

# ACE Models with the NLSY

William Howard Beasley (Howard Live Oak LLC, Norman)  
Joseph Lee Rodgers (University of Oklahoma, Norman)  
Kelly Meredith (University of Oklahoma, Norman)  
David Bard (University of Oklahoma Health Sciences Center, OKC)

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## Abstract

We describe how to use the NlsyLinks package to examine various biometric models, using the NLSY79.

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//Note to team: *Not only am I hoping to capitalize on all researchers initially interested in NLSY BG studies, I'm also hoping to attract a small slice of those that aren't initially interested in BG. If the vignette or articles are good, they should rank well among search engines for terms like "NLSY and R". Maybe some researchers using those terms (and not initially interested in BG) could stumble on the vignettes. If the examples are clear and are easy to run quickly, they may get interested in BG. Therefore, I'd like at least a few paragraphs explaining what BG is. This section is tentatively located in the appendix.*

## 1 Terminology

This package considers both Gen1 and Gen2 subjects. **Gen1** refers to subjects in the original NLSY79 sample (<http://www.bls.gov/nls/nlsy79.htm>). **Gen2** subjects are the biological offspring of the Gen1 females -i.e., those in the NLSY79 Children and Young Adults sample ( <http://www.bls.gov/nls/nlsy79ch.htm>). The NLSY97 is a third dataset that can be used for behavior genetic research (<http://www.bls.gov/nls/nlsy97.htm>), although this vignette focuses on the two generations in the NLSY79.

Standard terminology is to refer Gen2 subjects as 'children' when they are younger than age 15 (NLSY79-C), and as 'young adults' when they are 15 and older (NLSY79-YA); though they are the same respon-

dents, different funding mechanisms and different survey items necessitate the distinction. This cohort is sometimes abbreviated as ‘NLSY79-C’, ‘NLSY79C’, ‘NLSY-C’ or ‘NLSYC’.

The **SubjectTag** variable uniquely identify NLSY79 subjects when a dataset contains both generations. For Gen2 subjects, the **SubjectTag** is identical to their CID (*i.e.*, C00001.00 -the ID assigned in the NLSY79-Children files). However for Gen1 subjects, the **SubjectTag** is their CaseID (*i.e.*, R00001.00), with “00” appended. This manipulation is necessary to identify subjects uniquely in inter-generational datasets. A Gen1 subject with an ID of 43 becomes 4300. The **SubjectTags** of her four children remain 4301, 4302, 4303, and 4304.

The **expected coefficient of relatedness** of a pair of subjects is typically represented by the variable **R**. Examples are: Monozygotic twins have  $R=1$ ; dizygotic twins have  $R=0.5$ ; full siblings (*i.e.*, those who share both biological parents) have  $R=0.5$ ; half-siblings (*i.e.*, those who share exactly one biological parent) have  $R=0.25$ ; adopted siblings have  $R=0.0$ . Other possibilities exist too. The font (and hopefully their context) should distinguish the variable **R** from the software R.

A subject’s **ExtendedID** indicates their extended family. Two subjects will be in the same extended family if either: [1] they are Gen1 housemates, [2] they are Gen2 siblings, [3] they are Gen2 cousins (*i.e.*, they have mothers who are Gen1 sisters in the NLSY79), [4] they are mother and child (in Gen1 and Gen2, respectively), or [5] they are (aunt|uncle) and (niece|nephew) (in Gen1 and Gen2, respectively).

An **outcome variable** is directly relevant to the applied researcher; these might represent constructs like height, IQ, and income. A **plumbing variable** is necessary to manage BG datasets; examples are **R**, a subject’s ID, and the date of a subject’s last survey.

An ACE model is the basic biometrical model used by Behavior Genetic researchers, where the genetic and environmental effects are assumed to be additive. The three primary variance components are (1) the proportion of variability due to a shared genetic influence (typically represented as  $a^2$ , or sometimes  $h^2$ ), (2) the proportion of variability due to shared common environmental influence (typically  $c^2$ ), and (3) the proportion of variability due to unexplained/residual/error influence (typically  $e^2$ ).

