Composite indicators of cognitive function using IRT cocalibration in an integrative data analysis

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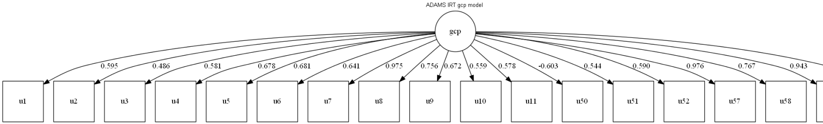
Our goal

- To provide a playing field for all FHL groups to explore differences in cognition by race or study, and help explain and quantify those differences using a common metric.
- To reach that goal, we used factor analysis with categorical variables (graded response IRT) to co-calibrate cognitive data across FH2012 datasets into composite scores...
  - for general cognitive performance (GCP), memory, executive function, and language
  - in ADAMS HRS, WHICAP, SENAS, DUKE ADRC, and NCODE datasets.
- Scoring procedure is naive to measurement differences attributable to dataset or race.

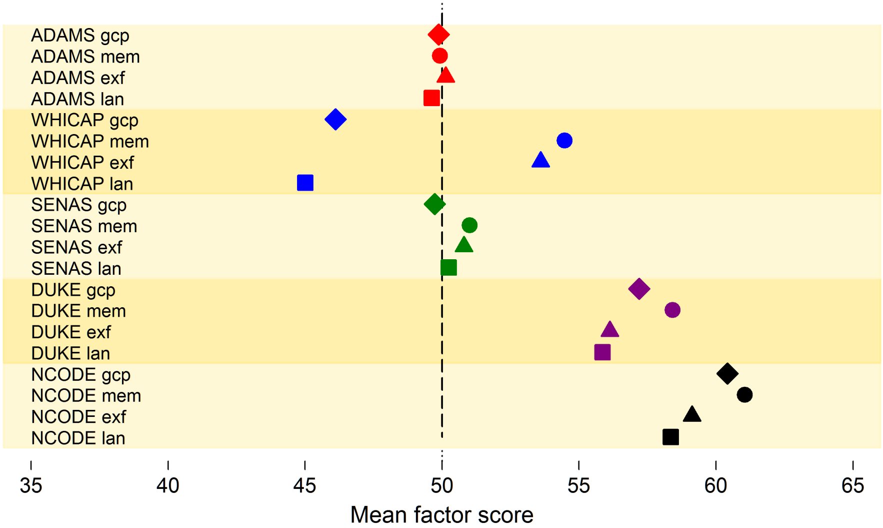
Method

- **Step 1.** Identify 47 common cognitive tests across all datasets
  - Discretize continuous variables into 9-10 categories
- **Step 2.** Parameter estimation using ADAMS HRS
  - Use complex survey weights to generalize estimates to the US population of adults over age 70
  - Save out parameters for later (factor loadings and item thresholds)

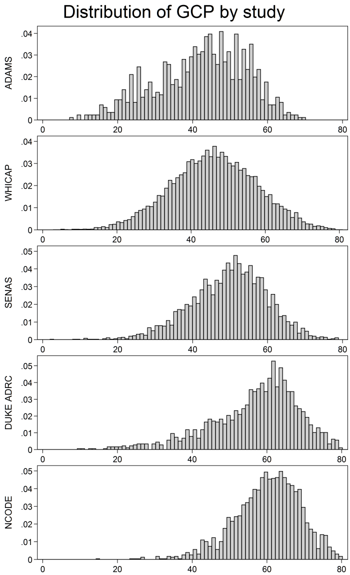


- **Step 3.** Mplus as a scoring machine
  - Pool all data
  - Cluster on ID to account for multiple records/person
  - Fix parameters of items in common with ADAMS to be the same as Step 2
- **Step 4.** Simulation: How bad did we do across datasets?
- **Step 5.** Test empirically in some models

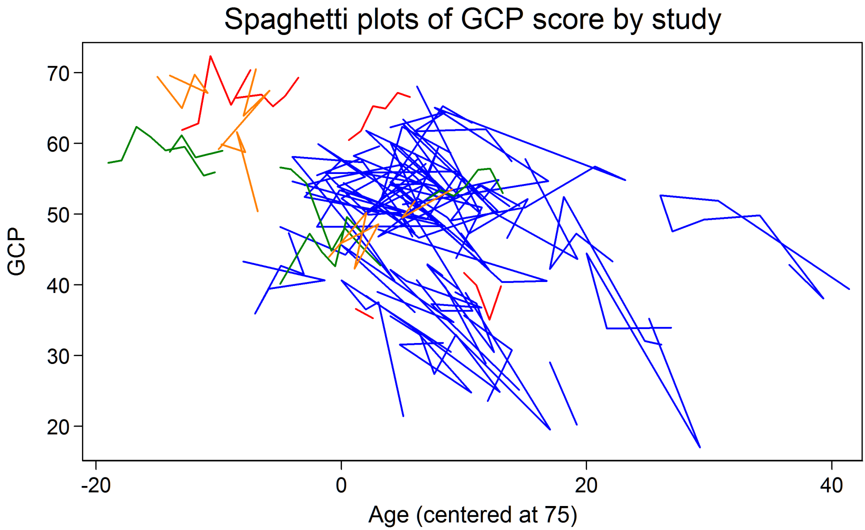
Mean factor scores by study



The scoring model clustered on participant ID to handle multiple visits/person.

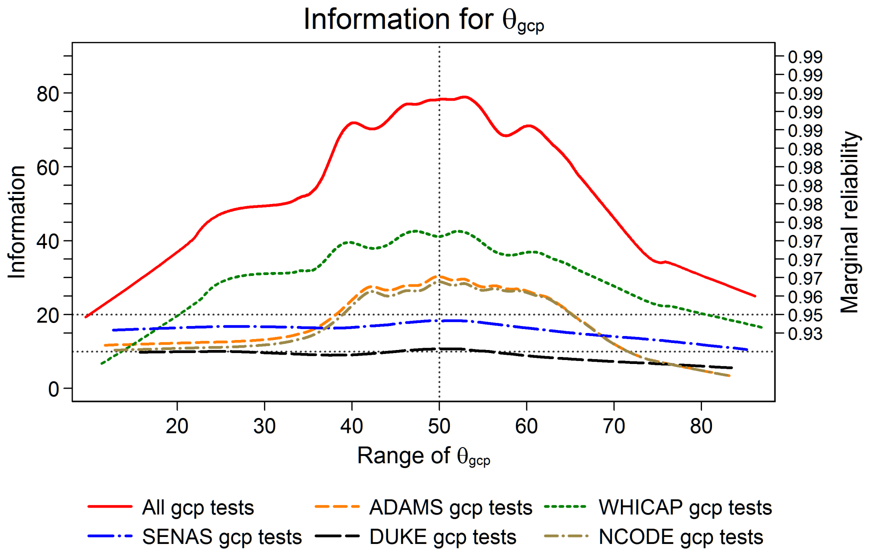

Distribution of GCP by study
ADAMS
WHICAP
SENAS
DUKE ADRC
NCODE
0
.01
.02
.03
.04
.05
0
20
40
60
80

Data are always messier in real life

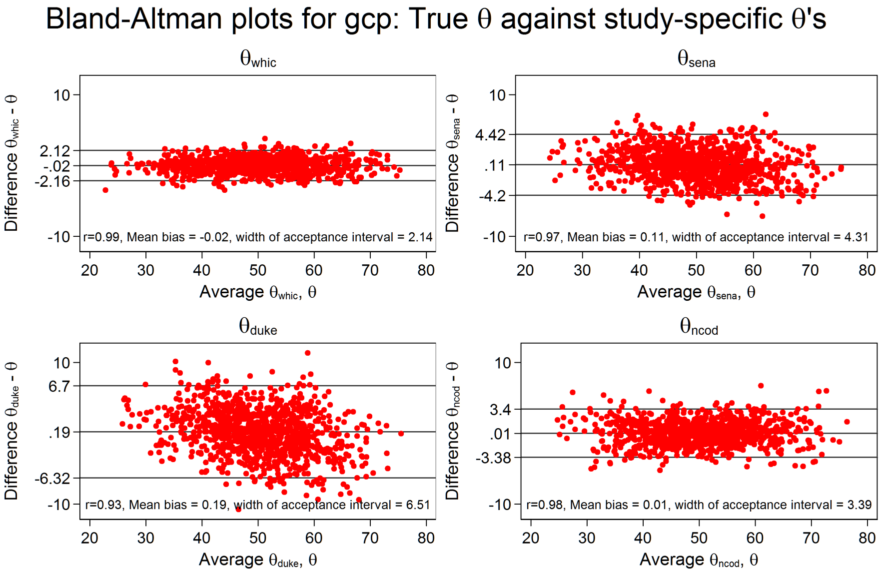


blue: WHICAP. green: SENAS. red: DUKE. orange: NCODE

How bad did we do?



How bad did we do?



Test the composite in models

- We ran 40 multiple-group multilevel (MLM) models of the kind your groups might estimate.
- MLM divides the variability in outcome into between-person and within-person levels.
    - Composite outcome: gcp, mem, exf, lan
    - Timescale: Time from BL, or Age from 75
    - Single and multiple group models
        - Single group
        - Dataset
        - Diagnostic classification
        - Race (white, black, hispanic)
        - Sex
- Model fits were mostly excellent

Limitations and issues

- Items contributing to each domain are up for debate
- We assume measurement invariance across study, race, and other factors
- Should be formally tested
- *(hint!)*

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Harmonization of cognitive data across Friday Harbor 2012 datasets

Description. In an integrative data analysis exercise, we used factor analysis (graded response IRT) to co-calibrate cognitive data across FH2012 datasets into composite scores for general cognitive performance (GCP), memory, executive function, and language in ADAMS HRS, WHICAP, SENAS, DUKE ADRC, and NCODE datasets. A total of 47 cognitive variables across all the datasets contributed to the factor analysis. ADAMS HRS contains sampling weights to account for the complex survey design that when used generalize to the US population of adults over age 70. To anchor our GCP, memory, executive function, and language scores to these US population norms, in the integrative data analysis we scaled factor loadings and item thresholds for items with counterparts in ADAMS (anchor items) to equal those from an ADAMS-only model. The remainder of this report documents results of the output, including use of the composites in various multi-level models of the type FH workgroups might try, as well as a simulation study.

Steps.

Parameter estimation.

We estimated factor analyses using categorical versions of tests in ADAMS' baseline data. We saved out item loadings and thresholds for the next step. This enabled us to use ADAMS weights here.

The scoring-machine models.

We pooled the datasets together. The CFA are graded-response IRT models using categorical versions of every cognitive variable, with study ID as a clustering variable. Our discretization procedure for continuous variables produced equally spaced intervals, which preserves floor and ceiling effects if present (needs to be shown theoretically, but this is what is happening). We used an MLR estimator, which assumes missing data are missing at random conditional on covariates.

The CFA models cluster on ID, so standard errors and model estimates are corrected for multiple observations per person. The scoring model does not take into account who came from which study, nor does it account in great detail for participants' repeated observations (other than by specifying a clustering variable). **The goal in this project is not to adjust for or explain study or race differences, but to provide a playing field where such differences can be explained and quantified on a common metric.**

We should expect factor scores to vary by study: although people's membership in a study should not affect their cognitive performance, each study had different recruitment methods and has a different mix of diagnostic profiles that should perform differently. The model we use as a scoring machine may not need to take group differences into account. Analytic models, the kind that will be done at FHL, are the place for that.

Table 1. Descriptive statistics for cognitive variables in each dataset (N=25155)

	data										
	ADAMS		WHICAP		SENAS		DUKE ADRC		NCODE		
Total [n (%)]	856	(100)	13756	(100)	3506	(100)	1871	(100)	5166	(100)	
memx gcpx adwrd Word recall sum of 3 trials [M (SD)]	4.7	(2.1)	.	(.)	5.7	(1.7)	7.1	(1.9)	7.4	(1.4)	F=697.1; P $<$ 0.001
lanx gcpx anbnttot BOSTON NAMING TEST TOTAL CORRECT [M (SD)]	8.0	(1.9)	8.6	(1.4)	8.8	(1.4)	.	(.)	9.6	(0.7)	F=390.4; P $<$ 0.001
exfx gcpx ansdmtot SYMBOL DIGIT MODALITY - TOTAL SCORE [M (SD)]	4.5	(1.8)	.	(.)	.	(.)	.	(.)	6.7	(1.6)	F=734.1; P $<$ 0.001
memx gcpx anwm1a WECHSLER LOGICAL MEM I STORY A TOTAL [M (SD)]	4.2	(2.4)	.	(.)	5.0	(2.4)	6.6	(2.5)	7.4	(1.8)	F=564.4; P $<$ 0.001
memx gcpx anwm1tot WECHSLER LOGICAL MEM I TOTAL FOR STORIES [M (SD)]	4.3	(2.3)	.	(.)	.	(.)	.	(.)	7.3	(1.8)	F=1209.2; P $<$ 0.00
memx gcpx anwm2a WECHSLER LOGICAL MEM II STORY A TOTAL [M (SD)]	3.2	(2.2)	.	(.)	4.1	(2.6)	5.9	(2.8)	6.6	(2.3)	F=519.3; P $<$ 0.001
memx gcpx anwm2tot WECHSLER LOG MEM II TOTAL FOR STORIES [M (SD)]	3.3	(2.2)	.	(.)	.	(.)	.	(.)	6.6	(2.2)	F=1204.4; P $<$ 0.00
memx gcpx bvrt BENTON VIS RETEN - TOTAL CORRECT SCORE [M (SD)]	4.2	(2.3)	.	(.)	.	(.)	6.8	(2.1)	7.2	(1.9)	F=519.2; P $<$ 0.001
lanx gcpx cat [M (SD)]	4.2	(1.5)	4.2	(1.4)	5.1	(1.5)	5.7	(1.8)	5.8	(1.5)	F=973.7; P $<$ 0.001
lanx gcpx cowat CNTR ORAL WORD ASSOC - TOTAL SCORE [M (SD)]	4.2	(1.7)	4.4	(1.8)	5.3	(1.9)	6.0	(1.7)	6.7	(1.4)	F=1038.3; P $<$ 0.00
exfx gcpx dsb [M (SD)]	3.8	(1.7)	.	(.)	4.4	(1.6)	5.4	(1.8)	5.9	(1.7)	F=440.7; P $<$ 0.001
exfx gcpx dsf [M (SD)]	5.1	(1.4)	.	(.)	4.9	(1.2)	5.5	(1.3)	5.7	(1.4)	F=140.1; P $<$ 0.001
gcpx mmse MMSE TOTAL CALCULATED SCORE [M (SD)]	7.3	(2.2)	.	(.)	8.5	(1.5)	9.2	(1.4)	9.5	(0.7)	F=596.7; P $<$ 0.001
memx gcpx praxdel DELAYED CONSTRUCTIONAL PRAXIS COMPLETED [M (SD)]	1.4	(1.3)	.	(.)	.	(.)	3.4	(1.8)	4.6	(1.5)	F=776.3; P $<$ 0.001
memx gcpx praxrecall CONSTRUCTIONAL PRAXIS TOTAL [M (SD)]	7.8	(1.4)	.	(.)	8.1	(1.1)	8.6	(0.9)	8.7	(0.6)	F=246.7; P $<$ 0.001
memx gcpx praxrecog CONSTR PRAXIS RECOG TOTAL [M (SD)]	3.9	(1.1)	.	(.)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
exfx gcpx traila [M (SD)]	7.8	(2.1)	.	(.)	.	(.)	.	(.)	9.3	(1.1)	F=578.4; P $<$ 0.001
exfx gcpx trailb [M (SD)]	5.5	(2.7)	.	(.)	5.7	(2.8)	7.1	(2.5)	7.4	(2.3)	F=171.4; P $<$ 0.001
memx gcpx mem01 total recall [M (SD)]	.	(.)	5.4	(1.6)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
memx gcpx mem02 lt recall [M (SD)]	.	(.)	3.7	(1.8)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
memx gcpx mem03 delayed recall [M (SD)]	.	(.)	4.5	(2.1)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.

memx gcpx mem04 delayed recognition [M (SD)]	.	(.)	8.6	(1.8)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
memx gcpx mem11 benton recognition [M (SD)]	.	(.)	6.5	(1.9)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
gcpx orient orientation [M (SD)]	.	(.)	9.0	(1.6)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
exfx gcpx abs01 similarities raw [M (SD)]	.	(.)	4.0	(2.3)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
exfx gcpx abs06 identities similarities total [M (SD)]	.	(.)	7.8	(1.2)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
lanx gcpx lan12 repetition [M (SD)]	.	(.)	8.4	(1.1)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
lanx gcpx lan13 comprehension [M (SD)]	.	(.)	5.7	(1.4)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
gcpx con01 rosen [M (SD)]	.	(.)	3.3	(1.1)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
gcpx con03 benton matching [M (SD)]	.	(.)	8.1	(1.9)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
exfx gcpx att01 shape time [M (SD)]	.	(.)	4.1	(2.1)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
exfx gcpx att12 tmx time [M (SD)]	.	(.)	4.1	(2.0)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
exfx gcpx color1t color trails test 1 time [M (SD)]	.	(.)	7.4	(1.6)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
exfx gcpx color2t color trails test 2 time [M (SD)]	.	(.)	6.6	(1.8)	.	(.)	.	(.)	.	(.)	F=0.0; P = 0.
lanx gcpx objnm Object Naming raw score [M (SD)]	.	(.)	.	(.)	5.6	(1.7)	.	(.)	.	(.)	F=0.0; P = 0.
gcpx ptrcg Pattern Recognition raw score [M (SD)]	.	(.)	.	(.)	6.0	(1.6)	.	(.)	.	(.)	F=0.0; P = 0.
gcpx sploc Spatial Localization raw score [M (SD)]	.	(.)	.	(.)	5.5	(1.8)	.	(.)	.	(.)	F=0.0; P = 0.
exfx gcpx lstsrt1 One List Sorting Total [M (SD)]	.	(.)	.	(.)	5.1	(1.6)	.	(.)	.	(.)	F=0.0; P = 0.
exfx gcpx lstsrt2 Two List Sorting Total [M (SD)]	.	(.)	.	(.)	2.2	(1.0)	.	(.)	.	(.)	F=0.0; P = 0.
lanx gcpx phontot Phonemic Fluency sum score (F L) [M (SD)]	.	(.)	.	(.)	4.0	(1.5)	.	(.)	.	(.)	F=0.0; P = 0.
lanx gcpx fruita [M (SD)]	.	(.)	.	(.)	4.2	(1.3)	.	(.)	.	(.)	F=0.0; P = 0.
memx gcpx avlt [M (SD)]	.	(.)	.	(.)	5.2	(1.6)	.	(.)	.	(.)	F=0.0; P = 0.
lanx gcpx vega [M (SD)]	.	(.)	.	(.)	3.9	(1.3)	4.4	(1.4)	.	(.)	F=130.3; P < 0.001
exfx gcpx traila150 [M (SD)]	.	(.)	.	(.)	7.2	(2.1)	8.0	(1.8)	.	(.)	F=140.7; P < 0.001
exfx gcpx rbans [M (SD)]	.	(.)	.	(.)	4.3	(1.4)	5.0	(1.5)	.	(.)	F=175.8; P < 0.001

lanx gcpx bnttotal [M (SD)]	.	(.)	.	(.)	7.6	(1.7)	8.3	(1.8)	.	(.)	F=134.3; $P < 0.001$
lanx gcpx bnt60 [M (SD)]	.	(.)	.	(.)	7.4	(1.8)	.	(.)	.	(.)	F=0.0; P = 0.

Cognitive variables used in the integrative data analysis.

Variable	No. studies	ADAMS	WHICAP	SENAS	DUKE	NCODE
adwrd	4	1		1	1	1
anbnttot	4	1	1	1		1
ansdmtot	2	1				1
anwm1a	4	1		1	1	1
anwm1tot	2	1				1
anwm2a	4	1		1	1	1
anwm2tot	2	1				1
bvrt	3	1			1	1
cat	5	1	1	1	1	1
cowat	5	1	1	1	1	1
dsb	4	1		1	1	1
dsf	4	1		1	1	1
mmse	4	1		1	1	1
praxdel	3	1			1	1
praxrecall	4	1		1	1	1
praxrecog	1	1				
traila	2	1				1
trailb	4	1		1	1	1
mem01	1		1			
mem02	1		1			
mem03	1		1			
mem04	1		1			
mem11	1		1			
orient	1		1			
abs01	1		1			
abs06	1		1			
lan12	1		1			
lan13	1		1			
con01	1		1			
con03	1		1			
att01	1		1			
att12	1		1			
color1t	1		1			
color2t	1		1			
objnm	1			1		
ptrcg	1			1		
sploc	1			1		
lstsrt1	1			1		
lstsrt2	1			1		
phontot	1			1		
fruita	1			1		
avlt	1			1		

vega	2			1	1	
traila150	2			1	1	
rbans	2			1	1	
bnttotal	2			1	1	
bnt60	1			1		
TOTAL	47	18	19	24	16	17

Distributions of discretized cognitive variables.

```
. findname u*
u8   u72  u7   u10  u58  u52  u44  u47  u39  u60  u70  u55  u68  u74  u65  u14
u5   u57  u9   u3   u50  u11  u45  u48  u40  u61  u71  u69  u75  u66  u63  u64
u6   u73  u4   u2   u51  u1   u46  u49  u59  u62  u54  u67  u76  u15  u13

. foreach x in `r(varlist)´ {
  2.    display in red "************ `x´ ************"
  3.    table `x´ data, row col
  4. }
************ u8 ************
```

memx gcpx adwrd Word recall, sum of 3 trials	data: ADAMS	SENAS	DUKE ADRC	NCODE	Total
1	89	15	12		116
2	51	55	30	4	140
3	114	189	53	26	382
4	126	300	69	63	558
5	141	415	129	150	835
6	144	442	163	297	1,046
7	100	384	223	501	1,208
8	80	275	410	719	1,484
9	11	79	365	496	951
Total	856	2,154	1,454	2,256	6,720

```
************ u5 ************
```

lanx gcpx anbnttot BOSTON NAMING TEST TOTAL CORRECT	data: ADAMS	WHICAP	SENAS	NCODE	Total
1	7	15	1		23
2	6	23	4		33
3	13	60	11	1	85
4	18	64	11	2	95
5	57	299	41	9	406
6	71	759	66	12	908
7	50	675	60	19	804
8	143	2,233	248	93	2,717
9	278	3,958	601	584	5,421
10	158	3,533	526	1,572	5,789
Total	801	11,619	1,569	2,292	16,281

```
************ u6 ************
```

exfx gcpx ansdmtot SYMBOL DIGIT MODALITY - TOTAL SCORE	data: ADAMS	NCODE	Total
1	15	4	19
2	59	26	85

3	99	64	163
4	102	129	231
5	97	245	342
6	74	474	548
7	55	514	569
8	27	529	556
9	3	230	233
Total	531	2,215	2,746

************ u72 ************

memx gcpx anwm1a WECHSLER LOGICAL MEM I STORY A TOTAL	ADAMS	SENAS	data DUKE ADRC	NCODE	Total
1	125	149	87	17	378
2	100	154	65	27	346
3	104	208	83	49	444
4	90	238	97	68	493
5	101	244	132	151	628
6	86	237	165	216	704
7	65	206	195	311	777
8	43	175	277	369	864
9	35	137	462	770	1,404
Total	749	1,748	1,563	1,978	6,038

************ u57 ************

memx gcpx anwm1tot WECHSLER LOGICAL MEM I TOTAL FOR STORIES	ADAMS	data NCODE	Total
1	92	11	103
2	95	20	115
3	113	55	168
4	116	85	201
5	95	161	256
6	92	226	318
7	62	309	371
8	52	383	435
9	31	658	689
Total	748	1,908	2,656

