**Is Having an Educationally Diverse Social Network Good for Health?**

Mark C. Pachucki, Diego F. Leal

**Supplementary Information**

In an effort to be maximally transparent with analysis of the relationship between education assortativity and health indicators, we report stepwise model estimation here. We observe that although the relationship between educational assortativity and our four outcomes remain essentially null, there is some evidence that there are differential returns to education assortativity depending upon one’s level of educational attainment. This is notable given the abundance of role diversity research that has shown beneficial health returns to network diversity. Sensitivity Tables 1a-1d (below) report stepwise model progression, though only Models 3,4,5 are reported in the body text.

• When we begin with a baseline model (1) with *educational attainment as the only SES variable* among the other confounders, we see trends that individuals who have less education (especially HS only or “Some college” education) have worse health indicators (MH, PH, worse exercise, higher BMI), relative to individuals in the college-educated reference group.

• In models (2), we add in *education assortativity*. Across the four models, the direction of the coefficients suggests that greater assortativity (less diversity) is associated with better health indicators (though only propensity to exercise regularly is marginally significant). This is important because it suggests that a more precise measurement of diversity (by way of assortativity) reveals a different story than prior research which has found evidence of a diversity benefit to health using a role diversity measure.

• In models (3), we add *subjective social status*. Here, we observe that across all four health models, the fit is the best, with the lowest BIC for each model in the series. More importantly, as we add a term for subjective social status, we observe that the coefficient for education assortativity attenuates, providing support that perception of one’s social status may be a mechanism linking network diversity and health.

• In models (4), we add *income tiers, wealth tiers, and employment status*. Here, although we do not see overall fit improving in any of the models, we believe it is critical to include key socioeconomic confounders different from education in order to better specify the relationship between education assortativity and health. Evidence in this regard comes from the fact that the coefficient for education assortativity decreases in size across all models.

• The fully-interacted models (5) are discussed at length in the manuscript.



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**Sensitivity Analysis: Comparison of Education Assortativity & Education Distance**

In their 2014 study, Smith and colleagues found *greater education homophily among less-educated individuals* in the GSS using both continuous and categorical versions of an education distance measure. As a sensitivity analysis, we replicated Smith and colleagues’ categorical variant of educational distance using the Gallup data (here, educational attainment was not measured in continuous years for egos, as it was in the GSS). Following Smith et al. (2014) we measured social distance by education between ego and her alters (i.e., education network diversity) as the average (absolute) difference in education (measured categorically) between ego and her alters.

Fig S1 at right shows how, in the Gallup sample, *education assortativity* and *education distance* share some degree of consistency at their extremes in terms of how they vary by ego education. More specifically, low-education egos have greater network diversity (as well as more dissimilar levels of education among alters), compared with high-education individuals, who have less diverse networks (and alters with more similar education levels). We note that this is somewhat different than Smith, et al. (2014) insofar as here, less-educated individuals appear to have *less* education homophily.

Figure S1. Distribution of network diversity measures by education categories.

Next, we examined how educational attainment and network characteristics are associated with both education assortativity and education distance in a multi-level model that adjusts for the full range of socio-demographic characteristics (Sensitivity Table 2, below). We find that less-educated individuals (<HS) and the most-educated individuals (postgraduate) have the most education distance (i.e. the least education homophily). Though a more thorough comparison and interpretation of measures is beyond the scope of this study, future work may productively interrogate this direction.

**References**

Smith, J. A., McPherson, M., & Smith-Lovin, L. (2014). Social distance in the United States: Sex, race, religion, age, and education homophily among confidants, 1985 to 2004. *American Sociological Review*, *79*(3), 432-456.



**Example Code # 1. R Script to Compute Educational Assortativity**

1 ## Is Having an Educationally Diverse Social Network Good for Health?

2 ## Pachucki, Mark C. & Diego F. Leal.

3 ## Code written by Diego F. Leal (www.diegoleal.info)

4 ## Last revision: 10/14/19 by DFL/MCP

5 ## Purpose: This is a simplified version of the code to clean wave 1 Gallup data and

6 ## to compute (1) educational assortativity and (2) education distance both based on

ego net data

7 ## For access to the full script, which includes other measures and robustness checks,

please contact the authors.

8

9

10 ## clear all

11 rm(list=ls())

12

13 library(reshape)

14 library(reshape2)

15 library(igraph)

16 library(readstata13)

17 library(foreign)

18 library("RColorBrewer")

19

20 # ## info for full replicability

21 # R version 3.3.2 (2016-10-31)

22 # Platform: x86\_64-redhat-linux-gnu (64-bit)

23 # Running under: Red Hat Enterprise Linux Server release 6.8 (Santiago)

24 #

25 # locale:

26 # [1] LC\_CTYPE=en\_US.UTF-8 LC\_NUMERIC=C LC\_TIME=en\_US.UTF-8

LC\_COLLATE=en\_US.UTF-8 LC\_MONETARY=en\_US.UTF-8 LC\_MESSAGES=en\_US.UTF-8

LC\_PAPER=en\_US.UTF-8

27 # [8] LC\_NAME=C LC\_ADDRESS=C LC\_TELEPHONE=C LC\_MEASUREMENT=en\_US.UTF-8 LC\_IDENTIFICATION=C

28 #

29 # attached base packages:

