (i.e., expected match). Applying paired samples t tests, we compared this expected match between respondents and their alters with the observed match. If the observed match exceeded the expected match, then homogeneity in personal networks of neighbors could not be explained as the result of the neighborhood composition alone.

We then tested whether observed homogeneity in personal networks could be explained by attraction and rejection biases. To this end, we first estimated *Fij*, which is the propensity of respondents to form ties with in-group members in their neighborhood. *Fij* can be construed as a function of the neighborhood composition and other contextual and individual-level variables that affect the likelihood of association. We then computed attraction and rejection biases for all variables of interest (i.e., gender, age, migration background, marital status, and work status) applying Equation 1 for attraction to similarity and Equation 2 for rejection of dissimilarity. The parameter estimates for attraction bias and rejection bias ranged from 0 to 1 and are best interpreted as probabilities: an attraction bias of 0 meant that individuals had 0 probability to prefer forming ties with similar others. In this case, all observed social ties were the result of a random draw from the opportunity structure provided by the neighborhood composition. If the attraction bias was 1, it meant that individuals preferred forming ties with similar others with probability 1. This meant that all observed social ties were the result of attraction to similarity. If the rejection bias was 1, individuals rejected every opportunity to associate with dissimilar others; if it was 0, then individuals formed ties with all dissimilar others they encountered.

To investigate how attraction and rejection biases change as the neighborhood composition changes, we plotted attraction biases (per respondents' ego networks) against the proportion of similar neighbors. We also plotted the rejection biases against the proportion of dissimilar others in the neighborhood. This enabled testing Hypotheses 3a and 3b by investigating whether attraction and rejection biases are larger or smaller in neighborhoods with varying proportions of similar neighbors.

Results

To establish whether there was homogeneity in personal networks, we calculated the observed and expected matches between respondents and alters. We obtained the observed match by dividing the number of ties to in-group neighbors by the total number of neighborhood ties (number of in-group alters/number of total alters). The expected match was obtained from the neighborhood composition data that were linked to respondents via their four-digit postal code. The expected match was equivalent to the proportion of in-group members living in the respondent's neighborhood. For example, if a respondent was female and lived in a neighborhood consisting of 40% female residents, then the expected match with regard to gender was 40%. The observed and expected matches ranged from 0 to 1 and can be interpreted as percentages.

For all characteristics of interest, we found that observed match significantly exceeded expected match. Observed match was strongest for migration background (84%), followed by marital status (65%), gender (59%), work status (50%), and age (43%). However, some of the observed match can be explained by a large share of in-group members living in respondents' neighborhoods. The large expected match with regard to migration background (71%) puts into perspective the large observed match in migration background (84%), because the observed match deviates from the expected

Table 5. Percentages of observed and expected match of respondents and their alters.

	Observed match	Expected match	Difference	*t*	*df*
Gender					
Male	0.72 (0.02)	0.47 (0.01)	0.25 (0.01)***	18.37	500
Female	0.47 (0.02)	0.48 (0.01)	−0.01 (0.01)	0.54	507
Total	0.59 (0.02)	0.47 (0.004)	0.12 (0.01)***	11.12	1,008
Age					
14–24	0.23 (0.13)	0.11 (0.03)	0.11 (0.12)	0.92	9
25–44	0.41 (0.03)	0.26 (0.01)	0.15 (0.03)***	5.11	151
45–64	0.48 (0.02)	0.28 (0.003)	0.21 (0.02)***	12.68	447
65 +	0.38 (0.02)	0.18 (0.004)	0.19 (0.02)***	12.22	444
Total	0.43 (0.01)	0.23 (0.003)	0.19 (0.01)***	18.16	1,054
Migration background					
Nonmigrant	0.90 (0.01)	0.77 (0.01)	0.13 (0.01)***	21.218	891
Migrant	0.29 (0.04)	0.22 (0.02)	0.08 (0.03)***	2.65	110
Total	0.83 (0.01)	0.71 (0.01)[a]	0.12 (0.01)***	19.59	1,002
Marital status					
Married	0.76 (0.01)	0.17 (0.004)	0.59 (0.01)***	46.47	644
Single	0.41 (0.02)	0.28 (0.01)	0.14 (0.02)***	6.30	303
Total	0.65 (0.02)	0.20 (0.004)	0.45 (0.01)***	34.17	948
Work status					
Working	0.66 (0.02)	0.68 (0.01)	−0.02 (0.02)	1.24	416
Not working	0.29 (0.03)	0.16 (0.01)	0.13 (0.03)***	4.43	113
Retired	0.38 (0.02)	0.17 (0.003)	0.21 (0.02)***	11.72	338
Total	0.50 (0.01)	0.41 (0.01)	0.09 (0.01)***	7.95	868

