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Laura Kelly April 23, 2012

Social networks and cardiovascular disease in South Asia: Preliminary findings from urban Delhi

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An abstract of
A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
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Abstract

Social networks and cardiovascular disease in South Asia: Preliminary findings from urban Delhi

By Laura Kelly

Background: Cardiovascular disease follows a unique Asian Indian phenotype in South Asia and continues to increase substantially among Asian Indian adults, particularly urban and migrant populations. Recent findings suggest clustering of chronic disease and cardiovascular risk within social networks. We employed a social network perspective to the cardiovascular disease epidemic among South Asians using a representative urban, adult population of Asian Indians.

Methods: This study analyzed existing social network analysis theory and methodology in the context of urban South Asian populations and cardiovascular disease risk. We developed a pilot to collect egocentric social network information of urban adults living in Delhi, India. The pilot was implemented as an amendment to an ongoing cardiometabolic surveillance study, COE-CARRS. The pilot additionally collected social network information relevant to cardiovascular health, though the instrument is modifiable for application among South Asians in other settings. Personal network information was linked with demographic and cardiometabolic data from COE-CARRS, and network attributes were modeled against the primary outcome of waist circumference in regression analyses.

Results: The average network size of urban Asian Indians is 3.8 persons. Family relationships, particularly kin, formed the majority of social networks, with female relatives named more often than males. Neighborhood relationships comprised only 5% of nominated networks on average, indicating the relevance of social space over physical space in personal networks. Regression analyses revealed little evidence of egocentric social network attributes' association with an individual's waist circumference.

Conclusion: Our instrument successfully captured social network information in urban Asian Indians, with particular relevance to cardiovascular risk factors. Future analyses will employ a longitudinal sociometric design to formally map the network topography of urban adult Indians. Furthermore, contextualization of religious belief, migratory status, and gender roles will be included in the sociometric design due to these attributes' potential relevance to chronic health, especially cardiovascular health.

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Chapter 1: Introduction to Social Networks and Cardiovascular Disease in India

A. Brief history of social network analysis application to chronic disease

In the past few decades, health scientists exploited a powerful methodology termed social network analysis, modeling health determinants within the context of social constructs, to advance understanding of health behavior and chronic disease risk. Social network analysis concerns the relationships between and among a set of network members termed actors and the implications of these relationships (ties). A personal social network concerns a focal actor (ego) and actors with ties to the ego (alters). Application of social network analytics to the Framingham heart study, a multigenerational CVD surveillance system, revealed the association of social network connections with several CVD risk factors: loneliness (J. T. Cacioppo, J. H. Fowler et al. 2009); happiness (Fowler and Christakis 2008); obesity (Christakis and Fowler 2007); tobacco use and cessation (Christakis and Fowler 2008); and alcohol consumption (Rosenquist, Murabito et al. 2010). A recent review of 35 studies on social networks and CVD found social network size, or number of social contacts, benefits on CVD mortality and incidence, including stroke, myocardial infarction, and congestive heart failure (Shaya, Yan et al. 2010).

Exploration of social networks in the context of CVD has yet to be applied to India, where the CVD disease burden holds the greatest threat and demands immediate characterization, understanding, and targeted intervention.

B. Cardiovascular disease in India

Cardiovascular disease (CVD) is the leading cause of morbidity and mortality globally, with 80% of the burden occurring in low to middle income countries (LMIC) (Joshi, Jan et al. 2008). Cardiovascular disease is also the leading cause of mortality in India, and 2030 estimates project CVD mortality accounting for 35% of national mortality in India, compared with 22% in China and 12% in the United States (Leeder 2004; Gaziano, Reddy et al. 2006). Annual deaths attributable to CVD are expected to double between 2004 and 2030, increasing from 2.7 million to an estimated 4.0 million (Patel, Chatterji et al. 2011). Current CVD mortality rates, particularly attributable to coronary artery disease, contribute significantly to India's high death rates (Patel, Chatterji et al. 2011; Narasimhan, McKay et al. 2012).

Traditional CVD risk factors such as hyperlipidemia, tobacco use, and hypertension do not account for increased CVD mortality rates observed in South Asians, as the prevalence of these risk factors are generally similar to Caucasians (Bhopal and Sengupta-Wiebe 2000; Raji, Seely et al. 2001; Lovegrove 2007). A growing body of evidence attributes this disparity to a theorized "Asian Indian Phenotype" of the metabolic syndrome (MetS) and a premature onset of MetS-associated diseases, type-2 diabetes or CVD (Joshi 2003; Mohan, Sandeep et al. 2007). The Asian Indian phenotype is primarily characterized by excess visceral adiposity, defined as intra-abdominal body fat, despite low body mass indexes (BMI) compared to other ethnic groups. Furthermore, Asian Indian CVD occurs at younger ages and with higher case-fatality rates than equivalent countries, leading to increased burdens on healthcare systems and greater cumulative loss of productive years of life (Srinath Reddy, Shah et al. 2005; Patel, Chatterji et al. 2011; Narasimhan, McKay et al. 2012). In India, life years lost in persons younger than 60 years is estimated to increase from 7.1 million in 2004 to 17.9 million in 2030, a projection higher than USA, Russia, and Chinese estimates combined (Patel, Chatterji et al. 2011). As a result, coronary heart disease in Asian Indian populations presents particular concern as the disease manifests in younger populations.

C. Urban Indian context

CVD complications appear greater in Indian urban and migrant populations, suggesting CVD risk correlates with India's developmental and residential transition from rural, traditional practices towards urbanization and globalization (Srinath Reddy, Shah et al. 2005; Gupta, Arnold et al. 2009). Indian urban or migrant populations exhibit a higher percent body fat at lower body mass index (BMI) and higher waist to hip ratio (WHR) compared to other ethnic groups (Joshi 2003). Insufficient physical activity and obesity prevalence are highest among urban residents, elderly persons, and higher SES (Patel, Chatterji et al. 2011). In urban Indian adult populations, prevalence of coronary artery disease (CAD) has increased six-fold over the past forty years, with recent estimates around 8-10% (Srinath Reddy, Shah et al. 2005). In post-independence India, the population growth in urban India exceeds growth at the rural level, with 2030 estimates of India's urban population upwards of 580 million (Gupta, Arnold et al. 2009). Novel targeted interventions for India's growing urban societies are essential to curb this population's alarming CVD epidemic.

D. Application of social network perspective to investigate the cardiovascular disease epidemic in urban Delhi

The unique pathogenesis of CVD among South Asians, in combination with the epidemic burden of CVD among urban Asian Indians, necessitates immediate prioritizing of CVD research and intervention. Increasing evidence of social network effects on chronic disease risk encourages the exploitation of network structure to curb the CVD epidemic and close health disparities which may exist across social networks.

This pilot aimed to quantify, describe, and analyze social networks among the urban Indian population of Delhi. While the motivation for this project concerns CVD, the social network instrument discussed herein is adaptable for the investigation of various health outcomes within India or similar populations.

Chapter 2: Conceptual Framework of Social Network Effect on Ego Waist Circumference

This dissertation reviewed existing social network analysis theory and methodology and applied a social network perspective to cardiovascular disease (CVD) in South Asians. To analyze the utility of social network analysis for this purpose, we developed a pilot instrument to collect social network information in Delhi, an urban Indian population characterized by continual growth and fluctuation, and to preliminarily assess individual CVD risk based on self (ego) and network attributes. With the primary outcome of waist circumference as an indicator of ego CVD risk, the pilot will address the following three research aims: (1) To develop an instrument to collection social network information in urban Asian Indians (2) To describe the social networks of urban Indian populations in both size, number of reported ties, and composition, prevalence of reported tie types; (3) To determine which characteristics of the alter, ego, and alter-ego relationship predict ego waist circumference.

We propose that network health behaviors associate with ego CVD risk in a causal manner, with network health behaviors predictive of ego risk of CVD. The conceptual model delineates how the social network attributes act singly or in combination with ego characteristics to influence the primary outcome of ego waist circumference (Figure 1).

We model the outcome of ego waist circumference, as a marker of CVD risk, in terms of network characteristics, both demographic and health behaviors. We hypothesize that network characteristics casually influences ego CVD health behaviors. Ego health behavior and CMD history may confound observed network demographics and network health behavior. Similarly, ego demographic characteristics may confound the association of ego CVD biomedical history, network demographics, and network health behavior with the outcome.

Chapter 3: Review of Cardiovascular Disease in India

A. Global cardiovascular disease burden

Cardiovascular disease (CVD) is the leading cause of morbidity and mortality globally, with a disproportionate proportion (80%) occurring in low to middle income countries (LMIC) (Joshi, Jan et al. 2008). CVD broadly defines a class of diseases affecting the heart or blood vessels. Risk factors for CVD include hypertension, hyperlipidemia, hypertriglyceridemia, obesity, diabetes and risk behavior (tobacco use, alcohol use, diet, and physical inactivity) (Michael J. Pencina, Ralph B. D'Agostino et al. 2009; Greenland, Alpert et al. 2010). Cumulatively, ischemic heart disease, stroke, and congestive heart failure account for approximately 80% of the global CVD morbidity and mortality burden (Gaziano, Reddy et al. 2006).

B. Burden of disease in India

India is the second most populous country globally, with a population of approximately 1.2 billion people accounting for 17% of the world population (James 2011). According to 2011 estimates from the World Health Organization (WHO), 20% of the population is below 15 years of age, 65% between 15 and 64 years, and only 5% ages 65 years or older. The urban population in India accounts for approximately 30% of the country’s population, with an annual urban population growth of 2.4% according to 2010-2015 estimates (CIA Factbook). Estimates from the United Nations predict an increase in Indian life expectancy with male and female life expectancy expected to reach 64.4 and 67.6

years, respectively, by 2015 (James 2011). United Nation 2010 estimates of male and female life expectancy in India are 62.8 and 65.7 years, respectively (United Nations 2010). In 2004, the Indian age-standardized mortality rate for non-communicable diseases was 713 per 100,000 persons, compared to the communicable disease age-standardized mortality rate of only 377 per 100,000 persons (World Health Organization 2008).

C. Cardiovascular disease in India

Cardiovascular disease is the leading cause of mortality in India, and 2030 estimates project CVD mortality accounting for 35% of national mortality in India, compared with 22% in China and 12% in the United States (Leeder 2004; Gaziano, Reddy et al. 2006). Annual deaths attributable to CVD are expected to double between 2004 and 2030 in India, increasing from 2.7 million to an estimated 4.0 million (Patel, Chatterji et al. 2011). CVD mortality rates, particularly attributable to coronary artery disease, contribute significantly to India's high death rates (Patel, Chatterji et al. 2011; Narasimhan, McKay et al. 2012).

a. Emerging Asian Indian phenotype

Traditional CVD risk factors include tobacco use, alcohol use, hyperlipidemia, MetS, and diabetes (Eaton 2005). However, traditional CVD risk factors cannot explain the stark distinctions between CVD mortality rates among different ethnic populations. For example, while prevalence of tobacco use, hyperlipidemia, and hypertension are observed to be similar among Caucasians and South Asian populations, South Asians have higher CVD mortality rates (Bhopal and Sengupta-Wiebe 2000; Raji, Seely et al. 2001; Lovegrove 2007).

These CVD risk disparities among South Asians compared to other ethnic groups encourage the theoretical "Asian Indian Phenotype" of the metabolic syndrome (MetS) and the concomitant premature onset of MetS-associated diseases, type-2 diabetes or CVD (Joshi 2003; Mohan, Sandeep et al. 2007). The Asian Indian Phenotype of MetS is characterized by increased insulin resistance, central adiposity, and dyslipidemia among South Asians despite younger ages and lower BMI (Raji, Seely et al. 2001; Joshi 2003; Lovegrove 2007; Mohan, Sandeep et al. 2007). The unique Asian Indian MetS corresponds to higher risk of MetS, CVD, and T2D among South Asians compared to other ethnic groups (Joshi 2003; Misra, Wasir et al. 2005; Lovegrove 2007; Ramaraj and Chellappa 2008; Isharwal, Misra et al. 2009; Misra and Khurana 2009).

Cardiovascular disease generally occurs at younger ages in Asian Indians and with higher case-fatality rates than equivalent countries, thus leading to increased burdens on healthcare systems and a greater cumulative loss of productive years of life (Srinath Reddy, Shah et al. 2005; Patel, Chatterji et al. 2011; Narasimhan, McKay et al. 2012). Estimates of the 2030 Indian coronary heart disease burden project that life-years lost in persons younger than 60 years will more than double from 7.1 million life-years lost in 2004 to 17.9 million in 2030, a projection higher than USA, Russia, and Chinese estimates combined (Patel, Chatterji et al. 2011). In Western countries, approximately 22% of CVD mortality occurs in young (less than 70 years of age) populations; in India, this proportion more than doubles with 50% of CVD mortality occurring in young persons (Gaziano, Reddy et al. 2006).

b. Metabolic mechanism of the Asian Indian phenotype

The biological risk of the Asian Indian phenotype may be linked to excess body fat, particularly visceral adiposity. In support of the conceptualized Asian Indian phenotype, consistent evidence documents South Asians exhibiting higher body fat percentages than Caucasians at matched BMIs (Deurenberg-Yap, Schmidt et al. 2000; Deurenberg, Deurenberg-Yap et al. 2002; Lear, Humphries et al. 2007; Lovegrove 2007). Furthermore, increased CVD risk and insulin resistance has been observed in South Asians compared to age-, gender-, and BMI- matched Caucasians (Yajnik 2002; Lovegrove 2007). Recent evidence suggests that the metabolic consequences of excess body fat may carry higher risks for MetS, CVD, and T2D in South Asians than Caucasians (Misra, Wasir et al. 2005; Lovegrove 2007). Central adiposity, in particular, differs among South Asians matched to Caucasians by total body weight and may better predict ethnic differences of CVD risk than traditional diagnostic risk criteria, such as the Framingham index (Lovegrove 2007; D. S. Prasad, Z. Kabir et al. 2011).