30 # [1] stats graphics grDevices utils datasets methods base

31 #

32 # other attached packages:

33 # [1] RColorBrewer\_1.1-2 brew\_1.0-6 readstata13\_0.9.0 igraph\_1.1.2

reshape2\_1.4.2 reshape\_0.8.7 bindrcpp\_0.2 dplyr\_0.7.3 plyr\_1.8.4

34 #

35 # loaded via a namespace (and not attached):

36 # [1] Rcpp\_0.12.12 assertthat\_0.2.0 R6\_2.2.2 magrittr\_1.5 rlang\_0.1.2 stringi\_1.1.5 tools\_3.3.2 stringr\_1.2.0 glue\_1.1.1 pkgconfig\_2.0.1 bindr\_0.1

37 # [12] tibble\_1.3.4

38 ########################### DATA PREPARATION ####################################

39

40 ## Recording initiation time

41 g.time <-Sys.time()

42

43 #Import data

44 setwd("/RELEVANT PATH HERE")

45 covars\_w1<-read.dta13("/RELEVANT PATH HERE")

46 covars\_w1$RESPONDENT\_ID<-as.character(covars\_w1$RESPONDENT\_ID)

47

48 ## generate a covars list for W1

49 covars\_trunc <- covars\_w1

50 rownames(data) <- NULL

51

52 #This observation gives R a crash, but just in Wave 2 for some reason - drop from all waves' analyses.

53 (covars\_trunc <- covars\_trunc[covars\_trunc$EMPLOYEE\_KEY\_VALUE != "4083317012\_78914\_01",

])

54

55 ## list of all variables names in the full data set

56 allColLabels<-colnames(covars\_trunc[,])

57

58 ## locate position of the the variable "Q18\_1\_1",

59 ## the first variable (from left to right) where ego reports an alter's name

60

61 for (i in 1:length(allColLabels))

62 {

63 if (allColLabels[i]=="Q18\_1\_1")

64 {

65 firstAlter<-i

66 }

67 }

68

69 ## replace empty strings " " in alters' names by NAs

70 for (i in (firstAlter):(firstAlter+7))

71 {

72 for (j in 1:nrow(covars\_trunc))

73 {

74 if (covars\_trunc[j,i] == " ")

75 {

76 covars\_trunc[j,i] <-NA

77 }

78 }

79 }

80

81

82 #restricted data set: Ego ID and Alters names, "covars\_trunc" is the full data set

83 mat <-covars\_trunc[,c("Q18\_1\_1", "Q18\_1\_2",

84 "Q18\_1\_3", "Q18\_1\_4", "Q18\_1\_5", "Q18\_1\_6",

85 "Q18\_1\_7", "Q18\_1\_8")]

86

87 #replace anything different from 0 for a 1 (0 represents an absent alter)

88 mat <-ifelse(is.na(mat[,]),NA,1)

89

90 #sum alters to get the size of each egonet

91 alters <-(rowSums(mat[],na.rm=T))

92 alters <-as.data.frame(alters)

93 mat <-cbind(covars\_trunc$RESPONDENT\_ID,mat,alters) ## covars\_trunc is the full data set

94

95 ## rename "RESPONDENT\_ID" column

96 names(mat)[names(mat) == "covars\_trunc$RESPONDENT\_ID"] <- "RESPONDENT\_ID"

97

98 ## merge full data set with the count of alters of each ego

99 mat2 <-as.data.frame(mat$RESPONDENT\_ID)

100 mat3 <-as.data.frame(mat$alters)

101 mat2 <-cbind(mat2,mat3)

102 colnames(mat2) <-c("RESPONDENT\_ID","alters")

103 covars\_trunc <-merge(covars\_trunc,mat2,by="RESPONDENT\_ID",sort=F)

104

105

106

107 ## list of all variables names in the full data set

108 allColLabels<-colnames(covars\_trunc[,])

109

110 ## locate position of the the variable "Q31A\_YR1", "how much do you like alter A"

111 ## the first variable (from left to right) where ego reports an alter's name

112

113 for (i in 1:length(allColLabels))

114 {

115 if (allColLabels[i]=="Q31A\_YR1")

116 {

117 firstAlter<-i

118 }

119 }

120

121 ## replace empty strings " " by NAs

122 for (i in (firstAlter):(firstAlter+7))

123 {

124 for (j in 1:nrow(covars\_trunc))

125 {

126 if (covars\_trunc[j,i] == " ")

127 {

128 covars\_trunc[j,i] <-NA

129 }

130 }

131 }

132

133

134 #restricted data set: Ego ID and Alters names, "covars\_trunc" is the full data set

135 mat <-covars\_trunc[,c("Q31A\_YR1", "Q31B\_YR1",

136 "Q31C\_YR1", "Q31D\_YR1",

137 "Q31E\_YR1", "Q31F\_YR1",

138 "Q31G\_YR1", "Q31H\_YR1")]

139

140 #make sure mat is a data.frame object

141 mat<-as.data.frame(mat)

142

143 avg.like <-(rowMeans(mat[],na.rm=T))

144 avg.like <-as.data.frame(avg.like)