Note. Standard errors are in parentheses.
[a]Expected counts for migration background are based on neighborhood percentages of first- and second-generation immigrants, adjusted by national percentages of first-generation immigrants to weigh out the proportion of second-generation immigrants. The expected match is calculated as follows: Number of alters × Percentage of same neighbors/number of alters.
**p* < .05. ***p* < .01. ****p* < .001.

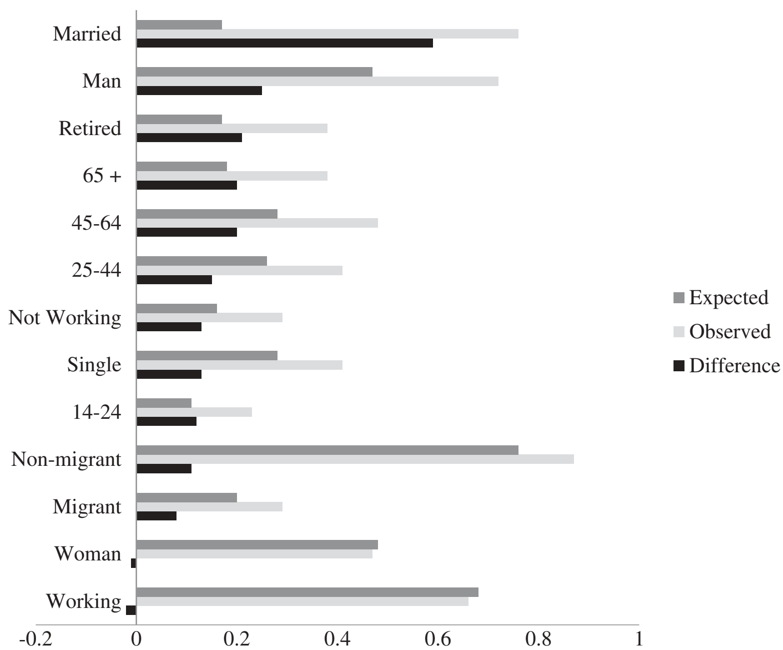

Figure 1. Percentages of observed and expected matches of respondents and their alters by groups.

match by only 12%. In contrast, the expected match of marital status was only 20%, but the observed match was 65%, meaning that the observed match exceeded the expected match by 45%. Comparing difference scores (i.e., expected match minus observed match) rather than observed match reveals a different picture: marital status shows the largest difference score (45%), followed by the other characteristics with some distance, namely, age (19%), gender and migration background (both 12%), and work status (9%).

To assess whether groups differentially associate with one another, we split up the analyses of observed and expected matches into subgroups (see Table 5 for mean comparisons and Figure 1 for a visualization of mean differences).

For women, the youngest age group, and working people, we find that observed matches are *not* significantly higher than expected matches. In contrast, men, older age groups, unemployed people, and retired people do display a significant excess in observed match. Both the retired and unemployed have significantly higher observed match, namely, 21% and 13%, respectively. With regard to migration background, both natives and migrants have more homogenous networks than expected, and the deviation is larger for natives (13%) than for migrants (8%). We also find that both single and married individuals report networks that exceed the expected match; however, the difference between observed and expected matches is much larger for married individuals (59%) than for single individuals (14%).