************ u73 ************

memx gcpx anwm2a WECHSLER LOGICAL MEM II STORY A TOTAL	ADAMS	SENAS	data DUKE ADRC	NCODE	Total
1	246	460	222	82	1,010
2	101	168	84	71	424
3	99	163	81	100	443

4	61	197	88	128	474
5	82	207	139	199	627
6	69	194	174	264	701
7	37	167	197	313	714
8	20	111	245	338	714
9	13	96	395	560	1,064
Total	728	1,763	1,625	2,055	6,171

************ u7 ************

memx gcpx anwm2tot WECHSLER LOG MEM II TOTAL FOR STORIES	data ADAMS	NCODE	Total
1	210	56	266
2	112	71	183
3	108	90	198
4	83	140	223
5	74	197	271
6	72	277	349
7	32	322	354
8	26	334	360
9	11	522	533
Total	728	2,009	2,737

************ u9 ************

memx gcpx bvrt BENTON VIS RETEN - TOTAL CORRECT SCORE	data ADAMS	DUKE ADRC	NCODE	Total
1	81	23	9	113
2	97	43	50	190
3	99	60	57	216
4	90	107	119	316
5	81	174	176	431
6	75	221	280	576
7	51	278	421	750
8	48	318	502	868
9	20	264	395	679
10	2	129	201	332
Total	644	1,617	2,210	4,471

************ u4 ************

lanx gcpx cat	data ADAMS	WHICAP	SENAS	DUKE ADRC	NCODE	Total
1	13	109	8	12	2	144
2	94	1,063	90	54	25	1,326
3	188	2,832	364	146	111	3,641
4	161	2,889	583	203	256	4,092
5	178	2,986	978	345	585	5,072
6	105	1,371	801	437	613	3,327
7	32	363	297	249	361	1,302
8	15	159	133	221	251	779

9	4	46	54	91	74	269
Total	790	11,818	3,308	1,758	2,278	19,952

************ u10 ************

lanx gcpx cowat CNTR ORAL WORD ASSOC - TOTAL SCORE	ADAMS	WHICAP	data SENAS	DUKE ADRC	NCODE	Total
1	24	248		8	1	281
2	104	1,350	5	44	3	1,506
3	130	2,174	5	71	29	2,409
4	137	2,400	8	159	99	2,803
5	130	2,246	10	340	321	3,047
6	80	1,304	11	374	508	2,277
7	45	833	10	347	510	1,745
8	17	434	2	238	458	1,149
9	6	224	3	105	246	584
Total	673	11,213	54	1,686	2,175	15,801

************ u3 ************

exfx gcpx dsb	ADAMS	SENAS	data DUKE ADRC	NCODE	Total
1	79	16	16	2	113
2	98	177	77	33	385
3	97	235	80	43	455
4	236	663	479	441	1,819
5	115	312	349	414	1,190
6	55	159	226	371	811
7	40	165	318	514	1,037
8	5	26	100	149	280
9	4	26	117	176	323
10	1			28	29
Total	730	1,779	1,762	2,171	6,442

************ u2 ************

exfx gcpx dsf	ADAMS	SENAS	data DUKE ADRC	NCODE	Total
1	4		1		5
2	14	19	12		45
3	50	156	67	77	350
4	165	523	295	422	1,405
5	264	652	638	620	2,174
6	101	196	272	272	841
7	109	207	389	536	1,241
8	31	26	95	222	374
9	4			33	37
Total	742	1,779	1,769	2,182	6,472

************ u58 ************

gcpx mmse MMSE TOTAL CALCULATE	data

D SCORE	ADAMS	SENAS	DUKE ADRC	NCODE	Total
1	8	3	3		14
2	28	7	11	1	47
3	21	8	6		35
4	65	33	24	1	123
5	74	79	28	3	184
6	77	102	23	10	212
7	98	181	66	23	368
8	177	480	152	150	959
9	169	812	371	719	2,071
10	139	632	1,091	1,385	3,247
Total	856	2,337	1,775	2,292	7,260

************ u50 ************

memx gcpx praxdel DELAYED CONSTRUCTIONAL PRAXIS COMPLETED	ADAMS	data DUKE ADRC	NCODE	Total
1	732	182	36	950
2	53	49	23	125
3	2	57	41	100
4	9	133	135	277
5		109	119	228
6	60	94	218	372
Total	856	624	572	2,052

************ u51 ************

memx gcpx praxrecall CONSTRUCTIONAL PRAXIS TOTAL	ADAMS	SENAS	data DUKE ADRC	NCODE	Total
1	2		3		5
2	2	2	2		6
3	17	11	11	1	40
4	14	25	10	2	51
5	35	39	6	9	89
6	27	63	16	7	113
7	61	433	37	21	552
8	320	576	375	664	1,935
9	259	976	1,247	1,577	4,059
Total	737	2,125	1,707	2,281	6,850

************ u52 ************

memx gcpx praxrecog CONSTR PRAXIS RECOG TOTAL	data ADAMS	Total
1	27	27
2	67	67

3	137	137
4	219	219
5	275	275
Total	725	725

************ u11 ************

exfx gcpx traila	data ADAMS	NCODE	Total
1	20	15	35
2	10	3	13
3	12	2	14
4	6	4	10
5	33	13	46
6	42	21	63
7	68	29	97
8	112	129	241
9	243	859	1,102
10	84	1,206	1,290
Total	630	2,281	2,911

************ u1 ************

exfx gcpx trailb	ADAMS	SENAS	data DUKE ADRC	NCODE	Total
1	54	290	148	143	635
2	15	53	20	25	113
3	25	62	34	42	163
4	29	83	57	46	215
5	37	123	73	79	312
6	41	173	102	142	458
7	58	281	210	301	850
8	74	326	420	617	1,437
9	32	238	540	697	1,507
10	5	17	87	122	231
Total	370	1,646	1,691	2,214	5,921

************ u44 ************

memx gcpx mem01 total recall	data WHICAP	Total
1	56	56
2	336	336
3	1,089	1,089
4	1,987	1,987
5	2,958	2,958
6	2,894	2,894
7	1,948	1,948
8	1,041	1,041
9	200	200
Total	12,509	12,509

************ u45 ************

memx gcpx mem02 lt recall	data WHICAP	Total

1	1,046	1,046
2	2,543	2,543
3	2,656	2,656
4	2,411	2,411
5	1,833	1,833
6	1,058	1,058
7	641	641
8	253	253
9	67	67
Total	12,508	12,508

************ u46 ************

memx gcpx mem03 delayed recall	data WHICAP	Total
1	1,252	1,252
2	814	814
3	2,663	2,663
4	1,671	1,671
5	1,686	1,686
6	2,460	2,460
7	725	725
8	532	532
9	616	616
Total	12,419	12,419

************ u47 ************

memx gcpx mem04 delayed recogniti on	data WHICAP	Total
1	46	46
2	37	37
3	209	209
4	215	215
5	332	332
6	903	903
7	713	713
8	974	974
9	3,895	3,895
10	5,030	5,030
Total	12,354	12,354

************ u48 ************

memx gcpx mem11 benton recogniti on	data WHICAP	Total
1	71	71
2	263	263
3	530	530
4	864	864
5	1,137	1,137
6	2,939	2,939
7	1,815	1,815

8	1,774	1,774
9	2,262	2,262
Total	11,655	11,655

************ u49 ************

gcpx orient orientati on	data WHICAP	Total
1	47	47
2	72	72
3	86	86
4	112	112
5	175	175
6	632	632
7	545	545
8	1,143	1,143
9	2,924	2,924
10	6,409	6,409
Total	12,145	12,145

************ u39 ************

exfx gcpx abs01 similarit ies raw	data WHICAP	Total
1	1,861	1,861
2	2,282	2,282
3	1,741	1,741
4	1,291	1,291
5	1,076	1,076
6	1,452	1,452
7	1,085	1,085
8	867	867
9	290	290
Total	11,945	11,945

************ u40 ************

exfx gcpx abs06 identitie s/similar ities total	data WHICAP	Total
1	10	10
2	24	24
3	65	65
4	81	81
5	301	301
6	837	837
7	2,391	2,391
8	3,961	3,961
9	3,760	3,760
Total	11,430	11,430

************ u59 ************

lanx gcpx lan12 repetition	data WHICAP	Total
1	12	12
2	12	12
3	38	38
4	85	85
5	203	203
6	439	439
7	1,014	1,014
8	2,316	2,316
9	7,849	7,849
Total	11,968	11,968

************ u60 ************

lanx gcpx lan13 comprehension	data WHICAP	Total
1	119	119
2	261	261
3	650	650
4	1,230	1,230
5	1,973	1,973
6	2,718	2,718
7	4,941	4,941
Total	11,892	11,892

************ u61 ************

gcpx con01 rosen	data WHICAP	Total
1	846	846
2	1,703	1,703
3	3,180	3,180
4	4,504	4,504
5	1,033	1,033
6	145	145
Total	11,411	11,411

************ u62 ************

gcpx con03 benton matching	data WHICAP	Total
1	23	23
2	79	79
3	189	189
4	342	342
5	458	458
6	1,592	1,592
7	1,168	1,168
8	1,643	1,643
9	2,575	2,575
10	3,642	3,642

Total	11,711	11,711

************ u70 ************

exfx gcpx att01 shape time	data WHICAP	Total
1	138	138
2	183	183
3	168	168
4	178	178
5	194	194
6	139	139
7	102	102
8	50	50
9	12	12
Total	1,164	1,164

************ u71 ************

exfx gcpx att12 tmx time	data WHICAP	Total
1	81	81
2	139	139
3	134	134
4	153	153
5	122	122
6	113	113
7	70	70
8	35	35
9	12	12
Total	859	859

************ u54 ************

exfx gcpx color1t color trails test 1 time	data WHICAP	Total
1	46	46
2	27	27
3	22	22
4	317	317
5	258	258
6	469	469
7	1,227	1,227
8	1,807	1,807
9	1,352	1,352
10	20	20
Total	5,545	5,545

************ u55 ************

exfx gcpx color2t color trails		

test 2 time	data WHICAP	Total
1	136	136
2	23	23
3	90	90
4	65	65
5	1,049	1,049
6	769	769
7	1,016	1,016
8	1,121	1,121
9	565	565
10	44	44
Total	4,878	4,878

************ u69 ************

lanx gcpx objnm Object Naming raw score	data SENAS	Total
1	19	19
2	100	100
3	263	263
4	509	509
5	640	640
6	799	799
7	535	535
8	326	326
9	126	126
Total	3,317	3,317

************ u67 ************

gcpx ptrcg Pattern Recogniti on raw score	data SENAS	Total
1	15	15
2	44	44
3	92	92
4	173	173
5	255	255
6	557	557
7	547	547
8	267	267
9	40	40
Total	1,990	1,990

************ u68 ************

gcpx sploc Spatial Localizat ion raw score	data SENAS	Total
1	92	92

2	158	158
3	149	149
4	444	444
5	492	492
6	757	757
7	640	640
8	224	224
9	73	73
Total	3,029	3,029

************ u75 ************

exfx gcpx lstsrt1 One List Sorting Total	data SENAS	Total
1	36	36
2	181	181
3	207	207
4	634	634
5	1,047	1,047
6	468	468
7	540	540
8	80	80
9	56	56
Total	3,249	3,249

************ u76 ************

exfx gcpx lstsrt2 Two List Sorting Total	data SENAS	Total
1	865	865
2	1,230	1,230
3	608	608
4	305	305
5	41	41
6	11	11
7	5	5
Total	3,065	3,065

************ u74 ************

lanx gcpx phontot Phonemic Fluency sum score (F, L)	data SENAS	Total
1	118	118
2	467	467
3	712	712
4	955	955
5	622	622
6	345	345
7	126	126
8	37	37
9	15	15

Total	3,397	3,397

************ u66 ************

lanx gcpx fruita	data SENAS	Total
1	17	17
2	116	116
3	340	340
4	643	643
5	372	372
6	189	189
7	69	69
8	17	17
Total	1,763	1,763

************ u15 ************

memx gcpx avlt	data SENAS	Total
1	24	24
2	77	77
3	425	425
4	672	672
5	830	830
6	669	669
7	376	376
8	249	249
9	84	84
Total	3,406	3,406

************ u65 ************

lanx gcpx	data		
vega	SENAS	DUKE ADRC	Total
1	43	48	91
2	184	106	290
3	464	268	732
4	408	416	824
5	382	517	899
6	161	270	431
7	18	77	95
8	8	20	28
Total	1,668	1,722	3,390

************ u63 ************

exfx gcpx	data		
traila150	SENAS	DUKE ADRC	Total
1	99	51	150
2	21	11	32
3	27	12	39
4	43	31	74
5	73	36	109
6	133	66	199
7	297	138	435
8	578	453	1,031
9	501	855	1,356
10	21	85	106

Total	1,793	1,738	3,531

************ u13 ************

exfx gcpx rbans	data SENAS	DUKE ADRC	Total
1	50	20	70
2	153	63	216
3	293	146	439
4	484	297	781
5	474	398	872
6	215	314	529
7	78	180	258
8	26	42	68
Total	1,773	1,460	3,233

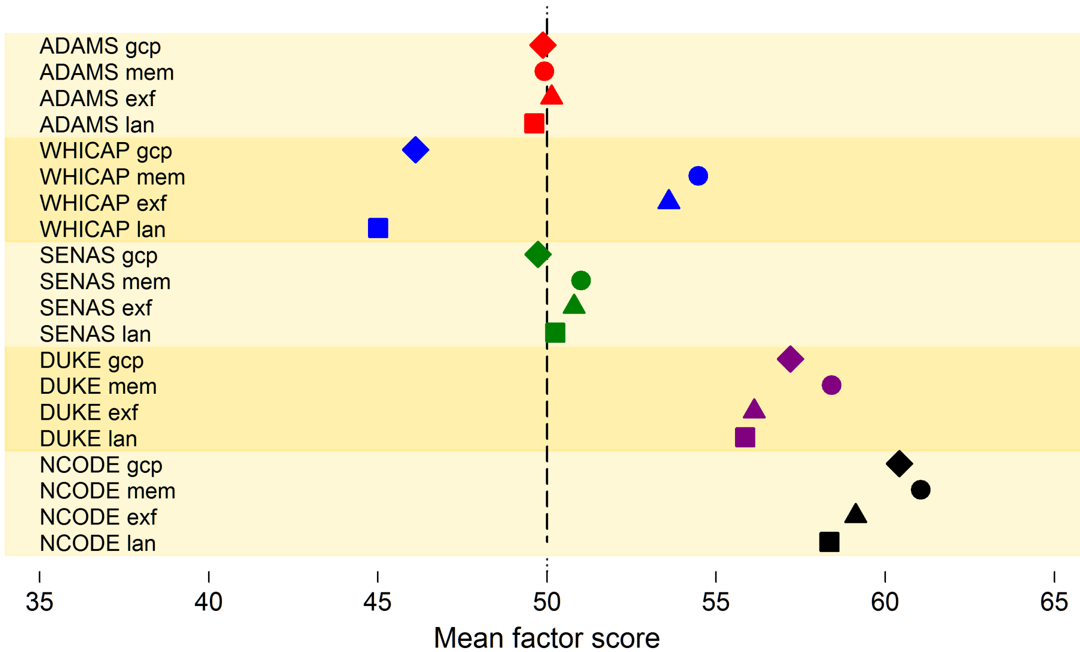
************ u14 ************

lanx gcpx bnttotal	data SENAS	DUKE ADRC	Total
1	4	16	20
2	16	30	46
3	32	27	59
4	69	33	102
5	117	35	152
6	133	50	183
7	345	160	505
8	401	277	678
9	501	759	1,260
10	149	333	482
Total	1,767	1,720	3,487

************ u64 ************

lanx gcpx bnt60	data SENAS	Total
1	11	11
2	35	35
3	41	41
4	56	56
5	124	124
6	181	181
7	300	300
8	463	463
9	659	659
Total	1,870	1,870

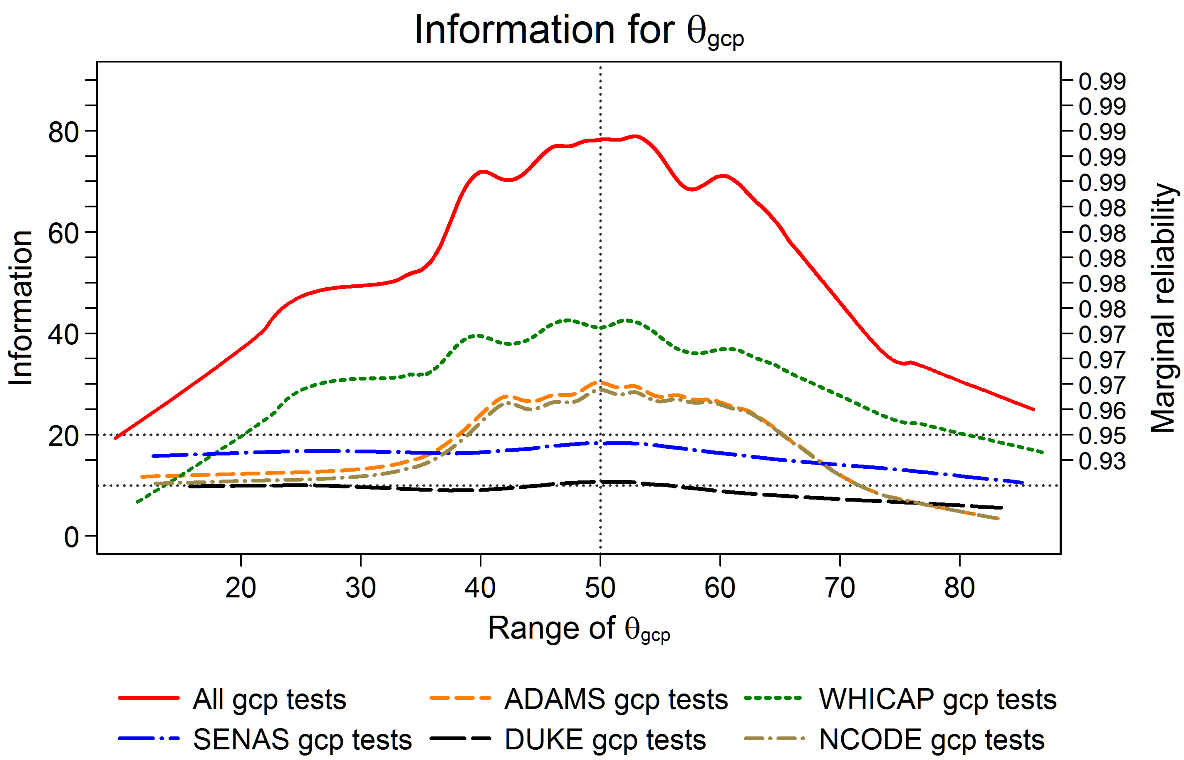
Mean factor scores by study



The scoring model clustered on participant ID to handle multiple visits/person.

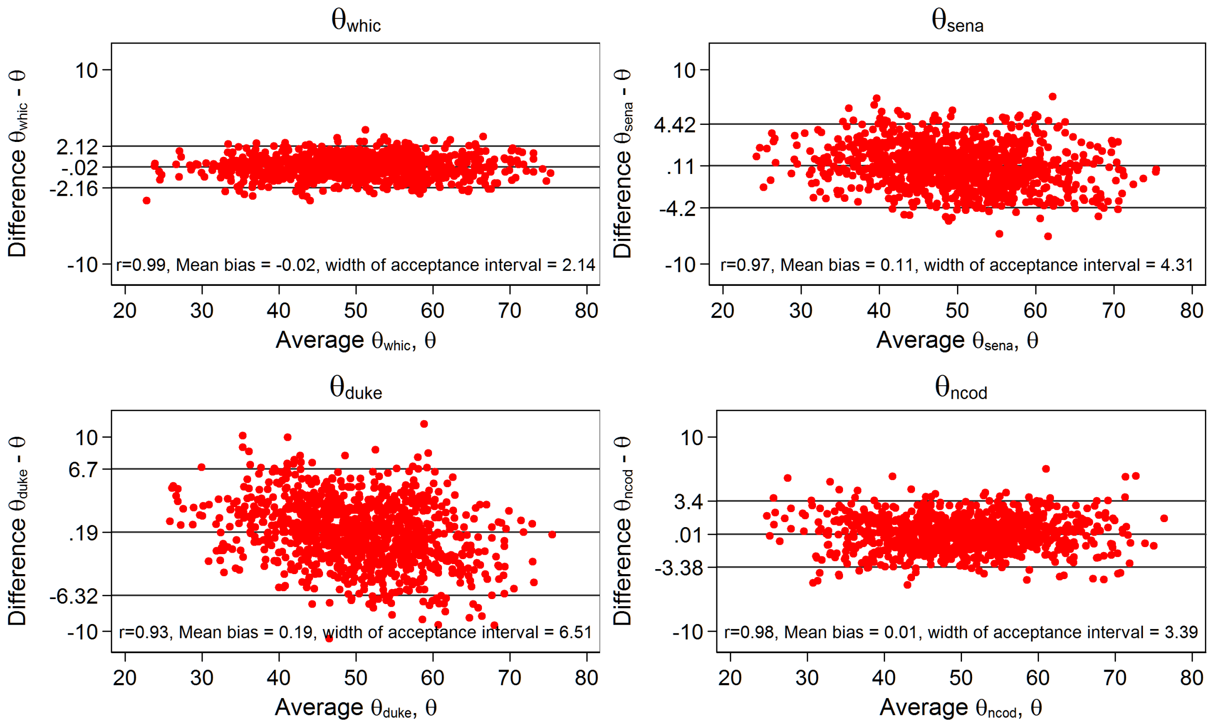
Simulation in R. It is reasonable to ask at least 2 questions at this point. First, how can we be certain we are measuring the same constructs across FH dataset if the measures differed? Second, how much information do the constructed scores provide over the range of cognitive function?

To address these things, we generated a random sample of 100,001 observations that included all cognitive test components used to construct each GCP across all FH2012 datasets, using parameters from the integrative data analysis. We estimated cognitive factor scores (GCP, memory, executive function, and language) in the simulated data using all 47 neuropsychological tests together as well as study-specific tests that came from each study.

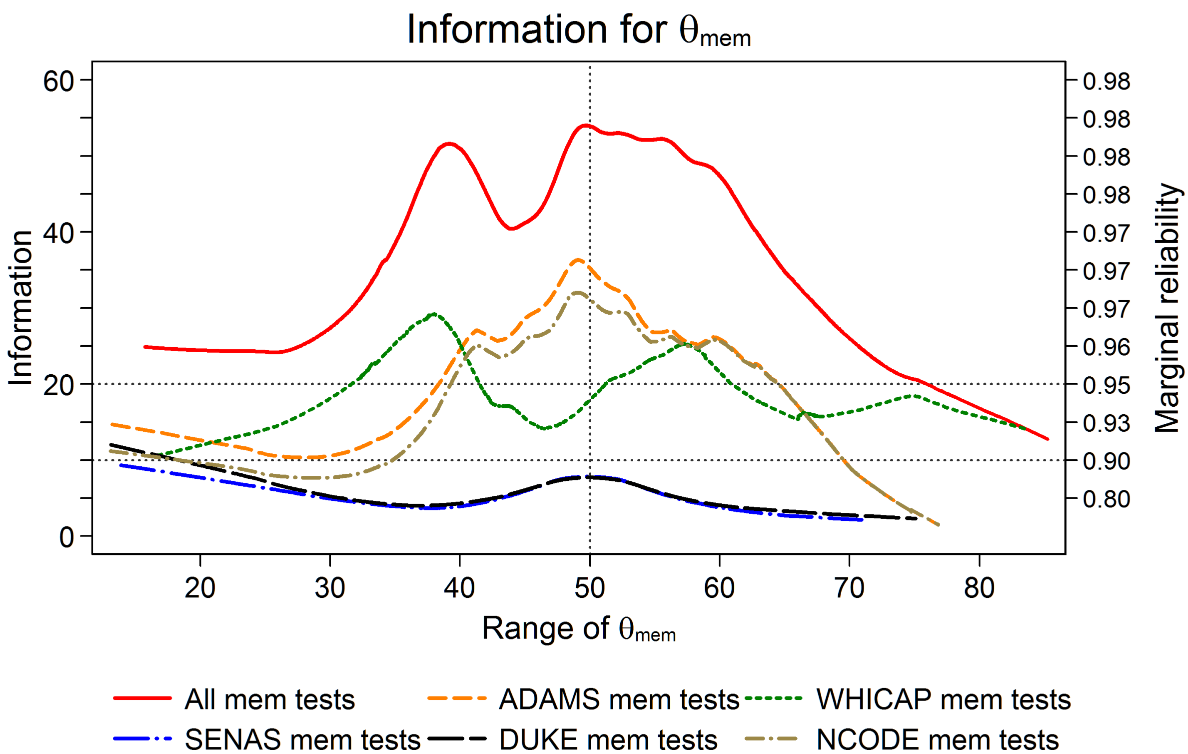


Information is a function of the standard error of measurement, $(1/SEM)^2$.
It is related to the test's reliability: Reliability = 1/(1-1/Information).

