Social network factors and cardiovascular health among baltimore public housing residents

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ARTICLE INFO

ABSTRACT

Social networks – or the web of relationships between individuals – may influence cardiovascular disease risk, particularly in low-income urban communities that suffer from a high prevalence of cardiovascular disease. Our objective was to describe the social networks of public housing residents – a low-income urban population – in Baltimore, MD and the association between these networks and blood pressure. We used cross-sectional survey data of randomly selected heads of household in two public housing complexes in Baltimore, MD (8/2014–8/2015). Respondents answered questions about 10 social network members, including attributes of their relationship and the frequency of interaction between members. We calculated measures of network composition (e.g., proportion of network members who were family members) and network structure (e.g., density), which we then dichotomized as "high" (upper quartile) and "low" (less than upper quartile). We used linear regression to test the association between network measures and mean systolic and diastolic blood pressure. The sample included 259 respondents (response rate: 46.6%). Mean age was 44.4 years, 85.7% were women, 95.4% Black, and 56.0% had a history of hypertension. A high proportion of older children (age 8–17 years) in the network (> 30%) was associated with a 4.0% (95%CI [0.07, 8.07], p = 0.047) higher mean systolic blood pressure (~4.9 mmHg greater). Other network attributes had no association with blood pressure. Social network attributes, such as having a high proportion of older children in one's network, may have particular relevance to blood pressure among low-income public housing residents, reinforcing the potential importance of social relationships to cardiovascular health.

1. Introduction

Elevated blood pressure is the leading cause of death in the US and worldwide (Forouzanfar et al., 2017; Lim et al., 2012), accounting for more cardiovascular disease (CVD) deaths than any other modifiable CVD risk factor (Danaei et al., 2009). Residents of public housing – a federal housing assistance program targeting nearly 10 million low-income Americans nationally (National Low Income Housing Coalition (2012)) – may be at particularly high risk for elevated blood pressure. Public housing is designed to address issues of affordability and access, but the physical and social reality of public housing, most frequently located within low-income and high-crime communities, has a myriad of effects including perceptions of stress, despair, and impaired social connectedness and behavior (Suglia, 2018).

A prior study of Boston residents and a national cross-sectional survey found that residents of public housing had greater prevalence of hypertension than the general public (Digenis-Bury et al., 2008; Helms et al., 2017). Such findings mirror other health disparities associated with public housing including high rates of diabetes, obesity, and poor mental health (Helms et al., 2017; Leventhal & Brooks-Gunn, 2003; Ludwig et al., 2011).

One factor potentially contributing to the burden of disease among

public housing residents may be social networks. Social networks can be defined as the web of relationships that exist between members of a community. Social network characteristics — including network size and composition — have been linked with CVD risk behaviors and outcomes in various community settings (Havranek et al., 2015; Kawachi et al., 1996; Kennedy-Hendricks et al., 2015; Mookadam & Arthur, 2004; Nagayoshi et al., 2014; Oladele et al., 2019). However, a substantial body of literature confirms distinct social network characteristics among low-income communities including fewer connections to individuals of higher socioeconomic position, high population turnover contributing to lower social cohesion, and greater network isolation (Campbell & Lee, 1992; Entwisle et al., 2007; Freudenburg, 1986; Kasarda & Janowitz, 1974; McPherson et al., 2006; Sampson, 1988; Schwartz et al., 2015). These distinct attributes may change how health information and behaviors diffuse through network connections, as well as how social influence and support affect behavior. However, little research to date has applied quantitative social network methods to specifically public housing residents to understand whether CVD risk factors like blood pressure differ by social network attributes within this population.

Our two objectives were to: 1) describe the social network characteristics of public housing residents in Baltimore, MD and 2) explore social network factors associated with higher blood pressure.

2. Materials and methods

2.1. Study design

This study is a secondary analysis of a cross-sectional survey conducted among a sample of public housing residents in Baltimore, MD from August 2014 to August 2015. Addresses of all households in two public housing communities were assigned a number, and then computer-based random number selector identified a simple random sample of 600 addresses (Gudzune et al., 2018). Of the 600 addresses selected, 44 were unoccupied and therefore ineligible, making the eligible number of households 556 for the in-person survey. Information was mailed to all sampled households and the study team made up to five attempts to administer the survey in person before labeling the household as a non-responder. The investigators administered the survey in the home or a local administrative building. For each household, one participant was designated as head of household and as many as three additional adults residing at the address could participate in the survey. Due to non-independence of responses within households and a large proportion of households having a single participant (median number of participants per household was one), we limited our analysis to heads of households. All participants were compensated with a $40 gift card. The Johns Hopkins University School of Medicine Institutional Review Board approved this study.

2.2. Dependent variables – measured blood pressure

Our dependent variables were mean systolic blood pressure (continuous) and mean diastolic blood pressure (continuous) measured by a trained member of the research team using a standardized protocol. We first measured the circumference of the upper arm and applied the appropriate size cuff (OMRON HEM-907XL). The participant was seated with both feet flat on the floor, back supported, and upper arm resting on a surface at the level of the heart. Three measurements were obtained at least five minutes apart and measures were averaged.