145 mat <-cbind(covars\_trunc$RESPONDENT\_ID,mat,avg.like) ## covars\_trunc is the full data set

146 names(mat)[names(mat) == "covars\_trunc$RESPONDENT\_ID"] <- "RESPONDENT\_ID"

147 mat2 <-as.data.frame(mat$RESPONDENT\_ID)

148 mat3 <-as.data.frame(mat$avg.like)

149 mat2 <-cbind(mat2,mat3)

150 colnames(mat2) <-c("RESPONDENT\_ID","avg\_like")

151 covars\_trunc <-merge(covars\_trunc,mat2,by="RESPONDENT\_ID",sort=F)

152

153 ############## MEASURE 1: EDUCATION ASSORTATIVITY #######################

154 ## Recording initiation time

155 e.time <-Sys.time()

156

157 ## create (super)lists to store all egonets in their different forms

158

159 allEgoNetsFullEdu <-vector("list",nrow(mat)) ## egonets in matrix format w/relationship type & including NAs

160 allEgoNetsEdu <-vector("list",nrow(mat)) ## egonets in matrix format w/relationship type NOT including NAs

161 allEgoNetsBinaryEdu <-vector("list",nrow(mat)) ## egonets in matrix format, relationship type is binarized

162 allEgoNetsIgraphEdu <-vector("list",nrow(mat)) ## allEgoNetsBinary in igraph format

163

164 ## list of all variables’ names in the full data set, find the position of variables "Q32A" and "alter\_ed\_5cat\_1",

165 ## relationship type between ego and alter and educational attainment of alter, respectively

166 allColLabels<-colnames(covars\_trunc[,])

167

168 for (i in 1:length(allColLabels))

169 {

170 if (allColLabels[i]=="Q32A")

171 {

172 colNumber<-i

173 }

174 if (allColLabels[i]=="alter\_ed\_5cat\_1")

175 {

176 colNumber3<-i

177 }

178 }

179

180 name\_no\_education

<-as.data.frame(matrix(ncol=3,nrow=(nrow(covars\_trunc)\*8))) ## create a df to store

alters with names and with no education info

181 colnames(name\_no\_education) <-c("RESPONDENT\_ID","ALTER\_NAME","ALTER\_#")

182

183 ########## recovering missing values in the education variable

184

185 count <- 0

186 for(a in 1:nrow(covars\_trunc)) ## for each ego

187 {

188 for (b in 1:8) ## for each of egos's alters

189 {

190 count <- count + 1

191 string<-(covars\_trunc[a,firstAlter + b - 1]) ## get the name of the bth

alter

192 if (is.na(covars\_trunc[a,firstAlter + b - 1]) == FALSE) ## if alter does have a name

193 {

194 if (((nchar(covars\_trunc[a,firstAlter + b - 1]) >= 2)) &

(is.na(covars\_trunc[a,colNumber3 + b - 1]))) ## if alters' name is a string of at

least two characters

195 {

196 name\_no\_education[count,1]<-covars\_trunc[a,"RESPONDENT\_ID"] ## store

egos's ID in the name\_no\_education object

197 name\_no\_education[count,2]<-covars\_trunc[a, firstAlter + b -1] ## store

alters' name in the name\_no\_education object

198 name\_no\_education[count,3]<-colnames(covars\_trunc)[firstAlter + b - 1] ## store

alters' number (e.e. alter\_2 or alter\_3) in the name\_no\_education object

199 }

200 }

201 }

202 }

203

204 name\_no\_education<-name\_no\_education[complete.cases(name\_no\_education),] ## get rid of NAs

205

206

207 #see the resulting data

208 View(covars\_trunc)

209

210 #creste variables to store missing data

211 covars\_trunc$missing\_education <-NA

212 covars\_trunc$missing\_rel\_type\_edu <-NA

213

214 ## create egonets based on the right number of dimensions

215 for (j in 1:nrow(mat))

216 {

217 egoNetName <-as.character(mat[j,1]) # store ego's ID

("RESPONDENT\_ID")

218 egoNetDim <-max(mat[,"alters"]) + 1 # store the egonets dims

(all are 9 by 9 matrices)

219 egoNet <-matrix(nrow=egoNetDim,ncol=egoNetDim) # create the matrix object

220 labels <-c(egoNetName,colnames(mat)[2:egoNetDim]) # label the matrix first row and first columns are the ego's ID ("RESPONDENT\_ID")

221 colnames(egoNet) <-labels

222 rownames(egoNet) <-labels

223

224 #star-like egonet (i.e. everyone is connected to ego, no connections between alters)

225 egoNet <-as.matrix(egoNet) #save egonet as a matrix

object

226 egoNet[,] <-9999 #all cells == 9999

227 egoNet[,1] <-10 #all cells in first column

= 10

228 egoNet[1,] <-10 #all cells in first row =

10

229 diag(egoNet) <-10 #all cells in main

diagonal = 10

230 egoNet[upper.tri(egoNet)] <- 0 #make cells in the upper

triangle = 0

231

232 allEgoNetsEdu[[j]]<-egoNet #store the egonet in

allEgoNets

233 }

234

235

236 ################## M2.Education assortativity MASTER LOOP###################

237 # This loop populates the egonets based on the info of covars\_trunc and calculates assortativity coeffcients based on education

