Research Paper

Overweight/obesity among social network members has an inverse relationship with Baltimore public housing residents' BMI

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ABSTRACT

The American Heart Association has encouraged networks research focused on cardiovascular disease and its risk factors, such as obesity. However, little network research has focused on minorities or low-income populations. Our objective was to characterize the relationship between body mass index (BMI) with social network overweight/obesity among public housing residents in Baltimore, MD - a predominantly black, low-income group. We conducted a cross-sectional survey of randomly selected public housing residences (8/2014–8/2015). Adults had their height and weight measured and reported their network members' weight statuses using pictograms. Our dependent variable was respondents' BMI, and independent variable was perceived exposure to overweight/obesity in the social network. We also explored network exposure to overweight/obesity among 1) family members and 2) friends. We used multivariable linear regression adjusted for significant covariates. Our sample included 255 adults with mean age of 44.4 years, 85.5% women, 95.7% black, and mean BMI of 33.2 kg/m^2. Most network members were overweight/obese (56.1%). For every 1% increase in network exposure to overweight/obesity, individuals' BMI decreased by 0.05 kg/m^2 ($p = 0.06$). As network exposure to overweight/obesity among friends increased, individuals' BMI significantly decreased by 0.06 kg/m^2 ($p = 0.04$). There was no significant relationship between BMI and network exposure to overweight/obesity among family members. In conclusion, among Baltimore public housing residents, a statistically significant, inverse association existed between individuals' BMI and overweight/obesity among friends in their social networks. Our results differ from relationships seen in prior studies of other populations, which may be due to racial and/or contextual differences between studies.

1. Introduction

The prevalence of obesity among U.S. adults is nearly 40% (Hales et al., 2015–2016), and obesity has been associated with an increased risk of death and morbidity including cardiovascular disease, diabetes mellitus, and some cancers (Flegal et al., 2007). In recent years, attention has focused on understanding how the environment may contribute to the current obesity epidemic, particularly given that neighborhood factors have been linked with obesity (Egger and Swinburn, 1997). An ecologic framework hypothesizes that elements of environment – including social networks within the social environment – may influence obesity (French et al., 2001). In fact, the American Heart Association has deemed social networks to be potentially powerful interventions, and has encouraged networks research focused on cardiovascular disease (Havranek et al., 2015).

Simulations have illustrated how overweight/obesity might spread through social networks (Bahr et al., 2009; Zhang et al., 2015). In theory, network influence may alter weight through mechanisms such as behavior modeling, access, and social norms of body image (Bandura, 1986). The hypothetical relationship between social networks and overweight/obesity has been examined in longitudinal cohorts – Framingham Heart Study and National Longitudinal Study of Adolescent to Adult Health (Add Health) (Christakis and Fowler, 2007; Trogdon et al., 2008) – that examine predominantly non-Hispanic whites. Less is known about other groups such as minorities or low-income, despite their greater prevalence of obesity (Kumanyika, 1994;

Levine, 2011).

Generally, network characteristics differ by race/ethnicity and socioeconomic factors (Marsden, 1988); therefore, examining networks among these groups is warranted. Few studies have explored the relationship between obesity and social networks among minority and/or low-income populations (Pollack et al., 2014; Winston et al., 2015). One low-income group is U.S. public housing residents. Public housing is operated by local public housing agencies, who receive funds from the U.S. Department of Housing and Urban Development to manage the properties and rent units to low-income households. Minorities may be overrepresented among public housing residents, as 45% are black, 32% are white and 21% are Hispanic (Coalition, 2012). Obesity is pervasive in the public housing population – the prevalence is > 50% (Ludwig et al., 2011). Research within this high-risk group would determine whether previously demonstrated associations between networks and overweight/obesity are similar to those seen in other populations.

Our objective was to characterize the association between body mass index (BMI) of adults living in public housing with perceived overweight/obesity within their social network. Similar to prior findings (Christakis and Fowler, 2007; Trogdon et al., 2008), we hypothesized that residents who perceive greater network exposure to overweight/obesity will have higher BMI. We also hypothesized that residents with higher interconnection among networks where overweight/obesity was common would have higher BMI, thus producing weight homogeneity propagated by behavior modeling and/or support for a network norm of overweight/obesity.