2.3. Independent variables – social network attributes

Our network variables were collected using an "egocentric" or personal social network approach that is widely used, including in a number of national surveys (Kessler, 2017; Smith et al., 2013; Waite et al., 2019). Using social network data collection software (Egonet, MD

Logix), we obtained a list of 15 people with whom the participant had been in contact with sometime in the past year (Appendix A), which was modified from a previous network study (Pollack et al, 2014). We limited this inquiry to network members age 8 or older, as subsequent questions about network members' behaviors and health status were not applicable to young children. From this list, the software randomly selected 10 network members for additional questions. We chose this method to optimize completeness while minimizing response burden and producing stable estimates of network structure (McCarty et al., 2007).

Based on prior literature, we derived variables that describe the composition of a person's social network including proportion of social network members who were: family members, friends, older children (ages 8–17 years), female gender, neighbors in the same public housing development, perceived as having high blood pressure, and who provided material support (Appendix B). Because network variables can be highly skewed and the relationship between blood pressure and network composition variables was not expected to be linear, we dichotomized each network variable into 'high' (≥upper quartile of the sample distribution) versus 'low' (< upper quartile). This cutoff identified individuals with distinct network characteristics (Gudzune et al., 2018, 2019), as opposed to normative characteristics as might be identified using mean or median.

We also calculated network density, which describes one aspect of network structure. Egocentric network density, is a standard measure calculated as the ratio of participant-reported social ties between network members divided by all possible ties between network members (excluding ties to the participant) (Perry et al., 2018). We similarly dichotomized network density into 'high' and 'low,' as defined above, because density is not a linear attribute of the network. Therefore, removing a tie or even a node in a very dense network (e.g., density > 50%) will have little effect on the overall properties of the network, but doing so in a sparse network (e.g., density < 10%) can have profound effects (Valente, 2010).

2.4. Covariates – individual-level demographics, health status, and healthcare access

We examined participant demographics, health status, and healthcare access as potential confounders. Participant demographics included age, gender, marital status, race (African American or not), education level (< high school, high school graduate, or > high school), food insecurity as a classification of socioeconomic position among low-income urban populations (Hager et al., 2010), residing in public housing more than 5 years, and neighborhood. Health status variables included depressive symptoms (Kroenke et al., 2003), self-reported history of hypertension, and a self-reported history of other cardiometabolic disease (i.e., myocardial infarction, congestive heart failure, cerebrovascular accident, or diabetes mellitus), smoking status (current smoker vs not), and body mass index (BMI) was calculated from height and weight measurements (Gudzune et al., 2019). Healthcare access variables included: insurance status (insured or not) and perceived access to a medical provider ("Is there a particular doctor's office, clinic, health center, or other place you usually go for regular check-ups, or if you are sick or need advice about your health?").

2.5. Analyses

We conducted bivariate analyses to test for differences in covariates by elevated blood pressure status as defined by Joint National Committee (JNC) VII guidelines (Chobanian et al., 2003), which were current at the time of data collection (blood pressure ≥ 140/90 mmHg or blood pressure ≥ 130/80 mmHg if self-reported diabetes mellitus) using *t*-test for continuous variables and Fischer's exact test for categorical variables.

For each network variable, we examined the association with mean systolic and mean diastolic blood pressure in bivariate analyses and multivariable analyses. All multivariable regression models were adjusted for age and gender, food insecurity, history of hypertension, history of other cardiometabolic disease, and BMI. We confirmed the selection of these variables using backward stepwise regression, which is a statistical procedure in which predictive covariates are selected by an automated algorithm to optimize model fit (Bruce & Bruce, 2017). This procedure did not identify current cigarette smoking as a necessary variable. Because blood pressure values were left skewed, we applied a natural log transformation for better regression model fit, which was confirmed by comparing Akaike information criterion (AIC) before and after transformation (see Appendix D for model AIC). Results from these log-transformed analyses provide the effect size in units of percent change. In addition, we modeled mean systolic and diastolic blood pressure outcomes without the log transformation, as an effect size in units of absolute blood pressure change may be more clinically interpretable. Finally, acknowledging prior studies that showed a differential social network effect by gender (Bland et al., 2019; Redondo-Sendino et al., 2005; Stringhini et al., 2012), we also repeated the log-transformed analyses restricting to only female participant surveys so as to isolate the size of the association among women. We used regression diagnostics to assess model assumptions and undue influence.

We conducted all analyses in R (R Core and Team, 2018), using tidyverse (Wickham, 2017), tableone (Yoshida, 2018), gmodels (Warnes et al., 2018), sandwich (Zeileis, 2006), msm (Zeileis, 2004), jtools (Long, 2019), MASS (Venables & Ripley, 2002), caret (Kuhn, 2020), and ggstance (Henry et al., 2019) packages.

3. Results

Of the 556 eligible households, 259 heads of households completed the survey and had their blood pressure measured (response rate 46.6%). Among participants, the mean age was 44.4 years, 85.7% were women, and 95.4% were African American/Black (Table 1). These demographics are similar to estimates from the US Department of Housing and Urban Development (HUD) data for these developments (US Department of Housing and Urban Development, 2019), where the head of household median age was between 25 and 49 years, 81–83% female, and 99% African American/Black. Statistical comparison with HUD data was unable to be performed.