The variables are scaled so that they account for all observed variability in the outcome variable; specifically:  $a^2 + c^2 + e^2 = 1$ . Using appropriate designs that can logically distinguish these different components (under carefully specified assumptions), the basic biometrical modeling strategy is to estimate the magnitude of  $a^2$ ,  $c^2$ , and  $e^2$  within the context of a particular model. For gentle introductions to Behavior Genetic research, we recommend Plomin (1990) and Carey (2003). For more in-depth ACE model-fitting strategies, we recommend Neale & Cardon (1992). //This paragraph may get moved to the yet-to-be-written introduction that precedes the Terminology section.

The **NLS Investigator** (<http://www.nlsinfo.org/investigator/>) is the best way to obtain the NLSY79 and NLSY97 datasets. See our vignette dedicated to the NLS Investigator by typing `vignette("NlsInvestigator")` or by visiting <http://cran.r-project.org/web/packages/NlsyLinks/>.

Before starting the real examples, first verify that the **NlsyLinks** package is installed correctly. If not, refer to [Appendix B](#).

```
> any(.packages(all.available=TRUE) == "NlsyLinks") #Should evaluate to TRUE.
[1] TRUE

> require(NlsyLinks) #Load the package into the current session.
> ?NlsyLinks #Open the package's documentation manual.
```

## 2 Example: DF analysis with a Simple Outcome for Gen2 Subjects, Using a Package Variable

The vignette’s first example uses a simple statistical model and all available Gen2 subjects. The **createPairLinksDoubleEntered** function will create a data frame where each represents one pair of siblings, respective of order (*i.e.*, there is a row for Subjects 201 and 202, and a second row for Subjects 202 and 201). This function examines the subjects’ IDs and determines who is related to whom (and by how much). By default, each row it produces has at least six values/columns: (i) ID for the older member of

the kinship pair: `Subject1Tag`, (ii) ID for the younger member: `Subject2Tag`, (iii) ID for their extended family: `ExtendedID`, (iv) their estimated coefficient of genetic relatedness: `R`, (*v and beyond*) outcome values for the older member; (*vi and beyond*) outcome values for the younger member.

A DeFries-Fulker (**DF**) Analysis uses linear regression to estimate the  $a^2$ ,  $c^2$ , and  $e^2$  of a univariate biometric system. The interpretations of the DF analysis can be found in Rodgers & Kohler (2005) and Rodgers, Rowe, & Li (1999). The steps are:

1. Use the [NLS Investigator](#) to select and download a Gen2 dataset.
2. Open R and create a new script (see [Appendix A](#)) and load the `NlsyLinks` package. If you haven't done so, first install the `NlsyLinks` package (see [Appendix B](#)).
3. Within the R script, load the linking dataset. Then select only Gen2 subjects. The 'Pair' version of the linking dataset is essentially a sparse matrix.
4. Load and assign the `ExtraOutcomes79` dataset.
5. Specify the outcome variable name and filter out all subjects who have a negative value in this variable. The NLSY typically uses negative values to indicate different types of missingness (see 'Further Information' below).
6. Create a double-entered file by calling the `CreatePairLinksDoubleEntered` function. At minimum, pass the (i) outcome dataset, the (ii) linking dataset, and the (iii) name(s) of the outcome variable(s).
7. Use `DeFriesFulkerMethod3` function (i.e., general linear model) to estimate the coefficients of the DF model.

```
> ### R Code for Example DF analysis with a simple outcome and Gen2 subjects
> #Step 2: Load the package containing the linking routines.
> require(NlsyLinks)
> #
> #Step 3: Load the LINKING dataset and filter for the Gen2 subjects
> data(Links79Pair)
> dsLinking <- subset(Links79Pair, RelationshipPath=="Gen2Siblings")
> summary(dsLinking) #Notice there are 11,075 records.
```

ExtendedID	Subject1Tag	Subject2Tag	R
Min. : 2	Min. : 201	Min. : 202	Min. : 0.2500
1st Qu.: 3159	1st Qu.: 315901	1st Qu.: 315902	1st Qu.: 0.2500
Median : 6116	Median : 611901	Median : 611902	Median : 0.5000
Mean : 5937	Mean : 593989	Mean : 593991	Mean : 0.4192
3rd Qu.: 8511	3rd Qu.: 851103	3rd Qu.: 851104	3rd Qu.: 0.5000
Max. : 12673	Max. : 1267301	Max. : 1267302	Max. : 1.0000
			NA's : 563.0000

```
RelationshipPath
Gen2Siblings:11075
```

```
> #
> #Step 4: Load the OUTCOMES dataset and the linking dataset, and then examine the summary.
> data(ExtraOutcomes79)
> dsOutcomes <- ExtraOutcomes79 #'ds' stands for 'DataSet'
> summary(dsOutcomes)
```