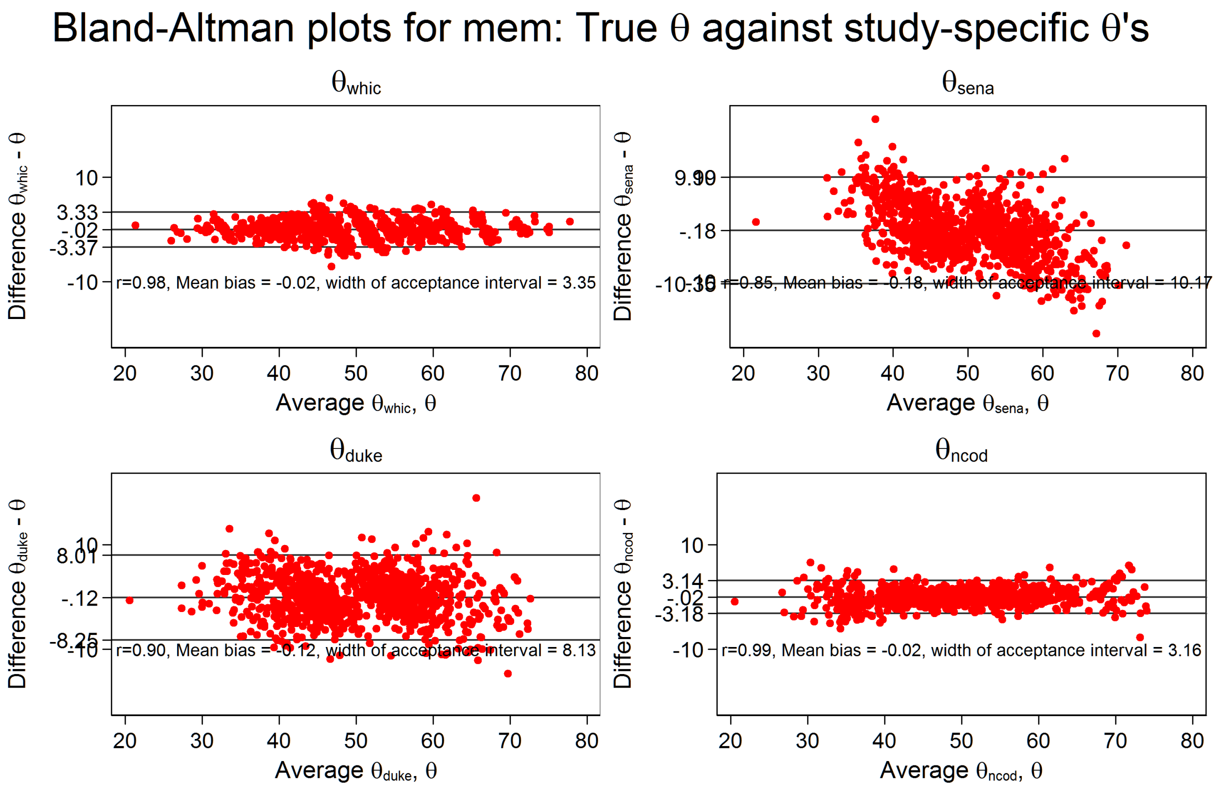
Bland-Altman plots for gcp: True θ against study-specific θ's



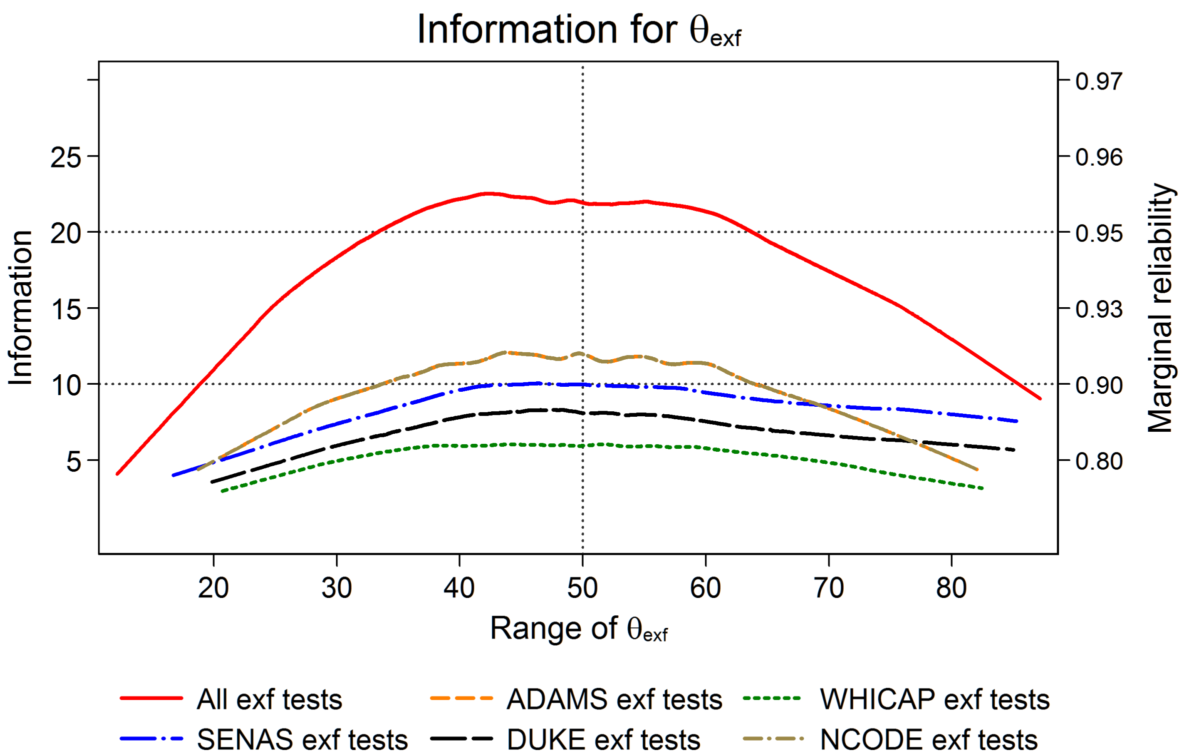
Bland-Altman graphs plot the difference in 2 scores on the Y axis against their mean on the X axis, and tell us about bias across the range of scores. The reference in all these plots is the true simulated theta score.



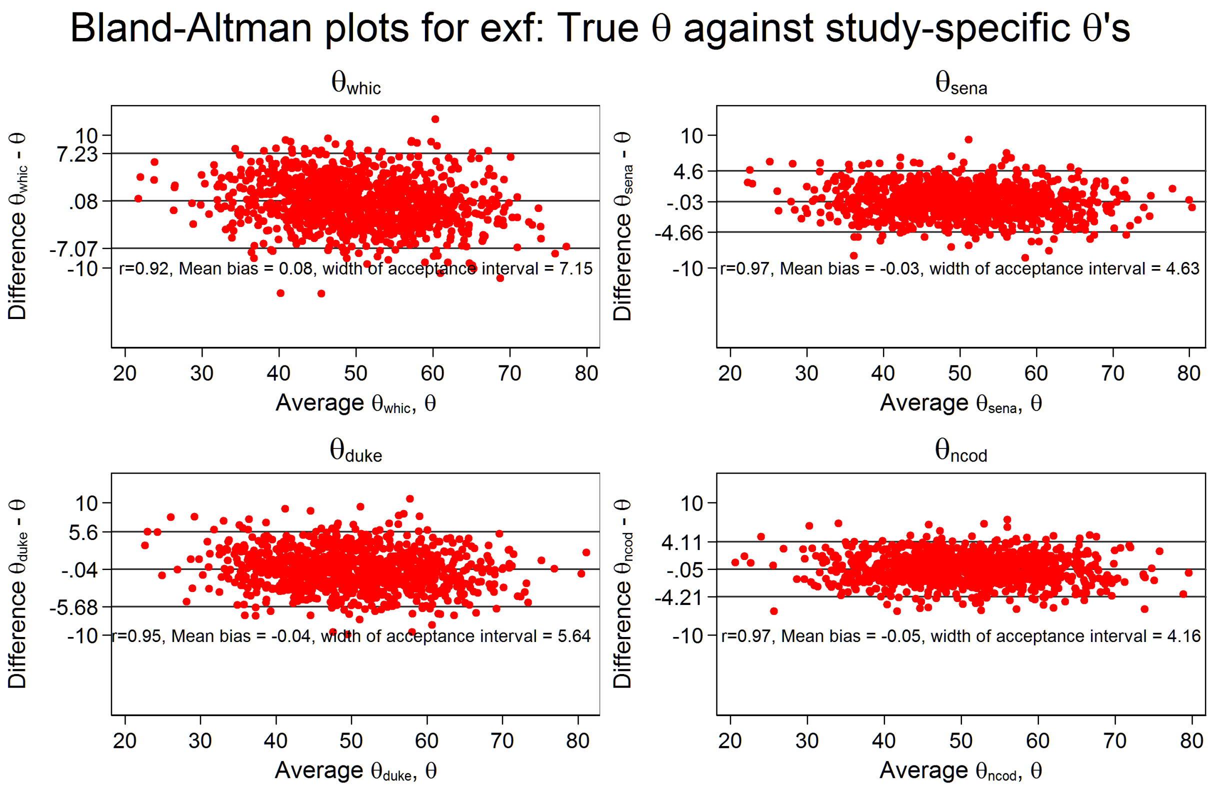
Information is a function of the standard error of measurement, $(1/SEM)^2$.
It is related to the test's reliability: Reliability = 1/(1-1/Information).



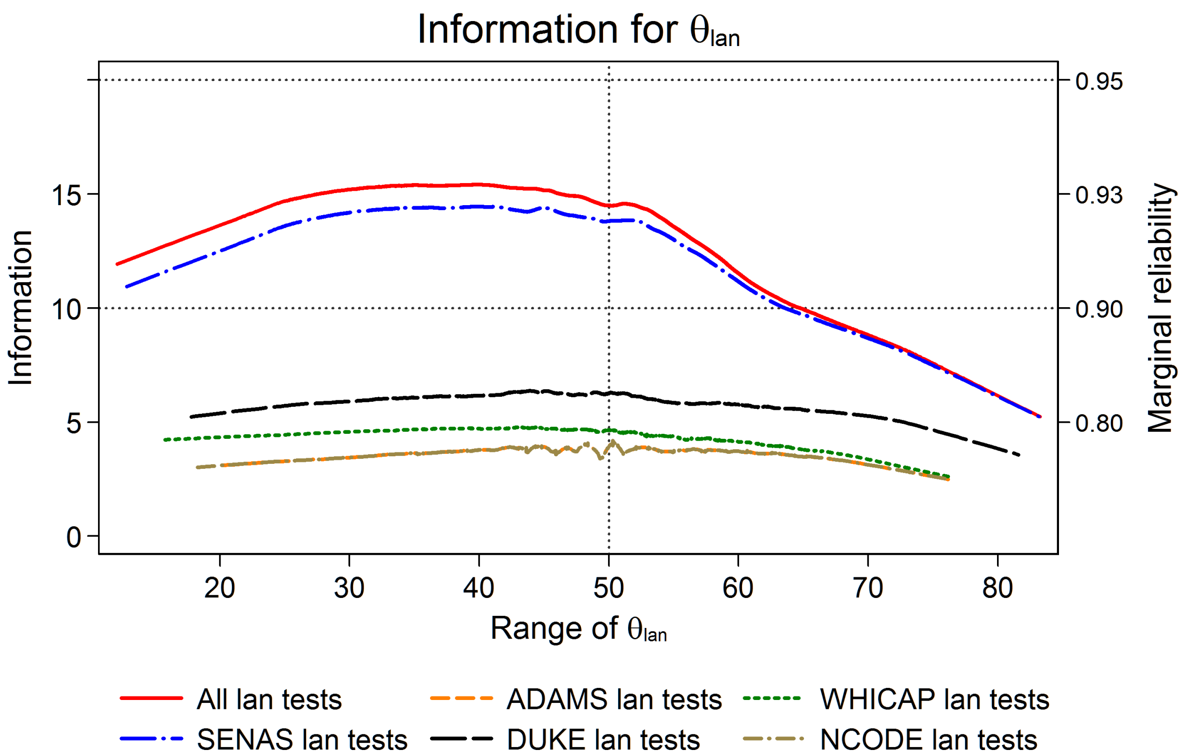
Bland-Altman graphs plot the difference in 2 scores on the Y axis against their mean on the X axis, and tell us about bias across the range of scores. The reference in all these plots is the true simulated theta score.



Information is a function of the standard error of measurement, $(1/SEM)^2$.
It is related to the test's reliability: Reliability = 1/(1-1/Information).

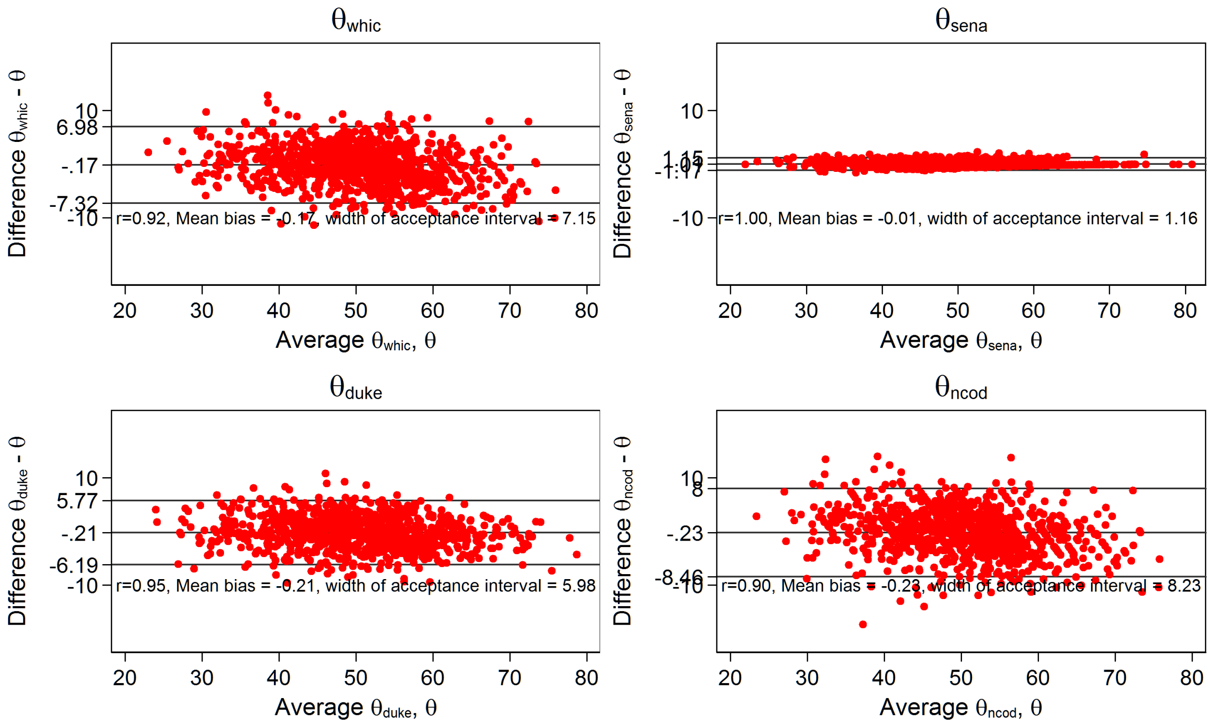


Bland-Altman graphs plot the difference in 2 scores on the Y axis against their mean on the X axis, and tell us about bias across the range of scores. The reference in all these plots is the true simulated theta score.



Information is a function of the standard error of measurement, $(1/SEM)^2$.
It is related to the test's reliability: Reliability = 1/(1-1/Information).

Bland-Altman plots for Ian: True θ against study-specific θ's



Bland-Altman graphs plot the difference in 2 scores on the Y axis against their mean on the X axis, and tell us about bias across the range of scores. The reference in all these plots is the true simulated theta score.

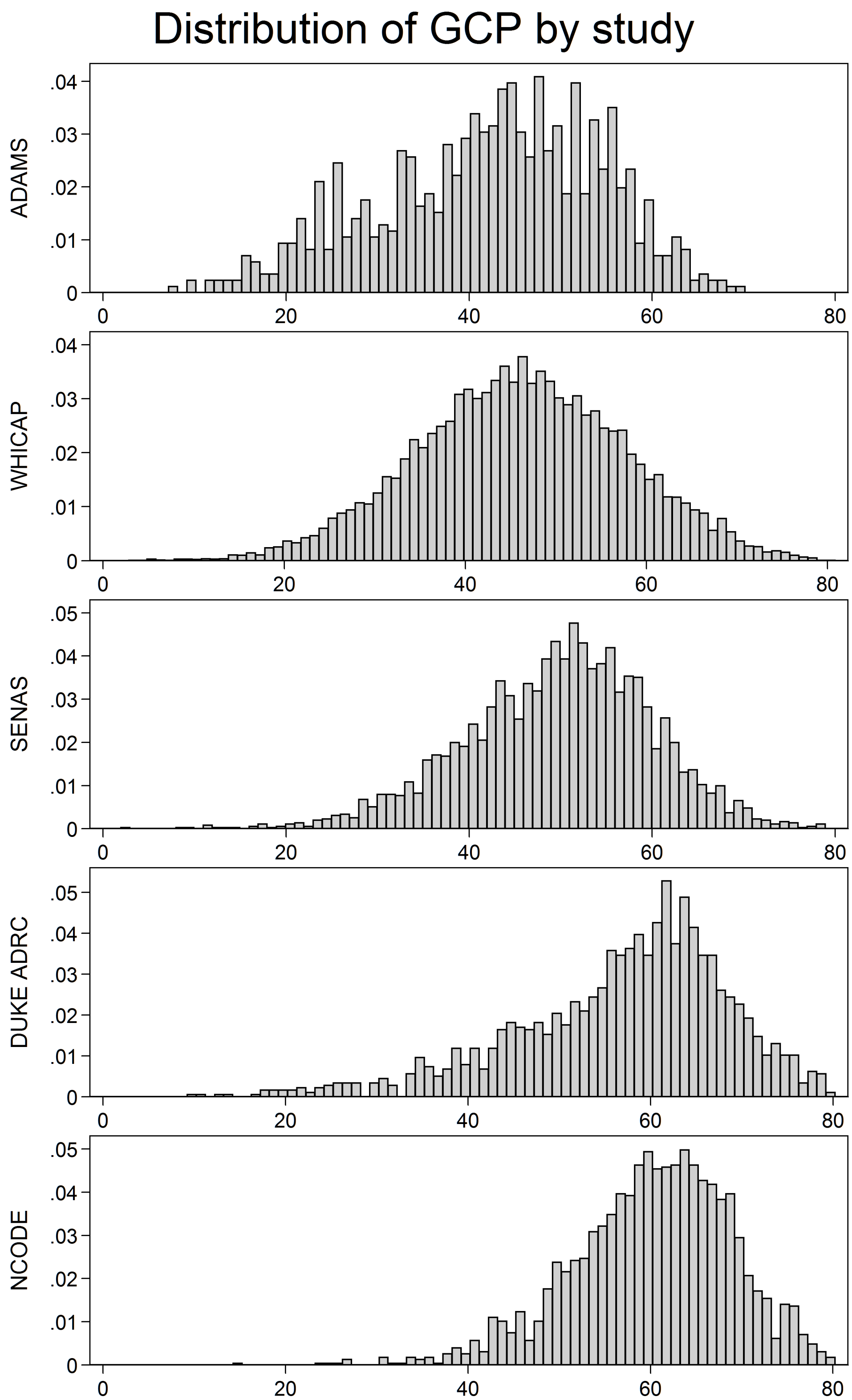
The next few pages provide descriptive and diagnostic plots of non-parametric and parametric aspects of the generated general cognitive composite (GCP), memory, executive function, and language factor scores.

We ran a series of multilevel models using the pooled dataset (excluding ADAMS) that assume quadratic growth to study diagnostic distributions and fit to the data. The timescale was either continuous time from the baseline visit, or age centered at 75 years. The multilevel model divides the variability in GCP into between-person and within-person levels and can tell us if our scores are useful for describing within-person change over time in addition to distinguishing between persons. Although the pseudo-R2 is decent (see following pages), there was a lot of residual variability. Residuals were calculated as differences between predicted and observed GCP scores. The quadratic term is negative (as expected: suggests decreasing cognition over time). Models shown here are quadratic with respect to time from baseline or age.

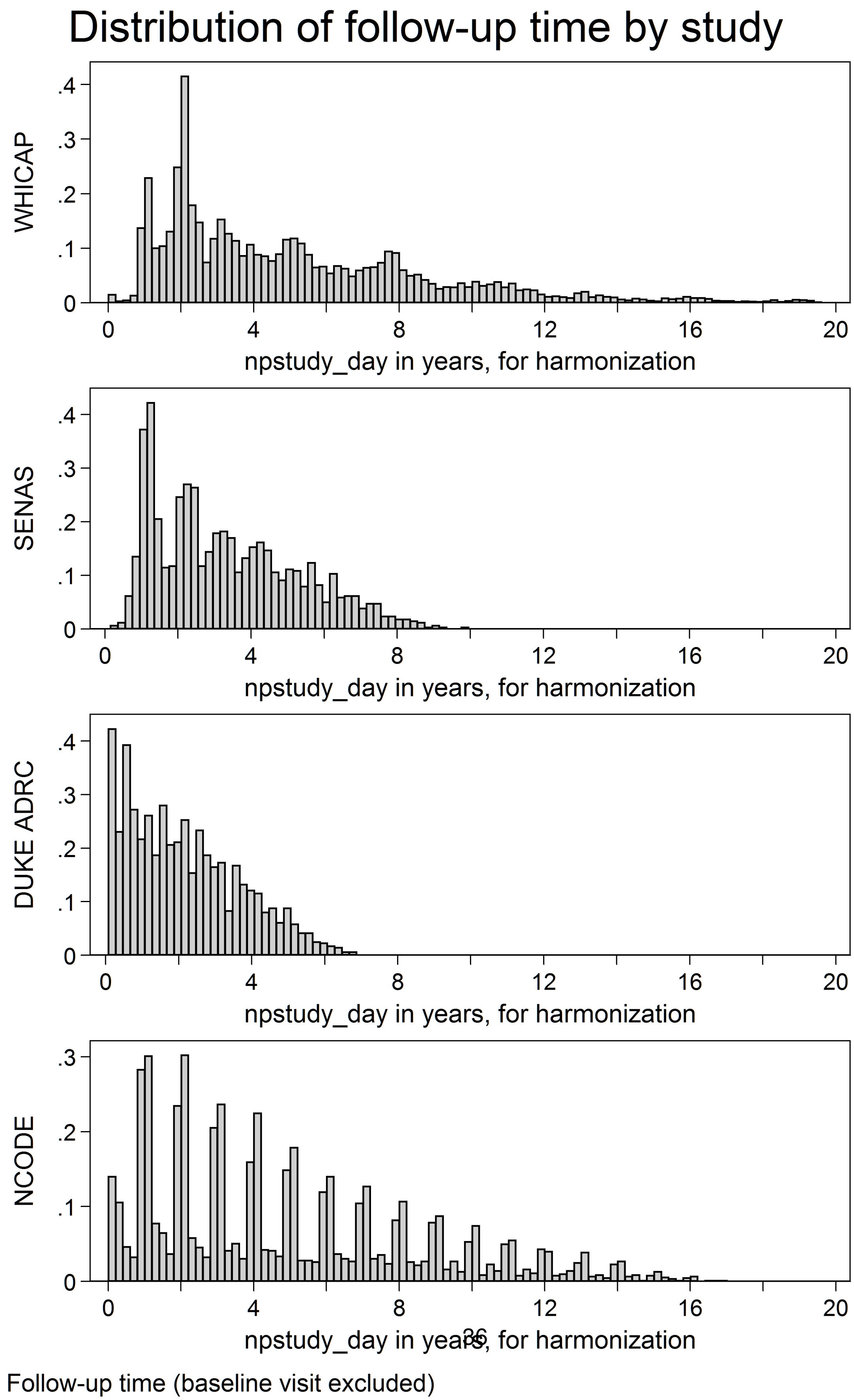
After the MLM spline, we show results from a series of multiple-group MLM models with groupings for study, diagnostic group, race, and sex. Aside from diagnostic groupings the fit does not really change, suggesting that neither study nor demographic variables contribute a whole lot to the variability in factor scores. The pseudo-R2 is great when we group by diagnosis, however, which suggests a lot of the variability in GCP score is explained by clinical diagnosis (Captain Obvious strikes).