This increase in Asian Indian CVD could be attributable to: (i) natural growth increasing total population size; (ii) ageing of the population; and (iii) vulnerability of population due to lifestyle transitions, primarily migration to urban centers (Shah and Mathur 2010).

D. Cardiovascular disease in urban India

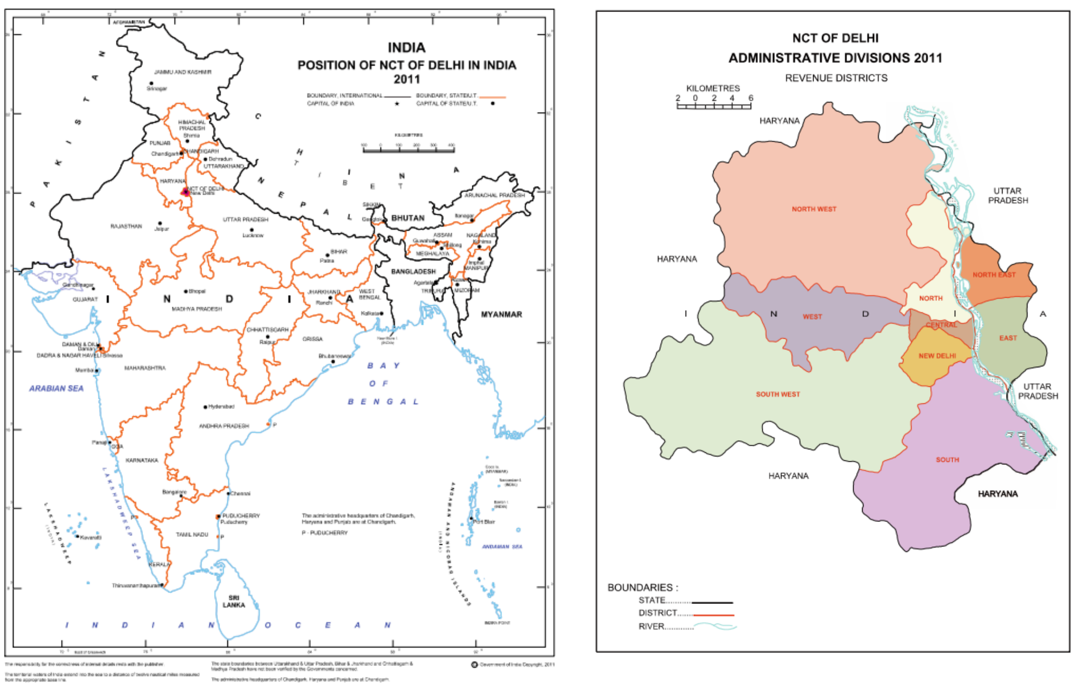
CVD complications appear greater in Indian urban and migrant populations, encouraging theory correlating increased CVD risk with India's developmental and residential transition from rural, traditional practices towards urbanization and globalization (Srinath Reddy, Shah et al. 2005; Gupta, Arnold et al. 2009). Rapid changes in lifestyle may compound health complications, such that traditional CVD risk factors interact with emerging risk factors particular to urban areas. Urban risk factors may include relatively rapid transitions to crowded living conditions, decreased physical activity, and consumption of novel, unhealthy diets (Misra, Misra et al. 2011).

Comparison of South Asian to other ethnicities in the INTERHEART study attributed 86% of acute myocardial incidence in South Asians to the cumulative CVD risk factors of obesity, visceral obesity, dyslipidemia, diabetes, and hypertension (Joshi, Islam et al. 2007). Recent evidence suggests the prevalence of all these risk factors, in addition to other known CVD risk factors such as insufficient physical activity, is significantly higher in urban compared to rural persons (Gupta 2008; Ebrahim, Kinra et al. 2010; Gupta, Shah et al. 2011; Misra, Misra et al. 2011; Patel, Chatterji et al. 2011). Additionally, urban South Asians exhibit higher prevalence of MetS then rural South Asians (Misra, Misra et al. 2011).

Recent evidence suggests that approximately 40% of deaths in urban areas are attributable to CVD compared to only 30% in rural areas (Gupta 2008). In urban Indian adult populations, prevalence estimates of coronary artery disease (CAD) have increased six-fold over the half century, with recent estimates around 8-10% (Srinath Reddy, Shah et al. 2005; Gupta 2008). Novel targeted interventions for India's growing urban societies are essential to curb this population's alarming CVD epidemic.

E. Delhi

a. Geographic context



A) B)

Figure 2: National Capital Territory (NCT) of Delhi (2011) **A)** Position of NCT of Delhi in relation to Indian country **B)** Administrative Divisions of NCT of Delhi into 9 revenue districts (Office of the Registrar General of India 2011)

The National Capital Territory (NCT) of Delhi, or Delhi, lies in northern India, bordering the states of Uttar Pradesh and Haryana (Figure 2A). The

Indian governmental administrative divisions divide Delhi into 9 revenue districts (Figure 2B) within three statutory towns: the Municipal Corporation of Delhi (MCD), the New-Delhi Municipal Council (NDMC), and the Delhi Cantonment Board (DCB) (Office of the Registrar General of India 2011). The MCD is the largest municipality by population globally and consists of 272 wards, of which 143 are urban wards. The DCM contributes 8 wards (Office of the Registrar General of India 2011).

b. Demographics

According to the 2011 Census of India, the population of Delhi is approximately 16.8 million, with 9.0 million (53.6%) males and 7.8 million (46.4%) females. The population is heavily gender-skewed compared to the national level, with a sex ratio of 1.15 males to females in Delhi compared to 1.06 nationally. The population varies by district within Delhi, with the largest district, the North West district (Figure 1B), accounting for 3.7 million persons or 22% of the total Delhi population. The population density of Delhi is 11.3 thousand persons per sq. km; however the districts east of the Yamuna River, the North East and East districts (Figure 1B), are the densest with a population density of approximately 37 and 27 thousand persons per sq. km., respectively. The proportion of children (0 to 6 years of age) in Delhi is 11.8%, compared to the national level of 13.1% (Office of the Registrar General of India 2011).

c. Cardiovascular disease in Delhi

Data from the New Delhi Birth Cohort phases 5 to 6 (roughly 2002-2007) report that incidence of CVD risk factors (mean BMI, waist circumference, hip circumference, the waist-to-hip ratio, and prevalence of overweight, obese, and central obesity) all increased significantly between 2002 and 2007 among the Delhi urban adults (average age in 2002 was for men 29.1 years and for women 29.2 years) (Huffman, Prabhakaran et al. 2011). The incidence of CVD and CVD risk factors within the New Delhi Birth Cohort occur at relatively young ages, consistent with the aforementioned Asian-Indian phenotype (Misra and Khurana 2009; D. S. Prasad, Z. Kabir et al. 2011; Huffman, Prabhakaran et al. 2011; Lear, Chockalingam et al. 2012).

In Delhi, the prevalence of persons at-risk for CVD morbidity and mortality will continue to increase as young persons develop CVD risk factors at younger ages combined with an overall increase in life expectancy for urban Indians. Evidence from urban Delhi adolescents supports this trend. Among Delhi adolescents (14-17 years of age), the prevalence of obesity, a key CVD risk factor, increased from 9.8% to 11.7% from 2006-2009, with a significantly higher risk of overweight (OR 1.28; 95% CI, 1.15–1.42) and obesity (OR 1.44; 95% CI, 1.24–1.66) status, after adjustment for age, gender and type of school (Gupta, Shah et al. 2011). If these adolescent trends hold, the Delhi population reaching adulthood will experience an increasing risk for CVD.

Chapter 4: Review of Social Network Analysis

A. Definitions and constructs

a. Description of social network analysis

Social network analysis (SNA) concerns the relationships, termed ties, between and among network members and the implications of these relationships for individuals' behavior, resources, health, and social norms (House, Landis et al. 1988; Wasserman and Faust 1994). Early social network analysis presumed the independence of network members and their actions, with social ties as the sole channel of information and influence between actors (Walker, Garber et al. 1994; Wasserman and Faust 1994). Accordingly, social ties are often conceptualized in terms of social capital, analogous to economic capital, assigning relative value to relationships in terms of strength, information, influence, and access (Coleman 1994; Lin 2002). Psychosocial mechanisms by which social capital is conferred are theorized in terms of: *(1)* social support (informational, financial, and emotional); *(2)* social influence (social comparison, norms, peer pressure, and behavioral influence); *(3)* social engagement (shared activities); *(4)* person-to-person contact (exposure); and *(5)* access to resources and material goods (Berkman and Kawachi 2000).

Social capital has often been tied to health (Macinko and Starfield 2001; Almedom 2005; De Silva, McKenzie et al. 2005; Abbott and Freeth 2008; Eriksson 2011). However operational definitions of social capital are often vague or context dependent, leading to cautionary or even contentious interpretations of social capital's influence on health measures (Kushner and Sterk 2005). Modern social network analytic approaches therefore bypass traditional social capital concepts by layering relevant individual measures (such as self and tie health status), contextual covariates (potential exogenous confounding variables), and structural network components. Ideally, social network analyses incorporate all potential determinants, internal and external, of health into a holistic model in order to tease out specific associations or causations on the outcome of interest.

Structurally, an individual's position within a relative social network can confer positional advantages or disadvantages relative to others within the network (Ladin and Hanto 2010). Several factors quantify these relative characteristics, most importantly network size (total number of network members); diversity (number of different types of ties); strength (strength, or directionality, of ties); connectedness (number of relationship ties per individual); centrality (degree of relative connectedness of an individual compared to the network structure); fragility (number of broken ties which isolate an individual); and homogeneity (degree of similarity between individuals and network members).

i. Social network theory

Social support, historically defined as emotional, instrumental, appraisal, or informational (Weiss 1974), has long been considered influential to an individual's health, however social network analysis broadens and deepens this concept (Smith and Christakis 2008). Analyzing health holistically at the network level can illuminate properties not apparent at the individual or dyad level (Watts and Strogatz 1998; Smith and Christakis 2008). A key finding supported through social network analysis is the influence of social integration, or connectedness within a network, on health outcomes, a concept theorized in social support research (Berkman and Syme 1979; House, Landis et al. 1988; Kaplan, Salonen et al. 1988; Palinkas, Wingard et al. 1990; Eng, Rimm et al. 2002; Pollard, Carlin et al. 2003; Bearman and Moody 2004; Kop, Berman et al. 2005; Gallegos-Carrillo, Mudgal et al. 2009; J. T. Cacioppo, J. H. Fowler et al. 2009; Troxel, Buysse et al. 2010). Persons on the periphery of a network, for example, are socially isolated compared to persons on the interior of the network. Such distinctions would not be apparent examining individual relationships, or dyadic level of social support.

In conjunction with social integration, the social network concept of weak ties, first proposed by Granovetter (Granovetter 1973), suggests network benefits of less social integration. Granovetter's research, in the context of the occupational hunt, discerned that novel information and access to new job opportunities came not from our close ties, strong in terms of kin relationship and frequency of contact, but from weak ties stemming from close relationships. His work thus deeply influenced the concept of social capital, or resources embedded within social networks (Lin 2002). Additionally, weak ties within a social network may prove beneficial for health intervention, though few examples exist. Bahr et al. recently simulated large social networks (n>10,000) with clustered obese persons, consistent with the topology of obese persons within the Framingham network (David B. Bahr, Raymond C. Browning et al. 2009). Interestingly, the simulations negated popular trends that a successful obesity intervention is to "lose weight with friends" (David B. Bahr, Raymond C. Browning et al. 2009). Clusters of obese persons tend to be small and unstable, with all persons on the edge of their minute cluster and therefore exposed to a competing cluster's influence. Rather, the authors discerned that a more successful strategy was to lose weight with your friend's friends, primarily due to the stability offered from inclusion in a second cluster. Thus, weak ties may also prove crucial in the context of chronic disease intervention.

ii. Mechanisms of social network effect

Social network effects manifest themselves through three possible mechanisms: homophily; induction; or shared environment (confounding). Homophily, or birds of a feather flock together, is an important consideration in determining causation of network effects on individual health outcomes (McPherson, Smith-Lovin et al. 2001). Homophily argues that tie dynamics (tie formation, tie retention, or tie dissolution) are pre-empted by actor characteristics. A person is more likely to form, retain, or dissolve ties with persons exhibiting similar behavioral or demographic characteristics. Thus, homophily confounds network causation of outcome incidence, behavior or disease. Induction alternatively argues that outcome incidence spreads causally through social ties similar to infections. An ego's adoption of a new behavior, for instance, is sensitive to the adoption of the behavior by alters' proximally close to the ego (Marsden and Friedkin 1993). Induction argues that tie formation preempts behavior modification, with behavior medication causally influenced and determined by structural social tie dynamics. Shared environment implies that contextual factors, such as the availability of sidewalks or fast-food establishments, will alter actor outcome incidence independent of network structure.

b. Social network instruments

Collection of network data is performed through the identification of network members and the relationships between these members, conceptualized as either egocentric or sociocentric. Networks are constructed from collected network information, of both actors and relationship ties between actors. Egocentric designs visualize a social network from the perspective of individual actors, termed *egos*, resulting local, or personal, network maps. Sociocentric instruments ubiquitously captures information on all network members, both egos and alters, ego-nominated network ties. Sociocentric instruments often employ census-type lists of all known network members, in either written or picture form, and qualify the relationship of the respondent with every network pre-identified member. Such designs necessitate network size restrictions in order to map an entire population. Small population studies, such as academic cohorts or companies, can cater sociocentric instruments using rosters (Butts 2008).