SubjectTag	SubjectID	Generation	MathStandardized
Min. : 201	Min. : 201	Min. : 2	Min. : 65.00
1st Qu.: 310302	1st Qu.: 310302	1st Qu.: 2	1st Qu.: 91.00
Median : 604607	Median : 604607	Median : 2	Median : 100.00
Mean : 601313	Mean : 601313	Mean : 2	Mean : 99.97
3rd Qu.: 876203	3rd Qu.: 876203	3rd Qu.: 2	3rd Qu.: 110.00
Max. : 1267501	Max. : 1267501	Max. : 2	Max. : 135.00
			NA's : 2353.00

```
Weight WeightForAge19To25 WeightStandardized
```

```

Min.    : 75.0    Min.    : 75.0    Min.    :-2.768e+00
1st Qu.: 130.0   1st Qu.: 140.0   1st Qu.: -7.059e-01
Median : 155.0   Median : 165.0   Median : -2.207e-01
Mean    : 161.9   Mean    : 172.1   Mean    : -4.252e-11
3rd Qu.: 186.0   3rd Qu.: 195.0   3rd Qu.: 4.739e-01
Max.    : 485.0   Max.    : 485.0   Max.    : 7.178e+00
NA's    :3475.0   NA's    :6380.0   NA's    : 3.475e+03
WeightStandardizedForAge19To25
Min.    :-2.772e+00
1st Qu.: -6.879e-01
Median : -1.969e-01
Mean    : -4.086e-11
3rd Qu.: 4.905e-01
Max.    : 7.489e+00
NA's    : 6.380e+03

> #
> #Step 5: This step isn't necessary for this example, because Kelly Meredith already
> # groomed the values. But if not if the negative values
> # (which represent NLSY missing or skip patterns) still exist, then:
> dsOutcomes$MathStandardized[dsOutcomes$MathStandardized < 0] <- NA
> #
> #Step 6: Create the double entered dataset.
> dsDouble <- CreatePairLinksDoubleEntered(
  outcomeDataset=dsOutcomes,
  linksPairDataset=dsLinking,
  outcomeNames=c('MathStandardized')
)
> summary(dsDouble) #Notice there are 22,150=(2*11,075) records.

  Subject1Tag    Subject2Tag    ExtendedID      R
Min.   :    201    Min.   :    201    Min.   :     2    Min.   :  0.2500
1st Qu.: 315752    1st Qu.: 315752    1st Qu.: 3158    1st Qu.:  0.2500
Median : 611901    Median : 611901    Median : 6116    Median :  0.5000
Mean    : 593990    Mean    : 593990    Mean    : 5937    Mean    :  0.4192
3rd Qu.: 851104    3rd Qu.: 851104    3rd Qu.: 8511    3rd Qu.:  0.5000
Max.    :1267302    Max.    :1267302    Max.    :12673    Max.    :  1.0000
                                     NA's    :1126.0000

  RelationshipPath MathStandardized_1 MathStandardized_2
Gen2Siblings:22150    Min.   :  65.00    Min.   :  65.00
                   1st Qu.:  89.00    1st Qu.:  89.00
                   Median :  98.00    Median :  98.00
                   Mean    :  98.29    Mean    :  98.29
                   3rd Qu.: 108.00    3rd Qu.: 108.00
                   Max.    : 135.00    Max.    : 135.00
                   NA's    :3791.00    NA's    :3791.00

> #
> #Step 7: Estimate the ACE components with a DF Analysis
> ace <- DeFriesFulkerMethod3(
  outcomeForSubject1=dsDouble$MathStandardized_1,
  outcomeForSubject2=dsDouble$MathStandardized_2,
  relatedness=dsDouble$R)
> ace

[1] "Results of ACE estimation: [show]"
      ASquared      CSquared      ESquared      CaseCount
8.595078e-01 3.879863e-02 1.016935e-01 1.658800e+04

```

*Further Information:* If the different reasons of missingness are important, further work is necessary. For instance, some analyses that use item Y19940000 might need to distinguish a response of “Don’t Know”

(which is coded as -2) from “Missing” (which is coded as -7). For this vignette example, we’ll assume it’s safe to clump the responses together.