Overall, we find evidence that supports our hypotheses that groups that engage more with the neighborhood (i.e., older people, married people, nonmigrants) have more homogenous networks (H1) and that groups that have more resources (i.e., men, older people, nonmigrants, and married people) have more homogenous networks (H2). With regard to employment status, we find mixed support for our hypotheses. Though employed people engage more with the neighborhood and have access to more resources, they do not have more homogeneous networks. Comparing retired and unemployed people to one another, we observe that retired people show more neighborhood engagement than unemployed people, and they also have more homogenous networks. In the Discussion section, we elaborate on possible explanations for these mixed findings.

We then sought to explain the observed homogeneity by attraction to similarity and rejection of dissimilarity (H3a–b).[1] Following the procedure by Huckfeldt (1983), we first estimated *Fij*, which is the propensity of egos to form friendships with in-group members in their neighborhood after a large number of possibilities for association. In our analyses, *Fij* was a linear function of the neighborhood composition, opportunities for association, and individual-level variables that affect the propensity to associate. Specifically, we estimated *Fij* based on the proportion of in-group members living in the neighborhood, degree of urbanization, neighborhood socioeconomic status (SES; average income per resident), respondents' moving history (moved in the past 5 years; 0 = no, 1 = yes), and respondents' group membership of interest (e.g., gender) to allow for differential association propensities. We adjusted for moving history and neighborhood SES to combat potentially biasing factors related to selection into neighborhoods. Furthermore, we controlled for the number of neighborhood ties to account for smaller networks that might otherwise bias *Fij* toward 0 and 1. We estimated *Fij* as a linear function of these variables using ordinary least squares regression with robust standard errors accounting for the clustered data structure (i.e., several respondents lived in the same neighborhood). Following this procedure resulted in a sequence of estimates for *Fij*, which we inserted into Equations 1 and 2 to obtain estimates of attraction and rejection biases.

Table 6 shows an overview of attraction and rejection biases for all groups. Attraction biases were largest for nonmigrants (M = 0.62 SD = 0.78), followed by respondents who were married (M = 0.54 SD = 0.15) and men (M = 0.43, SD = 0.15). With some distance, attraction biases were moderately high for those aged 45–64 (M = 0.29, SD = 0.12), aged 65 years or older (M = 0.25, SD = 0.13), and retired (M = 0.25, SD = 0.07). Rejection biases largely mirrored this pattern even though the groups were ranked differently. Married people displayed the highest rejection biases (M = 0.74, SD = 0.10), followed by retired people (M = 0.67, SD = 0.08), nonmigrants (M = 0.66, SD = 0.74), those aged 65 or older (M = 0.63, SD = 0.18), and those aged 45–64 (M = 0.56, SD = 0.13).

In the final set of analyses, we inspected the extent to which attraction and rejection biases related to the neighborhood composition. To this end, we plotted attraction biases (per respondents' ego

Table 6. Parameter estimates of attraction and rejection biases.

		Attraction bias		Rejection bias	
	df	Mean (*SD*)	*t*	Mean (*SD*)	t
Gender					
Male	532	0.43***(0.15)	67.82	0.59***(0.14)	96.72
Female	527	−0.08***(0.16)	11.32	−0.23***(0.39)	13.94
Age					
15–24	9	0.02(0.20)	0.32	−0.14 (0.23)	0.63
25–44	151	0.19***(0.13)	17.65	0.41***(0.28)	18.10
45–64	447	0.29***(0.12)	52.00	0.56***(0.13)	90.24
65 +	444	0.25***(0.13)	42.95	0.63***(0.18)	73.44
Migration background					
Nonmigrant	920	0.62***(0.78)	24.27	0.66***(0.74)	26.91
Migrant	135	−0.05***(0.10)	6.25	−0.08(0.59)	1.65
Employment status					
Working	421	−0.18***(0.20)	18.04	−0.28***(0.30)	19.33
Not working	125	0.13***(0.08)	18.77	0.45***(0.26)	19.51
Retired	367	0.25***(0.07)	69.15	0.67***(0.08)	157.28
Marital status					
Married	686	0.54***(0.15)	90.85	0.74***(0.10)	192.63
Single	372	−0.90***(0.58)	29.95	−2.43***(1.34)	34.78

Note. Estimates are average biases across respondents' personal networks, and they can be interpreted as probabilities. Negative estimates indicate that networks are on average heterogenous and likely not the result of attraction to in-group members or rejection of out-group members, respectively.
*$p < .05$. **$p < .01$. ***$p < .001$.