Compared to sociocentric methodologies which rely on predefined population maps, egocentric instruments rely on respondent recall for alter identification and thus can be performed in large, unrestricted populations (Carrington, Scott et al. 2005). As such, egocentric designs offer distinct advantages over sociocentric instruments. Egocentric designs generally incur a lower cost, amount to reduced respondent burden, and are free from organizational or geographical network limitations (alters are not known beforehand) (Wasserman and Faust 1994; Butts 2008; Valente 2010). Often egocentric instruments are undirected, relying on only ego-perceived relationship qualification such as ego-perceived social support (Wasserman and Faust 1994; Butts 2008; Valente 2010). Ego-perceived relationship strength is suggested to correlate with levels of tie strength such as closeness, level of contact, and duration of relationship (McCarty 1995) and thus conferring valuable information about social ties without additional researcher and respondent burden associated with the interviewing of alters.

Social networks can be operationalized through a Social Network Index (SNI), a composite quantification of an individual's personal social network. The Berkman-Syme SNI, developed for use among adult populations, compiles four types of self-reported social relationships: *(1)* marital status (married vs. unmarried); *(2)* sociability (frequency and contact with close friends and relatives on a three-tiered scale); *(3)* religious group affiliation (yes vs. no); and *(4)* membership in other social or community organizations (yes vs. no) (Berkman and Syme 1979). The Lubben SNI caters the Berkman-Syme SNI for use among elderly populations (Lubben 2003). The Cohen SNI also incorporates the Berkman-Syme SNI foundation, capturing information on 12 types of social relationships during the previous 2 weeks (Cohen, Doyle et al. 1997). SNIs sacrifice the complexity of network construction, but are convenient, numerical indicators of personal network information.

c. Egocentric Social Networks

Egocentric alter identification relies on the *name generation* methodology in which the ego is prompted to name social contacts, termed alters. Questions termed *name interpreters* then qualify these generated social ties. Name interpreters collect attribute data on the named alter, such as demographics, and the ego-alter relationship, such as type of relationship (family, friend, coworker, etc.), duration of the relationship, and frequency of contact. The number of captured alters can be unrestricted, but generally name generation and name interpretation are restricted to a pre-defined maximum set of alters (Valente 2010).

A classic example of an egocentric methodology is the General Social Survey (GSS). Conducted by the US National Opinion Research Center, the 1985 GSS provides one of the first examples of the use of name generation (Ronald S 1984; Bailey and Marsden 1999). Respondents were asked: *"Looking back over the last six months – who are the people with whom you discussed matter important to you?"* (GSS 1984, page 199) Name interpretation restriction was used, and attribute information was captured on the first five named alters, specifically relationship, sex, age, and religion. These data provided some of the earliest descriptions of American social support networks, or "conversation networks," as they were termed (Bailey and Marsden 1999). An application of a name generation approach in a poorer setting is the Malawi Diffusion and Ideational Change Project (MDICP), which employed unrestricted name nomination and restricted name interpretation up to 4 named alters similar to the methodology used in the GSS(Kohler, Behrman et al. 2007).

The GSS and MDICP name generators are *single-name generators*, in that egos name alters based on a single prompt. *Multiple-name generators* elicit alter identification from multiple prompts, such as differing scenarios. The Social Support Questionnaire (SSQ), for example, employs a 27-level name generator, in which egos must identify alters whom they turn to in twenty-seven different situations (Sarason, Levine et al. 1983). Multiple-name generators are long, incur high respondent burden, and are thus usually the sole focus of the research question (Carrington, Scott et al. 2005).

Name generator prompts vary by research setting or purpose, and respondent interpretation of the name generator prompt varies culturally. The GSS name generator was assessed using "think-aloud" probes, and respondent interpretation of the name generator varied depending on situation specifics, reported level of intimacy, and the nominal relationship hierarchy (Bailey and Marsden 1999). When applied to Chinese populations, Urban Chinese respondents to the GSS primarily named alters with whom they share leisure activity and in whom they confide, but who were not involved in conventionally "family" affairs, such as "making a major life decision" or attending to the sick (Danching 1998).

B. Social Networks and health

a. Brief history of social network applications to health

Social network analyses have been employed to investigate a variety of outcomes including: occupational behavior(Merrill and Hripcsak 2008; Lurie, Fogg et al. 2009) and decision-making (Chamie, Kwan et al. 2011; Coronges, Stacy et al. 2011; West 2011); construction project development (Chinowsky, Diekmann et al. 2008); crime/war networks (McIllwain 1999; Xu and Chen 2005); and diffusion of intervention(Valente, Chou et al. 2007).

Network approaches also have been applied to health research. There is evidence that both quantity and quality of social connections are important for health. The key network attributes of network size and network heterogeneity can be predictive of health patterns and dynamics (Valente 2010). Network size, a measure of social integration or connectedness within a network, predicts multiple health outcomes with smaller social networks generally associated with negative health events. After inoculation of healthy persons aged 18 to 55 years with experimental rhinovirus, those with fewer number of social ties were 4.2 times more likely to develop a cold than those with high social support, after adjustment for tobacco use, sleep quality, alcohol use, dietary vitamin C intake, catecholamine level, and personality type (introverted or extroverted) (Cohen, Doyle et al. 1997). In women suspected of myocardial ischemia, women with smaller social networks experienced twice as many stroke events during follow-up than women with larger social networks (Rutledge, Linke et al. 2008). Larger social networks associated with higher self-esteem and quality of life measurements in persons living with chronic mental illness (Eklund and Hansson 2007). Among older adults, network size was associated with lower depression scores (Palinkas, Wingard et al. 1990). Several studies in various populations corroborate an inverse association between network size and total mortality risk (Kaplan, Salonen et al. 1988; Eng, Rimm et al. 2002; Iwasaki, Otani et al. 2002; Rutledge, Matthews et al. 2003)

Network heterogeneity predicts psychosocial and physical health. Persons with more diverse or heterogeneous social networks, in terms number of different types of network tie relationships, exhibit lower overall mortality risk (House, Landis et al. 1988; J. C. Barefoot, M. Gronbaek et al. 2005), higher survival following a stroke (Berkman 1995), lower recurrence of cancer events (Helgeson 1998), lower ischemic heart disease risk (J. C. Barefoot, M. Gronbaek et al. 2005), and less susceptibility to experimental rhinovirus exposure (Cohen, Doyle et al. 1997).

b. Social networks and cardiovascular disease

Network size and heterogeneity have been shown to independently predict cardiovascular disease. Studies using longitudinal analysis of the networks constructed from Framingham Heart Study, a US multi-generational study capturing dynamic longitudinal social ties (Smith and Christakis 2008), found that social network measures were associated with several CVD risk factors: loneliness (J. T. Cacioppo, J. H. Fowler et al. 2009); happiness (Fowler and Christakis 2008); obesity (Christakis and Fowler 2007); tobacco use and cessation (Christakis and Fowler 2008); and alcohol consumption. Network size inversely associates with cardiovascular mortality risk (Kaplan, Salonen et al. 1988; Eng, Rimm et al. 2002; Rutledge, Linke et al. 2008). A recent review of 35 studies of social networks and CVD found network size benefits on CVD mortality and incidence, including stroke, myocardial infarction, and congestive heart failure (Shaya, Yan et al. 2010). Significantly, clusters of the CVD risk factors obesity (Christakis and Fowler 2007) and smoking behavior (Christakis and Fowler 2008) were discernable up to three degrees of separation, or the distance of three social ties, within the Framingham Study suggesting the association of CVD risk with social integration. In other words, network composition and structure predicts CVD risk, of both the individual and his/her social ties. These findings hold huge implications for CVD risk assessment, prevention and management.

Evidence of social network associations with CVD biomarkers substantiates observed network effects on CVD risk. In US men ≥60 years, elevated C-reactive protein (CRP), a risk factor for CVD, inversely associated with network size in a dose-dependent manner (Ford, Loucks et al. 2006). Social networks, as measured by the Berkman-Syme network index, inversely associated with the inflammatory marker interleukin-6 (Il-6) in the Framingham Heart cohort (Loucks, Sullivan et al. 2006). In asymptomatic US adults, social integration independently predicted coronary artery calcification (Kop, Berman et al. 2005) and blood pressure (Troxel, Buysse et al. 2010).

C. Social networks of urban Indian populations

No formal quantifications of social networks among urban India populations were identified within this literature review. One published study quantified social contacts of South Asians (specifically Pakistanis, Bangladeshis, and Indians) living in New Castle, UK in comparison to persons of European descent (Pollard, Carlin et al. 2003). Compared to Europeans, South Asian had larger households, were more likely to be married, more likely to attend a place of worship, and reported fewer contacts with friends or relatives on a regular basis.

a. Traditional living arrangements

Recent research emphasizes the differing living arrangements within modern Indian populations, with theoretical underpinnings from migration patterns. Evidence from the 2005-06 National Family Health Survey (NFHS-3) in Delhi (Gupta, Arnold et al. 2009) reported the average household size in Delhi of 4.5 persons. Living arrangements differ significantly between elderly men and women in urban India. Recent evidence from the Indian 52nd National Sample Survey (NSS) (Chaudhuri and Roy 2007) discerned that elderly (≥ 60 years) urban women were more likely to live alone than elderly urban men. The majority of the adult Indian population resides in joint households, with elderly Indian adults co-residing with their married children. Evidence using unit-level data of the Indian National Sample Survey Rounds on Morbidity and Health Care Expenditure at 1995 and 2004 report that 82% of elderly Indian adults co-reside with children, though the proportion declined 4% over the study period (Husain and Ghosh 2011). Modern migration and urbanization patterns may reduce prevalence of parental-married child co-residence (Mba 2002) and the likelihood of traditional living arrangements (Chaudhuri and Roy 2007). Living arrangement status may affect ego health status due to seeking of external or institutional support among those living in nuclear households or alone, compared to joint-household living arrangements. Evidence from the 1998-99 National Family Health Survey suggests that women living in nuclear families, compared to women in joint-households, were more likely to utilize institutional health services (Saikia and Singh 2009).

a. Urbanization and social networks

Urban Indian social networks are likely to vary by age and gender. In-migration to urban India cities is sex- and age-selective, with more unmarried men migrating towards urban areas than women and more persons of working age (Gupta, Arnold et al. 2009). During this transition, the social networks of urban Indian men are in flux. Migrants may form ties with new relations for a variety of reasons including strategic economic advancement, necessity for survival, or merely companionship.

Chapter 5: Development and Piloting of Social Network Instrument

A. Design and development

The social network pilot was designed to capture: (1) the personal networks of urban Delhi respondents, in size and composition; (2) alter attributes, with particular relevance to CVD risk; and (3) ego-alter relationship attributes, in terms of strength and homogeneity. Development of social network instrument began with a review of the literature for community-based social network questionnaires, social support instruments used among Indian communities or similar populations, and global surveys addressing social network interactions as they relate to health. For the first aim, a name generator was developed with reference to previous instruments: the National Longitudinal Study of Adolescent Health (Harris 2009) and the Malawi Diffusion and Ideational Change Project (Kohler, Behrman et al. 2007) which was conducted in a resource-poor setting. The primary source questionnaires used for name nomination and health-related network influence parameters are presented in Table 1.

An egocentric network design was chosen for the purposes of the pilot and implemented using a single-name generator of 5 "core" alters. Respondents were introduced to name generation with the following prompt:

I would like to ask you a few questions about the closest people in your life. Please think of people with whom you may discuss problems or with whom you would exchange advice (Appendix, S1).

Following introduction, name generation was delivered as follows:

Could you please tell me the names of the 5 people whom you consider to be closest to you? They can be family members, friends, acquaintances, or coworkers. Please begin with the person you are closest to (Appendix, S2).