### 3 Example: DF analysis with a univariate outcome from a Gen2 Extract

The vignette’s second example differs from the previous example in two ways. First, the outcome variables are read from a CSV ([comma separated values](#) file) that was downloaded from the [NLS Investigator](#). Second, the DF analysis is called through the function `AceUnivariate`; this function is a wrapper around some simple ACE methods, and will help us smoothly transition to more techniques later in the vignette.

The steps are:

1. Use the [NLS Investigator](#) to select and download a Gen2 dataset. Select the variables ‘length of gestation of child in weeks’ (C03280.00), ‘weight of child at birth in ounces’ (C03286.00), and ‘length of child at birth’ (C03288.00), and then download the \*.zip file to your local computer.
2. Open R and create a new script (see [Appendix A](#)) and load the `NlsyLinks` package.
3. Within the R script, load the linking dataset. Then select only Gen2 subjects.
4. Read the CSV into R as a `data.frame` using `ReadCsvNlsy79Gen2`.
5. Verify the desired outcome column exists, and rename it something meaningful to your project. It is important that the `data.frame` is reassigned (*i.e.*, `ds <- RenameNlsyColumn(...)`). In this example, we rename column C0328800 to `BirthWeightInOunces`.
6. Filter out all subjects who have a negative `BirthWeightInOunces` value. See the ‘Further Information’ note in the previous example.
7. Create a double-entered file by calling the `CreatePairLinksDoubleEntered` function. At minimum, pass the (i) outcome dataset, the (ii) linking dataset, and the (iii) name(s) of the outcome variable(s).
8. Call the `AceUnivariate` function to estimate the coefficients.

```
> ### R Code for Example of a DF analysis with a simple outcome and Gen2 subjects
> #Step 2: Load the package containing the linking routines.
> require(NlsyLinks)
> #
> #Step 3: Load the linking dataset and filter for the Gen2 subjects
> data(Links79Pair)
> dsLinking <- subset(Links79Pair, RelationshipPath=="Gen2Siblings")
> #
> #Step 4: Load the outcomes dataset and the linking dataset, and then examine the summary.
> # Your path might be: filePathOutcomes <- 'C:/BGRsearch/NlsExtracts/Gen2Birth.csv'
> filePathOutcomes <- file.path(path.package("NlsyLinks"), "extdata", "Gen2Birth.csv")
> dsOutcomes <- ReadCsvNlsy79Gen2(filePathOutcomes)
> summary(dsOutcomes)
```