After this series of multiple-group MLM spline models with time in study as the timescale of interest, we estimated models in which age (centered at 75) was the relevant timescale. Pseudo-R2's are not so great here.

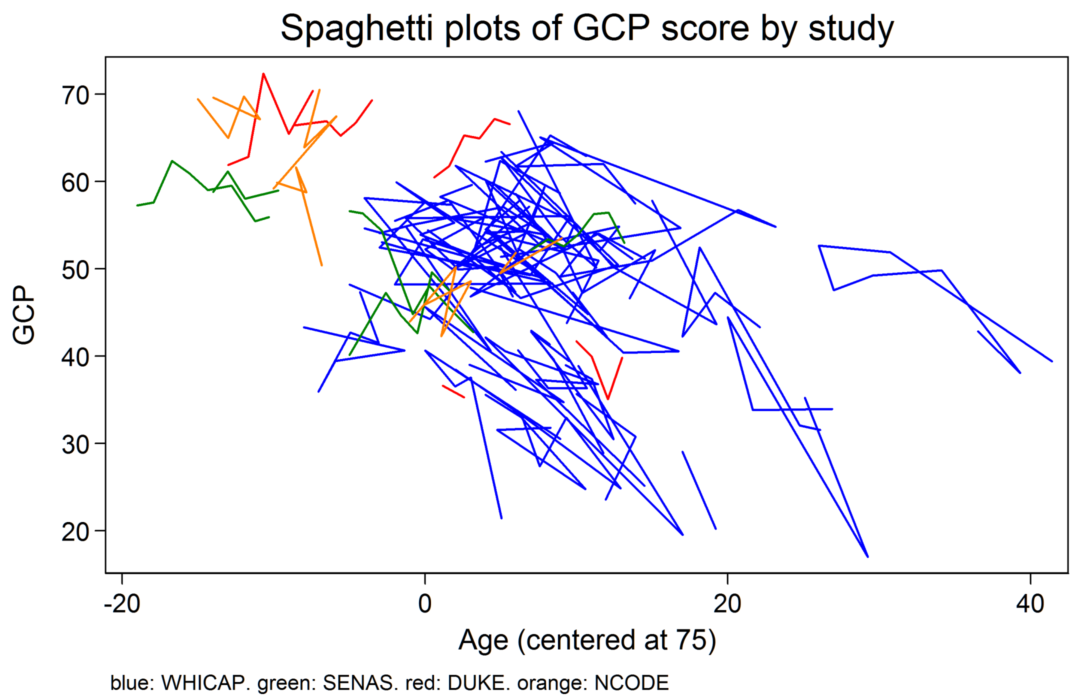
Histograms of GCP score by study gives us a picture of how the studies relate in terms of overall cognitive function. The mean score is supposed to be 50 (SD=10) in the general US population.


Distribution of GCP by study
ADAMS
WHICAP
SENAS
DUKE ADRC
NCODE
0
.01
.02
.03
.04
.05
0
20
40
60
80

Histograms of follow-up time by study tells us the distribution of visits does not vary too much across study; every dataset has considerable follow-up time, up to 22 years in WHICAP (though few persons exceed 15 years).


Distribution of follow-up time by study
WHICAP
SENAS
DUKE ADRC
NCODE
0
.1
.2
.3
.4
0 4 8 12 16 20
npstudy_day in years, for harmonization
Follow-up time (baseline visit excluded)

As with real data, individual trajectories are messy. But there is a general declining trend.



Now here is a multiple groups MLM model for gcp, the groups being defined by nogrp: . The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~t	20525	49.29167	11.32605	-3.197	86.88338
residgcp_n~t	20525	-.000186	3.034511	-20.63406	20.75037

-> data = ADAMS

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~t	0				
residgcp_n~t	0				

-> data = WHICAP

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~t	12947	46.19988	10.6035	-3.197	80.72215
residgcp_n~t	12947	.0873248	3.242715	-20.63406	20.75037

-> data = SENAS

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~t	3506	49.66039	9.210818	7.102	73.928
residgcp_n~t	3506	-.0809884	2.264779	-16.42105	14.1963

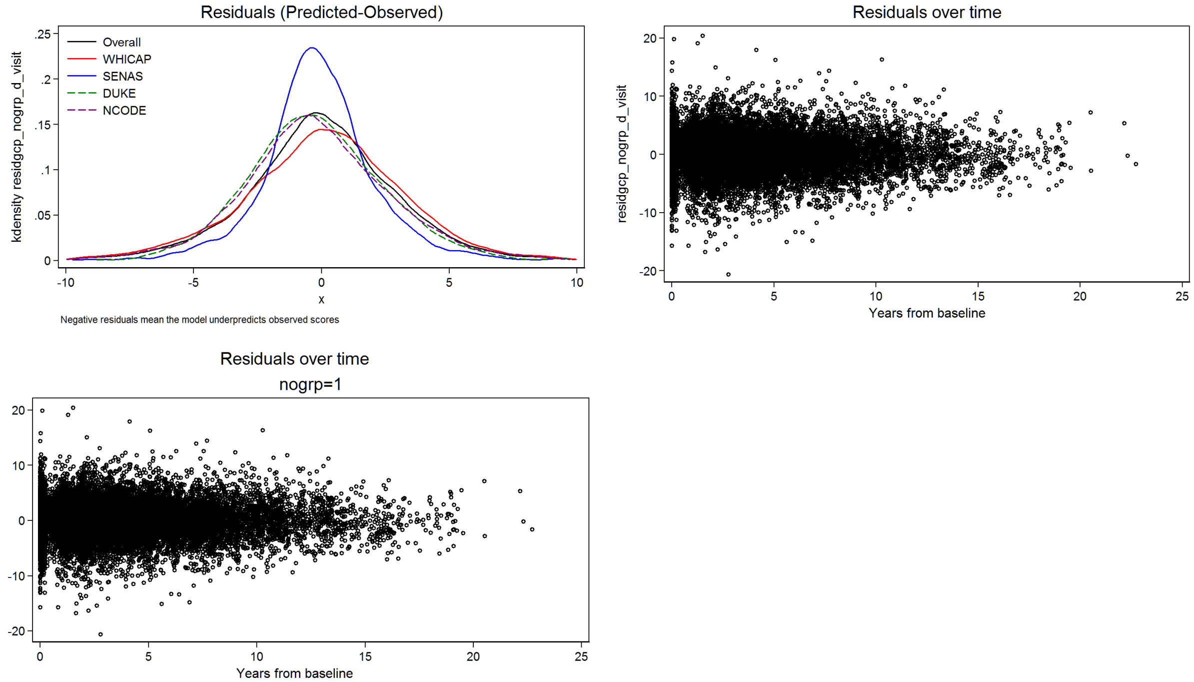
-> data = DUKE ADRC

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~t	1779	56.96548	11.14371	14.39598	86.88338
residgcp_n~t	1779	-.2304149	2.733186	-10.99275	11.18774

-> data = NCODE

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~t	2293	60.2315	8.240715	27.9346	84.22018
residgcp_n~t	2293	-.1921316	3.04844	-13.74183	17.87941

Diagnostic distributions for gcp model



Pseudo-R2: 0.940

Now here is a multiple groups MLM model for gcp, the groups being defined by nogrp: . The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~v	20525	49.29237	11.26383	-3.612	87.55095
residgcp_n~v	20525	.000507	3.262264	-20.43315	21.68084

-> data = ADAMS

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~v	0				
residgcp_n~v	0				

-> data = WHICAP

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~v	12947	46.17421	10.55503	-3.612	79.31038
residgcp_n~v	12947	.0616543	3.448275	-20.43315	21.68084

-> data = SENAS

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~v	3506	49.77489	9.082149	9.133	74.075
residgcp_n~v	3506	.0335048	2.591838	-18.43233	16.575

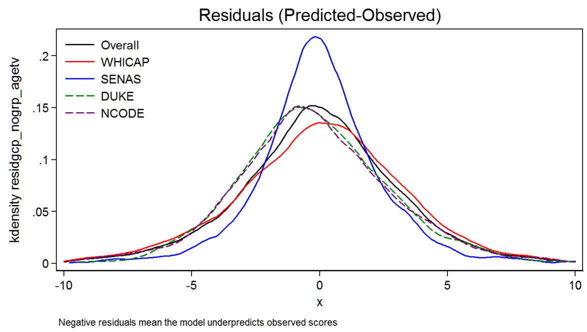
-> data = DUKE ADRC

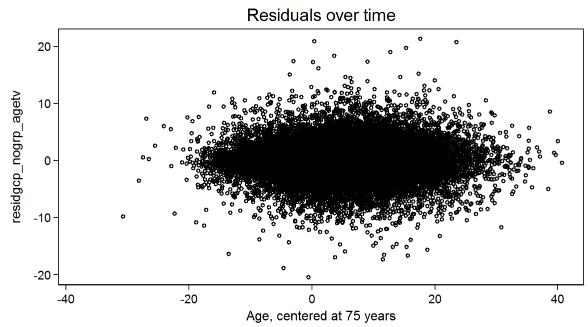
Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~v	1779	56.98609	11.03839	15.35757	87.55095
residgcp_n~v	1779	-.2097964	3.040558	-12.5224	13.08908

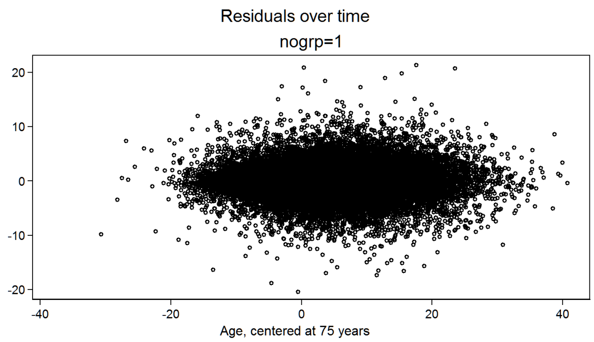
-> data = NCODE

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_nogr~v	2293	60.19159	8.130472	29.57268	82.8931
residgcp_n~v	2293	-.232042	3.252763	-13.38183	20.80704

Diagnostic distributions for gcp model







Pseudo-R2: 0.931

Now here is a multiple groups MLM model for gcp, the groups being defined by data: data(9=whic 10=SENA 11=DUKE 12=ncod). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~t	20525	49.29197	11.36059	-2.255	89.18357
residgcp_d~t	20525	.0001057	3.047793	-20.39631	20.93892

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~t	0				
residgcp_d~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~t	12947	46.11283	10.46184	-2.255	79.28045
residgcp_d~t	12947	.0002702	3.41213	-20.39631	20.93892

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~t	3506	49.74132	9.547463	5.586	75.009
residgcp_d~t	3506	-.0000633	1.792649	-13.37565	10.09014

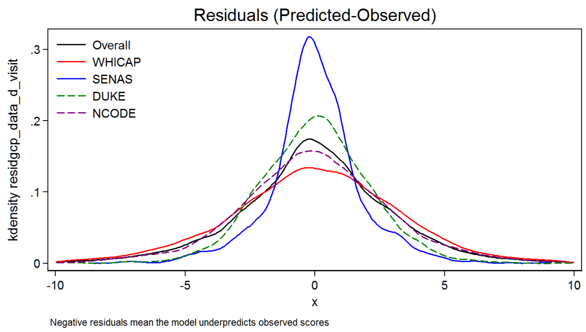
-> data = 11

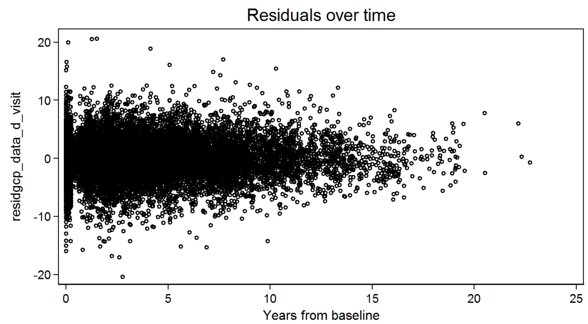
Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~t	1779	57.19561	11.487	12.66258	89.18357
residgcp_d~t	1779	-.000279	2.118533	-9.946711	9.862405

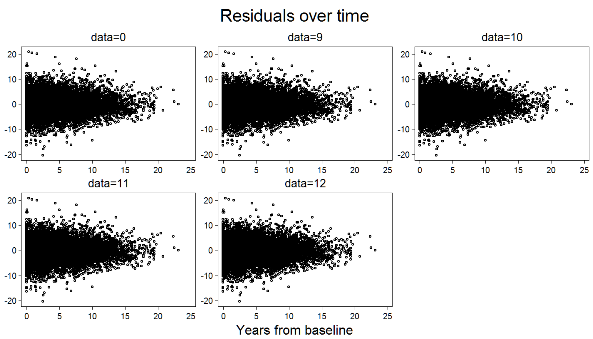
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~t	2293	60.42336	8.117593	29.70173	84.03703
residgcp_d~t	2293	-.0002668	3.003723	-13.84918	18.78424

Diagnostic distributions for gcp model







Pseudo-R2: 0.939

Now here is a multiple groups MLM model for gcp, the groups being defined by data: data(9=whic 10=SENA 11=DUKE 12=ncod). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~v	20525	49.29002	11.29737	-1.921	87.97021
residgcp_d~v	20525	-.0018376	3.231334	-20.55688	21.64466

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~v	0				
residgcp_d~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~v	12947	46.11	10.4391	-1.921	79.281
residgcp_d~v	12947	-.0025575	3.525473	-20.55688	21.64466

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~v	3506	49.74033	9.324884	7.852	75.023
residgcp_d~v	3506	-.0010507	2.252645	-15.08323	15.42524

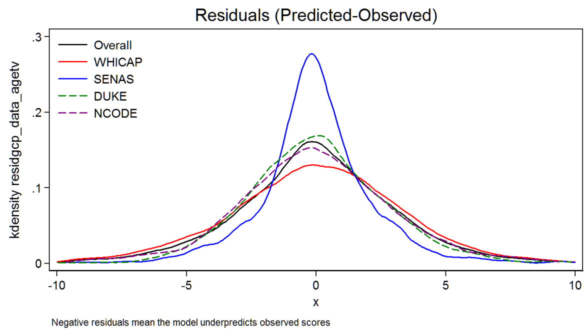
-> data = 11

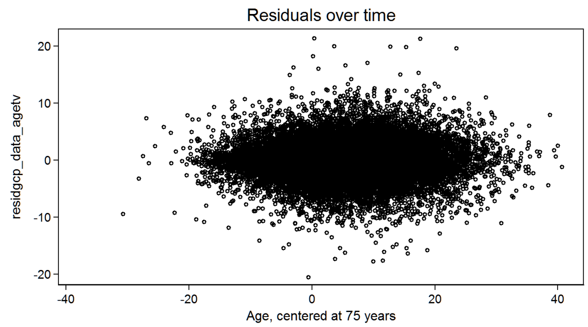
Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~v	1779	57.19733	11.32153	12.15291	87.97021
residgcp_d~v	1779	.0014353	2.702397	-10.76678	11.81957

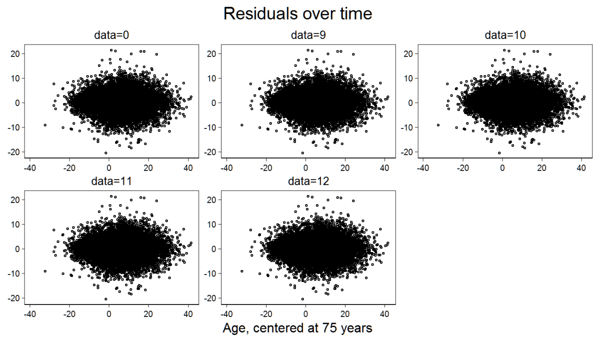
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_data~v	2293	60.42211	8.062962	29.05152	83.13659
residgcp_d~v	2293	-.0015154	3.141921	-13.77353	21.3014

Diagnostic distributions for gcp model







Pseudo-R2: 0.932

Now here is a multiple groups MLM model for gcp, the groups being defined by dxwor: dxwor(1=nor 2=mci 3=ade). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~t	18474	48.38489	11.13473	-1.323	86.29897
re~r_d_visit	18474	.0001366	3.178376	-21.43486	21.61459

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~t	0				
re~r_d_visit	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~t	12947	46.19472	10.61805	-1.323	79.96183
re~r_d_visit	12947	.0821615	3.33143	-21.43486	21.61459

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~t	2458	48.84306	9.253014	8.214	73.71537
re~r_d_visit	2458	-.0312974	2.590595	-15.29349	15.03532

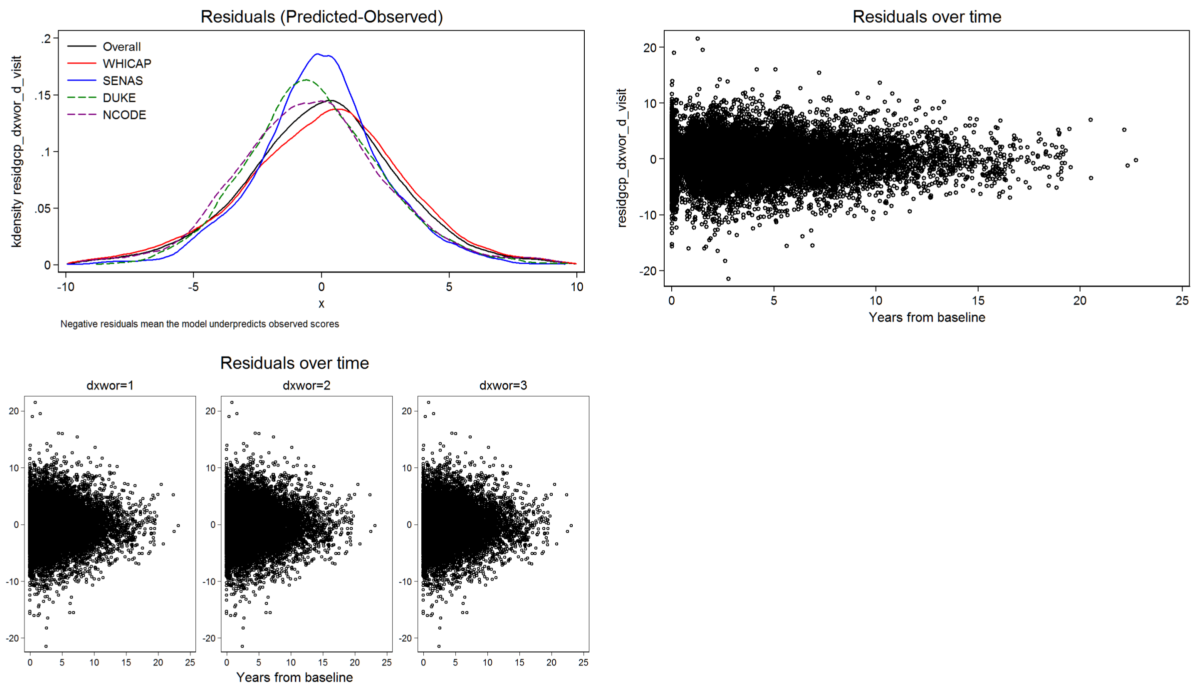
-> data = 11

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~t	1779	56.90612	11.23061	15.17189	86.29897
re~r_d_visit	1779	-.2897749	2.752205	-10.97167	10.86678

-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~t	1290	57.74205	8.420177	27.81513	76.11447
re~r_d_visit	1290	-.3633973	3.122624	-13.56254	15.98394

Diagnostic distributions for gcp model



Pseudo-R2: 0.932

Now here is a multiple groups MLM model for gcp, the groups being defined by dxwor: dxwor(1=nor 2=mci 3=ade). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~v	18474	48.38383	11.04566	2.263	86.90045
resi~r_agetv	18474	-.0009257	3.477429	-21.32847	21.70866

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~v	0				
resi~r_agetv	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~v	12947	46.17157	10.52291	2.263	79.11295
resi~r_agetv	12947	.0590134	3.597758	-21.32847	21.66732

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~v	2458	48.91347	9.083549	7.824	73.982
resi~r_agetv	2458	.0391155	3.11158	-19.25158	16.92542

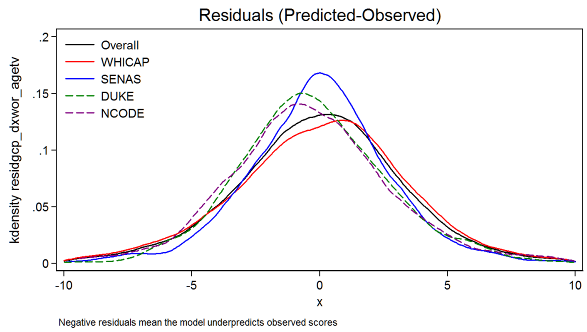
-> data = 11

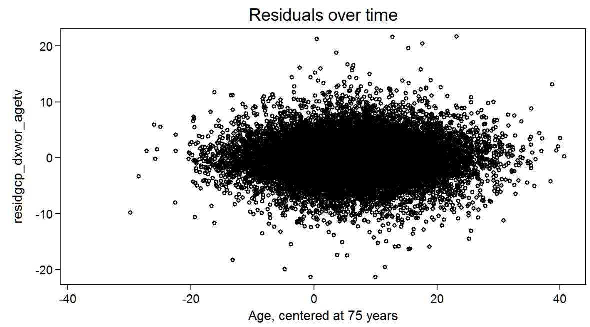
Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~v	1779	56.95323	11.14125	16.79413	86.90045
resi~r_agetv	1779	-.242656	3.06427	-13.39102	13.58474