Name interpretation questions followed, addressing the latter two aims of the pilot. Name interpretation questions captured attributes of each alter and the ego-alter relationship. Name interpretation followed, capturing alter gender, relationship type, geographic distance, and health communication frequency (Appendix, S3-S5, S9a-b). Respondents were asked to identify which alter they would speak under certain health-related or psychosocial conditions (Appendix, S6-S7). The extent of contact and shared activities relevant to CVD or CMD risk were captured (Appendix, S11-S14) with the previous fourteen days serving as the time frame. Ego-perceived health behavior of alters was captured through questions about the alter's tobacco use and weight (Appendix, S15-S16).

Special attention was paid to avoid linguistic or cultural misunderstandings with concurrent translation and pre-testing. After completion of the pilot questionnaire, interviewers were asked to note any relevant comments, including whether anyone else was present during the interview.

B. Piloting

This social network instrument was piloted as an amendment to the Center of Excellence – CardiometAbolic Risk Reduction in South Asia (COE-CARRS) Surveillance Study, a novel community-based sentinel surveillance system in

Delhi, India. Ethical clearance for the social network amendment was submitted and approved through a dual IRB application to the Emory Institutional Review Board and the Public Health Foundation of India Ethical Review Board.

The COE-CARRS Surveillance trained field team investigators, 9 members, collected social network data following training with the social network pilot instrument. One interviewer left mid-process due to logistical difficulties and was replaced by a newly trained interviewer. Interviewer pairs conducted household visits such that both household participants (one male, one female) could be interviewed concurrently. Within the household, respondents were interviewed in separate spaces as space allowed. To ensure data quality, interviewers were continually monitored throughout data collection by both COE-CARRS field team leaders and social network -specific field coordinators. Social network information was reviewed daily for discrepancies or obvious errors, which were addressed immediately. Retraining was conducted at monthly investigator meetings or as needed as determined by field team leaders.

The instrument had a high response rate of 96.6%. Over half (4/7=57%) of the refusals were to one interviewer. Personal characteristics did not predict response rate, and participants seemed willing to discuss their social networks. Based on interviewer feedback, only one refusal stemmed from a reluctance to share contacts information. The majority of refusals resulted from schedules, in either missing the respondent at home completely or the respondent's inability to delay leaving for occupational duties. In future, repeated attempts should be made.

Interviewer understanding of this prompt and name nomination presented the greatest challenge of the survey. Interviewers supplemented the prompt with reference to the discussion of health problems or health emergencies. Based on interviewer feedback, the clarification generally aided and supported respondent understanding.

Interviewers were often conducted in the presence of other persons. Other studies in India have also observed the communal nature of interviews conducted at the household level (Miltiades 2008). The collection of this additional data (the presence of other persons during the interview or ego mood) was added during the piloting process of SNAP and extracted from the interviewer comments section. As such, 131 respondents are missing this information. Of 77 respondents for which this data exists, 67 (87%) were interviewed in the presence of at least one other person.

Chapter 6: Social Networks and Cardiovascular Risk Analysis

A. Methodology

a. Data Sources

This social network pilot was implemented as an amendment to the COE-CARRS Surveillance Study. The baseline cross-sectional questionnaire of COE-CARRS Surveillance captured the prevalence of cardiometabolic disease (CMD) and associated risk factors among respondents.

COE-CARRS employs a multistage, cluster random sampling methodology to capture a representative sample within the urban Delhi population according to the WHO STEPwise methodology (World Health Organization). Delhi is divided into 9 revenue districts: the districts of New Delhi, North, and South West were excluded from the COE-CARRS recruitment, leaving 6 districts represented in the study. The New Delhi and the North districts are primarily commercial, and the South West district houses predominantly defense personnel with transient habitation. Each district is sub-divided into 3 sub-districts. Rural sub-districts were excluded from COE- CARRS recruitment. Urban sub-districts are further delineated into wards, which contain the census enumeration blocks (CEM). Using random selection at each stage, 20 wards were selected, 5 CEM within each ward, and 20 households within each CEM for a total of 2,000 households. Following the US Health Information National Trends Study (HINTS) household sampling methodology (Rizzo, Brick et al. 2004), a three-tier within household sampling was used to recruit one female and one male per household above 20 years of age for a total of 4,000 participants. A diagrammatic representation of COE-CARRS sampling in New Delhi is summarized in Figure 3.

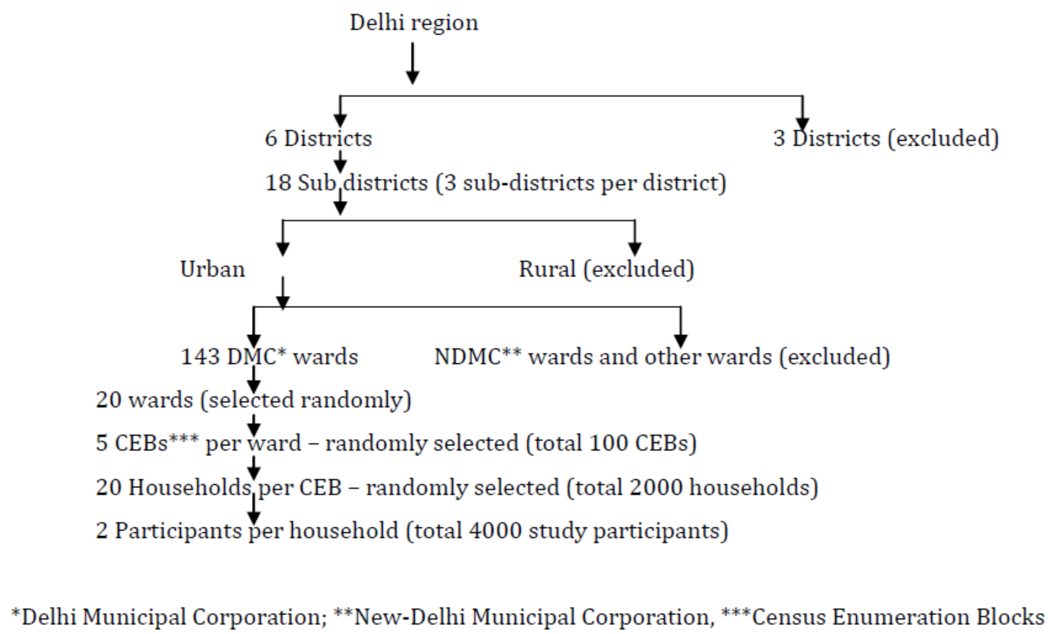


Figure 3: Schematic sampling scheme for COE-CARRS in Delhi, representative of urban adult Indians living in Delhi

Recruitment for the baseline cross-sectional component of COE-CARRS Surveillance took place 2010-2011. New COE-CARRS participants identified between May – October 2011 were simultaneously enrolled in the social networks pilot instrument. In accordance with the COE-CARRS methodology, interviewers recruited at the household level for up to two visits with one rescheduling. During household recruitment, participants were scheduled for a visit to a COE-CARRS Surveillance camp/clinic, or designated areas coordinated within each CEB, to collect biological samples and anthropometric measurements within approximately 7 days following the home visit. Recruitment for the social network pilot was also attempted at COE-CARRS Surveillance camps/clinics if respondent non-response during the household visit.

b. Primary outcome: waist circumference as the diagnostic criteria of South Asian CVD risk

The unique Asian Indian Phenotype is associated with CVD risk among Asian Indians. CVD risk indexes based on other ethnicities or indicators (BMI or waist to hip ratio) are not appropriate for CVD risk prediction among Asian Indians or South Asians. At a given BMI, South Asians exhibit higher body fat percentages than comparable ethnicities (Deurenberg-Yap, Schmidt et al. 2000; Deurenberg, Deurenberg-Yap et al. 2002; Lear, Humphries et al. 2007; Lovegrove 2007). However for a given waist-circumference, South Asians exhibit higher visceral adipose tissue (VAT) (Lear, Humphries et al. 2007). Recent evidence suggests that the elevated CVD risk observed in South Asians is mediated primarily through VAT among BMI- matched Europeans and Chinese populations (Lear, Chockalingam et al. 2012). Thus the use of waist circumference, as a measure of VAT, is more appropriate for South Asian CVD risk classification. Several recent reports corroborate the use of waist circumference to uniquely predict CVD (Cameron, Sicree et al. 2010) and CVD risk factors (Gill, Bhopal et al. 2011; Gray, Yates et al. 2011) among South Asian populations, compared to other ethnic populations (WHO Expert Consultation

2008). Waist circumference is therefore the primary outcome variable to measure CVR risk in South Asians within this study.

c. Ego attributes

Ego demographic, socio-economic, health behavior, and health history information was extracted from COE-CARRS data and merged with the social network information. Ego birthplace state was dichotomized into "Delhi" or "Other." Marital status was dichotomized into "Married" or "Not married." Similarly, employment status dichotomized into "Employed" or "Unemployed" and household income (rupees) per month was split into "Median or below" or "Above median" using the sample median of the 10,001-20,000 rupees/month category. Religion was dichotomized into "Hindu" or "Other." Caste/Tribe was dichotomized into those identifying with a caste or tribe and those who did not. Current alcohol use was dichotomized into "Currently use alcohol" or "Do not currently use alcohol." Prescribed diets were dichotomized into those on a "Special diet," including a diabetic, low-fat, high-fiber, low-salt, or weight-reducing diet, and those not on a health-oriented diet. Two composite cardiometabolic risk indexes were created ego CMD disease history and family CMD disease history. Any CMD ego-history comprised a history of any of the following diseases: Hypertension, Diabetes, Hyperlipidemia, Heart Disease, Stroke, or Kidney Disease. Any CMD family history comprised a family member with a history of any of the following diseases: Hypertension, Heart Disease, Diabetes, or Stroke.

Urban Indian social networks are likely to vary by age and gender. In-migration to urban India cities is sex- and age-selective, with more unmarried men migrating towards urban areas than women and more persons of working age (Gupta, Arnold et al. 2009). As such, ego age, gender, and marital status serve as ego control variables in regression analysis. Religion and caste also serve as control variables.

d. Alter attributes

Name interpretation in the social network pilot captures ego-perceived alter attributes of: gender, relationship to ego, geographic distance to ego, frequency of health communication, tobacco use and weight. Egos were asked to identify which alter, from the previously generated list, they would speak under certain health-related or psychosocial conditions. The strength of the tie, in terms of frequency of contact, was captured within the time frame of the previous fourteen days. Shared activities relevant to CVD or CMD risk (exercise with the aim of health, completion of small task, preparing a meal, smoking, or sharing a drink) were captured within the same time frame of the previous fourteen days.

e. Data management and analyses

COE-CARRS data was entered by trained COE-CARRS staff into a Microsoft Excel spreadsheet for data management. The social network pilot data was entered by the author and fellow Masters of Public Health candidate, Rekha Thammana into Microsoft Access and exported into Microsoft Excel. The author imported and merged Excel spreadsheets into SAS 9.2 2 (Cary, NC) for cleaning, coding, and analyses of data. Missing data were reviewed with interviewers daily and corrected were applicable.

Descriptive statistics and regression models were performed with reference to previous research. For the purposes of this study, the conceptual framework informed model design. A nested set model approach was used for regression analyses.

B. Results

a. Ego descriptive statistics

Of 208 ego respondents, 63% were non-native to Delhi, supporting previous research characterizing the heterogeneity and migratory appeal of the capital (Table 2). At the time of the survey, the mean age was 45.4 years, 50% male, 88% married, and 81% Hindu. Respondents reported an average of 9.5 years of formal education, 42% currently employed, and 19% identifying membership in a tribe or caste. The majority of household incomes per month were relatively low, at 3,000-10,000 rupees per month (35.1%). Regarding ego health characteristics, only 21% reported tobacco ever in life, with 19% current use of tobacco. Alcohol intake was uniformly low, with 18% reporting alcohol intake ever in life and 17% current alcohol intake. Approximately 15% of the respondents reported a special diet, and on average respondents reported respondents reported no anxiety or depression (96%). The average prevalence of self or family CMD history was 25% and 36%, respectively.

b. Network attributes

The average reported network size was 3.8 persons (Table 2). On average, network composition was 49% male, almost identical to the prevalence in the sample population. 81% of names alters were family relationships, and female relatives were reported more often than male relatives: 42% of those named were female relatives, and 38% of named alters were male relatives (Table 3). Similarly, female relatives were named most often for all five nominations, including position one indicating the closest contact. Within family ties, kin relationships were nominated most often in the networks. Husbands accounted for 10% of overall nominations, wives 11%, sons 11%, and daughters 9%. Friendship ties contributed the highest proportion of non-familial ties, with 18% of overall ties being friendship contacts. Interestingly, while the majority of alters (91%) lived in the same city as the ego, only 5% of named ties were neighbor contacts.

c. Network prediction of ego health

i. Bivariate association with ego waist circumference

The percentage of family ties in the reported network was positively associated with ego waist circumference (WC) exceeding the Action Level 2 cutoff point (Table 2). However, the percentage of ties in the social network living nearby (in the same city as the ego) associated negatively with ego WC. Regarding reported network health characteristics, the percentage of alters using tobacco and the percentage of alters fatter than the ego both negatively associated with ego WC. Open communication about health associated positively with ego WC for communication about both ego or alters' health. However, only communication about alter health associated significantly with ego WC, perhaps indicative that heavier egos were more aware and open about their social ties' health. These relationships disappeared in the analysis of dichotomous network health attributes; save health communication about alter health. Among first named, or closest, ties, alter tobacco use significantly and strongly protected against ego WC.

ii. Linear regression on ego waist circumference

Percentage of alters using tobacco and the percentage of alters fatter than the ego both negatively associated with ego WC in regression analyses using only the primary explanatory variables of full network alter health behaviors (Table 4). The incorporation of ego behavioral, biomedical, and demographic characteristics explained the majority of the variance in ego waist circumference. However, the percentage of fatter reported alters remained significant through subsequent iterations of the model. In the full model, each percentage point increase of fatter reported alters reduced ego waist circumference by 0.1cm on average.