Overall, mean systolic blood pressure was 126.8 mmHg (SD 21.0 mmHg), mean diastolic blood pressure was 80.4 mmHg (SD 13.4 mmHg), and 31.7% had elevated blood pressure per JNCVII criteria. Participants with elevated blood pressure had higher mean age (47.5 vs 43.0 years, p = 0.01), higher prevalence of a history of elevated blood pressure (89.0% vs 40.7%, p < 0.001), higher prevalence of other cardiometabolic diseases (45.1% vs 16.9%, p < 0.001), and higher BMI (33.9 kg/m² vs 31.4 kg/m², p = 0.05) than those without elevated blood pressure.

3.1. Social network attributes among public housing residents

Participants nominated a median of 15 network members (range 6–21). Overall, individuals typically nominated more family members in their networks (median proportion family 60% [IQR 40%, 80%]) than friends (median proportion friends 30% [IQR 10%, 50%]). Only 25.9% of participants nominated more friends than family members. Typically, most were female (median 60% [IQR 50%, 70%]) and the average personal network included at least one network member with hypertension (median 10% [IQR 0%, 30%]). Of note, a minority of social network members were older children aged 8–17 years (median 10% [IQR 0%, 20%]), and 90.6% of these children were also identified as family members. Few network members were neighbors in public housing (median 10% [IQR 0%, 30%]), but nearly all were located in Baltimore (median 100% [IQR 90%, 100%]) and the majority had daily

Table 1
Demographics, health, and network characteristics of randomly selected heads of household in public housing by elevated blood pressure status* in Baltimore, MD, 2014–2015.

	Overall Sample (N = 259)	Elevated BP (N = 82)	Not Elevated BP (N = 177)	P-value†
Demographics				
Mean Age in Years (SD)	44.4 (12.5)	47.5 (13.4)	43.0 (11.8)	0.01
Women (%)	85.7	80.5	88.1	0.13
African American (%)	95.4	95.1	95.5	1
Single (%)	77.6	78.0	77.4	1
High School Graduate (%)	66.8	65.9	67.2	0.89
Unemployed (%)	33.2	30.5	34.5	0.57
Food Insecure (%)	67.2	64.6	68.4	0.57
Health Status				
Depression (%)	30.1	32.9	28.8	0.56
Self-Reported Conditions (%)				
Hypertension (%)	56.0	89.0	40.7	< 0.01
Other Cardiometabolic Disease‡ (%)	25.9	45.1	16.9	< 0.01
Mean Body Mass Index, kg/m² (SD)	32.2 (9.6)	33.9 (10.6)	31.4 (9.1)	0.05
Current Cigarette Smoker (%)	72.2	80.5	68.4	0.05
Healthcare Access				
Insured (%)	98.1	96.3	98.9	0.33
Has Medical Provider (%)	96.9	98.8	96.0	0.44

Abbreviations: BP – Blood Pressure.
*Elevated blood pressure defined as elevated per JNC7 guidelines (> 140/90 if no comorbid diabetes mellitus, > 130/80 if diabetes present) (Chobanian et al., 2003).
† P-values calculated using two-tailed t-tests for continuous variables and Fisher Exact tests for categorical.
‡ Defined as self-reported history of myocardial infarction, congestive heart failure, cerebrovascular accident, and/or diabetes mellitus.

contact with the participant (median 60% [IQR 40%, 100%]). Approximately one third provided material support (median 30% [IQR 10%, 60%]). Network density was high (median density 55.6% [IQR 37.8%, 84.4%]). Appendix C presents bivariate analyses of network characteristics stratified by elevated blood pressure.

3.2. Social network factors associated with differences in blood pressure

In the multivariable models (Table 2) – adjusting for age, gender, food insecurity, history of hypertension, history of other cardiometabolic disease, and BMI – having a high proportion of older children (age 8–17 years) in one's network was associated with a 4.0% (95%CI 0.07, 8.01; p = 0.05) higher mean systolic blood pressure (equal to a 4.9 mmHg (95%CI −0.28, 10.10) difference in non-log transformed analyses). Having a high proportion of older children in one's network was associated with a 3.7% (95%CI −0.73, 8.34; p = 0.10) higher mean diastolic blood pressure (equal to 3.4 mmHg (95%CI −0.11, 6.91) difference in non-log transformed analyses). Having a high proportion of friends in one's network was associated with a −3.6% lower diastolic blood pressure (95%CI −7.64, 0.70; p = 0.10)(equal to −3.1 mmHg in non-log transformed analyses (95%CI −6.55, 0.40)).

In analyses restricting by female gender, we identified a similar pattern of results. A high proportion of older children was associated with higher systolic (4.4%, 95%CI [0.26, 8.65]; p = 0.04) and diastolic blood pressure (5.3%, 95%CI [0.73, 10.10]; p = 0.02).

Table 2

Adjusted associations between network variables and geometric mean systolic and diastolic blood pressures among public housing residents, Baltimore, MD, 2014–2015 (N = 259).

Network Variable*	Systolic Blood Pressure			Diastolic Blood Pressure		
	%BP Change†	95% Confidence Interval		%BP Change†	95% Confidence Interval	
High Network Family	1.4	[−2.16	5.18]	1.1	[−2.96	5.34]
High Network Friends	−2.2	[−5.88	1.60]	−3.6§	[−7.64	0.70]
High Network Older Children (age 8–17)	**4.0‡**	**[0.07**	**8.07]**	**3.7§**	**[−0.73**	**8.34]**
High Network Female	1.4	[−2.02	5.01]	1.0	[−2.87	5.08]
High Network Neighbors	0.7	[−2.93	4.37]	−0.4	[−4.41	3.79]
High Network Hypertension	−1.2	[−4.80	2.49]	−0.7	[−4.74	3.58]
High Network Material Support	2.2	[−1.62	6.21]	1.4	[−2.94	5.89]
High Network Density	1.2	[−2.50	5.15]	2.4	[−1.87	6.89]

Abbreviations: BP – blood pressure.