2. Methods

2.1. Study design and sample

We conducted a cross-sectional survey of randomly selected households in two public housing developments in Baltimore, MD from 8/2014 to 8/2015, which has been described previously (Gudzune et al., 2018). We randomly selected 600 addresses from a list of all residences in the developments, of which 556 appeared occupied during neighborhood inspection and were eligible for inclusion. We recruited these households by mailing postcards and using up to 5 door-knocking attempts. Up to four adults who lived in each household could participate in the survey, which was conducted in the local administrative building or residents' homes. We relied on the head of household to verify that any additional adults were residents. Given that residential status of these additional adults could not be verified with the housing authority, we limited our analyses to the heads of household to ensure that our respondents only included public housing residents. These other household members were interviewed, but their information was not further analyzed. Overall, 266 heads of household participated (48%). Participants received a $40 gift card as compensation. The Johns Hopkins University School of Medicine Institutional Review Board approved this study.

2.2. Social network data

We used social network software to facilitate data collection (EgoNet, MDLogix). Survey respondents completed an egocentric social network inventory where they were asked to generate a list of 15 people with whom they had contact with in the past year (i.e., face-to-face, phone, text message, mail, or e-mail), which tends to obtain a diverse group in terms of relationships and interactions. The software then randomly selected 10 names about which additional questions were asked to ascertain attributes and behaviors of these individuals as perceived by the respondent. This approach enables a thorough evaluation of the social network overall, while decreasing respondent burden (McCarthy et al., 2007). Supplemental Table S1 contains the social network questions (Supplemental Materials 1), which were

adapted from a previous survey (Pollack et al., 2014).

The respondent viewed a panel of numbered body weight figures and indicated the figure that best represented each network member's weight status (Stunkard et al., 1983). Similar to previous studies (Bhuiyan et al., 2003; Lynch et al., 2009), we assigned these silhouettes to specific body weight categories: underweight (Figure 1 or 2), normal weight (Figure 3 or 4), overweight (Figure 5), or obese (Figure 6 or greater). We elected to use this method, as individuals were unable to provide numeric estimates of network members' weight during survey pilot testing with community members. Viewing these silhouettes has been previously used to approximate BMI values for adults – recall of parents' weight as a child (Sorenson et al., 1983); however, the approach has not been used previously to estimate weight status among social network members. Therefore, we examined accuracy of perceived weight status in a subset of our sample, which is described in the online supplement (Supplemental Materials 2). In brief, we found that 52.4% accurately perceived the weight status of their network members. Given that respondents more often underestimated their network members' weight status when they inaccurately perceived weight status, we combined the overweight and obese categories to provide greater assurance that network members identified as overweight/obese were truly within this weight category (accuracy increased to 66.7%).

During this inquiry, the respondent also indicated how often they perceived that each of their network members had contact with one another (often, sometimes, rarely, or never/no contact) to evaluate the connectivity within the network. With this data, we used UCINET to calculate two density variables: 1) density of ties (network members perceived to have any contact with one another) and 2) density of close ties (network members perceived to have contact often with one another). Given that we employed an egocentric network approach, the frequency of contact between the survey respondents and each of their network members were not included in these density calculations (Valente, 2010). In general, density provides insight on how information or behaviors may diffuse through the network – populations with high density may respond differently to challenges than those with low density (Hanneman and Riddle, 2005).

2.3. Independent variables

Using this network data, we created our independent variables that were two network measures: 1) proportion of people in one's social network classified as overweight/obese – termed "personal network exposure," and 2) an interaction term between the personal network exposure and the density of their social network – termed "density-network interaction."

Personal network exposure is the degree to which a person's network members have a certain attribute, and generally reflects the overall composition of the network (Valente, 2010). We calculated the network exposure to overweight/obesity (continuous variable), which represents the proportion of the respondent's network members perceived as overweight/obese (Figure 5 or greater). In addition, we explored potential exposure–response by dichotomizing network exposure where "high" was the upper quartile and "not high" was less than the upper quartile based on our sample's distributions. Given prior results suggesting different influences of obesity by relationship type (Christakis and Fowler, 2007), we also explored network exposures to 1) family members with overweight/obesity and 2) friends with overweight/obesity by creating variables representing the proportion of the respondent's family member and friends, respectively, perceived as overweight/obese.