238

239 for (j in 1:nrow(covars\_trunc))

240 {

241 X<-allEgoNetsEdu[[j]] ## select the jth egonet in allEgoNetsEdu, that is, select the egonet of the ego in row j in the main data set (covars\_trunc)

242 Y<-melt(X) ## transform the egonet from matrix format to edgelist format

243 colnames(Y) <- c("X1","X2","value") ## rename columns of the edgelist. "value" = relationship type between alters

244

245 count<-0

246 for (i in 1:(9\*9)) ## at the beginning, all sociomatrices are 9

by 9 matrices. Equivalently, all edgelists have 81 (9 \* 9) rows

247 {

248 if(Y[i,3]==9999) ## using the cells in the lower triangle only:

249 {

250 Y[i,3]<-covars\_trunc[j,colNumber+count] ## replace the 9999 in the ith row of edgelist with value (i.e.relationship type) reported by ego between a given pair of his/her alters

251 count <- count + 1 ## go to next alter

252 }

253 }

254

255 Y<-acast(Y, X1~X2,value="value") ## from edgelist to sociomatrix format

256

257 Y[upper.tri(Y)]<- t(Y)[upper.tri(Y)] ## symmetrize the egonet

258

259

260 eduEgo <-covars\_trunc$DEMO\_EDUC\_5CAT ## store all egos' education in the object educationEgo

261 eduEgo <-eduEgo[j] ## store the jth ego's education in the object educationEgo

262 eduAlters <-covars\_trunc[j,(colNumber3):(colNumber3+7)] ## retrieve the

education of ego's alters from the main data set (covars\_trunc)

263 education <-cbind(eduEgo,eduAlters) ## bind ego's education and alters education

264 education <-t(education) ## transpose education to make it a vertical vector

265 colnames(education) <-covars\_trunc[j,"RESPONDENT\_ID"] ## rename "education" object with ego's unique ID

266 Y <-cbind(Y,education) ## bind the education vector to the egonet

267

268

269 #### This section deals with missing values in the relationship type between alters

270 ### the code assumes that if there is an NA is because one of the alters did not exist

271

272 U<-as.data.frame(matrix(ncol=1,nrow=8)) ## create an empty vector to store inexistent

alters

273 V<-as.data.frame(matrix(ncol=1,nrow=8)) ## create an empty vector to store alters

with missing info in their education identity

274 S<-as.data.frame(matrix(ncol=1,nrow=8)) ## create an empty vector to store alters

with missing info in their (RELATIONSHIP TYPE?)

275

276

277 for (q in 2:10) ## for each alter (i.e. for each columns in Y)

278 {

279 if(q<=9) ## alters are in columns 2 to 9

280 {

281 I<-unlist(Y[,q]) ## list all values of column q (i.e. the

relationship type between alter q and all other alters)

282 if(sum(is.na(I))>=7) ## if alter q has no ties to other alters (i.e. if alter q has 7 NAs)

283 {

284 U[q-1,1]<-q ## store the number q in the object U

285 }

286 }

287

288 if(q==10) ## go to the education identity info of the alters

289 {

290 I<-unlist(Y[,q]) ## list of values, that is, all education identities of alters

291 for (g in 2:length(I)) ## go through the list of alters' education identities

292 {

293 if (is.na(I[g])) ## if a given alter has a missing value, store its position (i.e.,its row number) in the ego network

294 {

295 V[g-1,1]<-g ## store that info in the object V

296 }

297 }

298 }

299 }

300

301 for (q in 2:9) ## for each alter (i.e. for each columns in Y)

302 {

303 I<-unlist(Y[,q]) ## list all values of column q (i.e. the relationship type between alter q and all other alters)

304 if ((sum(is.na(I)) < 7) & (sum(is.na(I)) >0)) ## if alter q is indeed present in the egonet (if it has at least one relationship with another alter in the egonet)

305 {

306 if (sum(!(is.na(I))) + length(U) == 9) ## if alter q is indeed present in the ego net, its relationships to alter + the number of "fully" missing alters (alters that ego do not report at all) must be = 7

307 {

308 S[q-1,1]<-q ## store the number q in the object U. If q >= 1, it means that some alters reported by ego have a NA in their relationship with other alters

309 }

310 }

311 }

312

313 ########### M2.CREATE LISTs W/ ISOLATED ALTERS (U) OR ALTERS W/NO EDUCATION INFO (V) #########

314 ## V and U are then merged and the final set of alters to calculate EDUCATION assortativity (W) excludes the alters in U or V

315

316 U<-U[complete.cases(U),] ## get rid of NAs in object U (keep alters with no conection to any other alter)

317 U<-unlist(U) ## make U a list

318 V<-V[complete.cases(V),] ## get rid of NAs in object V (keep alters with no education info)

319 V<-unlist(V) ## make V a list

320 U<-c(U,V) ## concatenate U and V

321 U<-unique(U) ## keep unique element of U (i.e., keep column with missing alters or keep rows with alters with missing education info)