*Network variables were dichotomized as 'high' if they were in the upper quartile: proportion family ($\geq 80\%$), proportion friends ($\geq 50\%$), proportion older children ($\geq 20\%$), proportion female ($\geq 70\%$), proportion neighbors living in the same public housing development ($\geq 30\%$), proportion who had high blood pressure ($\geq 30\%$), proportion providing material support ($\geq 60\%$), and network density ($\geq 84\%$).

†Estimates equal to (exp(beta)-1)*100, where beta is the coefficient of the association between each network variable and log-transformed blood pressure. All models are linear regression adjusted for age, gender, food insecurity, history of hypertension, history of other cardiometabolic disease, and body mass index.

‡$p \leq 0.05$.

§$p \leq 0.10$.

4. Discussion

To our knowledge, this study is the first to describe the associations of social network factors with blood pressure among Baltimore public housing residents. We found that having a high proportion of older children (age of 8–17 years) in one's network was significantly associated with higher blood pressure, even after adjusting for CVD risk factors. We also found that having a high proportion of friends in one's network was associated with lower blood pressure, which neared statistical significance. We did not find a significant association between blood pressure and other network attributes including network composition of family, females, neighbors, those with hypertension, or providing material support or network density. Prior studies have demonstrated an association between network composition of public housing residents and other cardiometabolic disease risk factors including diet, exercise, and smoking (Gudzune et al., 2018; Pollack et al., 2014; Shelton et al., 2011). Together, these findings provide preliminary evidence that the composition of public housing residents' social networks may affect risk factors for CVD, including blood pressure.

Several potential mechanisms may explain the association between high proportion of older children in the social network and blood pressure. Among public housing residents, children may pose a substantial strain on finances and other resources for these very low-income households that could negatively impact parents' self-care (Hayward et al., 2015). While we are unable to determine the exact relationship between the adult respondents and the older children in their network, nearly all children were identified as family members and may indicate a caregiver role. Caregiving for children, which is often done by women, may lead to trade-offs in the adult's diet, physical activity, and medical care seeking behaviors that are linked with CVD (Lee et al., 2003). Our sample was predominantly women, which reflects the composition of public housing. Caregiving has also been linked with increased stress that may negatively impact blood pressure (King et al., 1994). For example, Baltimore public housing residents have described concern for the safety of their children in a potentially hazardous physical environment due to crime (Hayward et al., 2015). Conversely, a greater number of older children in the social network may be a proxy for other relevant factors that influence blood pressure. Given that our sample was predominantly women, parity may explain our findings as greater parity may be independently associated with blood pressure (Ogunmoroti et al., 2019). We also note that other studies have reported positive influence of children on parent health

outcomes, notably weight loss among Black and Hispanic adults (Winston et al., 2015), which is opposite of our findings. The difference in direction of effect may be explained by how children were defined in these studies – we defined children by age (age 8–17 years) whereas the other study used familial relationship that included adult children. Additional research is needed to confirm our findings and to identify the mechanisms contributing to the association between higher blood pressure and having a high proportion of older children in the network.

Other research has described how networks dominated by family members, as opposed to "friend-focused" or "diverse" typologies, are associated with individuals who prioritize family responsibilities above their own health, at times to the detriment of their own health (Morris et al., 2016; Park et al., 2014). We found that having high proportion of friends in the social network was associated with lower blood pressure. Studies outside the public housing context have also found positive relationships between network friends and health outcomes. For example, a higher proportion of friends in one's network is associated with better mental health (Fiori et al., 2006).

Our results describing the social network composition and network structure of public housing residents may also help inform future studies targeting CVD in this population. For example, residents' social networks were dense (colloquially described as "tight-knit"), family-oriented, and geographically fragmented with few ties to neighbors in the same development. These network parameters may be important, because they can inform potential behavior change interventions. In such networks, one would expect that low-threshold behavior change (e.g., eating at fast food restaurants) might propagate quickly from one person to the next, but that these same networks would remain refractory to changing high-threshold behaviors (e.g., cooking healthy food at home) due to social norms causing inertia (Centola, 2018). A recent pilot study demonstrated how a social network intervention among public housing residents significantly reduced sugar-sweetened beverage intake, a low-threshold behavior (Gudzune et al., 2020). Furthermore, our findings suggest that diffusion of a behavioral intervention in this population may occur less readily between neighbors compared to individuals outside the public housing development, and a geographically targeted behavior change intervention may also need to promote neighborhood cohesion to be effective. In the future, a network-informed intervention might include addressing caregiver and child diet and exercise habits collectively to reduce adult blood pressure.