Similar yet stronger relationships were observed modeling dichotomous network health behaviors (Table 5). Egos with any alter using tobacco or any alter fatter than the ego were more likely to have lower WC, in regression analyses with only primary explanatory variables. The incorporation of ego behavioral, biomedical, and demographic characteristics did not significantly change alter tobacco use coefficient, which remained strongly protective on ego WC. The same relationship held in the analysis of only the first reported tie (Table 6).

iii. Logistic regression on ego waist circumference

Percentage of alters fatter than ego slightly yet significantly lowered the odds of ego Action Level 2 WC, in regression analyses using only the primary explanatory variables of full network alter health behaviors (Table 7). In the same model, the percentage of the full network with open communication about alters' health slightly and significantly heightened the odds of ego Action Level 2 WC. Only the percentage of alters fatter than ego maintained significance throughout each iteration of the model, with subsequent incorporation of ego behavioral, biomedical, and demographic characteristics. Interestingly, the percentage of alters fatter than ego significantly decreased that odds of ego Action Level 2 WC.

Different patterns emerge in modeling dichotomous network health behaviors (Table 8). In regression analyses with only the primary explanatory variables, egos communicating about alter health with any person in their network had 3.31 times the risk of exceeding the Action Level 2 WC compared to those without any alter in their network with whom they communicate about the alter's health. This association was confounded, however, with the incorporation of network demographics, ego biomedical history, and ego demographics. In the presence of all sets (first named alter health characteristics, first named alter demographics, ego health behaviors, ego biomedical history, and ego demographics), egos who exercised with their closest contact were less likely to have a WC exceeding the Action Level 2 cutoff than ego who did not exercise with their closest contact in the past fortnight (Table 9).

Chapter 7: Discussion, Conclusion, and Recommendations

A. Discussion

This study analyzed existing social network analysis theory and methodology in the context of urban South Asian populations and cardiovascular disease risk. The pilot project developed and implemented an instrument to capture social network connections among urban adults in Delhi, India (Aim 1), quantified these social networks (Aim 2), and preliminarily assessed whether network (Aim 3) composition or health behaviors associated with ego waist circumference.

Regarding the first aim, this instrument is the first social network instrument catered to South Asians living in India, and the first quantification of network data among this population to the author's knowledge. The instrument had an extremely high response rate, was culturally appropriate, and demonstrated a general willingness of the adult Delhi population to disclose social network information.

Regarding the second aim, networks were primarily composed of family relationships, especially kin relations. Female social ties were nominated slightly more often than males, at approximately the same gender proportion in the ego sample population. Of five possible nominations, respondents reported only 3.8 ties on average. Interestingly, while 91% of alters lived geographically close to the ego, only 5% of total tie nominations were neighborhood ties. Our results support the dominance of a social space over a physical one in the construction of interaction spheres (Wellman and Leighton 1979). These findings hold significant implications for cardiovascular interventions, as traditionally prevention programs capitalize on neighborhood boundaries and inadequately account for social topography.

In a sample representative of urban Delhi, there is little evidence that social network composition associates with ego waist circumference (Aim 3). This finding corroborates findings that social network size does not associate with waist circumference among South Asians living in the UK (Pollard, Carlin et al. 2003). Egos with alters fatter than themselves, either as a percentage of the total network, the presence of any fatter alter in the network, or a fatter closest contact, inversely associated ego waist circumference in linear regression analyses. The association was observed to be strongest in the analyses of the first named alter, suggesting that that closest contact influences ego waist circumference more significantly than the network as a whole. Similarly in logistic regression, egos who exercised with their closest contact were less likely to have a WC exceeding the Action Level 2 cutoff than ego who did not exercise with their closest contact in the past fortnight. As such, each dyadic relationship comprising a person's social network may not carry hold the same significance in the context of cardiovascular health.

A further interesting finding of our study is the apparent negative association between ego waist circumference and being Hindu, in linear and logistic regression. Findings that religious belief and attendance affects cardiovascular health (STAVIG, IGRA et al. 1984; Livingston, Levine et al. 1991) seem especially relevant considering the high prevalence of Hinduism (81%) in our sample. In the aforementioned study of South Asians living in the UK, South Asians demonstrated higher levels of contact with their networks at places of worship compared to Europeans, particularly for men (Pollard, Carlin et al. 2003). Thus, social capital may differ by gender and religious practice. Tarakeswhar et al. developed an index of Hindu religious pathways: (1) private devoting (inclusive of private practice at temple and in the home; (2) ethical action (degree to which lifestyle conforms to ethical mandates of Hinduism); (3) knowledge (knowledge of Hindu stories); and (4) physical adherence (yoga, abstinence, etc.) (Tarakeshwar, Pargament et al. 2003). They discerned that ethical action was predictive of metal and physical health in a small sample (n=182) of Hindus living in the United States (Tarakeshwar, Pargament et al. 2003; Koenig, King et al. 2012). Our instrument does not distinguish between these various pathways, but does support a potential relevance of Hinduism in the context of cardiovascular health. Our results further evidence a protective association between egos that are male and the risk of exceeding the Action Level 2 ego WC compared to egos that are female. Network composition and inherent network behaviors may vary culturally according to traditional religious patterns of social and kin relationships. Investigation into the influence of religion and gender within the Delhi population could expose network associations with cardiovascular health not apparent in our analyses presented here.

CVD risk is higher among urban internal migrants (Hernandez, Pasupuleti et al. 2012), particularly South Asian urban migrants (Srinath Reddy, Shah et al. 2005; Gupta, Arnold et al. 2009). Our sample is representative of the urban Delhi population, and 63% of respondents reported being migrants to Delhi. Migrants may congregate together upon arrival to a new city, but these social networks may dissipate over time due to novel opportunities (social, occupational, educational) or external pressures (Chiu and West 2007). Considering the strong cultural connotations of caste, religion, and gender among South Asian communities, migratory patterns of various ethnic or cultural groups should be considered in a social network perspective. Migrant Muslims, for example, may experience more social isolation in Delhi that migrant Hindus. The social network composition and dynamics within various migrant groups could manifest differential health effects.

Living arrangements may differ between migrants and non-migrants in urban Delhi. The majority of the adult Indian population resides in joint households, with elderly Indian adults co-residing with their married children. Evidence using unit-level data of the Indian National Sample Survey Rounds on Morbidity and Health Care Expenditure at 1995 and 2004 report that 82% of elderly Indian adults co-reside with children, though the proportion declined 4% over the study period (Husain and Ghosh 2011). However migration and urbanization may reduce co-residence (Mba 2002) and the likelihood of traditional living arrangements (Chaudhuri and Roy 2007). Household living arrangement may affect ego health status due to seeking of external or institutional support among those living in nuclear households or alone, compared to joint-household living arrangements. Evidence from the 1998-99 National Family Health Survey suggests that women living in nuclear families, compared to women in joint-households, were more likely to utilize institutional health services (Saikia and Singh 2009). Thus, the social network composition and dynamics within various migrant groups could manifest differential health effects in the context of CVD risk.

B. Limitations

Homophily, or birds of a feather flock together, is an important consideration in determining causation of network effects on individual health outcomes (McPherson, Smith-Lovin et al. 2001). Selection of social ties to those with similar health status or risk behavior may predate induction of network risk or risk behavior to an individual. Thus, homophily may predict the composition and dynamics of social networks (Marsden 1988; Louch 2000). Homophily cannot directed be tested in the cross-sectional analysis of this social network pilot, thus limiting the extent to causation from alters to ego can be explained. However, regression analyses control for both ego and alter demographic characteristics, thus allowing for direct assessment of confounding due to ego-alter homogeneity.

C. Future Work

Future applications of the social network instrument will include network topography assessment and longitudinal analyses, allowing for quantification of tie formation dynamics. In this way, causation can be assessed by the temporal component of outcome incidence in comparison to homogeneity observed in novel tie formation. In other words, name generation and name interpretation information will be collected for both egos and alters in a longitudinal, sociometric design. In a sociometric design, social networks of urban South Asians can be formally mapped and patterns exposed between and among network members. Additionally, considering the potential relevance and gender, migratory patterns, and religious practice, future work will comprehensively collect information (from egos and alters) on these three attributes.

D. Public health implications and recommendations

Academics and policy makers continue to emphasize the relevance of community in context of population health interventions, despite shifting conceptualization of the term with the advent of globalization, modern technology, and migration (Forrest 2008). Partially due to jurisdiction and realistic limitations, a spatially delineated neighborhood is often used interchangeably with community in terms of both conceptualization and operationalization by policy makers (Forrest and Kearns 2001; Kearns and Parkinson 2001). Evidence suggests that contemporary neighborhoods, particularly urban neighborhoods, require contextualization by policy makers in terms of cultural, life-course, and demographic variation (Cattell 2001; Forrest and Kearns 2001; Kearns and Parkinson 2001; Forrest 2008). Seminal work by Wellman promoted the shifting perception of community from a physical space to a social one (Wellman and Leighton 1979). In his analyses of social ties, Wellman discerned that close ties consisted of primarily kin, and geographically bound neighborhood ties were generally less intimate. He concluded that social ties are structural and comprise a measurable social environment, which transcends physical neighborhood boundaries. In other words, personal social networks replace neighborhoods in the facilitation of social support, control.

Another complementary yet competing sociological theory arose concurrently with the work of Wellman. Granovetter proposed that weak ties provide distinct and invaluable advantages to an individual (Granovetter 1973). His research, in the context of the occupational hunt, discerned that novel information and access to new job opportunities came not from our close ties, strong in terms of kin relationship and frequency of contact, but from weak ties stemming from close relationships. His work thus deeply influenced the concept of social capital, or resources embedded within social networks (Lin 2002).

Social network application on health outcomes has been primarily formative research at this point. Theoretically, interventions exploiting social network structure fall broadly into one of two models: those exploiting highly embedded individuals as "key persons" within a network or those targeting weak ties through less embedded persons. Interventions relying on community health workers (CHWs) generally assume the former scenario. CHWs are persons identified from the community who are trained as key conduits of intervention resources. CHW interventions commonly hypothesize behavior change at the individual level, propagated through the CHW's social network within their community (Viswanathan, Kraschnewski et al. 2010). In practice, success of CHW interventions is variable and context dependent (Viswanathan, Kraschnewski et al. 2010). Neighborhood attributes, such as the built environment and safety, influence the composition and dynamics of social networks and social capital (Cattell 2001). CHW networks and their subsequent interventions differ ethnically, culturally, and structurally; suggesting that interventions of this kind necessitate localized, flexible, culturally appropriate strategies (Cattell 2001; Chiu and West 2007; Viswanathan, Kraschnewski et al. 2010).

Alternatively, exploitation of weak ties within a social network may prove beneficial for health intervention, though few examples exist. Bahr et al. recently simulated large social networks (n>10,000) with clustered obese persons, consistent with the topology of obese persons within the Framingham network (David B. Bahr, Raymond C. Browning et al. 2009). Interestingly, the simulations negated popular trends that a successful obesity intervention is to "lose weight with friends" (David B. Bahr, Raymond C. Browning et al. 2009). Clusters of obese persons tend to be small and unstable, with all persons on the edge of their minute cluster and therefore exposed to a competing cluster's influence. Rather, the authors discerned that a more successful strategy was to lose weight with your friend's friends, primarily due to the stability offered from inclusion in a second cluster. Thus, weak ties may also prove crucial in the context of chronic disease intervention.

Christakis and Fowler's findings of social network effects on chronic health status in the Framingham heart network garnered prominent attention in the public and academic sphere. As opposed to the longstanding social network approached to infectious diseases, the longitudinal and multifaceted nature of chronic diseases requires comprehensive control of contextual factors. Currently, the methodologies and data sources available address this issue with varied success and little global structure or standards. As such, the claims of Christakis and Fowler sparked an ongoing debate as to the validity of their methodology and conclusions (Cohen-Cole and Fletcher 2008; Lyons 2010). Despite the controversy surrounding the Christakis and Fowler's findings, the work of Bahr et al. (David B. Bahr, Raymond C. Browning et al. 2009) demonstrates the significance and utility of social networks in combating chronic disease health. In India, interventions aimed at improving diet, increasing physical activity, or utilizing community resources (including healthcare facilities) may find success exploiting weak ties in urban adult social networks.