322

323 S<-S[complete.cases(S),] ## get rid of NAs in object V (keep alters with no education info)

324 S<-unlist(S) ## make S a list

325

326 covars\_trunc[j,"missing\_rel\_type\_edu"] <- length(S)

327

328 if (length(U)<8) ## if there is at least one alter with education info:

329 {

330 ifelse (length(U)>=1,W<-Y[-c(U),-c(U)],W<-Y) ## delete columns and rows with misssing info

331

332

333 #######M2.CREATE EGONETS BASED ON ALTERS WITH FULL EDUCATION & RELATIONAL INFO #########

334

335 attributes <-W[,(ncol(W))] ## create an node-attributes data set with the education info of the nodes

336 attributes <-as.data.frame(attributes) ## save the attributes object as data frame

337 colnames(attributes) <-"education" ## rename the column with education info with the label "education"

338 Y <-Y[,-(ncol(Y))] ## make Y the egonet with NAs

339 W <-W[,-(ncol(W))] ## make W the egonet with no NAs

340 Z <-ifelse(W[,]>1,1,0) ## make Z the binarized version of W

341 ZZ<-Z

342 ZZ

343 W[,1] <-1 ## populate the first column with 1s (ego's degree)

344 W[1,] <-1 ## populate the first row with 1s (ego's degree)

345 diag(W) <-0 ## populate main diagonal with 0s

346 diag(Z) <-0 ## populate main diagonal with 0s

347 Y[,1] <-1 ## technically, we should replace 1s w/numbers that represent relation type between ego & alters

348 Y[1,] <-1 ## technically, we should replace 1s by numbers that represent relation type between ego & alters

349 diag(Y) <-0 ## populate main diagonal with 0s

350

351 net<-graph\_from\_adjacency\_matrix(Z, mode = "undirected") %>% ##

creating the igraph object based on Z (binarized "egonet")

352 set\_vertex\_attr("education", value = attributes$education) ## setting education attribute

353

354

355 educationAssort <-assortativity\_nominal(net,

as.numeric(as.factor(V(net)$education)), directed = F) ## calculate education assortativity

356 covars\_trunc[j,"educationAssortativity"]

<-educationAssort

## store egos's education assortativity in the main data set (covars\_trunc)

357 covars\_trunc[j,"missing\_education"] <-covars\_trunc[j,"alters"] - (nrow(Z) - 1)

358

359 allEgoNetsFullEdu[[j]] <-Y ##store the full egonet (egonet with NAs) in the allEgoNetsFull list

360 allEgoNetsEdu[[j]] <-W ##store the egonet (egonet with NO NAs) in the allEgoNets list

361 allEgoNetsBinaryEdu[[j]] <-Z ##store the binarized egonet in the allEgoNetsBinary list

362 allEgoNetsIgraphEdu[[j]] <-net ##store the egonet as an igraph object in the allEgoNetsIgraph list

363 }

364 if (length(U)==8)

365 {

366 covars\_trunc[j,"educationAssortativity"] <-"no\_info"

367 covars\_trunc[j,"missing\_education"] <-length(U)

368 }

369 }

370

371

372 #generate data frame for education inspection

373 mat6 <-covars\_trunc[,c("RESPONDENT\_ID" ,"DEMO\_EDUC\_5CAT"

,"alter\_ed\_5cat\_1","alter\_ed\_5cat\_2","alter\_ed\_5cat\_3",

374 "alter\_ed\_5cat\_4" ,"alter\_ed\_5cat\_5","alter\_ed\_5cat\_6",

375 "alter\_ed\_5cat\_7" ,"alter\_ed\_5cat\_8","missing\_education",

376 "missing\_rel\_type\_edu", "educationAssortativity")]

377

378 ##### Sensitivity analysis (i.e., computing dyadic edu distance). See the supplementary

info of the published paper for more info ##

379

380 ## R&R.2 (9/17/19). Creating a Distance Measure following Smith, McPherson, and

Smith-Lovin's Social Distance in the United States (ASR, 2014)

381 ## Based on Table 1 of that article, ASR 2014 measures social distance as the

"absolute education difference between respondent and confidant"

382 ## Here we assume that what they did was to compute the absolute differences between

ego and her alters

383

384 #extract the labels of the variables in the mat6 object

385 mat6.labels<-colnames(mat6)

386

387 #find the position of the alter\_ed\_5cat\_1 variable (the edu level of the first alter)

in mat6

388 for (i in 1:length(mat6.labels))

389 {

390 if (mat6.labels[i]=="alter\_ed\_5cat\_1")

391 {

392 mat6.ego1<-i

393 }

394 }

395

396 #make sure mat6 is a data frame

397 mat6<-as.data.frame(mat6)

398

399 #create a new variable called 'eduDistanceSmith' This variable will contain the edu

distance

400 #following smith et al. Initially, the variable is populated with 99999s

401 mat6$eduDistanceSmith<-99999

402

403 #Loop to compute the absolute value of the average distance between ego and alter

404 for (iii in 1:nrow(mat6)) #for each ego

405 {

406 ego.alter.distance<-(matrix(99999,1,8)) #create a vector to store the dyadic

distances

407 for (jjj in 1:ncol(ego.alter.distance)) #for each possible alter

408 {

409 if ((mat6[iii,"educationAssortativity"]!= "no\_info") &

(mat6[iii,"educationAssortativity"]!= "NaN")) #if ego has at least two alters (this

will make the samples between assortativity and dyadic distance comparable)