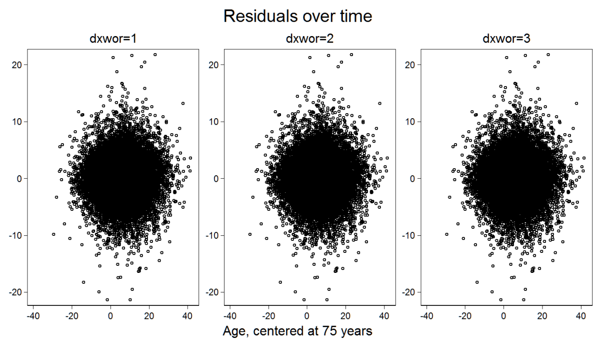
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_dxwo~v	1290	57.76002	8.298584	29.3119	75.95695
resi~r_agetv	1290	-.345433	3.413868	-13.40606	21.70866

Diagnostic distributions for gcp model







Pseudo-R2: 0.918

Now here is a multiple groups MLM model for gcp, the groups being defined by wbho: wbho(0=whit 1=blac 2=hisp). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~t	20113	49.2794	11.35836	-2.476	87.8705
residgcp_w~t	20113	.000132	3.057917	-20.54906	21.0286

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~t	0				
residgcp_w~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~t	12796	46.15337	10.55379	-2.476	80.15768
residgcp_w~t	12796	.0484863	3.306895	-20.54906	21.0286

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~t	3349	49.7644	9.290579	8.922	74.478
residgcp_w~t	3349	-.0941964	2.236383	-15.08978	14.75896

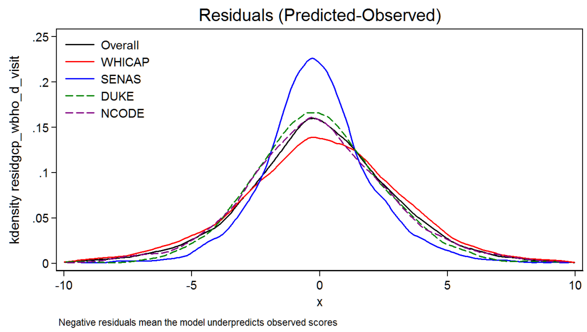
-> data = 11

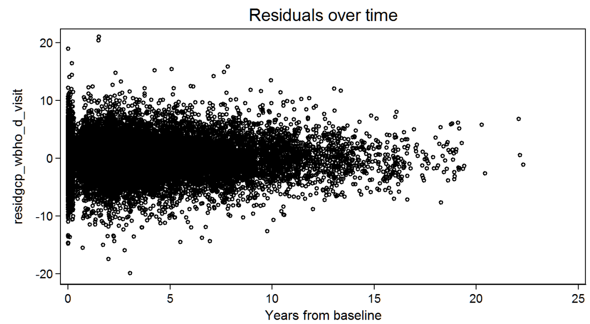
Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~t	1775	57.14675	11.16559	14.98323	87.8705
residgcp_w~t	1775	-.0826287	2.572611	-10.44293	10.38645

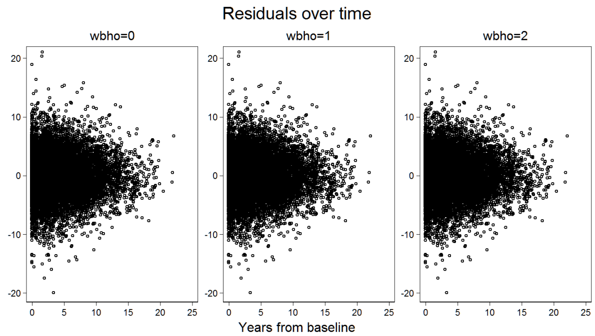
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~t	2193	60.41112	8.32645	27.84888	84.17272
residgcp_w~t	2193	-.0709737	2.988381	-13.72371	15.46514

Diagnostic distributions for gcp model







Pseudo-R2: 0.939

Now here is a multiple groups MLM model for gcp, the groups being defined by wbho: wbho(0=whit 1=blac 2=hisp). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~v	20113	49.277	11.29622	-2.121	87.77233
residgcp_w~v	20113	-.0022652	3.297072	-20.44277	21.7338

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~v	0				
residgcp_w~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~v	12796	46.10621	10.50948	-2.121	79.179
residgcp_w~v	12796	.0013287	3.515834	-20.44277	21.7338

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~v	3349	49.90919	9.141792	10.738	74.546
residgcp_w~v	3349	.0505907	2.588216	-16.80567	16.82293

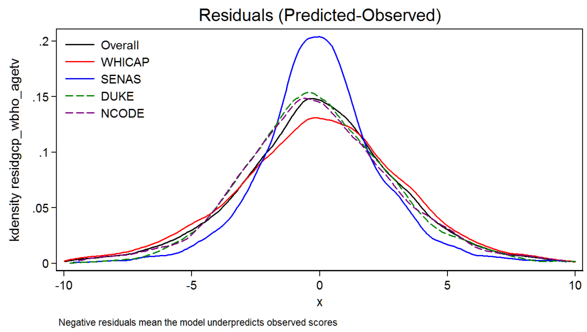
-> data = 11

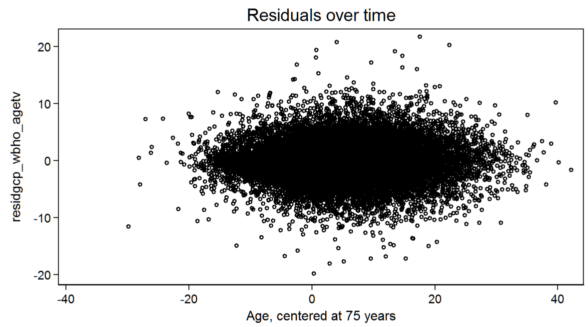
Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~v	1775	57.20173	10.9853	15.92583	87.77233
residgcp_w~v	1775	-.0276456	2.973243	-11.45581	12.72326

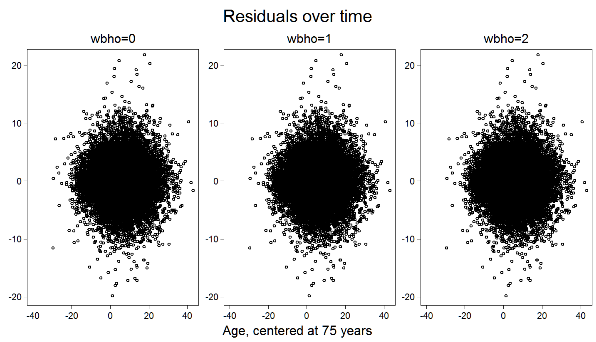
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_wbho~v	2193	60.39869	8.177682	29.8952	82.89985
residgcp_w~v	2193	-.0834107	3.192124	-13.60897	20.3869

Diagnostic distributions for gcp model







Pseudo-R2: 0.929

Now here is a multiple groups MLM model for gcp, the groups being defined by female: female(0=mal 1=fem). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~t	20525	49.29159	11.32711	-3.44	86.88028
residgcp_f~t	20525	-.0002695	3.034523	-20.5716	20.7897

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~t	0				
residgcp_f~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~t	12947	46.19905	10.6046	-3.44	80.99448
residgcp_f~t	12947	.0864942	3.244573	-20.5716	20.7897

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~t	3506	49.66373	9.212094	6.906	74.032
residgcp_f~t	3506	-.0776541	2.254631	-15.7943	13.73414

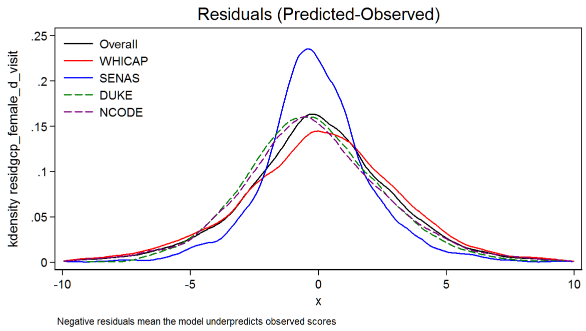
-> data = 11

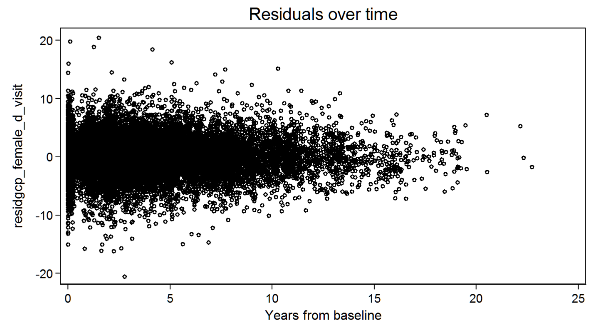
Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~t	1779	56.9656	11.14438	14.24202	86.88028
residgcp_f~t	1779	-.2302939	2.732739	-10.74189	11.56232

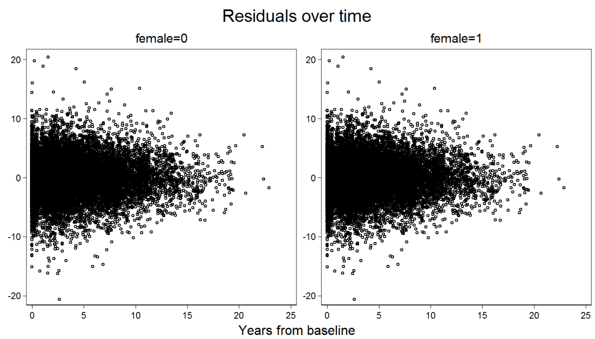
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~t	2293	60.23025	8.242484	28.01604	84.01502
residgcp_f~t	2293	-.1933818	3.049388	-13.65934	18.37125

Diagnostic distributions for gcp model







Pseudo-R2: 0.940

Now here is a multiple groups MLM model for gcp, the groups being defined by female: female(0=mal 1=fem). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~v	20525	49.29189	11.26479	-3.631	87.51662
residgcp_f~v	20525	.0000351	3.261411	-20.34037	21.76133

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~v	0				
residgcp_f~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~v	12947	46.17266	10.5538	-3.631	79.64902
residgcp_f~v	12947	.0601065	3.448466	-20.34037	21.76133

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~v	3506	49.77429	9.088116	9.074	74.131
residgcp_f~v	3506	.0329065	2.584248	-17.65064	16.6293

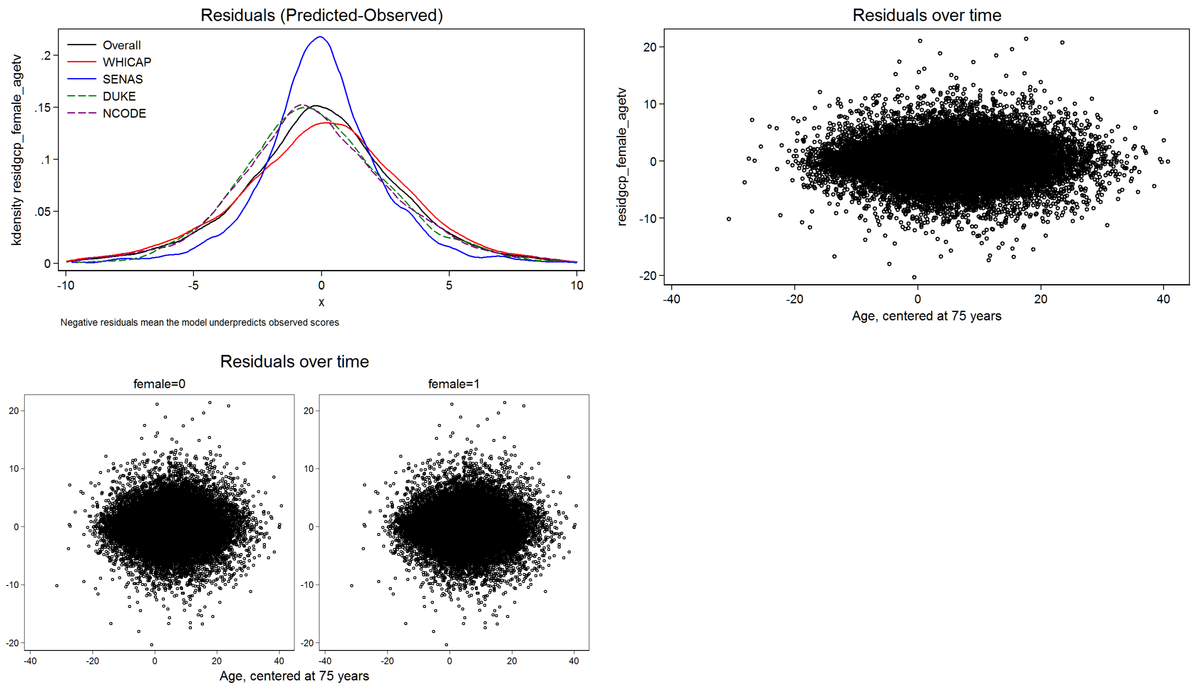
-> data = 11

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~v	1779	56.98704	11.0389	15.28773	87.51662
residgcp_f~v	1779	-.2088552	3.039716	-12.4301	13.12064

-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pygcp_fema~v	2293	60.19629	8.130408	29.70194	82.93745
residgcp_f~v	2293	-.227342	3.254355	-13.39074	21.01774

Diagnostic distributions for gcp model



Pseudo-R2: 0.931

Now here is a multiple groups MLM model for mem, the groups being defined by nogrp: . The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~t	20244	54.97144	10.792	22.01566	91.35575
residmem_n~t	20244	.0002611	4.78383	-28.74562	20.80755

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~t	0				
residmem_n~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~t	12705	54.46963	10.90762	22.01566	91.35575
residmem_n~t	12705	-.0083778	5.207585	-28.74562	20.80755

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~t	3476	51.26737	9.189094	26.52002	76.62159
residmem_n~t	3476	.2614528	3.601627	-17.639	17.77224

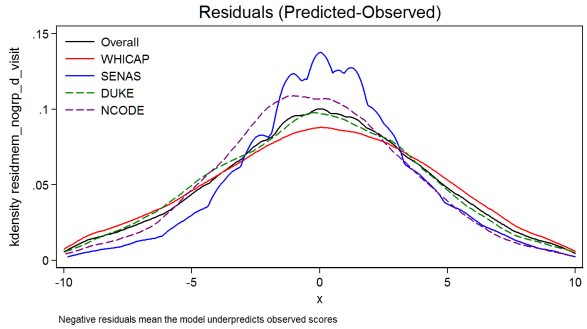
-> data = 11

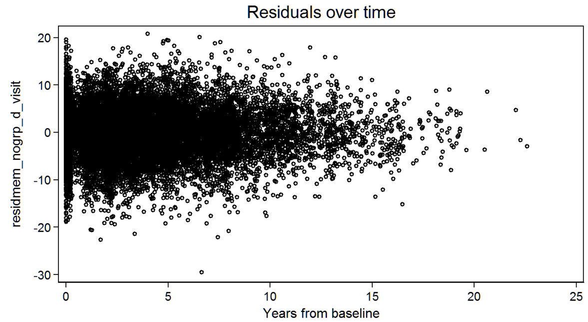
Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~t	1772	58.25805	11.30051	29.22615	79.12023
residmem_n~t	1772	-.1639012	4.390556	-17.39389	19.10094

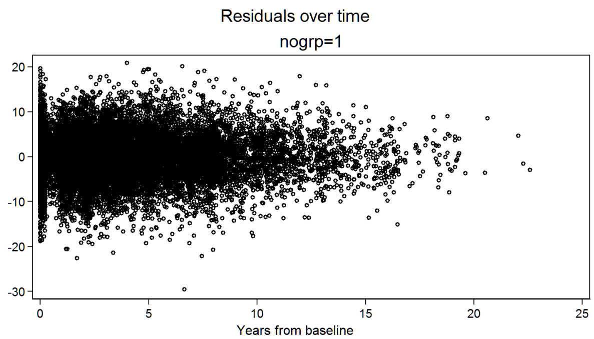
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~t	2291	60.83215	8.813051	30.26645	79.65502
residmem_n~t	2291	-.2211488	4.133583	-18.0211	20.65614

Diagnostic distributions for mem model







Pseudo-R2: 0.869

Now here is a multiple groups MLM model for mem, the groups being defined by nogrp: . The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~v	20244	54.97185	10.68359	17.785	90.076
residmem_n~v	20244	.0006775	5.112494	-28.93543	24.85238

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~v	0				
residmem_n~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~v	12705	54.38937	10.81503	17.785	90.076
residmem_n~v	12705	-.0886413	5.546621	-28.93543	24.85238

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~v	3476	51.50014	9.087344	27.23251	76.673
residmem_n~v	3476	.4942232	3.940999	-18.667	17.90404

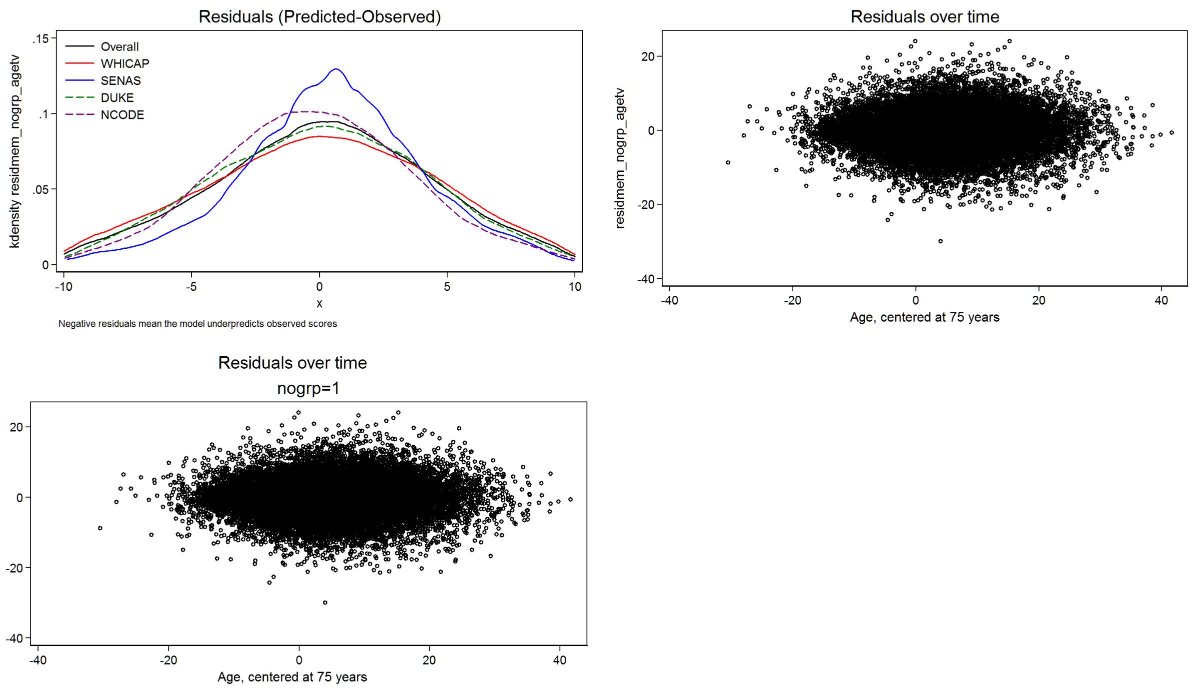
-> data = 11

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~v	1772	58.35242	11.16342	28.4948	79.53518
residmem_n~v	1772	-.0695221	4.642047	-17.38604	20.67449

-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_nogr~v	2291	60.85477	8.645897	30.75895	76.92989
residmem_n~v	2291	-.1985265	4.436975	-18.33705	23.78193

Diagnostic distributions for mem model



Pseudo-R2: 0.848

Now here is a multiple groups MLM model for mem, the groups being defined by data: data(9=whic 10=SENA 11=DUKE 12=ncod). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_data~t	20244	54.97108	10.82721	22.58769	90.862
residmem_d~t	20244	-.000095	4.828062	-29.00683	21.83904

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_data~t	0				
residmem_d~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_data~t	12705	54.47796	10.73558	22.58769	90.862
residmem_d~t	12705	-.0000479	5.442291	-29.00683	21.83904

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_data~t	3476	51.00581	9.553049	23.02459	78.48517
residmem_d~t	3476	-.0001058	3.15112	-15.399	16.95828

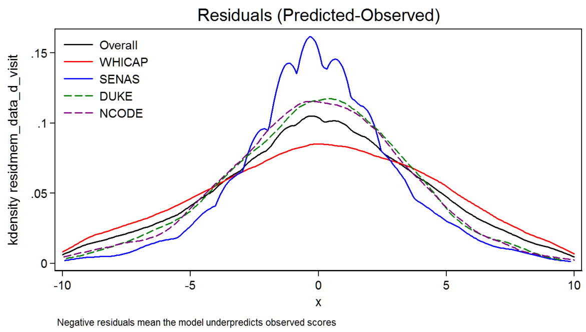
-> data = 11

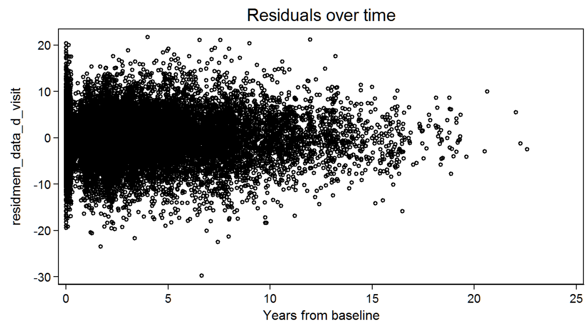
Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_data~t	1772	58.42158	11.88545	25.49473	82.14986
residmem_d~t	1772	-.0003651	3.719857	-16.18005	15.91097

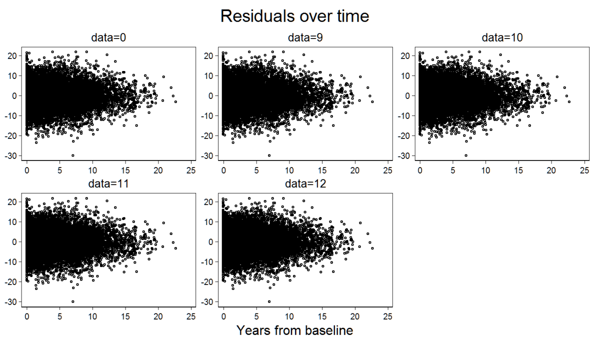
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_data~t	2291	61.05317	8.816166	30.43558	81.03561
residmem_d~t	2291	-.0001306	3.996892	-17.48095	21.53281

Diagnostic distributions for mem model







Pseudo-R2: 0.865

Now here is a multiple groups MLM model for mem, the groups being defined by dxwor: dxwor(1=nor 2=mci 3=ade). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~t	18219	54.44202	10.97722	22.58	89.35542
residmem_dx~	18219	-.0002023	5.052058	-30.04817	20.79071

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~t	0				
residmem_dx~	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~t	12705	54.38103	10.97625	22.58	89.35542
residmem_dx~	12705	-.0969817	5.356662	-30.04817	20.79071

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~t	2454	49.74341	9.455032	27.06915	76.57281
residmem_dx~	2454	.6601138	4.122211	-18.388	18.08322

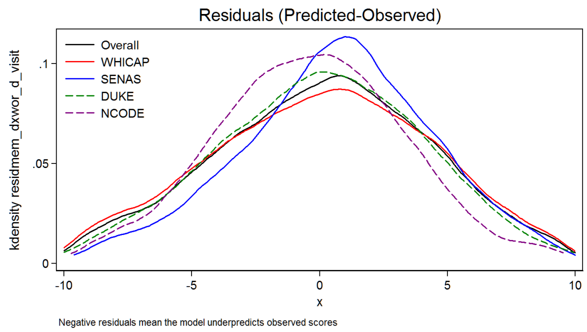
-> data = 11

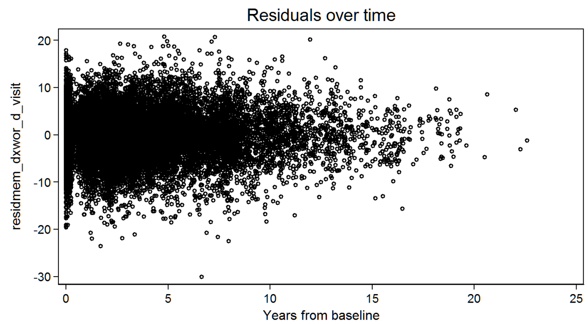
Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~t	1772	58.40761	11.42237	28.86776	78.7424
residmem_dx~	1772	-.0143391	4.434838	-17.17286	20.56428