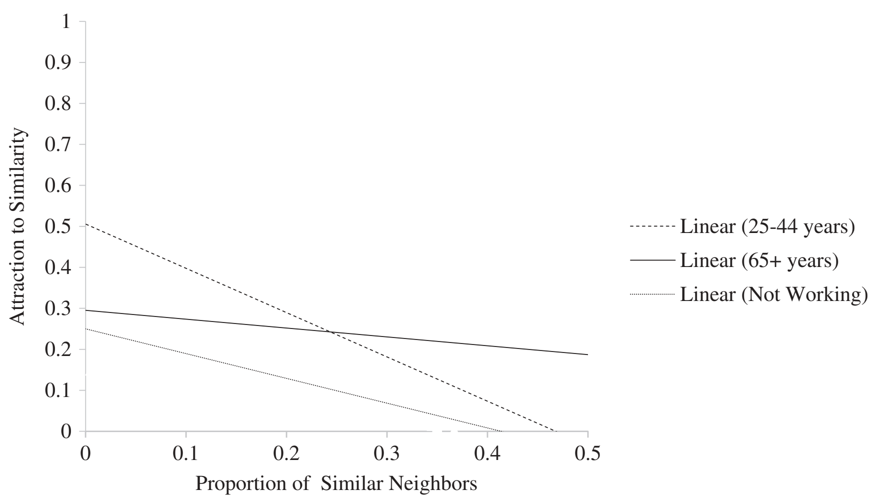

Figure 2. Conflict theory: Attraction to similar neighbors decreases as neighborhoods contain more similar neighbors.

networks) against the proportion of similar neighbors (Figures 2, 4, and 6). We also plotted the rejection biases against the proportion of dissimilar others in the neighborhood (Figures 3, 5, and 7).

We found three patterns of results that depended on group membership. In line with Hypothesis 3a, we found a decrease in attraction biases as the neighborhood contained more in-group members (Figure 2) and an increase in rejection biases as the neighborhood contained more out-group members (Figure 3). Those who were not employed, aged 25–44, and aged 65+ displayed this pattern. This pattern fits well with conflict theory, because an increased prevalence of out-group members with regard to age and work status increased the probability of rejecting out-group associations. Simultaneously, the attraction bias decreased as neighborhoods contained more in-

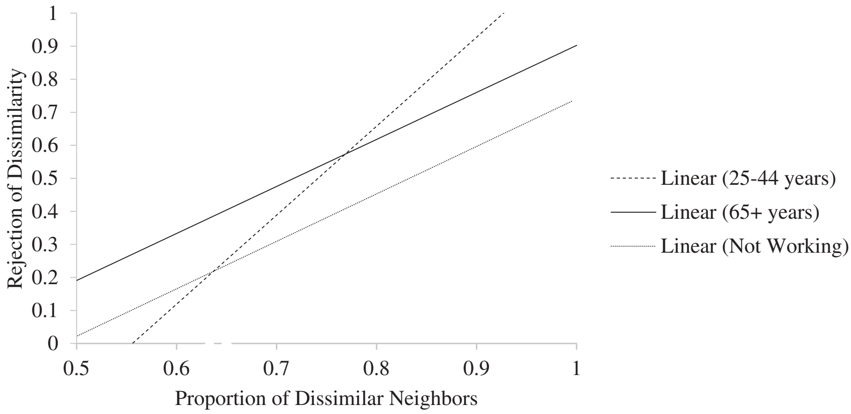

Figure 3. Conflict theory: Rejection of dissimilar neighbors increases as neighborhoods contain more dissimilar neighbors.