Until recently, no national program existed for CVD control in India. In 2008-2009, the WHO launched National Programme on Prevention and Control of Diabetes, Cardiovascular diseases and Stroke (NPCDS) in collaboration with the Ministry of Health and Family Welfare within the national Indian government. Following models implemented in other WHO member states, the primary aims of NPDCS were to (1) prevent and control non-communicable diseases in India, (2) generate public awareness of lifestyle and behavioral risks, (3) establish guidelines for early detection of non-communicable diseases, and (4) capacity building for health systems to prepare for the incident non-communicable disease burden. Specific strategies of the NPDCS include interventions for awareness at the community level and screening for high-risk persons. In accordance with established CVD prevention strategies, NPDCS recommendations for CVD prevention include reduction in waist circumference and BMI, reduction in tobacco and alcohol use, maintaining a healthy diet, increasing physical activity, and maintaining the appropriate drug regimen where applicable.

The NPCDS recommendations are linked to behavior modification and lifestyle change for CVD prevention or control. Evidence suggests clustering of these risk factors among social networks, in both negative health behavior and positive behavior change. Our study does not significantly indicate the association of dyadic social network attributes with an individual’s CVD risk in urban India, assessed in terms of waist circumference. However, our analyses were egocentric analyses and thus do not allow for identification of clusters within a network or weak ties. As mentioned above, longitudinal sociometric analyses is critical to analyze the social networks of urban adult Indians in the context of findings from other parts of the world. Our pilot is the first to successfully capture social network information in urban Indian adults, and can easily be adapted for longitudinal sociometric designs.

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Tables and Figures

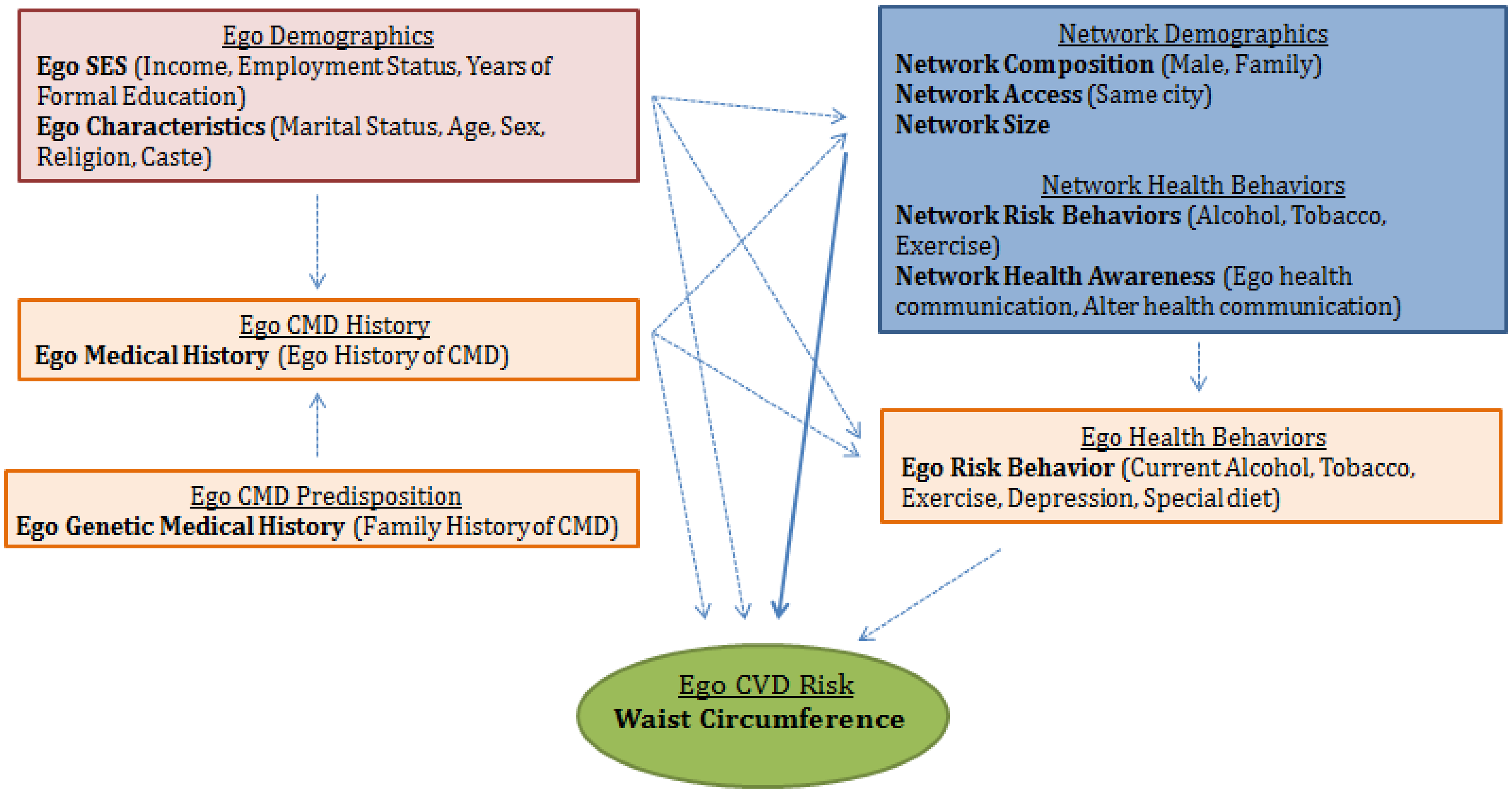

Figure 1: Determinants of ego waist circumference
Outcome of ego waist circumference (shaded green) modeled in terms of the primary explanatory variables: Network Characteristics (shaded blue). Ego CVD risk behavior and ego biomedical history (shaded orange) and ego demographic characteristics (shaded red) may confound the association between network characteristics and ego waist circumference. Potential confounding relationships are indication by a dashed arrow, and the presumed causal pathway between network characteristics and ego waist circumference is represented by the solid arrow.

Table 1: Primary source questions gathering social network information

Social Influence Concept	Source	Concept/Sample Items
Influences of friends on religious belief	THE ROLE OF INFORMAL CONVERSATIONS ON HEALTH AND AIDS BEHAVIOR IN MALAWI, 2004: MEN'S QUESTIONNAIRE R24	"Now I would like to ask you about the religion and religious practices of your closest friends."
	MDICP R25	How many people have you chatted with about your religion? I mean people other than your wife or partner. (IF LESS THAN FOUR ARE NAMED, PROBE)
	MDICP R26	Can you please give me the names of four of these?
	MDICP R27	Is (NAME) male or female?
	MDICP R28	What is your relationship to (NAME)?
	MDICP R29	Where does (NAME) stay?
	MDICP R33	Does (NAME) attend the same church/mosque that you are part of?
	MDICP R35	Is (NAME) more or less religious than you?
Health communication among friends	MDICP R37	Have you discussed AIDS with (NAME)?
	MDICP R39	Is (NAME) worried about getting AIDS?
Ego-perception of friend sexual behavior	MDICP S24	How about your best male married friend. Has he had sex with anyone other than his wife in the last yet?
	MDICP S25	How many people other than his wife has he slept with in the past 12 months?
	MDICP S26	How do you know he had these partners?
	MDICP S27	How many people overall has he had sex with?
Influences of friends on health	MDICP A29	"Now I'd like to ask you some questions about people you've chatted with about AIDS."
	MDICP A30	How many people have you chatted with about AIDS? I mean people other than your wife or partner. (IF LESS THAN FOUR ARE NAMED, PROBE)
	MDICP A31	Can you please give me the names of four of these?
	MDICP A32	Is (NAME) male or female?
	MDICP A33	What is your relationship to (NAME)?
	MDICP A34	Where does (NAME) stay?
	MDICP A39	How often do you speak with (NAME) about AIDS?
	MDICP A40	What does (NAME) think are the best ways to protect himself/herself from getting AIDS?

Name nomination in order of closeness	ADD-HEALTH Wave I: adolescent in-school questionnaire	YOUR MALE FRIENDS. "List your closest male friends. List your best male friend first, then your next best friend, and so on. Girls may include boys who are friends and boyfriends."
Shared activities recall period	ADD-HEALTH Wave I: adolescent in-school questionnaire ADD-HEALTH Wave I: adolescent in-school questionnaire ADD-HEALTH Wave I: adolescent in-school questionnaire ADD-HEALTH Wave I: adolescent in-school questionnaire	Darken the oval if: you went to his house in the past seven days. Darken the oval if: you met him after school to hang out or go somewhere in the last seven days. Darken the oval if: you talked with him about a problem in the last seven days. Darken the oval if: you talked with him on the telephone in the last seven days.
Name nomination in order of closeness	ADD-HEALTH Wave 1: Adolescent in-home interview; Section 20: Friends, Version A	First, please tell me the name of your 5 best male friends, starting with your best male friend. (If R is female, add: If you have a boyfriend, list him first. If not, begin with your best male friend.)
Shared activities recall period	ADD-HEALTH Wave 1: Adolescent in-home interview; Section 20: Friends, Version A ADD-HEALTH Wave 1: Adolescent in-home interview; Section 20: Friends, Version A ADD-HEALTH Wave 1: Adolescent in-home interview; Section 20: Friends, Version A ADD-HEALTH Wave 1: Adolescent in-home interview; Section 20: Friends, Version A	Did you go to (NAME)'s house during the past seven days? Did you meet (NAME) after school to hang out or go somewhere during the past seven days? Did you speak with (NAME) about a problem in the last seven days? Did you speak with (NAME) on the telephone in the last seven days?

Table 2: Descriptive statistics of adult Delhi population, by ego waist circumference action level, Delhi 2011

	Full sample (n=208)		Action level <2 WC[1] (n=89)		Action level 2 WC[2] (n=110)		Test[3] of Significance
	Mean or %	SE	Mean or %	SE	Mean or %	SE	
Ego Characteristics							
Birth state Delhi (%)	37.10	3.41	40.00	4.91	60.00	4.74	
Male (%)	49.50	3.48	52.08	5.01	47.92	4.72	**
Age (years)	45.40	0.97	40.57	1.40	48.72	1.29	**
Married (%)	87.50	2.30	45.14	3.33	54.86	3.19	
Hindu (%)	81.30	2.71	48.78	3.44	51.22	4.07	**
Tribe/Caste (%)	18.60	2.73	71.05	4.65	28.95	2.90	**
Formal Education (years)	9.90	0.40	8.17	0.60	11.00	0.52	**
Currently Employed (%)	42.30	3.43	51.22	5.08	48.78	4.61	
Income > median (%)	52.70	3.51	62.50	4.67	37.50	4.71	**
Ever used tobacco (%)	20.70	2.81	56.41	4.48	43.59	3.46	
Currently use tobacco (%)	18.80	2.71	57.14	4.37	42.86	3.29	
Ever used alcohol (%)	17.80	2.66	48.57	4.01	51.43	3.54	
Currently using alcohol (%)	16.80	2.60	48.48	3.93	51.52	3.46	
On special diet (%)	14.90	2.48	13.33	2.23	86.67	4.07	**[4]
Moderate anxiety/depression (%)	4.30	1.42	44.44	2.01	55.56	2.01	[4]
Any CMD self-history (%)	24.00	2.97	17.39	3.33	82.61	4.55	**
Any CMD family history (%)	36.40	3.36	34.78	4.76	65.22	4.71	*
Network Characteristics							
Network size	3.80	0.09	3.66	0.14	3.81	0.13	
Percentage full network demographic characteristics[5]							
% Alter male	49.40	1.91	52.71	3.06	46.32	2.51	
% Alter family	80.70	1.92	77.42	3.15	84.80	2.26	*
% Alter live in same city as ego	90.60	1.43	93.64	1.57	88.73	2.32	*
First named alter network demographic characteristics							
first named alter male (%)	50.00	3.56	51.06	5.14	48.94	4.89	*

first named family relationship (%)	86.06	2.41	42.77	3.93	57.23	2.87	
first named same city as ego (%)	92.31	1.85	44.86	2.78	55.14	2.49	
Percentage full network health characteristics[5]							
% Alter uses tobacco	11.60	1.81	15.33	3.25	8.46	1.98	*
% Alter slightly or much fatter	32.20	2.33	39.24	3.95	26.53	2.90	**
% Shared exercise in past 14 days	8.80	1.41	7.71	2.32	9.07	1.81	
% Shared tasks in the past 14 days	28.00	2.31	29.81	3.73	27.33	3.10	
% Often or regularly speaks about alter health	53.80	2.69	45.61	4.03	56.97	3.71	**
% Often or regularly speaks about ego health	52.20	2.75	49.55	4.10	56.67	3.85	
Any friend in full network health characteristics							
any alter tobacco use (%)	24.52	2.99	51.02	4.54	48.98	3.96	
any alter slightly or much fatter (%)	64.42	3.33	47.62	4.68	52.38	4.69	
any alter shared exercise in past 14 days (%)	25.00	3.01	37.50	4.24	62.50	4.27	
any alter shared tasks in past 14 days (%)	59.62	3.41	44.30	4.99	55.70	4.69	
any alter communicate about alter health (%)	79.33	2.81	57.14	4.43	42.86	3.54	*
any alter communicate about ego health (%)	80.77	2.74	43.13	4.17	56.88	3.62	
First named alter network health characteristics							
first alter tobacco use (%)	11.05	2.28	68.42	3.91	31.58	2.41	**
first alter slightly or much fatter (%)	32.21	3.25	51.56	4.89	48.44	4.31	
first alter shared exercise in past 14 days (%)	13.78	2.47	45.83	3.69	54.17	3.32	
first alter shared tasks in past 14 days (%)	43.46	3.60	46.91	5.20	53.09	5.01	
first alter communicate about alter health (%)	64.42	3.33	41.09	4.99	58.91	4.43	
first alter communicate about ego health (%)	65.87	3.30	43.51	4.87	56.49	4.49	