This study has several limitations. First, the cross-sectional design does not permit us to examine causality. Second, our response rate was

47%, which may be considered low. We note that this rate is within the range of other studies of public housing residents (18–84%)(Heinrich et al., 2010; Ludwig et al., 2011; Pollack et al., 2014), and our sample characteristics were similar to HUD demographics from these developments (US Department of Housing and Urban Development, 2019) and were comparable to other studies of public housing residents (Digenis-Bury et al., 2008; Ludwig et al., 2011; Pollack et al., 2014). However, we were unable to statistically compare our demographics with HUD data. Third, we limited network members to individuals aged 8 or older, and therefore, cannot determine the influence of younger children in our sample. Our data also did not ascertain the exact age of child network members, so we cannot determine whether different ages have different associations with blood pressure. Fourth, the egocentric network data collection approach relies on participant perceptions of their network members. This method is likely accurate when asking about gender or other visible qualities, but may be less accurate when assessing health history or less perceptible qualities. Nevertheless, there is both theoretical support (Israel, 1982) and empirical evidence (Valente et al., 1997) that perception influences behavior, regardless of the accuracy of those perceptions. Furthermore, we solicited the "most important" network members; however, there is no standardized metric for the closeness or importance of any individual relationship. We did not capture detailed relationship data such as cohabitation, dependence, or family structure. By randomly sampling 10 network members for additional inquiry, instead of collecting information on all network members, there is a risk of undervaluing important network influencers. Fifth, a prior qualitative assessment of this neighborhood suggested social environmental differences (e.g., social trust and cohesion) by neighborhood court (Hayward et al, 2015). An understanding of how these different microenvironments impact one another would require complete network ascertainment (sociometric data collection), which is beyond the scope of this study.

Children, who constitute more than one third of public housing residents (National Low Income Housing Coalition (2012)), can be simultaneously a source of social stress and collective motivation (Shan et al., 2014). Our social network study, which found an association between a high proportion of older children in one's social network and higher blood pressure, may identify a potential challenge to addressing CVD risk factors, such as hypertension, among public housing residents. Future research is needed to confirm our findings and clarify the mechanisms of this association, which may help inform future behavior interventions in these high-risk communities.

Sources of funding

CRediT authorship contribution statement

Benjamin P.L. Meza: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Meena Chatrathi:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Craig E. Pollack:** Conceptualization, Methodology, Validation, Writing - original draft, Writing - review & editing, Supervision. **David M. Levine:** Conceptualization, Validation, Writing - review & editing, Supervision. **Carl A. Latkin:** Methodology, Validation, Writing - review & editing, Supervision. **Jeanne M. Clark:** Conceptualization, Validation, Writing - review & editing, Supervision. **Lisa A. Cooper:** Validation, Writing - review & editing, Supervision. **Christina T. Yuan:** Methodology, Validation, Writing - review & editing, Supervision. **Nisa M. Maruthur:** Conceptualization, Validation, Writing - review & editing, Supervision. **Kimberly A. Gudzune:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pmedr.2020.101192.

References

Bland, S.H., Krogh, V., Winkelstein, W., Trevisan, M., 2019. Social network and blood pressure: a population study. Psychosom. Med. 53 (6), 598–607. http://www.ncbi.nlm.nih.gov/pubmed/1758945.

Bruce, P. C., & Bruce, A. (2017). Practical statistics for data scientists : 50 essential concepts. https://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=1517577.

Campbell, K. E., & Lee, B. A. (1992). Sources of Personal Neighbor Networks: Social Integration, Need, or Time? Social Forces, 70(4), 1077. https://search.proquest.com/docview/1291042125?accountid=11752.

Centola, D. (2018). How Behavior Spreads: The Science of Complex Contagions. Princeton University Press. http://proxy.cm.umoncton.ca/login?url=https://ebookcentral.proquest.com/lib/umoncton-ebooks/detail.action?docID=5351321.

Chobanian, A. V., Bakris, G. L., Black, H. R., Cushman, W. C., Green, L. A., Izzo, J. L., Jones, D. W., Materson, B. J., Oparil, S., Wright, J. T., Roccella, E. J., Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure. National Heart, Lung, and B. I., & National High Blood Pressure Education Program Coordinating Committee. (2003). Seventh report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure. Hypertension (Dallas, Tex. : 1979), 42(6), 1206–1252. https://doi.org/10.1161/01.HYP.0000107251.49515.c2.

Chobanian, A. V., Bakris, G. L., Black, H. R., Cushman, W. C., Green, L. A., Izzo Joseph L., J., Jones, D. W., Materson, B. J., Oparil, S., Wright Jackson T., J., Roccella, E. J., & Committee, and the N. H. B. P. E. P. C. (2003). The Seventh Report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood PressureThe JNC 7 Report. JAMA, 289(19), 2560–2571. https://doi.org/10.1001/jama.289.19.2560.

Danaei, G., Ding, E.L., Mozaffarian, D., Taylor, B., Rehm, J., Murray, C.J.L., Ezzati, M., 2009. The preventable causes of death in the United States: comparative risk assessment of dietary, lifestyle, and metabolic risk factors. PLoS Med. 6 (4). https://doi.org/10.1371/journal.pmed.1000058.

Digenis-Bury, E.C., Brooks, D.R., Chen, L., Ostrem, M., Horsburgh, C.R., 2008. Use of a population-based survey to describe the health of boston public housing residents. Am. J. Public Health 98 (1), 85–91. https://doi.org/10.2105/AJPH.2006.094912.