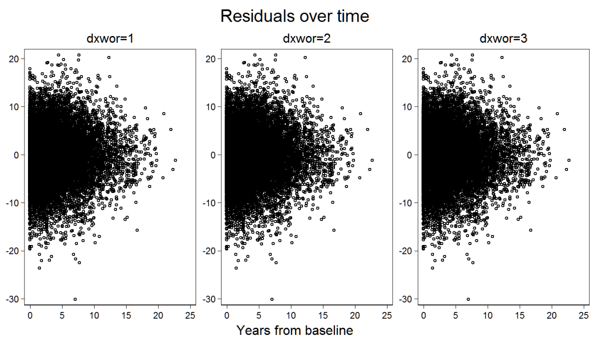
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~t	1288	58.53997	9.271377	30.5523	78.1214
residmem_dx~	1288	-.2841948	4.195046	-14.30099	19.17034

Diagnostic distributions for mem model







Pseudo-R2: 0.854

Now here is a multiple groups MLM model for mem, the groups being defined by dxwor: dxwor(1=nor 2=mci 3=ade). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~v	18219	54.44256	10.83182	20.142	89.412
residmem_d~v	18219	.000343	5.434882	-29.18286	28.36743

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~v	0				
residmem_d~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~v	12705	54.33445	10.82495	20.142	89.412
residmem_d~v	12705	-.1435618	5.749391	-29.18286	28.36743

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~v	2454	49.89312	9.295236	28.162	76.46497
residmem_d~v	2454	.8098192	4.596822	-19	18.18099

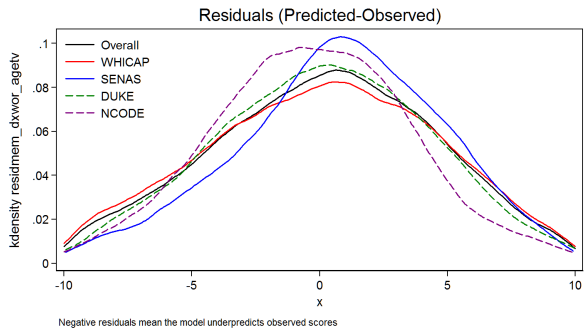
-> data = 11

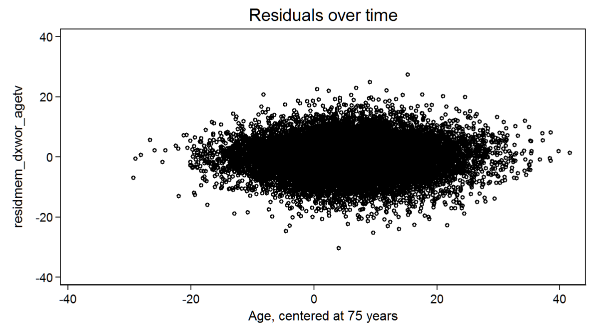
Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~v	1772	58.46324	11.32758	30.94237	78.90285
residmem_d~v	1772	.0412923	4.659467	-17.17272	21.75675

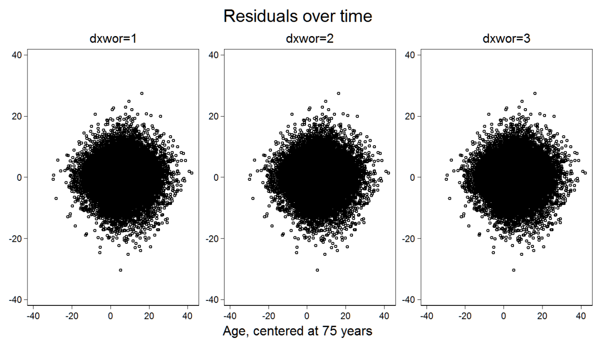
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_dxwo~v	1288	58.64539	9.131408	30.3628	77.00232
residmem_d~v	1288	-.1787772	4.493506	-14.81604	23.44246

Diagnostic distributions for mem model





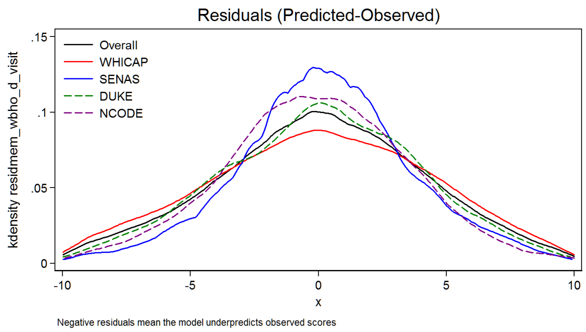


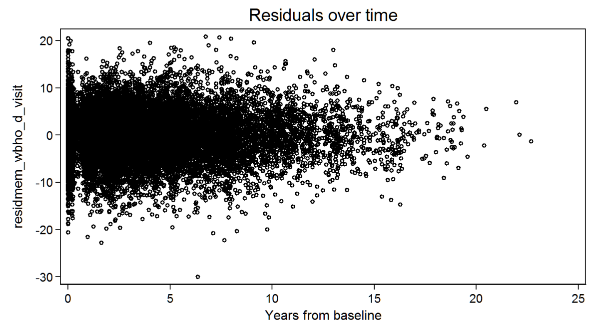
Pseudo-R2: 0.830

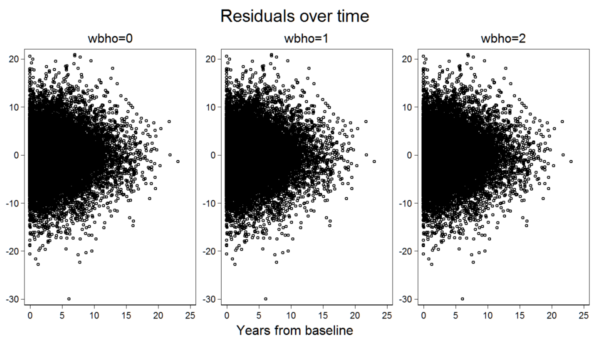
Now here is a multiple groups MLM model for mem, the groups being defined by wbho: wbho(0=whit 1=blac 2=hisp). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

```
    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
pymem_wbho~t |      19837    54.99924    10.82171    22.3679   92.24093
residmem_w~t |      19837    .0003212    4.817843   -29.2464     20.834

-------------------------------------------------------------------------
-> data = 0

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
pymem_wbho~t |          0
residmem_w~t |          0

-------------------------------------------------------------------------
-> data = 9

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
pymem_wbho~t |      12557    54.41058     10.8622    22.3679   92.24093
residmem_w~t |      12557   -.0648158    5.285023   -29.2464     20.834

-------------------------------------------------------------------------
-> data = 10

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
pymem_wbho~t |       3321      51.364    9.227555   24.95279     76.429
residmem_w~t |       3321    .2561816    3.620111    -16.771    17.5944

-------------------------------------------------------------------------
-> data = 11

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
pymem_wbho~t |       1768    58.49662    11.45156   28.41268   80.18759
residmem_w~t |       1768    .0355927    4.196003  -17.03119   18.15446

-------------------------------------------------------------------------
-> data = 12

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
pymem_wbho~t |       2191    61.06094     8.98376   29.56369   80.70149
residmem_w~t |       2191   -.0426486    3.987493  -17.47911   18.67749
```

Diagnostic distributions for mem model







Pseudo-R2: 0.867

Now here is a multiple groups MLM model for mem, the groups being defined by wbho: wbho(0=whit 1=blac 2=hisp). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_wbho~v	19837	54.99843	10.71209	19.017	90.57795
residmem_w~v	19837	-.0004902	5.145447	-29.27965	23.21559

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_wbho~v	0				
residmem_w~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_wbho~v	12557	54.32013	10.77413	19.017	90.57795
residmem_w~v	12557	-.1552635	5.612652	-29.27965	23.16655

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_wbho~v	3321	51.62077	9.118865	26.315	76.784
residmem_w~v	3321	.5129563	3.939114	-18.214	17.64899

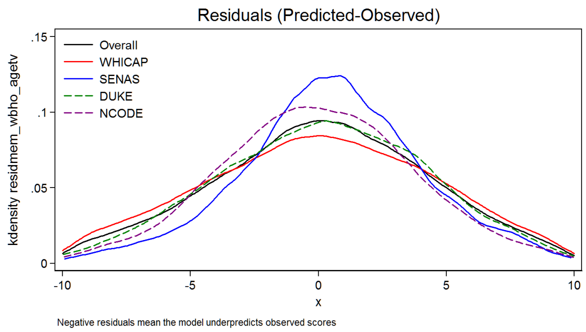
-> data = 11

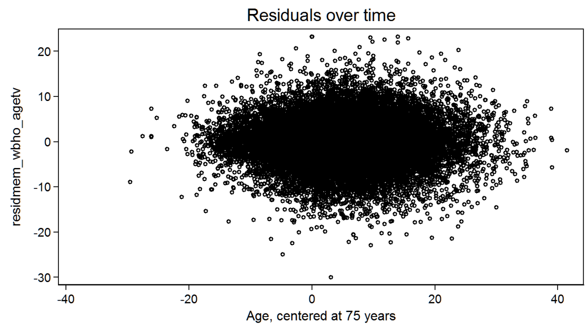
Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_wbho~v	1768	58.61054	11.28698	27.24117	80.3439
residmem_w~v	1768	.1495124	4.546812	-17.1756	20.56934

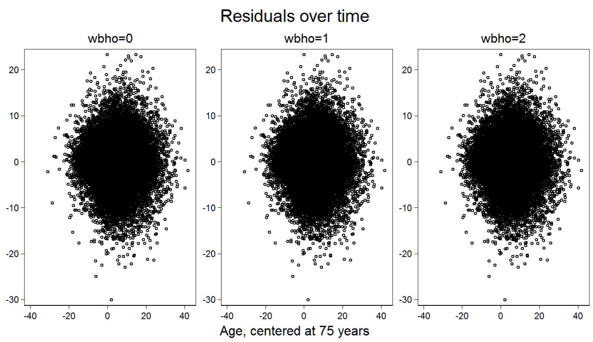
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_wbho~v	2191	61.09084	8.794951	30.27258	78.43071
residmem_w~v	2191	-.0127556	4.293533	-18.08011	23.21559

Diagnostic distributions for mem model





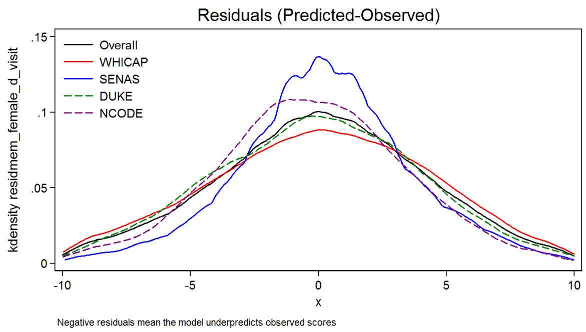


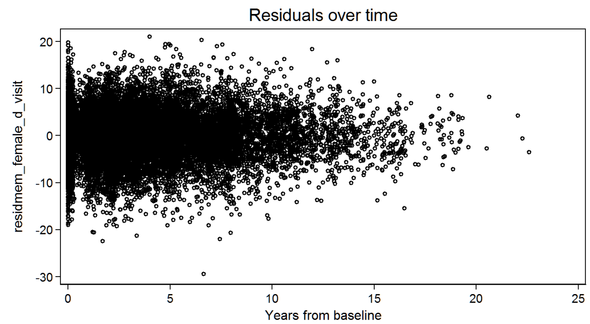
Pseudo-R2: 0.846

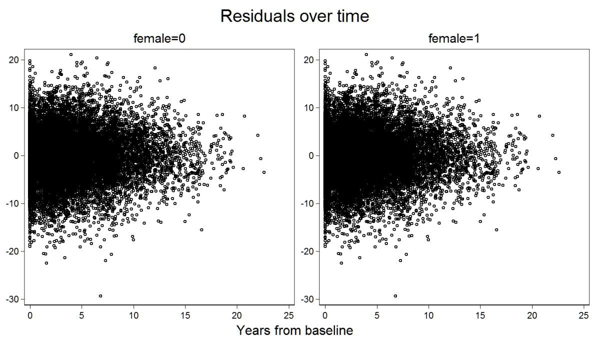
Now here is a multiple groups MLM model for mem, the groups being defined by female: female(0=mal 1=fem). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pymem_fema~t |     20244    54.97121    10.79604   21.99659   92.39658
residmem_f~t |     20244    .0000359    4.781552  -28.61593   21.02531

-------------------------------------------------------------------------------
-> data = 0

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pymem_fema~t |         0
residmem_f~t |         0

-------------------------------------------------------------------------------
-> data = 9

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pymem_fema~t |     12705    54.47019    10.91036   21.99659   92.39658
residmem_f~t |     12705   -.0078222    5.206209  -28.61593   21.02531

-------------------------------------------------------------------------------
-> data = 10

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pymem_fema~t |      3476    51.26913    9.205537   25.98468   76.63417
residmem_f~t |      3476     .263211    3.590758    -17.693   17.84561

-------------------------------------------------------------------------------
-> data = 11

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pymem_fema~t |      1772    58.24979    11.30345   29.11107   79.28501
residmem_f~t |      1772   -.1721571    4.387436  -17.49755   19.28497

-------------------------------------------------------------------------------
-> data = 12

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pymem_fema~t |      2291     60.8308     8.81358   30.33376   79.24125
residmem_f~t |      2291   -.2225018    4.136318  -17.94711   20.99248
```

Diagnostic distributions for mem model







Pseudo-R2: 0.869

Now here is a multiple groups MLM model for mem, the groups being defined by female: female(0=mal 1=fem). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_fema~v	20244	54.97125	10.68808	17.881	90.328
residmem_f~v	20244	.0000732	5.11311	-28.92136	25.31152

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_fema~v	0				
residmem_f~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_fema~v	12705	54.3897	10.81461	17.881	90.328
residmem_f~v	12705	-.088314	5.549144	-28.92136	25.31152

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_fema~v	3476	51.49999	9.119124	26.991	76.769
residmem_f~v	3476	.4940769	3.92749	-18.621	17.96416

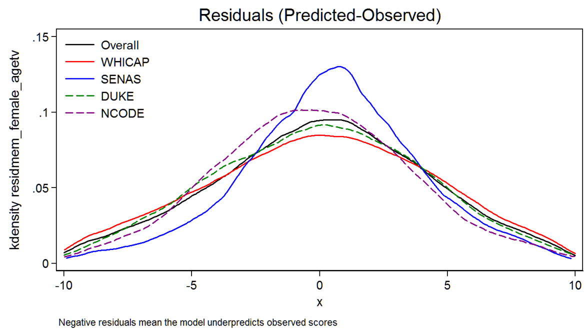
-> data = 11

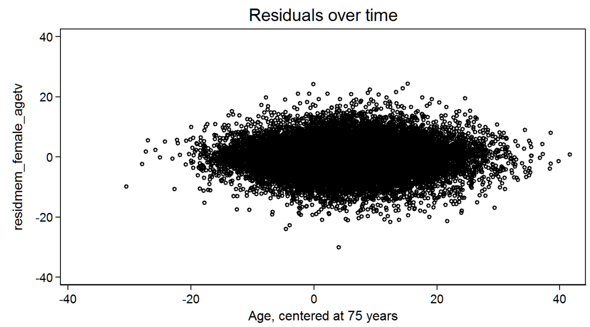
Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_fema~v	1772	58.34299	11.16121	27.82351	79.47798
residmem_f~v	1772	-.078952	4.644662	-17.57394	20.7655

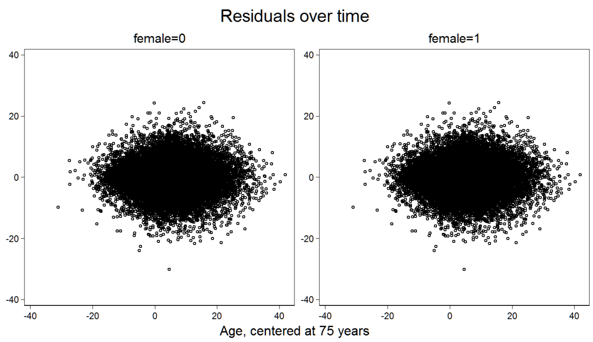
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pymem_fema~v	2291	60.85513	8.651926	30.53201	76.82729
residmem_f~v	2291	-.1981656	4.441755	-18.30308	23.8907

Diagnostic distributions for mem model







Pseudo-R2: 0.848

Now here is a multiple groups MLM model for exf, the groups being defined by nogrp: . The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_nogr~t	19485	53.98537	9.341149	21.23059	87.35873
residexf_n~t	19485	-.0000275	3.81393	-20.35322	20.787

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_nogr~t	0				
residexf_n~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_nogr~t	12029	53.5977	8.81989	28.84736	87.35873
residexf_n~t	12029	.0008723	4.109776	-20.35322	18.83635

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_nogr~t	3400	50.99742	9.402155	21.23059	78.908
residexf_n~t	3400	.2011494	3.538165	-17.928	20.787

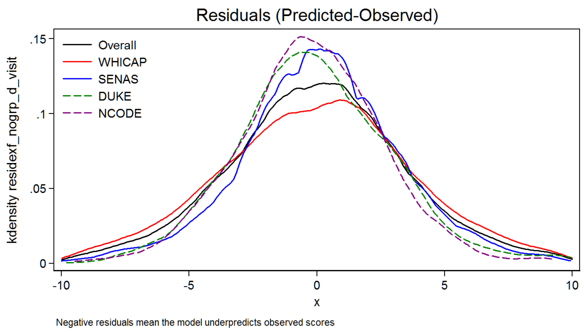
-> data = 11

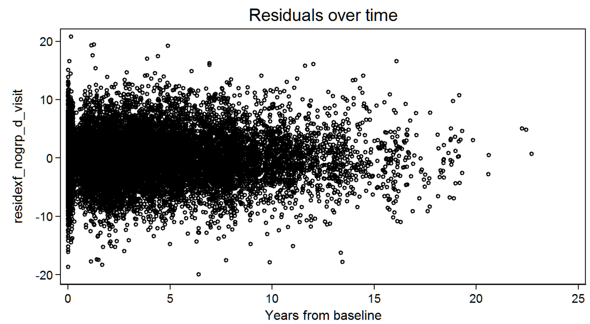
Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_nogr~t	1771	56.00329	10.12216	26.32677	82.24784
residexf_n~t	1771	-.1124241	3.203895	-15.3187	14.02311

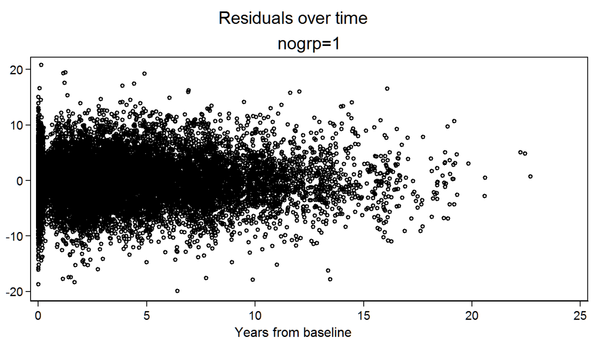
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_nogr~t	2285	58.90821	9.069664	27.72434	79.806
residexf_n~t	2285	-.2169954	2.904808	-12.45115	17.25208

Diagnostic distributions for exf model





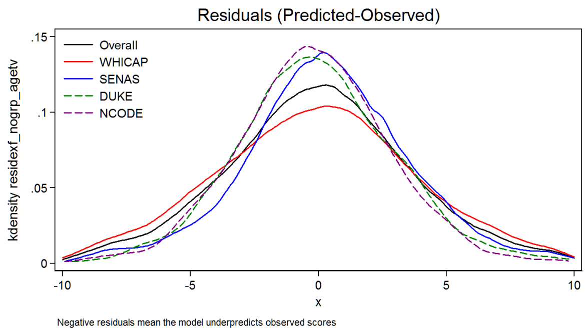


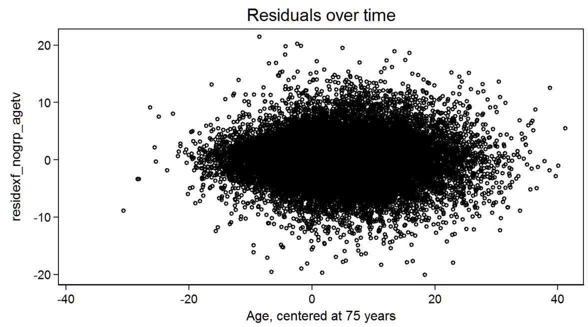
Pseudo-R2: 0.884

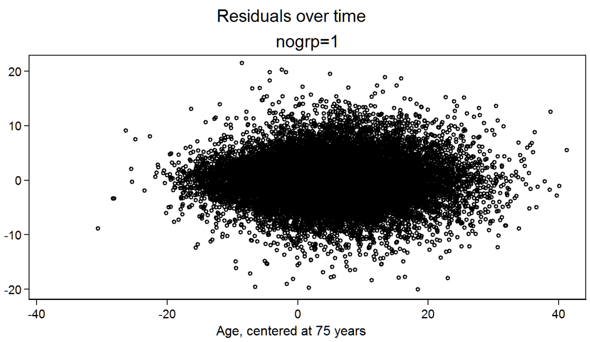
Now here is a multiple groups MLM model for exf, the groups being defined by nogrp: . The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pyexf_nogr~v |     19485    53.98456    9.245987   24.92071     87.281
residexf_n~v |     19485     -.00084    4.079316  -20.48273     21.475

--------------------------------------------------------------------------------
-> data = 0
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pyexf_nogr~v |         0
residexf_n~v |         0

--------------------------------------------------------------------------------
-> data = 9
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pyexf_nogr~v |     12029    53.52282    8.704315   30.64697     87.281
residexf_n~v |     12029   -.0740034    4.372563  -20.48273     19.702

--------------------------------------------------------------------------------
-> data = 10
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pyexf_nogr~v |      3400    51.16472    9.316355   24.92071     80.298
residexf_n~v |      3400    .3684523    3.890039    -20.061     21.475

--------------------------------------------------------------------------------
-> data = 11
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pyexf_nogr~v |      1771    56.10764    10.12427   25.66068   83.69083
residexf_n~v |      1771   -.0080768    3.368594    -15.473   15.18641

--------------------------------------------------------------------------------
-> data = 12
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pyexf_nogr~v |      2285    58.96564    8.966619    28.4617     80.417
residexf_n~v |      2285   -.1595683    3.114638  -14.58798   19.23233
```

Diagnostic distributions for exf model







Pseudo-R2: 0.866

Now here is a multiple groups MLM model for exf, the groups being defined by data: data(9=whic 10=SENA 11=DUKE 12=ncod). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~t	19485	53.98529	9.338373	18.84211	84.86353
residexf_d~t	19485	-.0001106	3.863043	-20.26962	19.08509

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~t	0				
residexf_d~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~t	12029	53.5966	8.478216	29.64381	84.86353
residexf_d~t	12029	-.0002274	4.366825	-20.26962	19.08509

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~t	3400	50.79603	9.855658	18.84211	80.014
residexf_d~t	3400	-.0002358	2.994602	-18.24014	18.164