410 {

411 ego.alter.distance[jjj]<-mat6[iii,"DEMO\_EDUC\_5CAT"] - mat6[iii,mat6.ego1+jjj-1]

#subtract egos and alter's level of education

412 }

413 if (mat6[iii,"educationAssortativity"]== "no\_info") #if ego does not have

two or more alters

414 {

415 ego.alter.distance[jjj]<-99999 #simply put an 99999 as the distance between ego and each of her alters

416 }

417 if (mat6[iii,"educationAssortativity"]== "NaN") #if ego and all her

alters have the same level of education (i.e., if there is perfect assortativity)

418 {

419 ego.alter.distance[jjj]<-0 #simply put a 0 as the distance between ego and each of her alters

420 }

421 }

422 mat6[iii,"eduDistanceSmith"]<-abs(rowMeans(ego.alter.distance,na.rm=T)) #compute the

average distance between ego and her alters, then take the absolute value of the distance

423 }

424

425

426 for (iii in 1:nrow(mat6)) #this loops replaces 99999 for "no\_info" in the education distance (i.e., egos with less than two alters)

427 {

428 if(mat6[iii,"eduDistanceSmith"] == 99999)

429 {

430 mat6[iii,"eduDistanceSmith"] <- "no\_info"

431 }

432 }

433

434 #bind the new edu distance variable (eduDistanceSmith) to the main data set (covars\_trunc)

435 covars\_trunc<-cbind(covars\_trunc,mat6$eduDistanceSmith)

436

437 #add a label to the new variable (eduDistanceSmith) in the context of the main data set (covars\_trunc)

438 colnames(covars\_trunc)[ncol(covars\_trunc)]<-"eduDistanceSmith"

439

440 ##### end of changes related to R&R.2 (i.e., computing dyadic edu distance) ##############

441

442 #count how many "no info" instances there are (answer: 5942). Remember, "no\_info"

entries mean that ego does not have 2 or more alters with education info.

443 count\_noinfoedu <-as.data.frame(table(covars\_trunc$educationAssortativity, useNA

= "always"))

444 sum(count\_noinfoedu[, "Freq"][1:nrow(count\_noinfoedu)]) ## check that all egos (20366)

have a gender\_assortativity value

445

446 #check how much time did the R script take to run

447 print(Sys.time() - e.time)

448

449

450 ###### M2.TEST ASSORTATIVITY EDUCATION CODE #########

451

452 #tabulate distribution

453 # When this new variable is > 0,it means that, for a given alter,

454 #the sum of its relationships + the known number of absent alters in the egonet

455 #(i.e. the # of "structural NAs") reported by ego is different from 7. In other words,

456 #if a given ego has "missing\_rel\_type" > 0 that's an indication of inconsistencies in the data.

457 count\_missingreltypeedu<-as.data.frame(table(covars\_trunc$missing\_rel\_type\_edu, useNA =

"always"))

458 count\_missingeducation<-as.data.frame(table(covars\_trunc$missing\_education, useNA =

"always")) # 8 missing alters = # no info in the count\_noinfoedu object = 5942

459

460

461 #### TEST EDUCATION ASSORTATIVITY CODE for ego 20365, (assortativity = -0.2)

462 #show education info of ego and alters

463 as.factor(V(net)$education)

464 #manually check education values

465 covars\_trunc[20365,"DEMO\_EDUC\_5CAT"] # 4

466 covars\_trunc[20365,"alter\_ed\_5cat\_1"] # 4

467 covars\_trunc[20365,"alter\_ed\_5cat\_2"] # 3

468 covars\_trunc[20365,"alter\_ed\_5cat\_3"] # 3

469 covars\_trunc[20365,"alter\_ed\_5cat\_4"] # 3

470 covars\_trunc[20365,"alter\_ed\_5cat\_5"] # 3

471

472

473 attributes2edu <-matrix(c(4,4,3,3,3,3),nrow=6,ncol=1)

474 attributes2edu <-as.data.frame(attributes2edu)

475 colnames(attributes2edu) <-"education"

476

477 net2edu<-graph\_from\_adjacency\_matrix(allEgoNetsBinaryEdu[[20365]], mode =

"undirected") %>% ## creating the igraph object based on Z (binarized "egonet")

478 set\_vertex\_attr("education",

value=attributes2edu$education) ##setting education attribute

479

480

481 assortativity\_nominal(net, as.numeric(as.factor(V(net)$education)), directed = F) ##

calculate education assortativity

482

483 # END TEST ASSORTATIVITY EDUCATION CODE

484

485 #save data

486 save.image("WAVE 1.Rdata")

487 #export analytic data frame to Stata version #

488 write.dta(covars\_trunc1, WAVE 1.dta')

**Example Code # 2. Stata Do-file to Compute Multilevel Models**

// Pachucki, Mark C. & Diego F. Leal

// Is Having an Educationally Diverse Social Network Good for Health?