Density-network composition interaction combines degree connectivity among network members (i.e., proportion of existing connections in a network relative to all possible connections) with personal network exposure to an attribute (Haynie, 2001), and represents the strength and direction of effect from the network. For density-network

composition interaction for overweight/obesity (continuous variable), we created interaction terms between network exposure to overweight/obesity and each of the density measures described above (density of ties and density of close ties).

2.4. Dependent variables

Our dependent variables were weight status of survey respondents. We measured participants' height and weight using the same methods described in the "Moving to Opportunities" evaluation (Ludwig et al., 2011), and then calculated body mass index (BMI). For the few participants that self-reported height and/or weight ($n = 14$), we used these values to calculate BMI. We examined BMI as a continuous variable, and we also dichotomized BMI into normal weight ($18.5 \leq BMI \leq 24.9 \, kg/m^2$) and 'overweight/obese' ($\geq 25 \, kg/m^2$) groups.

2.5. Covariates

We considered several individual and network attributes as potential covariates. Individual-level attributes of the respondent included age, gender, race, educational attainment (did not graduate high school vs. high school graduate/equivalent), marital status (married/significant other vs. not), unemployment status (employed/student vs. unemployed/disabled), intakes of fruit/vegetables (servings/day) and added sugar (tsp/day) as determined using questions and standard methods of the NHIS 5-factor dietary screener (National Cancer Institute, 2005), leisure-time physical activity (moderate/high vs very low/low) using a validated screener (Ainsworth et al., 1993), smoking status (current smoker vs not), and self-reported history of hypertension, diabetes mellitus, or cancer. We identified perception of one's own body weight as 'accurate' if a respondent's perception of their own body weight status (using the same body weight silhouettes described above) matched his/her measured BMI or 'inaccurate' if not matching (Bhuiyan et al., 2003; Lynch et al., 2009). Network attributes included network size and network proportion comprised of children, family members, females, race concordant, neighbors, and daily contact with respondent.

2.6. Analyses

We used STATA (College Station, TX) to perform all statistical analyses. To evaluate whether clustering occurred by housing development, we calculated intraclass correlation coefficient (ρ) (Singer, 1998). No substantial clustering existed (ρ < 0.10); therefore, we did not use multilevel models.

For our primary analysis, we limited our sample to 255 adult head of households who had a BMI value (1 excluded as refused to provide weight) and had $BMI \geq 18.5 \, kg/m^2$ (10 underweight excluded). We adjusted all models for significant characteristics identified in bivariate analyses ($p < 0.10$), which included fruit/vegetable intake, physical activity, smoking status, hypertension, cancer, and network exposure to females. We used multivariable linear regression to examine the association of BMI with network exposure to overweight/obesity and to explore potential exposure–response effect to 'high' network exposure to overweight/obesity. Given that our outcome of overweight/obesity was common, we used multivariable Poisson regression with a robust error variance to estimate the relative risk of overweight/obesity with network exposure to overweight/obesity among all adults. The validity of this model to estimate relative risk with binary outcomes has been previously described (Zou, 2004). We used multivariable linear regression to examine the association of BMI with network exposure to overweight/obesity among the specified subgroups (family members, friends).

We used multivariable linear regression models to examine the associations between BMI and the two density-network composition interaction terms for overweight/obesity (i.e., interaction between

network exposure to overweight/obesity with density of ties and density of close ties). These models were adjusted for all variables listed above, as well as personal network exposure to overweight/obesity and density.

2.7. Sensitivity analyses

We conducted several sensitivity analyses: 1) limit to only participants with measured BMI values ($n = 242$) (Supplemental Materials 3), 2) include all participants with a BMI value including underweight ($n = 265$) (Supplemental Materials 4), 3) adjusts for gender in addition to other model covariates as p-value was 0.11 in bivariate analyses ($n = 255$) (Supplemental Materials 5), 4) include only adults in determination of network exposure to overweight/obesity as the body weight figures only displayed images of adult silhouettes and has only been previously tested regarding recall of adult weight status ($n = 255$) (Supplemental Materials 6), and 5) include all participants from each household with a BMI value, not just the head of household ($n = 356$) (Supplemental Materials 7).