SubjectTag	SubjectID	ExtendedID	Generation
Min. : 201	Min. : 201	Min. : 2	Min. : 2
1st Qu.: 310302	1st Qu.: 310302	1st Qu.: 3103	1st Qu.: 2
Median : 604607	Median : 604607	Median : 6045	Median : 2
Mean : 601313	Mean : 601313	Mean : 6008	Mean : 2
3rd Qu.: 876203	3rd Qu.: 876203	3rd Qu.: 8757	3rd Qu.: 2
Max. : 1267501	Max. : 1267501	Max. : 12675	Max. : 2
SubjectTagOfMother	C0005300	C0005400	C0005700
Min. : 200	Min. : 1.000	Min. : -3.000	Min. : -3
1st Qu.: 310300	1st Qu.: 2.000	1st Qu.: 1.000	1st Qu.: 1981

```

Median : 604600      Median :3.000      Median : 1.000      Median :1985
Mean   : 601311      Mean   :2.338      Mean   : 1.489      Mean   :1986
3rd Qu.: 876200      3rd Qu.:3.000      3rd Qu.: 2.000      3rd Qu.:1990
Max.   :1267500      Max.   :3.000      Max.   : 2.000      Max.   :2008
C0328000      C0328600      C0328800
Min.   : -7.00      Min.   : -7.0      Min.   : -7.00
1st Qu.:37.00      1st Qu.: 99.0      1st Qu.:18.00
Median :39.00      Median :115.0      Median :20.00
Mean   :33.51      Mean   :103.9      Mean   :16.51
3rd Qu.:39.00      3rd Qu.:128.0      3rd Qu.:21.00
Max.   :51.00      Max.   :768.0      Max.   :48.00

> #
> #Step 5: Verify and rename an existing column.
> VerifyColumnExists(dsOutcomes, "C0328800") #Should return '11' in this example.

[1] 11

> dsOutcomes <- RenameNlsyColumn(dsOutcomes, "C0328800", "BirthWeightInOunces")
> #
> #Step 6: For this item, a negative value indicates the parent refused, didn't know,
> #   invalidly skipped, or was missing for some other reason.
> #   For our present purposes, we'll treat these responses equivalently.
> dsOutcomes$BirthWeightInOunces[dsOutcomes$BirthWeightInOunces < 0] <- NA
> #
> #Step 7: Create the double entered dataset.
> dsDouble <- CreatePairLinksDoubleEntered(
+   outcomeDataset=dsOutcomes,
+   linksPairDataset=dsLinking,
+   outcomeNames=c('BirthWeightInOunces')
+ )
> #
> #Step 8: Estimate the ACE components with a DF Analysis
> ace <- AceUnivariate(
+   outcomeForSubject1=dsDouble$BirthWeightInOunces_1,
+   outcomeForSubject2=dsDouble$BirthWeightInOunces_2,
+   relatedness=dsDouble$R,
+   method="DeFriesFulkerMethod3"
+ )
> ace

[1] "Results of ACE estimation: [show]"
      ASquared      CSquared      ESquared      CaseCount
4.822847e-01 4.685057e-02 4.708647e-01 1.482200e+04

```

## 4 Example: Multiple group SEM of a Simple Outcome for Gen2 Subjects

The example differs from the first one by the statistical mechanism used to estimate the components. The first example uses *multiple regression* to estimate the influence of the shared genetic and environmental factors. This example uses *structural equation modeling* (SEM) to estimate the same influences.

The `CreatePairLinksSingleEntered` function will create a data frame where each represents one unique pair of siblings, *irrespective of order*. Other than producing half the number of rows, this function is identical to `CreatePairLinksDoubleEntered`.

The steps are:

(Steps 1-5 proceed as identically to the first example.)

6. Create a *single*-entered file by calling the `CreatePairLinksSingleEntered` function. At minimum, pass the (i) outcome dataset, the (ii) linking dataset, and the (iii) name(s) of the outcome variable(s).
7. Declare the names of the manifest variables corresponding to the two members in each pair. Assuming you've followed the preceding steps and the variable is called 'ZZZ', the variable for the first members will be 'ZZZ\_1', while the second members will be 'ZZZ\_2'.
8. Create a GroupSummary `data.frame`, which identifies the R groups that should be considered by the model. Save these values of R in a new vector. Inspect the output to see if the groups show unexpected or fishy differences.
9. Create a clean `data.frame` to pass to the SEM function. This variable contains only the necessary rows and columns.
10. Estimate the SEM with the `lavaan` package. The function returns an `S4` object, which shows the basic ACE information.
11. Inspect details of the SEM, beyond the ACE components. In this example, we look at the fit stats and the parameter estimates. The `lavaan` package has additional methods that may be useful for your purposes.

```
> ### R Code for Example lavaan estimation analysis with a simple outcome and Gen2 subjects
> #Steps 1-5 are explained in the vignette's first example:
> require(NlasyLinks)
> data(Links79Pair)
> dsLinking <- subset(Links79Pair, RelationshipPath=="Gen2Siblings")
> data(ExtraOutcomes79)
> dsOutcomes <- ExtraOutcomes79
> dsOutcomes$MathStandardized[dsOutcomes$MathStandardized < 0] <- NA
> #
> #Step 6: Create the single entered dataset.
> dsSingle <- CreatePairLinksSingleEntered(outcomeDataset=dsOutcomes,
  linksPairDataset=dsLinking, outcomeNames=c('MathStandardized'))
> #
> #Step 7: Declare the names for the two manifest variables.
> m1Name <- "MathStandardized_1" #Stands for Manifest1
> m2Name <- "MathStandardized_2" #Stands for Manifest2
> #
> #Step 8: Summarize the R groups and determine which groups can be estimated.
> dsGroupSummary <- RGroupSummary(dsSingle, m1Name, m2Name)
> rLevels <- dsGroupSummary[dsGroupSummary$Included, "R"]
> dsGroupSummary
```