// Code written by Mark Pachucki

// Multilevel model specifications of data from waves 1-3

// Last revision: 11/17/19 by MCP

//

// R data from Waves 1,2,3 with assortativity vars have been imported from R,

// merged on ID, transformed to long format, w/xtset denoting panel data.

use "/WAVE123\_long\_20191117.dta", replace

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*0. Table 2 - Education Assortativity as outcome

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

//OLS - assortativity as outcome (baseline Wave 1 only)

regress edu\_ass\_n\_0\_5 ib4.DEMO\_EDUC\_5CAT ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME Q14 ib3.Q15 ///

ib3.demo\_region if time==1

est store edass\_rc\_OLS\_v0

est save edass\_rc\_OLS\_v0, replace

save, replace

//MLM - assortativity as outcome

mixed edu\_ass\_n\_0\_5 ib4.DEMO\_EDUC\_5CAT ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME Q14 ib3.Q15 ///

ib3.demo\_region time ///

|| ID:, covariance(independent)

est store edass\_rc\_v1

est save edass\_rc\_v1, replace

save, replace

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*SI. Sensitivity Tables 1a-d, Network ed. assortativity & health (Model 1)

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

//A. BMI

quietly mixed BMIcorr ib4.DEMO\_EDUC\_5CAT ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q14!=. & Q15!=. ///

|| ID: , covariance(independent)

est store bmi\_rc\_v0

est save bmi\_rc\_v0, replace

save, replace

//B. Exercise Regularly

quietly melogit exer\_bin ib4.DEMO\_EDUC\_5CAT ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q14!=. & Q15!=. ///

|| ID:, covariance(independent) or noheader

est store exer\_rc\_v0

est save exer\_rc\_v0, replace

save, replace

//C. Excellent Self-reported Mental Health

quietly melogit Q10\_bin ib4.DEMO\_EDUC\_5CAT ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q14!=. & Q15!=. ///

|| ID:, covariance(independent) or noheader

est store mh\_rc\_v0

est save mh\_rc\_v0, replace

save, replace

//D. Excellent Self-reported Physical Health

quietly melogit Q8\_bin ib4.DEMO\_EDUC\_5CAT ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q14!=. & Q15!=. ///

|| ID:, covariance(independent) or noheader

est store ph\_rc\_v0

est save ph\_rc\_v0, replace

save, replace

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*SI. Sensitivity Tables 1a-d, Network ed. assortativity & health (Model 2)

\* This model adds education assortativity

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

//A. BMI

quietly mixed BMIcorr ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q14!=. & Q15!=. ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent)

est store bmi\_rc\_v1

est save bmi\_rc\_v1, replace

save, replace

//B. Exercise Regularly

quietly melogit exer\_bin ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q14!=. & Q15!=. ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or noheader

est store exer\_rc\_v1

est save exer\_rc\_v1, replace

save, replace

//C. Excellent Self-reported Mental Health

quietly melogit Q10\_bin ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q14!=. & Q15!=. ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or noheader

est store mh\_rc\_v1

est save mh\_rc\_v1, replace

save, replace

//D. Excellent Self-reported Physical Health

quietly melogit Q8\_bin ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q14!=. & Q15!=. ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or noheader

est store ph\_rc\_v1

est save ph\_rc\_v1, replace

save, replace

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*Table 3. Network education assortativity and health (Model 1)

\*Also reported in:

\*SI. Sensitivity Tables 1a-d, Network ed. assortativity & health (Model 3)

\* This model adds subjective social status

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

//A. BMI

quietly mixed BMIcorr ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP Q14 ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q15!=. ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent)

est store bmi\_rc\_v1\_5

est save bmi\_rc\_v1\_5, replace

save, replace

//B. Exercise Regularly

quietly melogit exer\_bin ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP Q14 ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q15!=. ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or noheader

est store exer\_rc\_v1\_5

est save exer\_rc\_v1\_5, replace

save, replace

//C. Excellent Self-reported Mental Health

quietly melogit Q10\_bin ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP Q14 ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q15!=. ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or noheader

est store mh\_rc\_v1\_5

est save mh\_rc\_v1\_5, replace

save, replace

//D. Excellent Self-reported Physical Health

quietly melogit Q8\_bin ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP Q14 ///

ib3.demo\_region time if employ!=. & DEMO\_INCOME!=. & Q15!=. ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or noheader

est store ph\_rc\_v1\_5

est save ph\_rc\_v1\_5, replace

save, replace

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*Table 3. Network education assortativity and health (Model 2)

\*Also reported in:

\*SI. Sensitivity Tables 1a-d, Network ed. assortativity & health (Model 4)

\* This model adds income, wealth, employment status

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

//A. BMI

quietly mixed BMIcorr ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME Q14 ib3.Q15 ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent)

est store bmi\_rc\_v2

est save bmi\_rc\_v2, replace

save, replace

//B. Exercise Regularly

quietly melogit exer\_bin ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME Q14 ib3.Q15 ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or noheader

est store exer\_rc\_v2

est save exer\_rc\_v2, replace

save, replace

//C. Excellent Self-reported Mental Health

quietly melogit Q10\_bin ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME Q14 ib3.Q15 ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or noheader

est store mh\_rc\_v2

est save mh\_rc\_v2, replace

save, replace

//D. Excellent Self-reported Physical Health

quietly melogit Q8\_bin ib4.DEMO\_EDUC\_5CAT edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME Q14 ib3.Q15 ib3.demo\_region time ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or noheader

est store ph\_rc\_v2

est save ph\_rc\_v2, replace

save, replace

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*Table 3. Network education assortativity and health (Model 3)