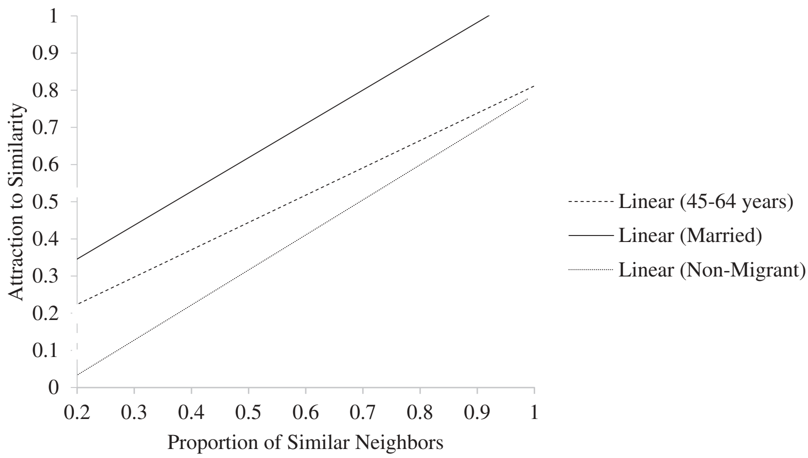

Figure 4. Contact theory: Attraction to similar neighbors increases as neighborhoods contain more similar neighbors.

group members. One possible interpretation is that the networks become more similar to the neighborhood composition as neighborhoods contain more in-group members, which means that homogeneity in networks of neighbors is less well explained by preferences for similarity. Another interpretation is that the attraction bias increases as out-group prevalence increases.

The second pattern of results showed that attraction to similarity rises as the proportion of similar neighbors rises (see Figure 4) and rejection of dissimilarity declines as the proportion of dissimilar others increases (see Figure 5). Married individuals, those aged 45–64, and nonmigrants displayed this pattern, which is in line with Hypothesis 3b. This pattern closely fits contact theory, because having more contact with out-group members decreases the probability of rejection. This contact effect seems to extend to the in-group, because more contact with in-group members relates to a larger probability of seeking out associations with them.

Finally, we found patterns that we did not hypothesize for men and retired people. For both men and retired people, an increase in the proportion of similar neighbors was positively associated with the attraction bias (see Figure 6). Thus, living among more similar others, they were

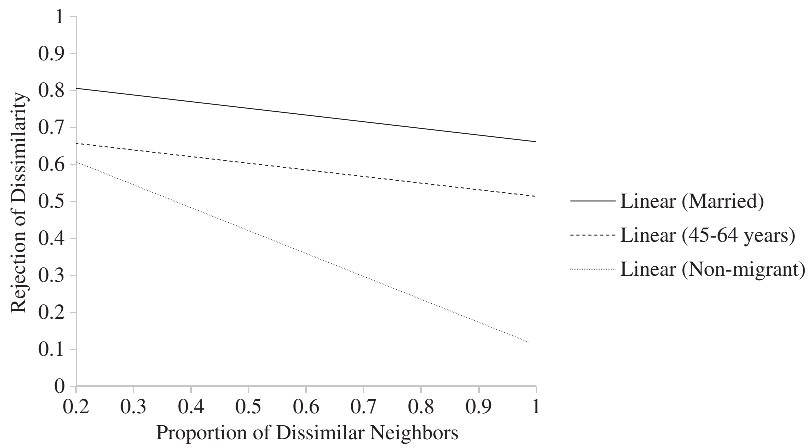

Figure 5. Contact theory: Rejection of dissimilar neighbors decreases as neighborhoods contain more dissimilar neighbors.

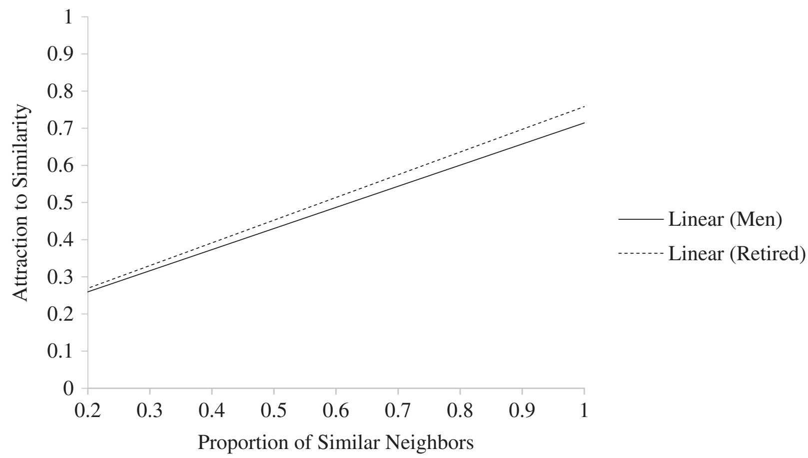

Figure 6. Ingroup favoritism: Attraction to similar neighbors increases as neighborhoods contain more similar neighbors.