3. Results

We included 255 adult public housing residents. Mean age was 44.4 years, most were women (85.5%) and identified as black (95.7%) (Table 1). Overweight/obesity (77.6%) was common. While we do not have access to demographics of non-responding households, our sample characteristics are similar to other studies of Baltimore City public housing residents (Levine, 2011). On average, networks were comprised mostly of family members (57.1%), women (61.7%), and individuals that were race concordant with the respondent (94.2%) (Table 1). Most network members were overweight/obese (56.1% (SD 21.6)) (Table 1) – on average, 31.3% of all network members were family with overweight/obesity (SD 21.0) and 19.7% were friends with overweight/obesity (SD 20.1). As compared to normal weight residents, overweight/obese residents had significantly lower daily fruit/vegetable intake, were less likely to be physically active, current smokers, or have a history of cancer, but were more likely to have hypertension (Table 1). Overweight/obese residents had significantly lower network exposure to overweight/obesity (Table 1).

As the network exposure to overweight/obesity increased by 1%, individuals' BMI changed by $-0.05 \, kg/m^2$ (95%CI -0.10 to 0.00, $p = 0.06$) in the multivariable adjusted model. Individuals with 'high' perceived network exposure to overweight/obesity had $4.22 \, kg/m^2$ lower BMI than those with a 'not high' exposure (95%CI -6.98 to -1.46, $p < 0.01$) (Fig. 1). The relative risk of overweight/obesity was significantly lower for individuals who had a high network exposure to overweight/obesity as compared to a 'not high' exposure (RR 0.75, 95%CI 0.61 to 0.93, $p = 0.01$). Results of the sensitivity analyses are available in the online supplemental materials (Supplemental Materials 3–7). In brief, we found similar results to these primary results.

In multivariable models, we also examined network exposure to overweight/obesity among specific subgroups: family members and friends (Fig. 1). There was no significant difference in respondents' BMI as network exposure to overweight/obesity among family members increased (β 0.02, 95%CI -0.04 to 0.08, $p = 0.48$). As the network exposure to overweight/obesity among friends increased, individuals' BMI significantly changed by $-0.06 \, kg/m^2$ (95%CI -0.12 to -0.00, $p = 0.04$).

There were no significant differences in network density between normal weight and overweight/obese residents (Table 1). We also found no statistically significant associations between respondent BMI and either density-network composition interaction for overweight/obesity (Table 2).

Table 1
Characteristics of public housing residents from Baltimore, MD in study sample (2014–2015).

	Overall	Normal weight $18.5 \, \text{kg/m}^2 \leq \text{BMI} \leq 24.9 \, \text{kg/m}^2$	Overweight/obese BMI $\geq 25 \, \text{kg/m}^2$	*p*-Value[a]
	(*n* = 255)	(*n* = 57)	(*n* = 198)	
Attributes of egos				
Mean age in years	44.4 (SD 12.5)	46.1	43.9	0.25
Women	85.5%	79.0%	87.4%	0.11
Black race	95.7%	96.5%	95.5%	0.73
High school graduate/equivalent or beyond	65.5%	68.4%	64.7%	0.60
Married/significant other	31.8%	29.8%	32.3%	0.72
Unemployed	34.1%	33.3%	34.3%	0.89
Median fruit/vegetable servings/day[b]	4.4 (IQR 2.9–6.8)	5.0	4.1	0.01
Median added sugar tsp./day[b]	21.2 (IQR 11.7–39.9)	22.7	20.5	0.24
Moderate to high physical activity[c]	20.8%	33.3%	17.2%	0.01
Current cigarette smoker	62.0%	77.2%	57.6%	0.01
Self-reported history of …				
Hypertension	56.1%	40.4%	60.6%	0.01
Diabetes mellitus	20.4%	14.0%	22.2%	0.18
Cancer	6.7%	14.0%	4.6%	0.01
Mean BMI in kg/m^2	33.2 (SD 9.8)	22.1	36.5	< 0.01
Inaccurate self-perceived body weight	15.7%	17.5%	15.2%	0.66
Perceived attributes of social networks				
Small network size (< 10 people named)	7.1%	7.0%	7.1%	0.99
Mean % children	10.4 (SD 13.0)	8.9	10.8	0.33
Mean % family members	57.1 (SD 27.4)	53.0	58.3	0.22
Mean % females	61.7 (SD 16.5)	58.4	62.7	0.08
Mean % race concordant	94.2 (SD 19.6)	95.1	94.0	0.69
Mean % neighbors	19.0 (SD 20.6)	18.2	19.2	0.73
Mean % daily contact with ego	63.0 (SD 31.0)	63.5	62.8	0.88
Mean % overweight/obese	56.1 (SD 21.6)	64.9	53.6	< 0.01
Network measures				
Mean density of ties	0.59 (SD 0.28)	0.58	0.59	0.80
Mean density of close ties	0.27 (SD 0.25)	0.30	0.26	0.34