Entwisle, B., Faust, K., Rindfuss, R.R., Kaneda, T., 2007. Networks and contexts: variation in the structure of social ties. Am. J. Sociol. 112 (5), 1495–1533. http://10.0.4.62/511803.

Fiori, K.L., Antonucci, T.C., Cortina, K.S., 2006. Social network typologies and mental health among older adults. J. Gerontol. Series B, Psychol. Sci. Social Sci. 61 (1), P25–32. https://doi.org/10.1093/geronb/61.1.p25.

Forouzanfar, M.H., Liu, P., Roth, G.A., Ng, M., Biryukov, S., Marczak, L., Alexander, L., Estep, K., Abate, K.H., Akinyemiju, T.F., Ali, R., Alvis-Guzman, N., Azzopardi, P., Banerjee, A., Bärnighausen, T., Basu, A., Bekele, T., Bennett, D.A., Biadgilign, S., Murray, C.J.L., 2017. Global burden of hypertension and systolic blood pressure of at least 110 to 115mmHg, 1990–2015. JAMA – J. Am. Med. Assoc. 317 (2), 165–182. https://doi.org/10.1001/jama.2016.19043.

Freudenburg, W.R., 1986. The density of acquaintanceship: an overlooked variable in community research? Am. J. Sociol. 92 (1), 27–63. http://www.jstor.org/stable/2779716.

Gudzune, K.A., Opara, O., Martinez, J.C., Doshi, R.S., Levine, D.M., Latkin, C.A., Clark, J.M., 2020. Social network intervention reduces added sugar intake among baltimore public housing residents: a feasibility study. Nutrit. Metabolic Insights 13. https://doi.org/10.1177/1178638820909329.

Gudzune, K.A., Peyton, J., Pollack, C.E., Young, J.H., Levine, D.M., Latkin, C.A., Clark, J.M., 2018. Perceived diet and exercise behaviors among social network members with personal lifestyle habits of public housing residents. Health Educ. Behav. 45 (5), 808–816. https://doi.org/10.1177/1090198118757985.

Gudzune, K. A., Peyton, J., Pollack, C. E., Young, J. H., Levine, D. M., Latkin, C. A., & Clark, J. M. (2019). Overweight/obesity among social network members has an inverse relationship with Baltimore public housing residents' BMI. Preventive Medicine Reports, 14(January), 100809. https://doi.org/https://doi.org/10.1016/j.pmedr.2019.01.013.

Hager, E.R., Quigg, A.M., Black, M.M., Coleman, S.M., Heeren, T., Rose-Jacobs, R., Cook, J.T., Ettinger de Cuba, S.A., Casey, P.H., Chilton, M., Cutts, D.B., Meyers, A.F., Frank, D.A., 2010. Development and validity of a 2-item screen to identify families at risk for food insecurity. Pediatrics 126 (1), e26–32. https://doi.org/10.1542/peds.2009-3146.

Havranek, E.P., Mujahid, M.S., Barr, D.A., Blair, I.V., Cohen, M.S., Cruz-Flores, S., Davey-Smith, G., Dennison-Himmelfarb, C.R., Lauer, M.S., Lockwood, D.W., Rosal, M., Yancy, C.W., 2015. Social determinants of risk and outcomes for cardiovascular disease: a scientific statement from the American Heart Association. Circulation 132 (9), 873–898. https://doi.org/10.1161/CIR.0000000000000228.

Hayward, E., Ibe, C., Young, J.H., Potti, K., Jones, P., Pollack, C.E., Gudzune, K.A., 2015. Linking social and built environmental factors to the health of public housing residents: a focus group study. BMC Public Health 15 (1), 351. https://doi.org/10.1186/s12889-015-1710-9.

Heinrich, K.M., Lee, R.E., Regan, G.R., Reese-Smith, J.Y., Howard, H.H., Haddock, C.K., Poston, W.S.C., Ahluwalia, J.S., 2010. How does the built environment relate to body mass index and obesity prevalence among public housing residents? Am. J. Health Promotion : AJHP 22 (3), 187–194. https://doi.org/10.4278/ajhp.22.3.187.

Helms, V., Steffen, B. L., Rudd, E. C., & Sperling, J. (2017). A Health Picture of HUD-Assisted Adults, 2006–2012. 2006–2012. https://www.huduser.gov/portal//portal/sites/default/files/pdf/Health-Picture-of-HUD-Assisted-Children.pdf.

L. Henry H. Wickham W. Chang ggstance: Horizontal "ggplot2" Components 2019 https://cran.r-project.org/package=ggstance.

Israel, B.A., 1982. Social networks and health status: linking theory, research, and practice. Patient Counselling Health Educ. 4 (2), 65–79. https://doi.org/10.1016/S0190-2040(82)80002-5.

Kasarda, J.J.M.D., Janowitz, M., 1974. Community attachment in mass society. Am. Sociol. Rev. 39 (3), 328–339. https://doi.org/10.2307/2094293.

Kawachi, I., Colditz, G.A., Ascherio, A., Rimm, E.B., Giovannucci, E., Stampfer, M.J., Willett, W.C., 1996. A prospective study of social networks in relation to total mortality and cardiovascular disease in men in the USA. J. Epidemiol. Community Health 50 (3), 245–251. https://doi.org/10.1136/jech.50.3.245.