\*Also reported in:

\*SI. Sensitivity Tables 1a-d, Network ed. assortativity & health (Model 5)

\* This model adds interaction education x assortativity

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

//A. BMI

quietly mixed BMIcorr ib4.DEMO\_EDUC\_5CAT##c.edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME b4.DEMO\_EDUC\_5CAT ib3.Q15 Q14 ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent)

quietly margins DEMO\_EDUC\_5CAT, at(edu\_ass\_n\_0\_5=(-1(0.1)0.5))

marginsplot

graph save Graph "BMI\_marginsplot\_assort.gph", replace

est store bmi\_rc\_v3

est save bmi\_rc\_v3, replace

save, replace

//B. Exercise Regularly

quietly melogit exer\_bin ib4.DEMO\_EDUC\_5CAT##c.edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME b4.DEMO\_EDUC\_5CAT ib3.Q15 Q14 ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or

est store exer\_rc\_v3

est save exer\_rc\_v3, replace

save, replace

quietly margins DEMO\_EDUC\_5CAT, at(edu\_ass\_n\_0\_5=(-1(0.1)0.5)) ///

predict(mu fixedonly) vsquish

marginsplot

graph save Graph "exer\_marginsplot\_assort.gph", replace

est store exer\_rc\_v3

est save exer\_rc\_v3, replace

save, replace

//C. Excellent Self-reported Mental Health

quietly melogit Q10\_bin ib4.DEMO\_EDUC\_5CAT##c.edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME b4.DEMO\_EDUC\_5CAT ib3.Q15 Q14 ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or

quietly margins DEMO\_EDUC\_5CAT, at(edu\_ass\_n\_0\_5=(-1(0.1)0.5)) ///

predict(mu fixedonly) vsquish

marginsplot

graph save Graph "MH\_marginsplot\_assort.gph", replace

est store mh\_rc\_v3

est save mh\_rc\_v3, replace

save, replace

//D. Excellent Self-reported Physical Health

quietly melogit Q8\_bin ib4.DEMO\_EDUC\_5CAT##c.edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME b4.DEMO\_EDUC\_5CAT ib3.Q15 Q14 ///

ib3.demo\_region time ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or

quietly margins DEMO\_EDUC\_5CAT, at(edu\_ass\_n\_0\_5=(-1(0.1)0.5)) ///

predict(mu fixedonly) vsquish

est store ph\_rc\_v3

est save ph\_rc\_v3, replace

save, replace

marginsplot

graph save Graph "PH\_marginsplot\_assort.gph", replace

est store ph\_rc\_v3

est save ph\_rc\_v3, replace

save, replace

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* Table 4: Tie strength moderation

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

//A. BMI

quietly mixed BMIcorr c.avg\_like##c.edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME ib4.DEMO\_EDUC\_5CAT ib3.Q15 Q14 ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent)

est store bmi\_rc\_table4

est save bmi\_rc\_table4, replace

save, replace

//B. Exercise Regularly

quietly melogit exer\_bin c.avg\_like##c.edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME b4.DEMO\_EDUC\_5CAT Q14 ib3.Q15 ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or

est store exer\_rc\_table4

est save exer\_rc\_table4, replace

save, replace

//C. Excellent Self-reported Mental health

quietly melogit Q10\_bin c.avg\_like##c.edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME b4.DEMO\_EDUC\_5CAT Q14 ib3.Q15 ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or

est store mh\_rc\_table4

est save mh\_rc\_table4, replace

save, replace

//D. Excellent Self-reported Physical Health

quietly melogit Q8\_bin c.avg\_like##c.edu\_ass\_n\_0\_5 ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME b4.DEMO\_EDUC\_5CAT ib3.Q15 Q14 ib3.demo\_region time ///

ib3.demo\_region time ///

|| ID:edu\_ass\_n\_0\_5, covariance(independent) or

est store ph\_rc\_table4

est save ph\_rc\_table4, replace

save, replace

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*SI. Sensitivity Table 2 - Education Assortativity & Education Distance

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

//MLM - assortativity as outcome

mixed edu\_ass\_n\_0\_5 ib4.DEMO\_EDUC\_5CAT ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME Q14 ib3.Q15 ///

ib3.demo\_region time ///

|| ID:, covariance(independent)

est store edass\_rc\_v1

est save edass\_rc\_v1, replace

save, replace

//MLM - education distance as outcome

mixed eduDistanceSmith\_num ib4.DEMO\_EDUC\_5CAT ///

graphdensity alters avg\_close avg\_like ///

DEMO\_GENDER DEMO\_AGE marital ib1.DEMO\_RACE HISP ///

ib2.employ ib4.DEMO\_INCOME Q14 ib3.Q15 ///

ib3.demo\_region time ///

|| ID:, covariance(independent)

est store edass\_rc\_v1ssmith

est save edass\_rc\_v1ssmith, replace

save, replace