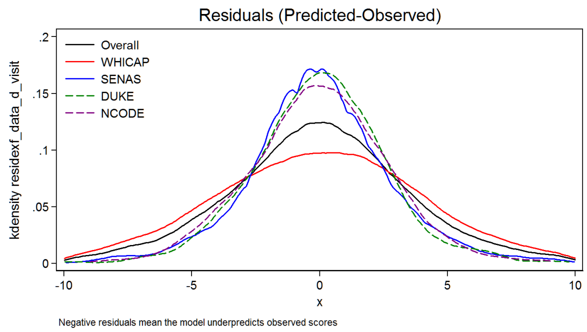
-> data = 11

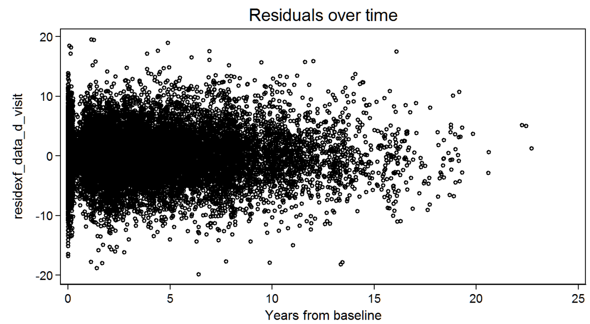
Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~t	1771	56.11559	10.71664	22.96434	84.19573
residexf_d~t	1771	-.0001193	2.709142	-16.09127	11.35782

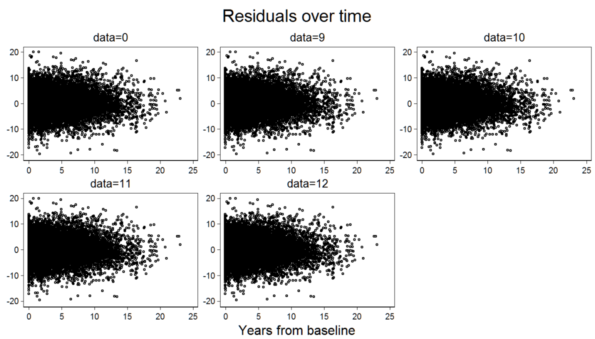
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~t	2285	59.1259	9.270107	27.0394	80.37
residexf_d~t	2285	.0006976	2.801512	-11.73207	17.39733

Diagnostic distributions for exf model







Pseudo-R2: 0.880

Now here is a multiple groups MLM model for exf, the groups being defined by data: data(9=whic 10=SENA 11=DUKE 12=ncod). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~v	19485	53.98441	9.247798	20.79552	86.656
residexf_d~v	19485	-.0009867	4.088823	-20.77769	21.10736

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~v	0				
residexf_d~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~v	12029	53.59638	8.431295	29.17013	86.656
residexf_d~v	12029	-.0004424	4.53669	-20.77769	21.10736

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~v	3400	50.79459	9.584994	20.79552	80.655
residexf_d~v	3400	-.0016825	3.491717	-17.594	19.58

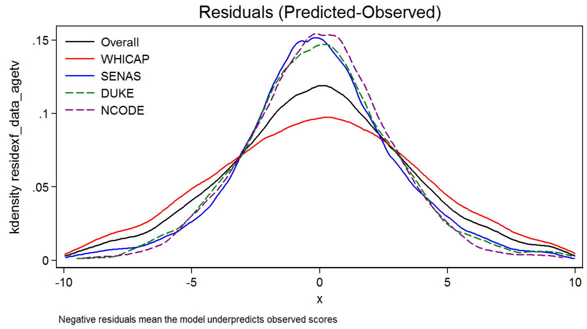
-> data = 11

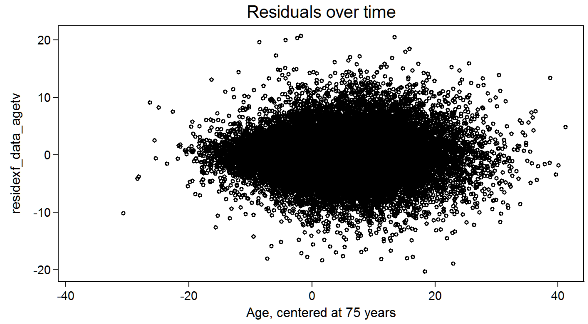
Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~v	1771	56.11177	10.59162	23.58373	83.61945
residexf_d~v	1771	-.0039481	3.195707	-16.77397	14.67709

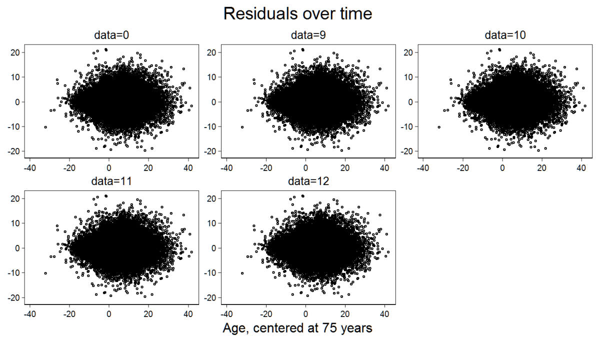
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_data~v	2285	59.12468	9.255146	26.51051	81.128
residexf_d~v	2285	-.0005211	2.859121	-12.10089	17.03113

Diagnostic distributions for exf model







Pseudo-R2: 0.865

Now here is a multiple groups MLM model for exf, the groups being defined by dxwor: dxwor(1=nor 2=mci 3=ade). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~t	17515	53.4817	9.187443	22.96913	85.70932
residexf_dx~	17515	.000313	4.023366	-20.46207	21.346

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~t	0				
residexf_dx~	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~t	12029	53.51902	8.833048	30.42634	85.70932
residexf_dx~	12029	-.0778088	4.190014	-20.46207	18.79571

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~t	2433	50.02609	9.193058	22.96913	75.12746
residexf_dx~	2433	.3994282	4.099229	-17.836	21.346

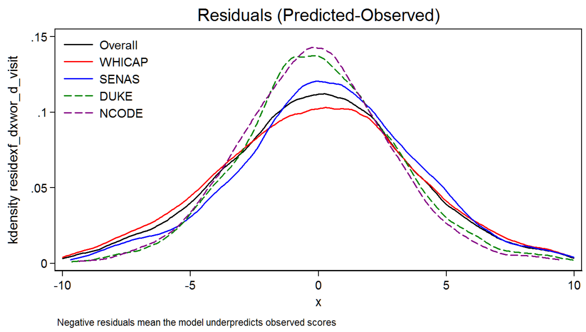
-> data = 11

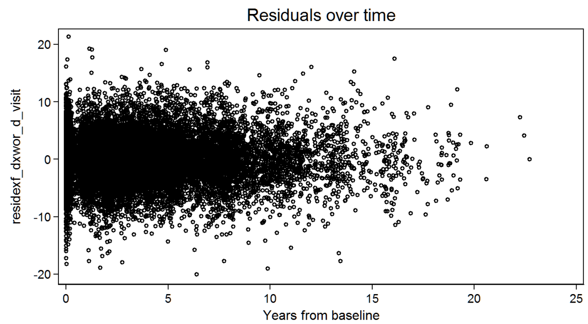
Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~t	1771	56.17512	10.07968	27.69136	82.40565
residexf_dx~	1771	.0594095	3.261173	-14.85471	12.40958

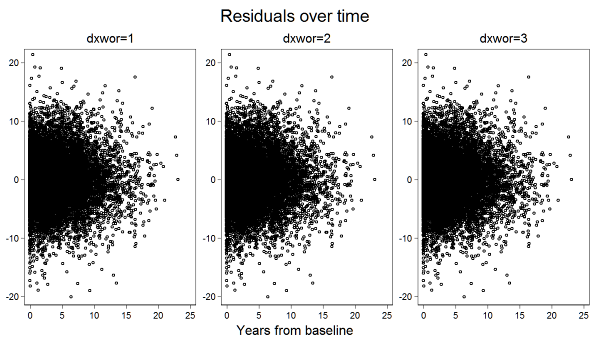
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~t	1282	55.96896	9.039287	28.90009	77.07262
residexf_dx~	1282	-.1057557	3.082108	-13.05937	16.90085

Diagnostic distributions for exf model







Pseudo-R2: 0.867

Now here is a multiple groups MLM model for exf, the groups being defined by dxwor: dxwor(1=nor 2=mci 3=ade). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~v	17515	53.48194	9.057787	26.225	86.72
residexf_d..	17515	.0005455	4.357268	-21.111	21.19069

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~v	0				
residexf_d..	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~v	12029	53.47362	8.689915	32.10622	86.72
residexf_d..	12029	-.1232065	4.497955	-20.79091	21.19069

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~v	2433	50.13498	9.047258	26.225	73.704
residexf_d..	2433	.5083257	4.624377	-21.111	21.043

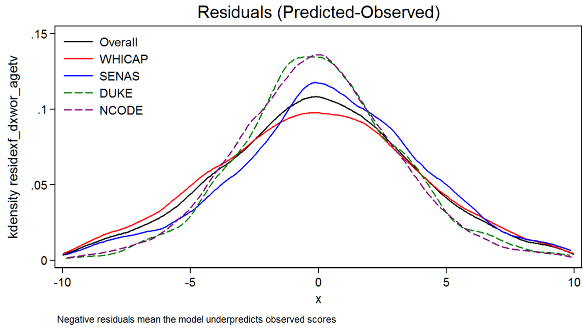
-> data = 11

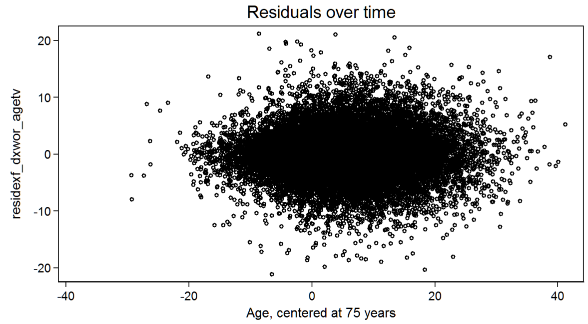
Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~v	1771	56.25349	10.06056	28.61892	83.46247
residexf_d..	1771	.1377792	3.449854	-15.9438	14.82889

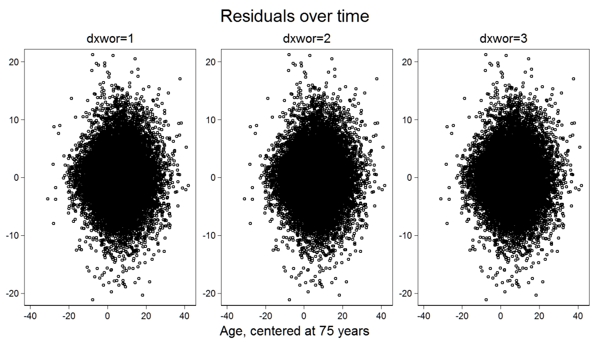
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_dxwo~v	1282	56.08318	8.873707	29.07351	77.253
residexf_d..	1282	.008457	3.450636	-16.05386	20.43851

Diagnostic distributions for exf model







Pseudo-R2: 0.842

Now here is a multiple groups MLM model for exf, the groups being defined by wbho: wbho(0=whit 1=blac 2=hisp). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~t	19088	53.99741	9.362925	23.87976	90.7412
residexf_w~t	19088	-.0001201	3.874047	-20.22599	21.611

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~t	0				
residexf_w~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~t	11887	53.49088	8.77037	30.32535	90.7412
residexf_w~t	11887	-.0875061	4.207614	-20.22599	19.44192

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~t	3249	51.14928	9.466562	23.87976	80.516
residexf_w~t	3249	.2877378	3.587888	-17.315	21.611

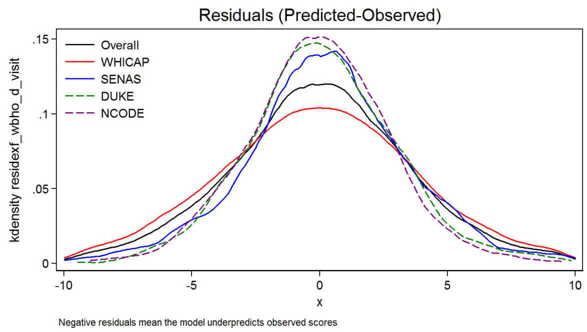
-> data = 11

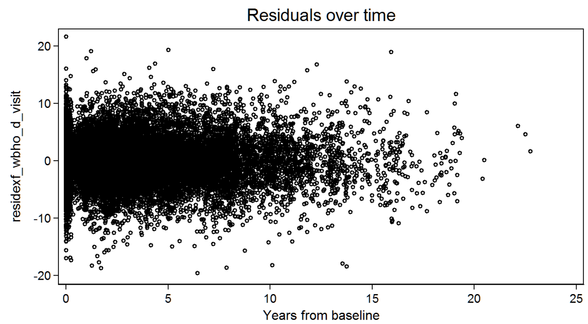
Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~t	1767	56.23939	10.27127	26.50441	83.25782
residexf_w~t	1767	.0989873	3.029278	-15.19043	12.97082

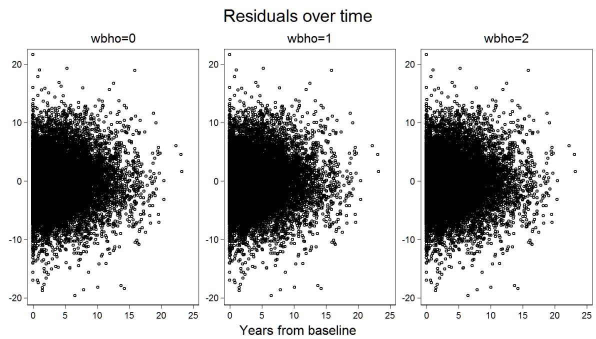
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~t	2185	59.17507	9.197155	26.46106	79.897
residexf_w~t	2185	-.0328963	2.841636	-11.18978	17.19981

Diagnostic distributions for exf model







Pseudo-R2: 0.880

Now here is a multiple groups MLM model for exf, the groups being defined by wbho: wbho(0=whit 1=blac 2=hisp). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~v	19088	53.99681	9.268434	25.287	86.472
residexf_w~v	19088	-.0007188	4.121213	-20.40677	21.541

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~v	0				
residexf_w~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~v	11887	53.41499	8.675892	30.90811	86.472
residexf_w~v	11887	-.1633916	4.440899	-20.40677	20.93127

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~v	3249	51.32421	9.382227	25.287	81.129
residexf_w~v	3249	.4626663	3.907213	-18.80369	21.541

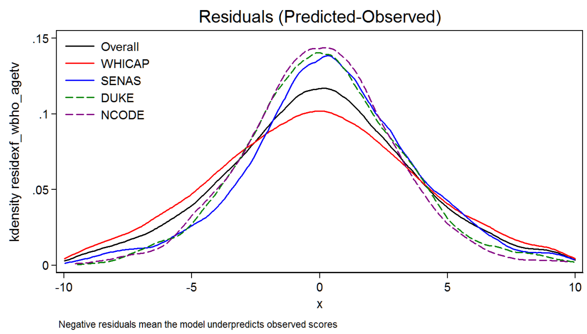
-> data = 11

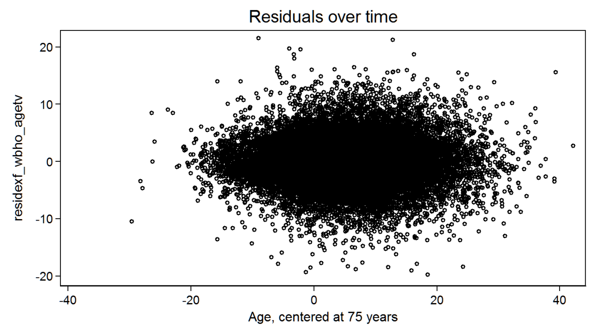
Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~v	1767	56.3494	10.19835	26.13779	84.08077
residexf_w~v	1767	.2089944	3.288036	-15.29841	15.25438

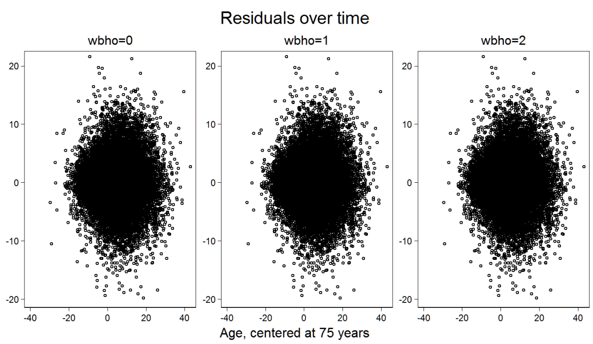
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_wbho~v	2185	59.2336	9.03946	27.64119	80.547
residexf_w~v	2185	.0256386	3.026247	-12.99385	16.70926

Diagnostic distributions for exf model







Pseudo-R2: 0.863

Now here is a multiple groups MLM model for exf, the groups being defined by female: female(0=mal 1=fem). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~t	19485	53.98515	9.34346	21.68419	86.93401
residexf_f~t	19485	-.0002495	3.814695	-20.34874	20.919

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~t	0				
residexf_f~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~t	12029	53.59697	8.820342	29.06065	86.93401
residexf_f~t	12029	.0001502	4.113233	-20.34874	18.82556

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~t	3400	50.99701	9.40781	21.68419	78.844
residexf_f~t	3400	.2007403	3.530968	-18.193	20.919

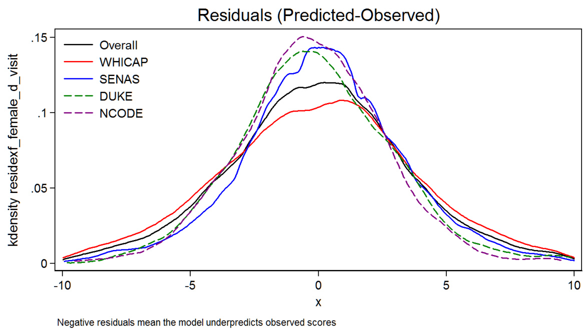
-> data = 11

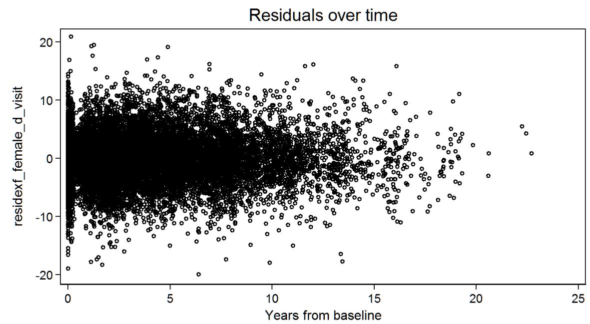
Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~t	1771	56.00438	10.12347	25.95942	82.25496
residexf_f~t	1771	-.111338	3.202065	-15.29884	14.15786

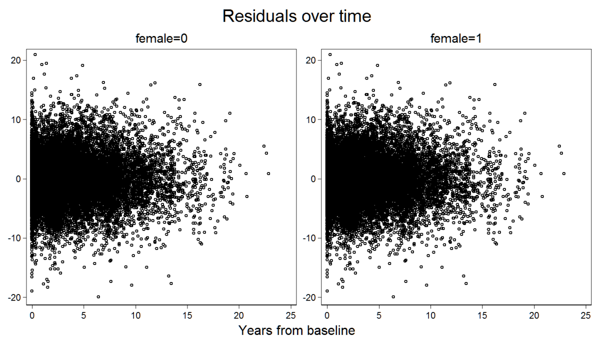
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~t	2285	58.90988	9.076333	27.42114	79.805
residexf_f~t	2285	-.2153202	2.902403	-12.70113	17.16009

Diagnostic distributions for exf model







Pseudo-R2: 0.884

Now here is a multiple groups MLM model for exf, the groups being defined by female: female(0=mal 1=fem). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~v	19485	53.98574	9.248698	24.92149	87.398
residexf_f~v	19485	.0003374	4.07484	-20.5853	21.584

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~v	0				
residexf_f~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~v	12029	53.52653	8.703179	30.53486	87.398
residexf_f~v	12029	-.0702959	4.373058	-20.5853	20.07

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~v	3400	51.15678	9.330158	25.367	80.416
residexf_f~v	3400	.3605169	3.87111	-20.374	21.584

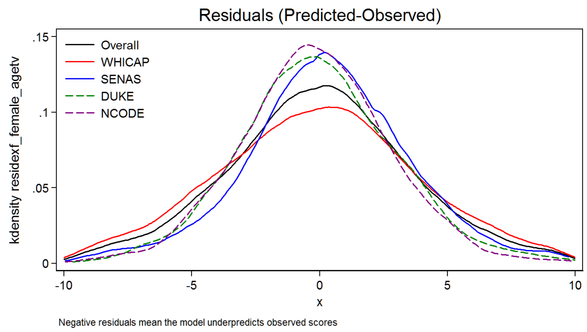
-> data = 11

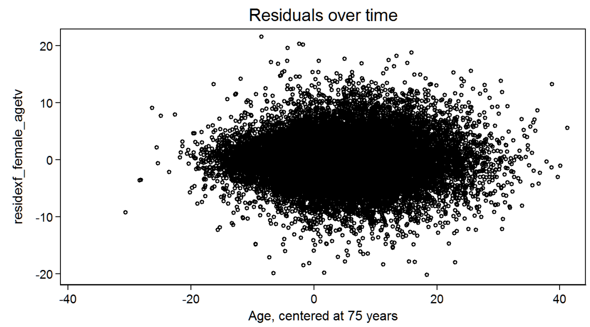
Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~v	1771	56.11086	10.12322	24.92149	83.53894
residexf_f~v	1771	-.004854	3.366455	-15.36347	15.23901

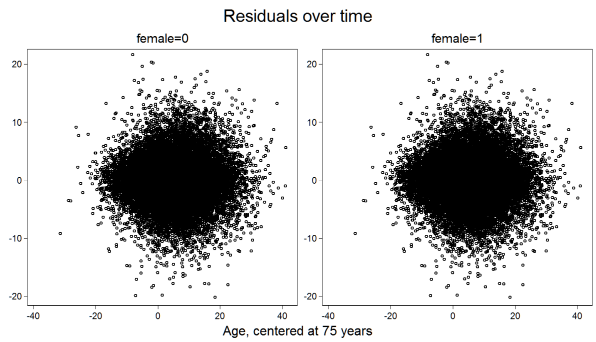
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pyexf_fema~v	2285	58.96547	8.972624	28.17134	80.349
residexf_f~v	2285	-.159736	3.099676	-14.92429	17.46207

Diagnostic distributions for exf model







Pseudo-R2: 0.866

Now here is a multiple groups MLM model for lan, the groups being defined by nogrp: . The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~t	19637	48.48405	10.41276	8.908831	78.99034
residlan_n~t	19637	.0000343	3.333506	-23.15058	24.569

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~t	0				
residlan_n~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~t	12068	45.16355	9.33918	8.908831	76.64657
residlan_n~t	12068	.1509094	3.408766	-16.5569	24.569

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~t	3505	50.06918	9.292711	13.496	78.53912
residlan_n~t	3505	-.1811538	2.907137	-23.15058	18.68694

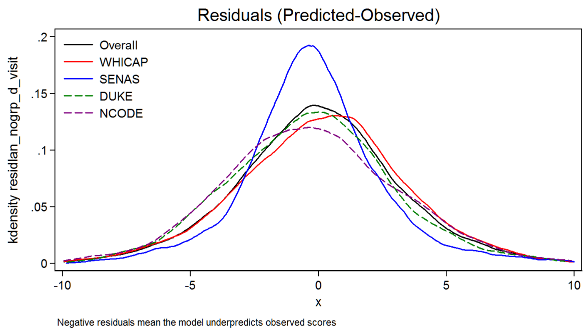
-> data = 11

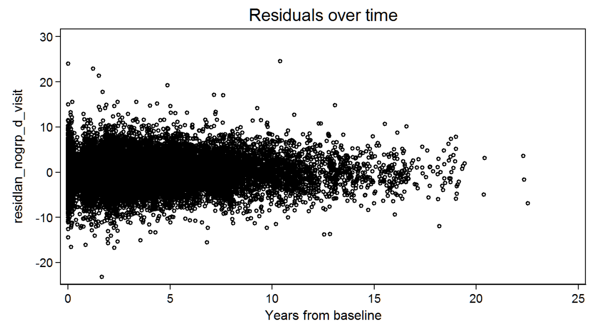
Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~t	1771	55.55287	10.62286	16.36954	78.99034
residlan_n~t	1771	-.3118625	3.269223	-12.27892	12.8136