Kennedy-Hendricks, A., Schwartz, H.L., Griffin, B.A., Burkhauser, S., Green, H.D., Kennedy, D.P., Pollack, C.E., 2015. Health implications of social networks for children living in public housing. Health Place 36, 145–151. https://doi.org/10.1016/j.healthplace.2015.11.001.

Kessler, R. C. (2017). National Comorbidity Survey: Adolescent Supplement (NCS-A), 2001-2004. Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/ICPSR28581.v6.

King, A.C., Oka, R.K., Young, D.R., 1994. Ambulatory blood pressure and heart rate responses to the stress of work and caregiving in older women. J. Gerontol. 49 (6), 239–245. https://doi.org/10.1093/geronj/49.6.M239.

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2003). The Patient Health Questionnaire-2: validity of a two-item depression screener. Medical Care, 41(11), 1284–1292. https://doi.org/10.1097/01.MLR.0000093487.78664.3C.

Kuhn, M. (2020). caret: Classification and Regression Training. https://cran.r-project.org/package=caret.

Lee, S., Colditz, G., Berkman, L., Kawachi, I., 2003. Caregiving to children and grandchildren and risk of coronary heart disease in women. Am. J. Public Health 93 (11), 1939–1944. https://doi.org/10.2105/ajph.93.11.1939.

Leventhal, T., Brooks-Gunn, J., 2003. Moving to opportunity: an experimental study of neighborhood effects on mental health. Am. J. Public Health 93 (9), 1576–1582. https://doi.org/10.2105/ajph.93.9.1576.

Lim, S.S., Vos, T., Flaxman, A.D., Danaei, G., Shibuya, K., Adair-Rohani, H., Amann, M., Anderson, H.R., Andrews, K.G., Aryee, M., Atkinson, C., Bacchus, L.J., Bahalim, A.N., Balakrishnan, K., Balmes, J., Barker-Collo, S., Baxter, A., Bell, M.L., Blore, J.D., Ezzati, M., 2012. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. Lancet 380 (9859), 2224–2260. https://doi.org/10.1016/S0140-6736(12)61766-8.

Long, J. A. (2019). jtools: Analysis and Presentation of Social Scientific Data. https://cran.r-project.org/package=jtools.

Ludwig, J., Sanbonmatsu, L., Gennetian, L., Adam, E., Duncan, G.J., Katz, L.F., Kessler, R.C., Kling, J.R., Lindau, S.T., Whitaker, R.C., McDade, T.W., 2011. Neighborhoods, obesity, and diabetes–a randomized social experiment. New England J. Med. 365 (16), 1509–1519. https://doi.org/10.1056/NEJMsa1103216.

McCarty, C., Killworth, P.D., Rennell, J., 2007. Impact of methods for reducing respondent burden on personal network structural measures. Social Networks 29 (2), 300–315. https://doi.org/10.1016/j.socnet.2006.12.005.

McPherson, M., Smith-Lovin, L., Brashears, M.E., 2006. Social isolation in America: changes in core discussion networks over two decades. Am. Sociol. Rev. 71 (3), 353–375. https://search.proquest.com/docview/218830661?accountid=11752.

Mookadam, F., Arthur, H.M., 2004. Social support and its relationship to morbidity and mortality after acute myocardial infarction. Arch. Intern. Med. 164 (14), 1514. https://doi.org/10.1001/archinte.164.14.1514.

Morris, R.L., Kennedy, A., Sanders, C., 2016. Evolving 'self'-management: exploring the role of social network typologies on individual long-term condition management. Health Expectations : Int. J. Public Participation Health Care Health Policy 19 (5), 1044–1061. https://doi.org/10.1111/hex.12394.

Nagayoshi, M., Everson-Rose, S.A., Iso, H., Mosley, T.H., Rose, K.M., Lutsey, P.L., 2014. Social network, social support, and risk of incident stroke: atherosclerosis risk in communities study. Stroke 45 (10), 2868–2873. https://doi.org/10.1161/STROKEAHA.114.005815.

National Low Income Housing Coalition (NLIHC). (2012). Who Lives in Federally Assisted Housing? Characteristics of Households Assisted by HUD programs. Housing Spotlight, 2(2). http://www.nlihc.org/.

Ogunmoroti, O., Osibogun, O., Kolade, O.B., Ying, W., Sharma, G., Vaidya, D., Michos, E.D., 2019. Multiparity is associated with poorer cardiovascular health among women from the Multi-Ethnic Study of Atherosclerosis. Am. J. Obstetr. Gynecol. 221 (6), 631.e1–631.e16. https://doi.org/10.1016/j.ajog.2019.07.001.

Oladele, C.R., Thompson, T.-A., Wang, K., Galusha, D., Tran, E., Martinez-Brockman, J.L., Adams, O.P., Maharaj, R.G., Nazario, C.M., Nunez, M., Nunez-Smith, M., 2019. Egocentric health networks and cardiovascular risk factors in the ECHORN cohort study. J. General Internal Med. https://doi.org/10.1007/s11606-019-05550-1.

Park, S., Smith, J., Dunkle, R.E., 2014. Social network types and well-being among South Korean older adults. Aging Mental Health 18 (1), 72–80. https://doi.org/10.1080/13607863.2013.801064.