Abbreviations: BMI – body mass index; IQR – interquartile range.

[a] *p*-Values comparing normal weight and overweight/obese groups calculated using unpaired t-tests, Chi^2 tests or Wilcoxon-Mann-Whitney tests, as appropriate.

[b] Calculated from the National Health Interview Survey Five-Factor Dietary Screener (National Cancer Institute, 2005).

[c] Estimated from a four-item leisure time physical activity screener (Ainsworth et al., 1993).

Mean Body Mass Index (BMI) by Different Network t Exposures to Overweight/Obesity
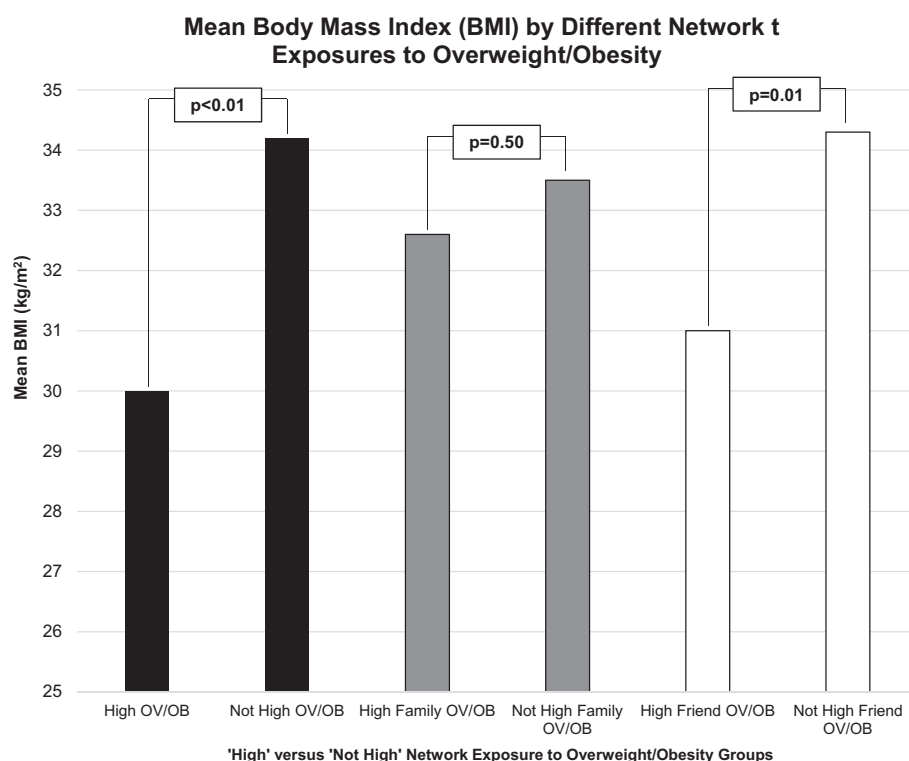
Fig. 1. Adjusted Mean Body Mass Index by Different Network Exposures to Overweight/Obesity among Baltimore Public Housing Residents (2014–2015). Personal network exposure is the degree to which network members have a certain attribute. Therefore, network exposure to overweight/obesity represents the proportion of their network members perceived as overweight/obese. For each comparison, we dichotomized the network exposure where "high" was the upper quartile and "not high" was less than the upper quartile based on our sample's distributions. Mean body mass index between groups estimated using results from linear regression model, which was adjusted for fruit/vegetable intake, physical activity, smoking status, hypertension, cancer, and network exposure to females. Four different comparisons are reported. Black bars compare 'high' network exposure to overweight/obesity among all network members to 'not high' exposure. Gray bars compare 'high' network exposure to overweight/obesity among family members to 'not high' exposure. White bars compare 'high' network exposure to overweight/obesity among friends to 'not high' exposure. Abbreviations: BMI – body mass index; OV/OB – overweight/obesity.