	R	Included	PairCount	M1Variance	M2Variance	M1M2Covariance	Correlation
1	0.250	TRUE	2719	169.1291	207.0233	40.66048	0.2172970
2	0.375	TRUE	43	187.7209	220.9302	28.66334	0.1407482
3	0.500	TRUE	5508	230.9663	233.3492	107.59822	0.4634764
4	0.750	FALSE	2	220.5000	18.0000	63.00000	1.0000000
5	1.000	TRUE	22	319.1948	343.1169	277.58874	0.8387893

```

  Determinant PosDefinite
1    33360.38         TRUE
2    40651.64         TRUE
3    42318.42         TRUE
4         0.00        FALSE
5    32465.62         TRUE
> #
> #Step 9: Create a cleaned dataset
> dsClean <- CleanSemAceDataset(dsDirty=dsSingle, dsGroupSummary=dsGroupSummary,
  m1Name=m1Name, m2Name=m2Name)
> #
```

```

> #Step 10: Run the model
> ace <- AceLavaanGroup(dsClean, rLevels, m1Name, m2Name)
> ace

[1] "Results of ACE estimation: [show]"
      ASquared      CSquared      ESquared      CaseCount
0.6701032    0.1167060    0.2131907 8292.0000000

> #
> #Step 11: Inspect the output
> require(lavaan) #Load the package to access methods of the lavaan class.
> GetDetails(ace)

lavaan (0.4-13) converged normally after 61 iterations
  Number of observations per group
  1                                2719
  2                                43
  3                               5508
  4                                22

  Estimator                                ML
  Minimum Function Chi-square             435.491
  Degrees of freedom                      16
  P-value                                0.000

Chi-square for each group:

  1                                290.182
  2                                22.151
  3                               118.815
  4                                4.343

> #Examine fit stats like Chi-Squared, RMSEA, CFI, etc.
> fitMeasures(GetDetails(ace)) #'fitMeasures' is defined in the lavaan package.

      chisq      df      pvalue  baseline.chisq
      435.491    16.000      0.000      1491.127
  baseline.df  baseline.pvalue      cfi      tli
      4.000      0.000      0.718      0.929
      logl unrestricted.logl      npar      aic
     -67585.491    -67367.746      4.000    135178.982
      bic      ntotal      bic2      rmsea
    135207.074    8292.000    135194.363    0.112
  rmsea.ci.lower  rmsea.ci.upper  rmsea.pvalue      srmr
      0.103      0.122      0.000      0.126

>
> #Examine low-level details like each group's individual parameter estimates
> #
> #      and standard errors. Uncomment the following line to view the entire
> #      output (which is roughly four PDF pages).
> #summary(GetDetails(ace))

```

## A Appendix: Creating and Saving R Scripts

TODO: write something here.



## B Appendix: Installing the NlsyLinks Package

TODO: write something here.

## C Appendix: References

Carey, Gregory (2002). *Human Genetics for the Social Sciences*. Sage.

Plomin, Robert (1990). *Nature and nurture: an introduction to human behavioral genetics*. Brooks/Cole Publishing Company.

Rodgers, Joseph Lee, & Kohler, Hans-Peter (2005). Reformulating and simplifying the DF analysis model. *Behavior Genetics*, 35 (2), 211-217.

Rodgers, Joseph Lee, Rowe, David C., & Li, Chengchang (1994). Beyond nature versus nurture: DF analysis of nonshared influences on problem behaviors. *Developmental Psychology*, 30 (3), 374-384.

Neale, Michael C., & Cardon, Lou R. (1992). *Methodology for genetic studies of twins and families*. Norwell, MA: Kluwer Academic Publishers. (Also see Neale & Maes: <http://www.vipbg.vcu.edu/OpenMxFall09/NMbook05.pdf>).

## D Notes

This package's development was largely supported by the NIH Grant 1R01HD65865, "NLSY Kinship Links: Reliable and Valid Sibling Identification" (PI: Joe Rodgers; Vignette Construction by Will Beasley)