disproportionately more likely to form associations with in-group members. Regarding the rejection bias, retired individuals were more likely to reject dissimilar others when more out-group members lived in their neighborhoods (see Figure 7). For men, the probability of rejecting associations with dissimilar others was stable across varying proportions of dissimilar others living in the neighborhood. Men's pattern most closely fits the idea of in-group favoritism, where people become more positive of their in-group without displaying an increase in out-group derogation. Retired individuals seem to display a more extreme version of in-group favoritism, which includes not only being more positive toward one's in-group but also more negative toward the out-group.

Discussion

Focusing on different social groups, this study investigated how homogeneity arises in personal networks of neighbors. Though we do replicate previous findings that neighborhood composition matters (e.g., Hipp & Perrin, 2009; Huckfeldt, 1983; Verbrugge, 1977), our findings add more

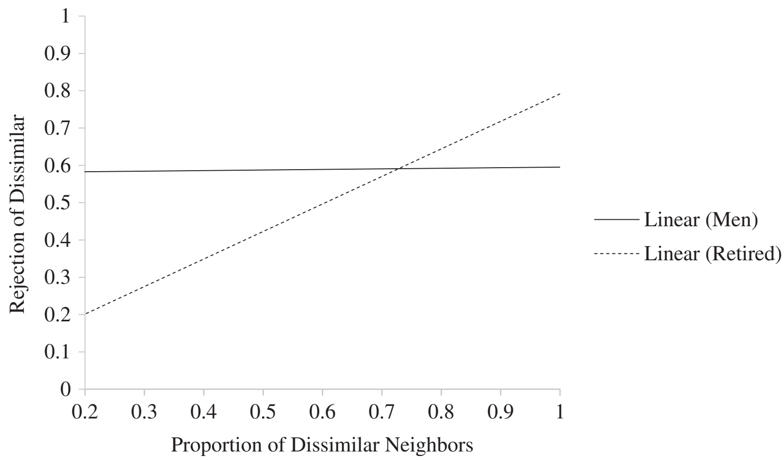

Figure 7. Out-group indifference among men and out-group aversion among retired individuals.

nuance. We show that social groups differ in their homophilous tendencies and that the neighborhood composition affects them differently.

Variations in network homogeneity by social groups

In line with social capital theory (e.g., Flap & Volker, 2004; Lin & Erickson, 2008), we show that groups controlling more resources have stronger tendencies to have homogeneous networks. Men, those aged 45–64, nonmigrants, retired individuals, and married individuals had more homogenous networks than women, other age groups, migrants, the unemployed, and single individuals. Moreover, women's networks mirrored the neighborhood composition and they leaned toward heterophily. Social capital theory can explain this. Women control fewer resources compared to men and thus they benefit from reaching out to men to build up more social capital and improve their life chances (see Burt, 2001; Lin, 2001).

Surprisingly, employed individuals reported networks that were slightly *less* homogeneous than the neighborhood composition. This is particularly surprising because employed individuals also reported more neighborhood engagement than unemployed or retired people, which should have led to more homogenous networks. A potential explanation might be that our measure of neighborhood engagement captures concrete, structured activities, such as meeting for coffee. It does not capture random encounters emerging from unstructured activities, such as bumping into each other in the park. Future research could disentangle what types of neighborhood engagement are most relevant to building up neighborhood networks.