Table 2

Results of regression models that examine association of Baltimore public housing residents' body mass index with network measures including density-network composition interaction for overweight/obesity.

	Model 1 (Interaction density of all ties-network OV/OB)			Model 2 (Interaction density of close ties-network OV/OB)		
	β	95% CI	*p*-Value	β	95% CI	*p*-Value
Intercept	29.54	21.27–37.82	0.00	32.88	25.96–39.81	0.00
Interaction terms						
Density of ties × network OV/OB	−0.15	−0.33-0.02	0.09	–	–	–
Density of close ties × network OV/OB	–	–	–	−0.09	−0.29-0.11	0.39
Network characteristics						
Network exposure OV/OB	0.03	−0.08-0.15	0.54	−0.02	−0.10-0.05	0.53
Density of ties	7.26	−2.94-17.46	0.16	–	–	–
Density of close ties	–	–	–	1.53	−11.15-14.21	0.31
Control variables						
Network exposure females	0.07	−0.01-0.14	0.07	0.07	−0.00 − 0.14	0.06
Fruit/vegetable intake	-0.14	−0.45-0.18	0.39	−0.16	−0.48-0.15	0.31
Moderate to high physical activity	−5.21	−8.07-(−2.35)	< 0.01	−5.20	−8.05-(−2.35)	< 0.01
Current cigarette smoker	−1.82	−4.25-0.60	0.14	−1.89	−4.31-0.54	0.13
Self-reported history of hypertension	3.08	0.68–5.47	0.01	3.16	0.78–5.54	0.01
Self-reported history of cancer	−3.82	−8.47-0.82	0.11	−3.73	−8.37-0.91	0.12

Abbreviations: OV/OB – overweight/obesity. We used multivariable linear regression models to examine the associations between BMI and the two density-network composition interaction terms for overweight/obesity. These models were adjusted for fruit/vegetable intake, physical activity, smoking status, hypertension, cancer, network exposure to females, as well as personal network exposure to overweight/obesity and density.

4. Discussion

We found inverse associations between public housing residents' BMI and overweight/obesity among their social networks. Adults who had 'high' network exposure to overweight/obesity had significantly lower BMI and relative risk of being overweight/obese themselves as compared to adults with 'not high' exposure, and this association may be driven by exposure to overweight/obesity among friends rather than family members. Given that our findings were contrary to our hypotheses and prior study results (Christakis and Fowler, 2007; Trogdon et al., 2008; Pollack et al., 2014), we conducted several sensitivity analyses and our findings were robust to these examinations. Below we consider potential rationale to explain our results and their implications.

First, our results contrast prior network associations documented in other populations, which may be due to racial differences in our Baltimore-based sample of predominantly black, low-income public housing residents. Blacks have smaller and less diverse social networks than whites (Marsden, 1988), suggesting that they may interact uniquely with their networks. In the predominantly white populations assessed in Framingham and Add Health studies, the risk of overweight/obesity increased with increasing prevalence of network overweight/obesity (Christakis and Fowler, 2007; Trogdon et al., 2008). The differing results may be attributable to differences in race and/or economic status between our sample and these other studies. While the direction of the relationship is opposite, both our study and Framingham identified friends with overweight/obesity to have the greatest influence on adult respondents' weight status. Therefore, future network interventions that focus on friends might be advantageous to promote health-related behavior change in adults, although more research is needed to understand how the behavioral or social targets may need to differ by population (e.g., promoting inclusion of normal weight network members may be beneficial among whites but not among blacks).

Second, contextual differences between low-income populations may contribute to our different results. A prior cross-sectional survey of public housing residents (69% black) in Montgomery County, Maryland found a small positive, but non-significant relationship between obesity and network exposure to obesity (Pollack et al., 2014). Montgomery County has a higher socioeconomic status and more resources than Baltimore (e.g., median household income $99,763 versus $47,350)

(Data, 2016), which might explain the different findings. More social network investigations among minority and low-income populations are warranted to confirm our findings. Particular attention should be paid to examine how contextual differences, such as county-level socioeconomics, influence results, as public health initiatives may need to address these economic and physical environmental factors rather than take a social network approach.