Perry, B. L., Pescosolido, B. A., & Borgatti, S. P. (2018). Egocentric network analysis foundations, methods, and models.

Pollack, C.E., Green, H.D., Kennedy, D.P., Griffin, B.A., Kennedy-Hendricks, A., Burkhauser, S., Schwartz, H., 2014. The impact of public housing on social networks: a natural experiment. Am. J. Public Health 104 (9), 1642–1649. https://doi.org/10.2105/AJPH.2014.301949.

R Core Team. (2018). R: A Language and Environment for Statistical Computing. https://www.r-project.org/.

Redondo-Sendino, Á., Guallar-Castillón, P., Banegas, J.R., Rodríguez-Artalejo, F., 2005. Relación entre la red social y la hipertensión arterial en los ancianos Españoles. Rev. Esp. Cardiol. 58 (11), 1294–1301. https://doi.org/10.1016/S1885-5857(06)60417-9.

Sampson, R.J., 1988. Local friendship ties and community attachment in mass society: a multilevel systemic model. Am. Sociol. Rev. 53 (5), 766–779. https://doi.org/10.2307/2095822.

Schwartz, H., Burkhauser, S., Griffin, B.A., Kennedy, D.P., Green, H.D., Kennedy-Hendricks, A., Pollack, C.E., 2015. Do the Joneses help you keep up? a natural experiment in exposure to nonpoor neighbors. Housing Policy Debate 25 (2), 320–352. https://doi.org/10.1080/10511482.2014.956324.

Shan, H., Muhajarine, N., Loptson, K., Jeffery, B., 2014. Building social capital as a pathway to success: community development practices of an early childhood intervention program in Canada. Health Promot. Int. 29 (2), 244–255. https://doi.org/10.1093/heapro/das063.

Shelton, R.C., McNeill, L.H., Puleo, E., Wolin, K.Y., Emmons, K.M., Bennett, G.G., 2011. The association between social factors and physical activity among low-income adults living in public housing. Am. J. Public Health 101 (11), 2102–2110. https://doi.org/10.2105/AJPH.2010.196030.

Smith, T. W., Hout, M., & Marsden, P. V. (2013). General Social Survey, 1972-2012. Roper Center for Public Opinion Research, University of Connecticut [distributor], Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/ICPSR34802.v1.

Stringhini, S., Berkman, L., Dugravot, A., Ferrie, J.E., Marmot, M., Kivimaki, M., Singh-Manoux, A., 2012. Socioeconomic status, structural and functional measures of social support, and mortality: the British Whitehall II Cohort Study, 1985–2009. Am. J. Epidemiol. 175 (12), 1275–1283. https://doi.org/10.1093/aje/kwr461.

Suglia, S.F., 2018. Subsidized housing and health: time for a multidisciplinary approach. Am. J. Public Health 108 (8), 975–976. https://doi.org/10.2105/AJPH.2018.304544.

US Department of Housing and Urban Development. (2019). Picture of Subsidized Households. Picture of Subsidized Households. https://www.huduser.gov/portal/datasets/assthsg.html.

Valente, T.W., 2010. Social Networks and Health: Models, Methods, and Applications. Oxford University Press.

Valente, T. W., Watkins, S. C., Jato, M. N., van der Straten, A., & Tsitsol, L. P. (1997). Social network associations with contraceptive use among Cameroonian women in voluntary associations. Social Science & Medicine (1982), 45(5), 677–687. https://doi.org/10.1016/S0277-9536(96)00385-1.

Venables, W.N., Ripley, B.D., 2002. Modern Applied Statistics with S (Fourth). Springer. http://www.stats.ox.ac.uk/pub/MASS4.

Waite, L. J., Laumann, E. O., Levinson, W. S., Lindau, S. T., & O'Muircheartaigh, C. A.

(2019). National Social Life, Health, and Aging Project (NSHAP): Wave 1, [United States], 2005-2006. Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/ICPSR20541.v9.

Warnes, G. R., Bolker, B., Lumley, T., from Randall C. Johnson are Copyright SAIC-Frederick, R. C. J. C., by the Intramural Research Program, I. F., of the NIH, Institute, N. C., & for Cancer Research under NCI Contract NO1-CO-12400., C. (2018). gmodels: Various R Programming Tools for Model Fitting. https://cran.r-project.org/package=gmodels.

H. Wickham tidyverse: Easily Install and Load the "Tidyverse" 2017 https://cran.r-project.org/package=tidyverse.

Winston, G.J., Phillips, E.G., Wethington, E., Devine, C., Wells, M., Peterson, J.C., Hippolyte, J., Ramos, R., Martinez, G., Eldridge, J., Charlson, M., 2015. Social network characteristics associated with weight loss among black and hispanic adults. Obesity (Silver Spring, Md.) 23 (8), 1570–1576. https://doi.org/10.1002/oby.21155.

Yoshida, K., & Bohn., J. (2018). tableone: Create "Table 1" to Describe Baseline Characteristics. https://cran.r-project.org/package=tableone.

Zeileis, A., 2004. Econometric computing with HC and HAC covariance matrix estimators. J. Stat. Softw. 11 (10), 1–17. https://doi.org/10.18637/jss.v011.i10.

Zeileis, A., 2006. Object-oriented computation of sandwich estimators. J. Stat. Softw. 16 (9), 1–16. https://doi.org/10.18637/jss.v016.i09.