Married individuals reported networks that were four times more homogeneous than those of singles. Neighborhood engagement could explain this finding. Married individuals often have children, which is why they are more likely to engage in shared activities with other married parents. Because family constellations are becoming more complex (Thomson, 2014), it is no longer self-evident that married individuals tend to have children. In our study, we did observe that 86% of married individuals had children. Among individuals who had at least one child, 73% were married and only 27% were not. At least in our study, mechanisms that tie parents together primarily concern married individuals. A kindergarten in a neighborhood represents a focus that brings together parents (Small, 2009). Thus, parents—who are mostly married—increase their chance of meeting similar others. Single individuals might also select themselves into shared foci; however, there are fewer foci explicitly fostering the interactions between single individuals. This might explain why their networks are less homogeneous than those of married individuals.

Comparing neighborhood engagement and access to resources, we encountered a surprising finding: groups that engage more with the neighborhood are largely the same groups that have access to more resources. Though we initially argued that neighborhood engagement (H1) is a necessary condition for acting on one's preferences for resources (H2), the almost perfect alignment between neighborhood engagement and resources raises the possibility that this relationship is reversed: maybe resourceful groups engage more with their neighborhoods, because having access to many resources facilitates engaging with the neighborhood. Those who have more financial capital might be better equipped to facilitate a neighborhod barbeque. Those with more social capital might have the necessary contacts to prevent the municipality from implementing reforms that would lower neighborhood wellbeing (e.g., removing benches in a park). Though it is an interesting observation that neighborhood engagement and resources coincide, this regularity also hampers our ability to empirically distinguish between these two mechanisms. We believe that exploring whether access to resources facilitates neighborhood engagement is a fruitful avenue for future research.

Variations in network homogeneity by neighborhood composition

We suggested two theories, conflict theory and contact theory, to explain how the neighborhood composition could relate to attraction to similarity and rejection of dissimilarity. According to conflict theory, groups perceive each other as competitors and threats. Conflict theory predicts that an increase in out-group members will increase the rejection of dissimilar others, because their increased prevalence is threating. To buffer against this threat, people might want to stick with their in-group. We find that the unemployed, young adults, and older people display this pattern, meaning that Hypothesis 3a is confirmed for these groups. As the number of dissimilar neighbors increases, both their rejection and attraction biases increase.

Contact theory predicts that exposure to out-group members decreases prejudice and increases the likelihood of friendly association (Allport, 1954; Pettigrew & Tropp, 2006). An increase in dissimilar neighbors would thus make individuals more positive about dissimilar neighbors and more likely to associate with them. We find this pattern for middle-aged individuals, married individuals, and nonmigrants, for whom rejection bias decreases as they live in neighborhoods that contain more dissimilar neighbors. Simultaneously, their attraction bias increases as they live in neighborhoods with more similar neighbors. Thus, for middle-aged individuals, married individuals, and nonmigrants, Hypothesis 3b is confirmed.

Finally, we found an unexpected pattern for men and retired people. As they lived among more in-group members, their attraction bias increased, whereas rejection bias remained stable (for men) or rejection increased as they were surrounded by more dissimilar others (for retired people). We label the finding for men "in-group favoritism," because in-group favoritism occurs when groups are motivated to advance the well-being of their own group, whereas they are relatively indifferent to other groups (Balliet et al., 2014). For retired people, we find a blend of in-group favoritism and conflict theory, because they not only favor their own group but they also seem averse toward otherness when opportunities for out-group contact increase.

These findings again stress the heterogeneity of neighborhood effects for different social groups. Not only does network homogeneity vary by social groups, but variations in neighborhood composition also affect different groups differently. Though being surrounded by more out-group members leads to fewer ties between some social groups, for other groups the opportunity of more intergroup contact incentivizes intergroup ties.

Limitations and future directions

This study has several limitations that offer opportunities for future research. First, we investigated one social dimension at a time, meaning that we treated different group memberships as mutually exclusive. In reality, individuals are simultaneously members of many groups. Depending on how these group memberships intersect, preferences for similarity can actually produce intergroup contact (Blau & Schwartz, 1982). To address this, we reported correlations between the social dimensions under investigation and found that with the exception of age and work status, social dimensions were largely independent. To the extent that group memberships do intersect, investigating them simultaneously could give a more refined picture as to where people insist on similarity and where they tolerate dissimilarity.