Third, our results may be explained by network influence. A prior modeling study found that peer influence served as a buffer to adolescent overweight when the overweight prevalence was low, but negative peer influence (e.g., "doing the opposite" of their peers) had a reducing effect on adolescent BMI when prevalence of overweight was high (Zhang et al., 2015). Given that over 75% of our sample was overweight/obese, our results may be explained by negative network influence, where public housing residents are "doing the opposite" when most of their network members are overweight/obese. Additional research in needed to explore the reasons contributing to the inverse association between residents' BMI and perceived overweight/obesity among their social networks, which would inform how network interventions might be used to reduce obesity in this population.

Finally, the results may also vary due to study design factors. Both Framingham and Add Health analyses were longitudinal (Christakis and Fowler, 2007; Trogdon et al., 2008). Framingham measured BMI for both respondents and networks members, and inferred network ties and their direction (Christakis and Fowler, 2007). Add Health used self-reported BMI for both respondents and networks members, and named friends and classmates to define network ties (Trogdon et al., 2008). The cross-sectional study of Montgomery County, MD public housing residents calculated BMI based on self-reported measures and directly asked respondents to identify network members as overweight/obese rather than using pictograms (Pollack et al., 2014). Our study was cross-sectional, used measured BMI for respondents, and applied an egocentric approach to name network members, assess respondents' perceptions of network members' BMI, and determine network ties. In theory, perceptions of network members are meaningful and have implications for individuals' behavior, regardless of their perceptions' accuracy (Data, 2016). However, people may perceive their network members' BMI based in part on their own weight, although we did not find a significant association between inaccurate self-perceived body weight and the public housing residents' weight status. Misperceptions of others' body weight might still contribute to our results. Future

network studies among minority and low-income populations should consider employing a longitudinal design, measuring height and weight for both respondents and network members, and using strategies to identify perceptions and tie directionality within the network.

Beyond network composition, we also explored connectivity through network density and density-network composition interaction. The connections between network members are important for understanding social behavior, and density can provide insights into the speed at which information or behaviors might diffuse among network members (Hanneman and Riddle, 2005). Density-network composition interaction represents the strength and direction of effect from the network. We found no association between public housing residents' BMI and network density or density-network composition interaction for overweight/obesity – having highly connected or "strong" social networks did not have an association with BMI. These results may suggest that the connectivity among network members may not be relevant to overweight/obesity in this population; however, the small sample size of our study may have limited the power to detect differences, particularly for the interaction term.

This study has several limitations. The response rate to our survey was 48%; however, previous response rates range from 18% to 84% among public housing residents (Pollack et al., 2014; Coalition, 2012; Heinrich et al., 2008). While our dependent variable, BMI, is a common indicator of overweight/obesity, we acknowledge that it does not comprehensively reflect health status, particularly among minorities. We only ascertained perceived BMI on a subset of network members rather than a participant's whole network, which could attenuate associations. This subset was selected at random by the software to minimize attenuation. Response bias may be present, if public housing residents felt that they needed to provide a desirable answer to the research team. We used pictograms to assist survey respondents in identifying weight status of their network members, which extends a strategy previously applied to recall of parents' weight as a child (Sorenson et al., 1983). We were able to determine accuracy of these perceptions among a subsample, which was relatively high. However, this subsample was comprised of individuals who lived in the same household. The accuracy of using these pictograms to estimate weight status of network members with whom the respondent may interact less often remains unknown. Given that others have theorized that perceived behaviors may influence individuals' behavior regardless of whether or not their perceptions are accurate (Israel, 1982), an argument might be made that perceptions of network members' weight status may similarly matter more to an individual than actual weight status.

In conclusion, we found inverse associations between Baltimore public housing residents' BMI and the overall composition of overweight/obesity within their social networks. Given our differing results from prior studies, more network investigations among minority and low-income populations are needed, particularly given networks potential as an intervention tool.

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Disclosure

The authors declare no conflicts of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pmedr.2019.01.013.

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