** Significant at a=0.10 ** Significant at a=0.05*

[1]Based on Misra et al. 2009 consensus statement: < 90 cm for males; < 80 cm for females

[2]Based on Misra et al. 2009 consensus statement: ≥ 90 cm for males; ≥ 80 cm for females

[3]Reporting two-tailed p-value on t-test statistic (continuous risk factor) or chi-square statistic (dichotomous risk factor) on Action Level <2 WC vs. Action Level 2 WC

[4]Fisher exact test statistic used due to cell count below 5

[5]Missing values are not included in the percentage calculation (To account for persons not completing 5 nominations)

Table 3: Tie composition of ego-nominated networks, overall and by position nomination from closest (position 1) (n=208)

Tie Type	Overall (n=780) n°(%)*	Position 1 (n=201) n°(%)*	Position 2 (n=193) n°(%)*	Position 3 (n=181) n°(%)*	Position 4 (n=125) n°(%)*	Position 5 (n=80) n°(%)*
Male Relative	37.7	42.3	34.8	37.8	18.9	14.4
husband	10.1	28.4	1.6	6.1	4.8	2.5
son	11.2	4	17.6	12.2	9.6	13.8
son-in-law	0.3	0	0	0	0.8	1.3
father	2.1	2	2.1	2.8	0.8	2.5
brother	9	3	10.4	13.3	10.4	8.8
father-in-law	0.3	0.5	0.5	0	0	0
brother-in-law	2.7	2	2.6	4.4	3.2	0
cousin	1	1	0.5	1.7	0	2.5
uncle	0.8	1.5	0.5	1.1	0	0
nephew	0.4	0	0.5	0.6	0.8	0
Female Relative	42.1	46.8	39.9	38.1	41.6	45
wife	10.6	30.4	4.2	5.5	1.6	2.5
daughter	8.5	5	9.8	9.9	9.6	8.8
daughter-in-law	2.2	0	1	2.8	4	6.3
mother	6	5	8.8	7.2	3.2	3.8
sister	6.9	4.5	8.3	6.6	8.8	7.5
sister-in-law	5.3	2	4.2	3.9	11.2	10
mother-in-law	0.9	0	2.6	0	0	2.5
cousin	0.9	0	0.5	1.7	2.4	0
aunt	0.3	0	0	0	0	2.5
niece	0.5	0	0.5	0.6	0.8	1.3
Non-relative	18.3	10.4	22.3	18.8	23.2	20
friend	12.7	8	14.5	13.4	18.4	10
workmate	1	0.5	1	0.6	1.6	2.5
neighbor	4.6	2	6.7	5	3.2	7.5
Other	1.9	0.5	1.6	1.1	4.8	3.8

° n refers to ties *Missing values are not included in the percentage calculation (To account for persons not completing 5 nominations)

Table 4: Linear regression of ego waist circumference (cm) on network (% full network) and ego characteristics

	Primary Independent Set		Alter Network Demographics		Ego Current Health Behavior		Ego CMD History		Ego Demographics	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Alter Network Health Behavior										
percentage network tobacco use	-0.08**	(0.04)	-0.06	(0.04)	-0.07*	(0.04)	-0.06	(0.04)	-0.04	(0.04)
percentage network slightly or much fatter	-0.10**	(0.03)	-0.11**	(0.03)	-0.10**	(0.03)	-0.10**	(0.03)	-0.09**	(0.03)
percentage network shared activity in past 14 days	-0.02	(0.05)	0.00	(0.05)	-0.01	(0.05)	-0.02	(0.05)	-0.05	(0.05)
percentage network shared tasks in past 14 days	-0.04	(0.03)	-0.04	(0.03)	-0.02	(0.03)	-0.02	(0.03)	0.00	(0.03)
percentage network communicate about alter health	0.06	(0.05)	0.06	(0.05)	0.09*	(0.05)	0.05	(0.05)	0.02	(0.05)
percentage network communicate about ego health	0.00	(0.05)	-0.01	(0.05)	-0.05	(0.05)	-0.01	(0.05)	0.03	(0.05)
Alter Network Characteristics										
network size			-0.41	(0.87)	-0.56	(0.87)	-0.60	(0.86)	-0.90	(0.90)
percentage network male			-0.03	(0.04)	-0.01	(0.04)	-0.01	(0.04)	0.01	(0.04)
percentage network family			0.04	(0.04)	0.05	(0.04)	0.04	(0.04)	0.04	(0.04)
percentage network in same city as ego			-0.02	(0.05)	-0.04	(0.05)	-0.03	(0.04)	-0.06	(0.05)
Ego Current Health Behavior										
ego current alcohol use (Alcohol use = 1)					2.82	(2.88)	1.97	(2.83)	2.05	(3.04)
ego current tobacco use (Tobacco use = 1)					-1.89	(2.65)	-1.46	(2.59)	-0.99	(2.86)
ego current depression status (Depressed = 1)					5.23	(4.29)	6.43	(4.25)	7.50*	(4.29)
on special diet (Diet = 1)					11.03**	(2.61)	7.02**	(3.50)	6.31**	(3.52)
Ego CMD History										
ego history of CMD (History of CMD = 1)							5.71**	(2.88)	3.06	(3.27)
ego family history of CMD (History of CMD = 1)							2.95	(1.92)	2.74	(2.03)
Ego Demographics										
ego age in years									0.13	(0.08)
ego marital status (Married = 1)									0.21	(2.77)
ego gender (Male = 1)									0.02	(2.96)
ego religion (Hindu = 1)									-5.91**	(2.51)
ego caste (Caste = 1)									0.16	(2.88)
ego income (Above median = 1)									-4.13*	(2.45)
ego employment status (Employed = 1)									1.13	(2.65)
ego years of formal education									-0.04	(0.23)
N	182		182		182		182		182	

** Significant at a=0.10 ** Significant at a=0.05*

Table 5: Linear regression of ego waist circumference (cm) on network (any alter) and ego characteristics

	Primary Independent Set		Alter Network Demographics		Ego Current Health Behavior		Ego CMD History		Ego Demographics	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Alter Network Health Behavior										
any alter tobacco use (Network tobacco = 1)	-3.98*	(2.16)	-2.82	(2.45)	-3.28	(2.43)	-2.33	(2.39)	-1.72	(2.40)
any alter slightly or much fatter (Fatter = 1)	-4.60**	(1.92)	-5.19**	(2.03)	-4.83**	(1.96)	-4.83**	(1.92)	-4.46**	(1.94)
any alter shared exercise in past 14 days (Exercise = 1)	2.10	(2.25)	2.17	(2.51)	1.40	(2.44)	0.47	(2.40)	-1.77	(2.52)
any alter shared tasks in past 14 days (Tasks = 1)	-1.95	(1.94)	-2.25	(2.00)	-1.04	(1.95)	-1.47	(1.93)	0.03	(2.02)
any alter communicate about alter health (Communicate = 1)	4.77	(4.07)	3.95	(4.21)	6.52	(4.06)	3.37	(4.13)	2.34	(4.15)
any alter communicate about ego health (Communicate = 1)	-1.31	(4.16)	-1.29	(4.25)	-3.79	(4.10)	-0.69	(4.14)	0.57	(4.19)
Alter Network Characteristics										
network size			0.37	(0.92)	0.14	(0.91)	0.08	(0.90)	-0.60	(0.94)
percentage network male			-0.04	(0.04)	-0.02	(0.04)	-0.02	(0.04)	0.01	(0.04)
percentage network family			0.05	(0.04)	0.05	(0.04)	0.04	(0.04)	0.03	(0.04)
percentage network in same city as ego			-0.02	(0.05)	-0.03	(0.05)	-0.03	(0.05)	-0.05	(0.05)
N	182		182		182		182		182	

** Significant at a=0.10 ** Significant at a=0.05*

Table 6: Linear regression of ego waist circumference (cm) on network (first named alter) and ego characteristics

	Primary Independent Set		Alter Network Demographics		Ego Current Health Behavior		Ego CMD History		Ego Demographics	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Alter Network Health Behavior										
first alter tobacco use (Network tobacco = 1)	-8.43**	(3.27)	-8.29**	(3.36)	-7.75**	(3.22)	-6.80**	(3.09)	-4.47	(3.29)
first alter slightly or much fatter (Fatter = 1)	-4.94**	(2.15)	-5.40**	(2.17)	-5.27**	(2.07)	-4.59**	(2.01)	-4.47**	(2.06)
first alter shared exercise in past 14 days (Exercise = 1)	0.27	(3.31)	0.35	(3.36)	0.26	(3.31)	-0.96	(3.18)	-1.92	(3.27)
first alter shared tasks in past 14 days (Tasks = 1)	-3.21	(2.11)	-3.31	(2.12)	-2.83	(2.05)	-3.02	(2.03)	-1.98	(2.18)
first alter communicate about alter health (Communicate = 1)	3.65	(4.16)	3.82	(4.30)	5.92	(4.15)	2.50	(4.13)	-0.43	(4.36)
first alter communicate about ego health (Communicate = 1)	0.75	(4.15)	0.26	(4.24)	-2.67	(4.11)	1.16	(4.08)	3.67	(4.33)
Alter Network Characteristics										
network size			-0.42	(0.94)	-0.75	(0.93)	-0.89	(0.90)	-1.12	(0.95)
percentage network male			-0.04	(0.04)	-0.02	(0.04)	-0.02	(0.04)	-0.01	(0.04)
percentage network family			0.05	(0.04)	0.05	(0.04)	0.03	(0.04)	0.03	(0.04)
percentage network in same city as ego			-0.02	(0.05)	-0.04	(0.05)	-0.02	(0.05)	-0.03	(0.06)
N	166		166		166		166		166	

** Significant at a=0.10 ** Significant at a=0.05*

Table 7: Logistic regression of Action Level 2[1] ego waist circumference (cm) on network (% named network) and ego characteristics

	Primary Independent Set		Alter Network Demographics		Ego Current Health Behavior		Ego CMD History		Ego Demographics	
	OR	**SE**	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**
Alter Network Health Behavior										
percentage network tobacco use	0.99	(0.01)	1.00	(0.01)	1.00	(0.01)	1.00	(0.01)	1.01	(0.01)
percentage network slightly or much fatter	0.99**	(0.00)	0.99**	(0.00)	0.99**	(0.01)	0.99**	(0.01)	0.99**	(0.01)
percentage network shared activity in past 14 days	1.00	(0.01)	1.00	(0.01)	1.00	(0.01)	1.00	(0.01)	0.99	(0.01)
percentage network shared tasks in past 14 days	1.00	(0.00)	1.00	(0.00)	1.00	(0.01)	1.00	(0.01)	1.00	(0.01)
percentage network communicate about alter health	1.02*	(0.01)	1.02	(0.01)	1.02*	(0.01)	1.02	(0.01)	1.01	(0.01)
percentage network communicate about ego health	0.99	(0.01)	0.99	(0.01)	0.98**	(0.01)	0.99	(0.01)	1.00	(0.01)
Alter Network Characteristics										
network size			1.11	(0.15)	1.12	(0.16)	1.12	(0.16)	0.87	(0.20)
percentage network male			0.99	(0.01)	0.99	(0.01)	1.00	(0.01)	1.01	(0.01)
percentage network family			1.01	(0.01)	1.01	(0.01)	1.01	(0.01)	1.01	(0.01)
percentage network in same city as ego			0.99	(0.01)	0.98**	(0.01)	0.99**	(0.01)	0.98**	(0.01)
Ego Current Health Behavior										
ego current alcohol use (Alcohol use = 1)					1.60	(0.55)	1.48	(0.57)	1.64	(0.69)
ego current tobacco use (Tobacco use = 1)					0.49	(0.49)	0.50	(0.51)	1.23	(0.66)
ego current depression status (Depressed = 1)					1.38	(0.78)	1.67	(0.81)	4.64	(1.03)
on special diet (Diet = 1)					7.28**	(0.62)	4.35**	(0.80)	4.02	(0.88)
Ego CMD History										
ego history of CMD (History of CMD = 1)							2.63	(0.56)	1.50	(0.74)
ego family history of CMD (History of CMD = 1)							1.56	(0.37)	1.40	(0.45)
Ego Demographics										
ego age in years									1.03	(0.02)
ego marital status (Married = 1)									1.30	(0.60)
ego gender (Male = 1)									0.21**	(0.67)
ego religion (Hindu = 1)									0.29**	(0.60)
ego caste (Caste = 1)									0.83	(0.61)
ego income (Above median = 1)									0.20**	(0.53)
ego employment status (Employed = 1)									1.67	(0.60)
ego years of formal education									1.00	(0.05)
N	182		182		182		182		182	