Second, social class is an important marker of distinction including several factors that are not currently captured in our analyses because even though we have information on the education of egos and alters, this information is not available to us at the neighborhood level. At the neighborhood level, we have information on income levels but we do not have this type of information at the alter level. Because of the difficulty of aligning the different data sources, we settled on a simple measure of employment status. We have therefore provided measures of financial, cultural, and social resources by employment status at the ego level (see Table 4). We are aware that this does not directly capture homogeneity with regard to social class. However, we hope that it at least provides some more nuance to help the reader understand how employment status relates to other measures of social class in our data.

Third, in our analyses, we treated neighborhood composition as a given opportunity structure. As mentioned in the theory section (titled Opportunity structure: Neighborhood composition), this opportunity structure is not randomly generated. In particular, the middle class tends to move from less wealthy neighborhoods to more affluent neighborhoods, leaving behind neighborhoods of concentrated poverty (Atkinson, 2006). We therefore empirically controlled for moving history and neighborhood SES. Still, our respondents might have already exerted some of their preference for similarity or rejection of dissimilarity when choosing their neighborhoods. If this is true, then we might have underestimated the individual choice to associate with in-group members or to reject out-group members. Our understanding of homogeneity in neighborhood networks could be further advanced by studying the conditions that lead social groups to live in different neighborhoods.

Evidence on different impacts of neighborhood composition on different groups has clear implications for urban policy. Fine-grained strategies that consider the varying impact of neighborhood compositions for different groups are needed. In both Europe and the United States, socioeconomic mixing policies (e.g., Moving to Opportunity) assume that life chances of residents can be improved by mixing neighborhoods in terms of residents' SES. This improvement in life chances is thought to occur via social mechanisms, such that residents of higher SES function as role models and offer support or advice to residents of lower SES (for a critical review, see Miltenburg, 2017). Our findings suggest that more fine-grained policy strategies are needed to achieve this. We find that whether mixing is positively or negatively related to out-group rejection depends on group membership. In the case of nonmigrants, married individuals, and middle-aged adults—the economically strongest groups in our study—the results of mixing are promising. The more neighborhoods are mixed, the smaller the rejection bias. Existing mixing policies at the neighborhood level might thus be effective for these groups.

In the case of other groups, mixing at the neighborhood level might be a necessary condition for intergroup ties, but it is not a sufficient one. In some cases—for instance, older and retired individuals—social mixing is associated with more out-group rejection. This suggests that neighborhood mixing can defeat its purpose when not combined with additional incentives to mingle and meet. The finding that married individuals have the most homogenous networks hints at the importance of shared foci for establishing social relationships. If it is true that daycare centers draw people together, then desegregating the spaces where individuals actually meet, such as daycare centers, community centers, or going-out places like bars or cafés, might be more effective than mixing at the neighborhood level.

Notes

1. We focus on groups whose networks were more homogenous than would be expected given the neighborhood composition. This is because heterogeneous networks cannot be explained by attraction to similarity and rejection of dissimilarity, and they produce negative attraction and rejection bias estimates that are uninterpretable. This applies to personal networks of women and individuals who are single. For the sake of completeness, we report these estimates; however, they know no meaningful interpretation. Please note that networks that are more heterogeneous than expected given the neighborhood composition can be rethought in terms of outbreeding bias (i.e., a propensity of affiliating with out-group members). Several applications are described in Skvoretz (1983). We applied the formula $F = (1 - \theta)Sj$, where θ denotes the outbreeding bias, which is the probability of seeking encounters with out-group members. For women, the outbreeding bias was 0.08 (SD = 0.16) and for singles it was 0.41 (SD = 0.12). For more details on outbreeding in our sample, we invite the interested reader to contact the corresponding author via email.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributor

Marina Tulin is a PhD candidate in sociology at the *University of Amsterdam* and a visiting scholar at *Stanford University*. Her PhD research is on the conditions and consequences of personal networks. She is interested in both psychological and contextual factors that contribute to the emergence of network homogeneity with regard to a range of relevant social characteristics. She studies how network homogeneity contributes to inequality in life chances and health/wellbeing.

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