** Significant at a=0.10 ** Significant at a=0.05* [1]Based on Misra et al. 2009 consensus statement: ≥ 90 cm for males; ≥ 80 cm for females

Table 8: Logistic regression of Action Level 2[1] ego waist circumference (cm) on network (any alter) and ego characteristics

	Primary Independent Set		Alter Network Demographics		Ego Current Health Behavior		Ego CMD History		Ego Demographics	
	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
Alter Network Health Behavior										
any alter tobacco use (Network tobacco = 1)	0.74	(0.34)	0.91	(0.40)	0.94	(0.43)	1.11	(0.44)	1.22	(0.51)
any alter slightly or much fatter (Fatter = 1)	0.73	(0.31)	0.63	(0.33)	0.64	(0.34)	0.63	(0.36)	0.56	(0.41)
any alter shared exercise in past 14 days (Exercise = 1)	1.41	(0.36)	1.31	(0.40)	1.18	(0.43)	1.03	(0.44)	0.50	(0.54)
any alter shared tasks in past 14 days (Tasks = 1)	0.90	(0.31)	0.87	(0.32)	1.06	(0.34)	1.00	(0.36)	1.05	(0.42)
any alter communicate about alter health (Communicate = 1)	3.31*	(0.71)	2.90	(0.73)	4.96**	(0.81)	3.09	(0.78)	3.28	(0.93)
any alter communicate about ego health (Communicate = 1)	0.49	(0.72)	0.52	(0.74)	0.32	(0.81)	0.52	(0.78)	0.52	(0.94)
Alter Network Characteristics										
network size			1.15	(0.15)	1.14	(0.16)	1.14	(0.16)	0.86	(0.19)
percentage network male			0.99	(0.01)	1.00	(0.01)	1.00	(0.01)	1.01	(0.01)
percentage network family			1.01	(0.01)	1.01	(0.01)	1.01	(0.01)	1.01	(0.01)
percentage network in same city as ego			0.99	(0.01)	0.99	(0.01)	0.99	(0.01)	0.98**	(0.01)
N	182		182		182		182		182	

* *Significant at a=0.10* ** *Significant at a=0.05* [1]Based on Misra et al. 2009 consensus statement: ≥ 90 cm for males; ≥ 80 cm for females

Table 9: Logistic regression of Action Level 2[1] ego waist circumference (cm) on network (first named alter) and ego characteristics

	Primary Independent Set		Alter Network Demographics		Ego Current Health Behavior		Ego CMD History		Ego Demographics	
	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
Alter Network Health Behavior										
first alter tobacco use (Network tobacco = 1)	0.40*	(0.53)	0.40*	(0.56)	0.41	(0.59)	0.48	(0.61)	0.67	(0.70)
first alter slightly or much fatter (Fatter = 1)	0.68	(0.34)	0.63	(0.34)	0.60	(0.36)	0.67	(0.38)	0.63	(0.43)
first alter shared exercise in past 14 days (Exercise = 1)	0.85	(0.51)	0.73	(0.54)	0.70	(0.57)	0.55	(0.62)	0.29*	(0.73)
first alter shared tasks in past 14 days (Tasks = 1)	0.81	(0.33)	0.79	(0.34)	0.85	(0.36)	0.80	(0.39)	0.93	(0.46)
first alter communicate about alter health (Communicate = 1)	3.24*	(0.70)	2.88	(0.73)	4.57*	(0.82)	2.78	(0.78)	1.94	(0.92)
first alter communicate about ego health (Communicate = 1)	0.48	(0.71)	0.53	(0.73)	0.31	(0.81)	0.57	(0.77)	0.80	(0.90)
Alter Network Characteristics										
network size			1.08	(0.15)	1.05	(0.16)	1.03	(0.17)	0.83	(0.20)
percentage network male			0.99	(0.01)	1.00	(0.01)	1.00	(0.01)	1.00	(0.01)
percentage network family			1.01	(0.01)	1.01	(0.01)	1.01	(0.01)	1.00	(0.01)
percentage network in same city as ego			0.99	(0.01)	0.99	(0.01)	0.99	(0.01)	0.99	(0.01)
N	166		166		166		166		166	

** Significant at a=0.10 ** Significant at a=0.05* [1]Based on Misra et al. 2009 consensus statement: ≥ 90 cm for males; ≥ 80 cm for females

Appendix: Social Network Pilot Instrument

NO.	QUESTION	RESPONSE	{A}	{B}	{C}	{D}	{E}
S1	*"Next I would like to ask you a few questions about the closest people in your life. Please think of people with whom you may discuss problems or with whom you would exchange advice. I will ask you for their names to keep track of them for the following questions, but the names will be kept confidential and will not be made available to anyone except the investigators of the study."*						
S2	Could you please tell me the names of the 5 people whom you consider to be closest to you? They can be family members, friends, acquaintances, or coworkers. Please begin with the person you are closest to.	1. WRITE THE FIVE NAMES IN APPROPRIATE RESPONSE COLUMN. THE PERSON LISTED FIRST IS {A}, SECOND IS {B}, AND SO ON. 2. IF LESS THAN FIVE ARE NAMED, ASK *"IS THERE ANOTHER PERSON WHO YOU WOULD CONSIDER CLOSE TO YOU? AGAIN THIS PERSON CAN BE A FAMILY MEMBER, FRIEND, COWORKER, OR AQUAINTANCE."*	____	____	____	____	____
S3	Is ___ male or female? READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT _____?" FOR {B}-{E}. REPEAT QUESTION IF NECESSARY.	Male.............................. 1 Female.............................. 2 (Not applicable.............................. 77)	____	____	____	____	____
S4	What is _____'s relationship to you? READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT _____?" FOR {B}-{E}. REPEAT QUESTION IF NECESSARY.	Male Relative husband.............................. 1 son.............................. 2 father.............................. 3 brother.............................. 4 father-in-law.............................. 5 brother-in-law.............................. 6 cousin.............................. 7 paternal grandfather.............................. 8 maternal grandfather.............................. 9 other male relative SPECIFY (______)... 99 Female Relative wife.............................. 10 daughter.............................. 11 mother.............................. 12 sister.............................. 13 sister-in-law.............................. 14 mother-in-law.............................. 15 cousin.............................. 16 paternal grandmother.............................. 17 maternal grandmother.............................. 18 other female relative SPECIFY (______).. 99 Non-relative friend.............................. 19 workmate.............................. 20 neighbor.............................. 21 other SPECIFY (______).............................. 99	____ ____	____ ____	____ ____	____ ____	____ ____

NO.	QUESTION	RESPONSE	{A}	{B}	{C}	{D}	{E}
S5	Where does ____ live in relation to you? **READ SCALE.** READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT ____?" FOR {B}-{E}. REPEAT QUESTION AND SCALE IF NECESSARY.	Same household........0 Same building........1 Same neighborhood........2 Same ward........3 Same city........4 Another city or village........5 (Not applicable........77)	____	____	____	____	____
S6	Of the 5 people listed, whom would you be most likely to contact if you had a health emergency or if you needed help? MARK APPROPRIATE CODE FOR CHOSEN PERSON	1. MARK 1 FOR CHOSEN PERSON 2. IF "DON'T KNOW" OR "REFUSED" MARK FOLLOWING CODE IN {A} BOX (Not applicable........77) (Don't know........98) (Refused........99)	__ __	____	____	____	____
S7	Of the 5 people listed, whom would you be most likely to speak with about a health problem? MARK APPROPRIATE CODE FOR CHOSEN PERSON	1. MARK 1 FOR CHOSEN PERSON 2. IF "DON'T KNOW" OR "REFUSED" MARK FOLLOWING CODE IN {A} BOX (Not applicable........77) (Don't know........98) (Refused........99)	__ __	____	____	____	____
S8	Of the 5 people listed, whom would you be most likely to contact if were feeling overwhelmed or anxious? MARK APPROPRIATE CODE FOR CHOSEN PERSON	1. MARK 1 FOR CHOSEN PERSON 2. IF "DON'T KNOW" OR "REFUSED" MARK FOLLOWING CODE IN {A} BOX (Not applicable........77) (Don't know........98) (Refused........99)	__ __	____	____	____	____
S9	How often do you speak to ____ about: **READ SCALE.** FOR 9a-9b, READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT ____?" FOR {B}-{E}. REPEAT QUESTION AND SCALE IF NECESSARY. ASK **HORIZONTALLY** FOR EACH QUESTION, SUCH THAT YOU ASK 9b FOR ALL PERSONS {A}-{E} BEFORE MOVING ON TO 9c.						
S9a	your own health?	Never........1 Very seldom........2 Sometimes........3 Often........4 Regularly........5 (Not applicable........77) (Don't know........98) (Refused........99)	__ __	__ __	__ __	__ __	__ __
S9b	____'s health?		__ __	__ __	__ __	__ __	__ __

NO.	QUESTION	RESPONSE	{A}	{B}	{C}	{D}	{E}
S10	*"Now I'm going to ask you some additional questions about activities you have done in the past **fourteen** days with the people you listed."*						
S11	Have you communicated with ____ in person, by phone, SMS, or email in the past **fourteen** days? READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT _____?" FOR {B}-{E}. REPEAT QUESTION IF NECESSARY.	No............ 0 Yes............ 1 (Not applicable............ 77) (Don't know............ 98) (Refused............ 99)	___ ___	___ ___	___ ___	___ ___	___ ___
S12	In the past **fourteen** days, how many days have you shared snacks with _____? READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT _____?" FOR {B}-{E}. REPEAT QUESTION IF NECESSARY.	NUMBER OF DAYS_____ (Not applicable............ 77) (Don't know............ 98) (Refused............ 99)	___ ___	___ ___	___ ___	___ ___	___ ___
S13	In the past **fourteen** days, how many days have you shared meals with _____? READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT _____?" FOR {B}-{E}. REPEAT QUESTION IF NECESSARY.	NUMBER OF DAYS_____ (Not applicable............ 77) (Don't know............ 98) (Refused............ 99)	___ ___	___ ___	___ ___	___ ___	___ ___
S14	During the past **fourteen** days, have you done any of the following activities together with _____? FOR 14a-14e, READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT _____?" FOR {B}-{E}. REPEAT QUESTION AND SCALE IF NECESSARY. ASK **HORIZONTALLY** FOR EACH QUESTION, SUCH THAT YOU ASK 9b FOR ALL PERSONS {A}-{E} BEFORE MOVING ON TO 9c.						
S14a	Exercised, done yoga, jogged, or gone to the gym with the purpose of maintaining or improving your health?	No............ 0 Yes............ 1 **(Not applicable............ 77)** **(Don't know............ 98)** **(Refused............ 99)**	___ ___	___ ___	___ ___	___ ___	___ ___
S14b	Walked or performed small tasks outside of the home, such as walking to the store?		___ ___	___ ___	___ ___	___ ___	___ ___
S14c	Prepared a meal together or gone grocery shopping?		___ ___	___ ___	___ ___	___ ___	___ ___
S14d	Had an alcoholic beverage?		___ ___	___ ___	___ ___	___ ___	___ ___
S14e	Used tobacco in any form (smoking, chewing, snuff, etc.)?		___ ___	___ ___	___ ___	___ ___	___ ___

NO.	QUESTION	RESPONSE	{A}	{B}	{C}	{D}	{E}
S15	To the best of your knowledge, does ____ use any form of tobacco (smoking, chewing, snuff, etc.)? READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT _____?" FOR {B}-{E}. REPEAT QUESTION IF NECESSARY.	No........ 0 Yes........ 1 (Not applicable........ 77) (Don't know........ 98) (Refused........ 99)	___ ___	___ ___	___ ___	___ ___	___ ___
S16	How would you describe _____'s weight compared to your own weight? **READ SCALE.** READ QUESTION FOR PERSON {A}, AND ASK "HOW ABOUT _____?" FOR {B}-{E}. REPEAT QUESTION AND SCALE IF NECESSARY.	Much skinnier........ 1 Slightly skinnier........ 2 Same........ 3 Slightly fatter........ 4 Much fatter........ 5 (Not applicable........ 77) (Don't know........ 98) (Refused........ 99)	___ ___	___ ___	___ ___	___ ___	___ ___
S17	*"That concludes our interview. Thank you for your time."*						

COMMENTS FROM INTERVIEWER:
These notes should include any point of significance, such as the respondent's behavior (whether they were open or closed, vague or precise, etc.) or the home environment. PLEASE NOTE who, if any, was present during the interview. Also note any problems or difficultly pertaining to specific questions.