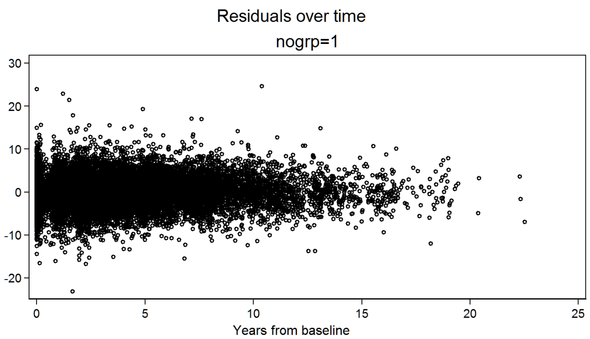
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~t	2293	58.07713	7.613594	29.25186	75.07371
residlan_n~t	2293	-.2761658	3.539686	-12.14178	24.31667

Diagnostic distributions for lan model







Pseudo-R2: 0.920

Now here is a multiple groups MLM model for lan, the groups being defined by nogrp: . The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~v	19637	48.48251	10.3553	10.629	79.45054
residlan_n~v	19637	-.0015072	3.546709	-25.86814	27.22651

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~v	0				
residlan_n~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~v	12068	45.12969	9.27852	10.629	76.388
residlan_n~v	12068	.1170514	3.615518	-18.2385	27.063

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~v	3505	50.17607	9.174274	15.16	77.215
residlan_n~v	3505	-.0742686	3.202156	-25.86814	21.45715

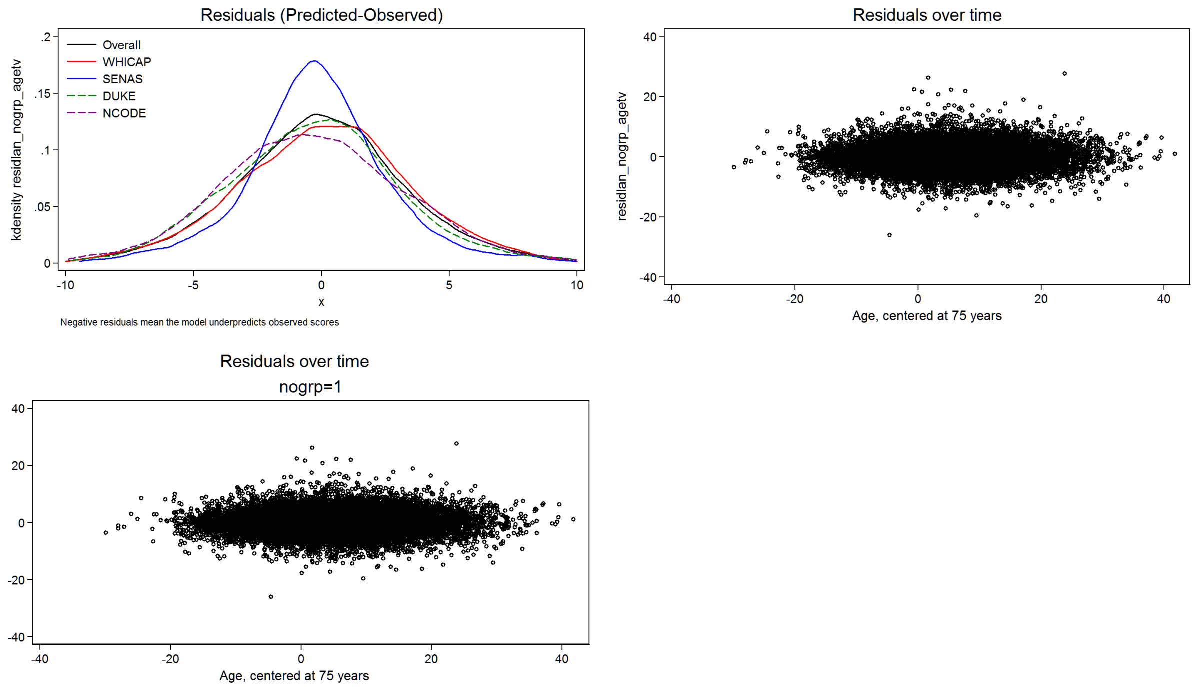
-> data = 11

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~v	1771	55.58172	10.54677	17.50984	79.45054
residlan_n~v	1771	-.283017	3.476044	-14.01049	14.00838

-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_nogr~v	2293	58.05646	7.525396	29.87423	76.09767
residlan_n~v	2293	-.2968334	3.702516	-12.34852	27.22651

Diagnostic distributions for lan model



Pseudo-R2: 0.909

Now here is a multiple groups MLM model for lan, the groups being defined by data: data(9=whic 10=SENA 11=DUKE 12=ncod). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_data~t	19637	48.48386	10.46003	9.72582	81.24856
residlan_d~t	19637	-.0001511	3.32326	-18.4544	25.801

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_data~t	0				
residlan_d~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_data~t	12068	45.01258	9.157767	9.72582	75.40195
residlan_d~t	12068	-.0000644	3.583575	-16.736	25.801

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_data~t	3505	50.24976	9.585727	13.062	79.68108
residlan_d~t	3505	-.0005782	2.348102	-18.4544	11.0856

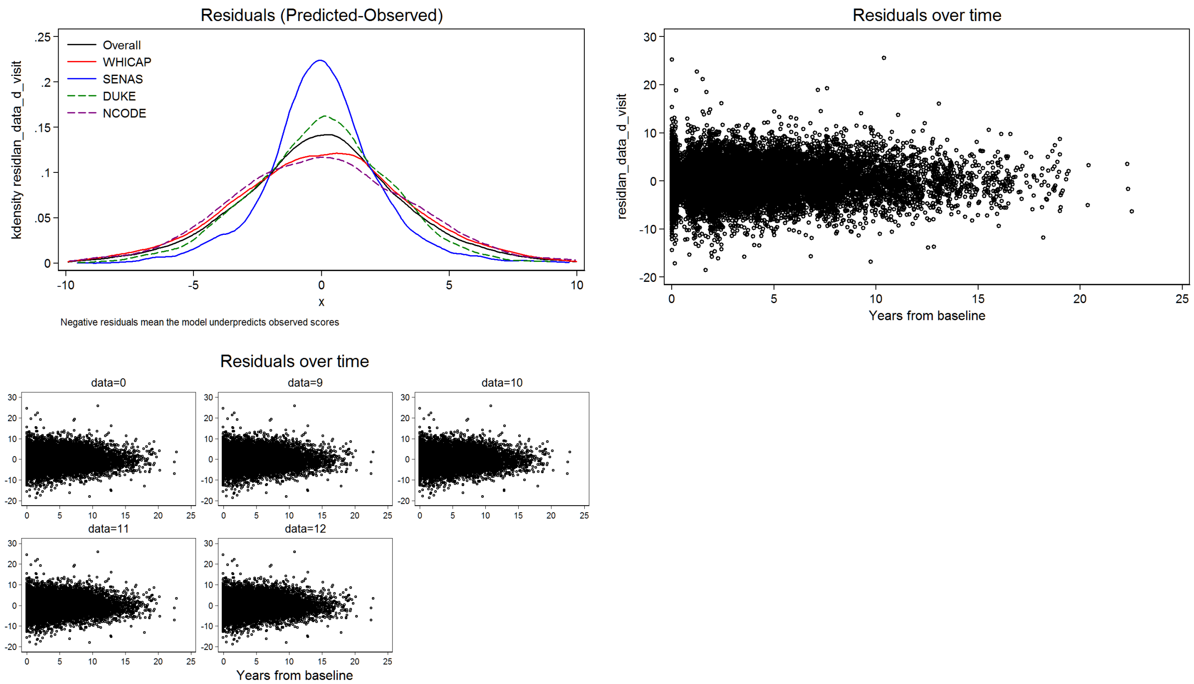
-> data = 11

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_data~t	1771	55.86429	10.97336	14.78592	81.24856
residlan_d~t	1771	-.0004487	2.721198	-9.523821	10.15596

-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_data~t	2293	58.35357	7.38918	31.0034	75.06241
residlan_d~t	2293	.0002755	3.585793	-12.21288	25.29885

Diagnostic distributions for lan model

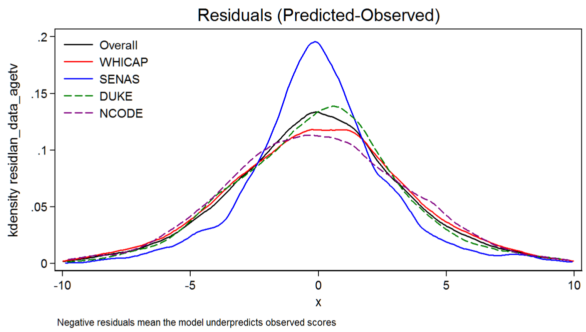


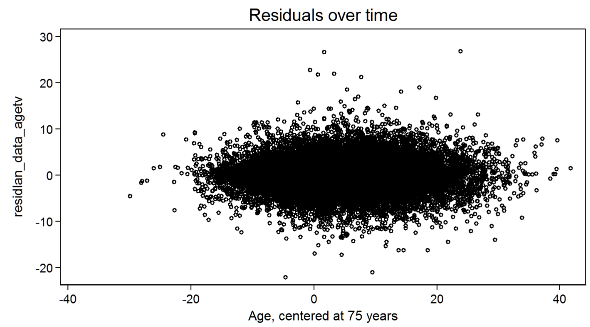
Pseudo-R2: 0.920

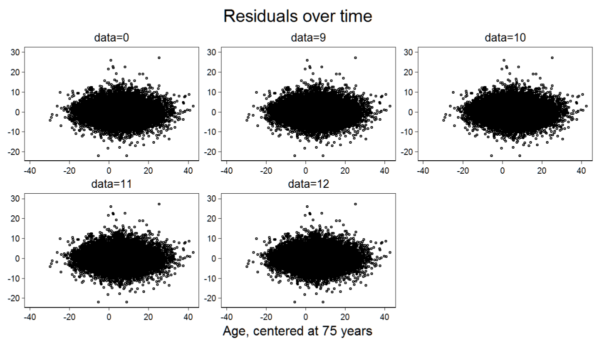
Now here is a multiple groups MLM model for lan, the groups being defined by data: data(9=whic 10=SENA 11=DUKE 12=ncod). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pylan_data~v |     19637    48.48428    10.38376     10.306   79.30823
residlan_d~v |     19637    .0002641    3.523659  -22.06289     27.179

----------------------------------------------------------------------------
-> data = 0

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pylan_data~v |         0
residlan_d~v |         0

----------------------------------------------------------------------------
-> data = 9

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pylan_data~v |     12068    45.01306    9.139089     10.306      75.88
residlan_d~v |     12068    .0004152    3.687493  -20.15287     27.179

----------------------------------------------------------------------------
-> data = 10

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pylan_data~v |      3505    50.25006     9.28322     16.055   78.11167
residlan_d~v |      3505   -.0002692    2.926778  -22.06289   18.02394

----------------------------------------------------------------------------
-> data = 11

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pylan_data~v |      1771    55.86617    10.81249     14.446   79.30823
residlan_d~v |      1771    .0014329    3.262629  -11.51235   12.65266

----------------------------------------------------------------------------
-> data = 12

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pylan_data~v |      2293    58.35267    7.363635   30.99161   75.02409
residlan_d~v |      2293   -.0006188    3.669666    -12.451   26.60499
```

Diagnostic distributions for Ian model







Pseudo-R2: 0.910

Now here is a multiple groups MLM model for lan, the groups being defined by dxwor: dxwor(1=nor 2=mci 3=ade). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~t	17586	47.55828	10.27496	9.363	78.93726
residlan_dx~	17586	.0002306	3.431977	-20.38978	26.719

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~t	0				
residlan_dx~	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~t	12068	45.13669	9.392055	9.363	76.31351
residlan_dx~	12068	.1240484	3.489554	-16.10494	26.719

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~t	2457	49.48321	9.704082	13.696	77.7739
residlan_dx~	2457	-.1475261	3.208792	-20.38978	15.51742

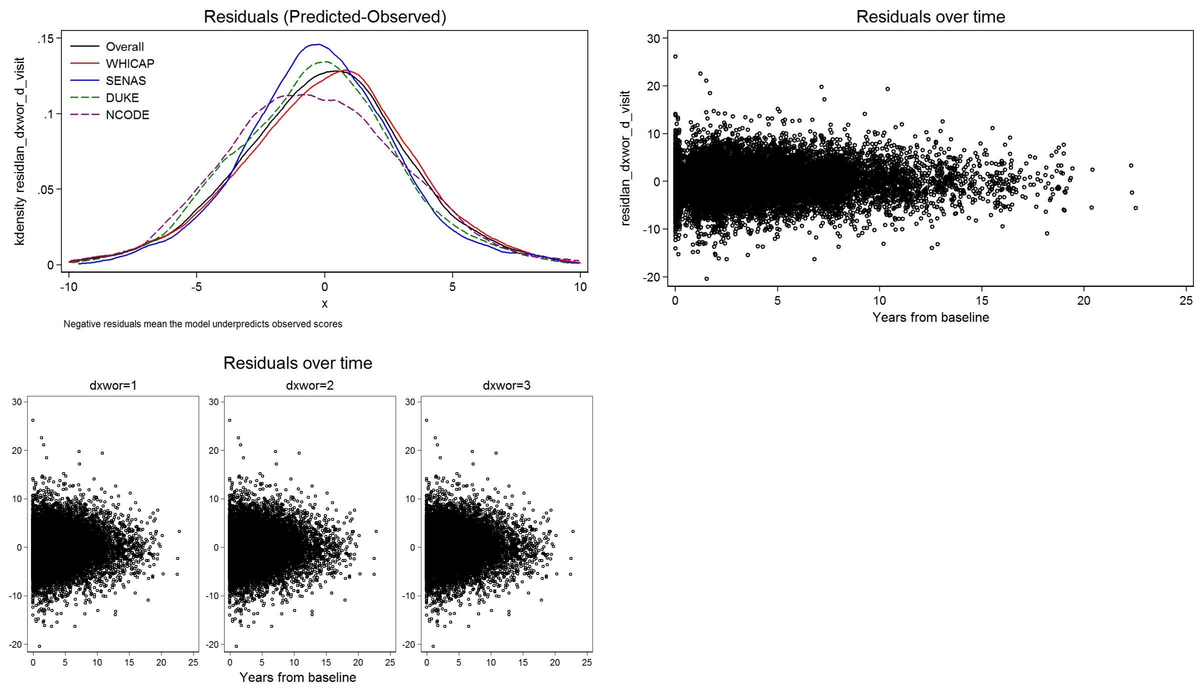
-> data = 11

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~t	1771	55.5118	10.70063	16.6687	78.93726
residlan_dx~	1771	-.3529365	3.210689	-11.34857	11.779

-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~t	1290	55.62688	7.988425	29.15758	75.02823
residlan_dx~	1290	-.3918135	3.522381	-13.53641	19.4499

Diagnostic distributions for lan model



Pseudo-R2: 0.911

Now here is a multiple groups MLM model for lan, the groups being defined by dxwor: dxwor(1=nor 2=mci 3=ade). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~v	17586	47.55828	10.18444	9.081	79.22016
residlan_d..	17586	.0002329	3.701672	-25.54645	27.412

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~v	0				
residlan_d..	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~v	12068	45.1162	9.283548	9.081	76.293
residlan_d..	12068	.1035553	3.718905	-22.91339	27.412

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~v	2457	49.53288	9.546753	13.544	77.559
residlan_d..	2457	-.0978564	3.72653	-25.54645	21.60262

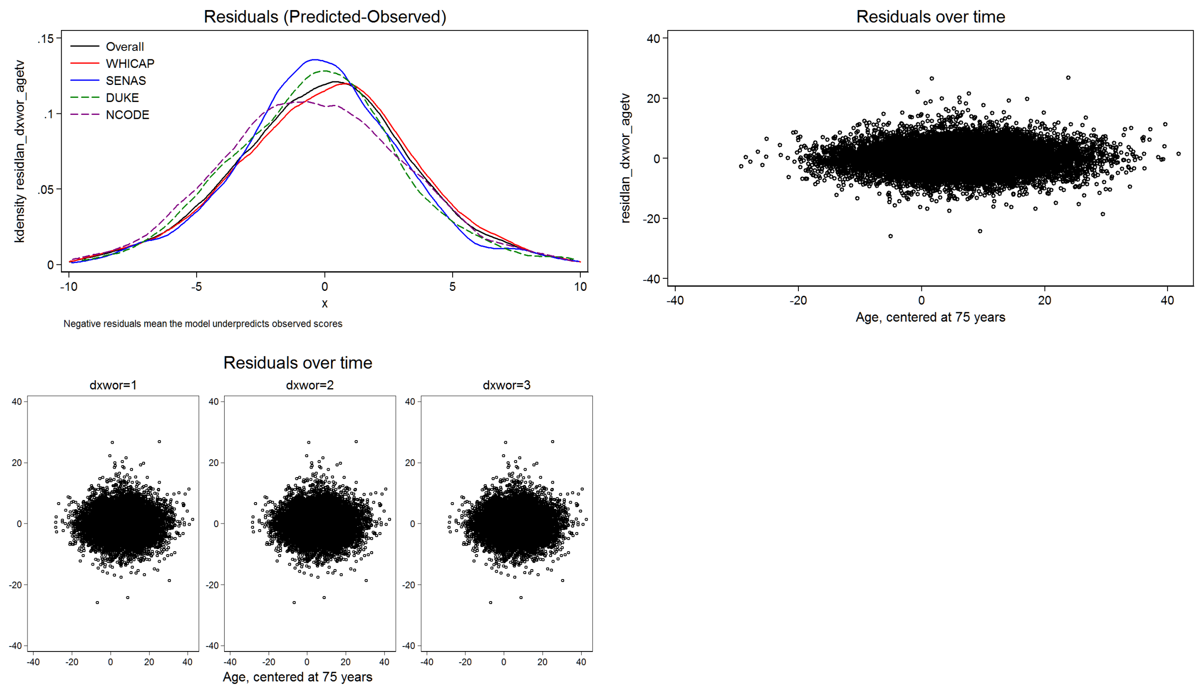
-> data = 11

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~v	1771	55.56591	10.638	16.06219	79.22016
residlan_d..	1771	-.298829	3.474762	-14.74741	14.57941

-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_dxwo~v	1290	55.64974	7.891005	30.21701	75.54302
residlan_d..	1290	-.368954	3.747502	-13.1082	26.97223

Diagnostic distributions for lan model



Pseudo-R2: 0.897

Now here is a multiple groups MLM model for lan, the groups being defined by wbho: wbho(0=whit 1=blac 2=hisp). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~t	19233	48.48768	10.42528	10.75551	79.64178
residlan_w~t	19233	-.0000303	3.356108	-21.23558	26.457

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~t	0				
residlan_w~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~t	11925	45.11597	9.277581	10.75551	77.7417
residlan_w~t	11925	.10702	3.483438	-16.825	26.457

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~t	3348	50.19499	9.241054	15.223	79.19582
residlan_w~t	3348	-.2234853	2.872677	-21.23558	15.49557

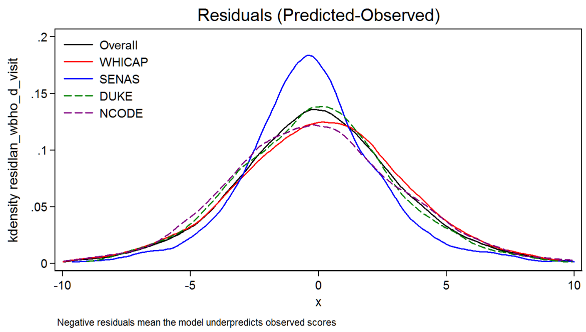
-> data = 11

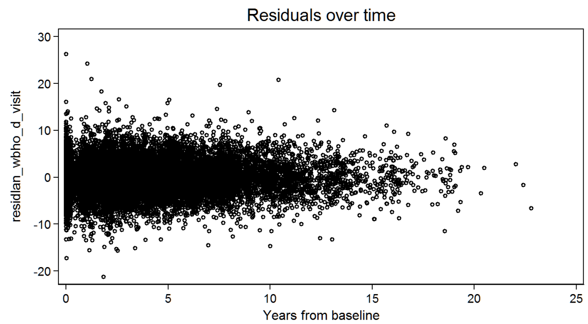
Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~t	1767	55.75708	10.63306	17.19236	79.64178
residlan_w~t	1767	-.1304233	3.123349	-12.19065	11.89457

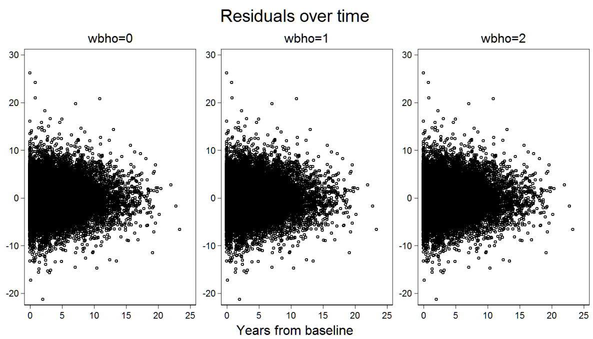
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~t	2193	58.35849	7.583298	28.37531	75.50192
residlan_w~t	2193	-.1359374	3.490498	-12.33915	21.31484

Diagnostic distributions for lan model







Pseudo-R2: 0.918

Now here is a multiple groups MLM model for lan, the groups being defined by wbho: wbho(0=whit 1=blac 2=hisp). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~v	19233	48.48879	10.36407	11.261	79.37591
residlan_w~v	19233	.0010717	3.585404	-24.26501	28.321

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~v	0				
residlan_w~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~v	11925	45.06707	9.229385	11.261	76.217
residlan_w~v	11925	.0581222	3.688368	-20.33618	28.321

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~v	3348	50.33907	9.085848	16.865	77.55781
residlan_w~v	3348	-.0793974	3.211798	-24.26501	20.15549

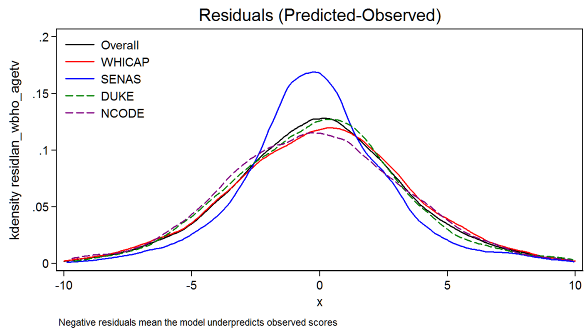
-> data = 11

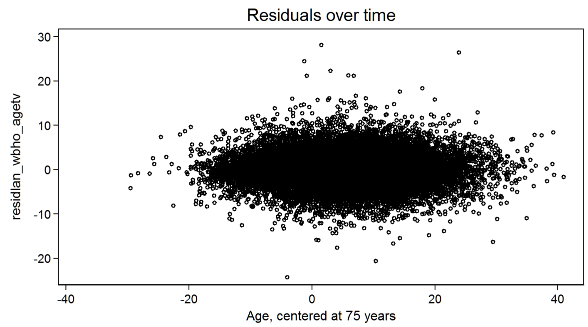
Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~v	1767	55.82337	10.45721	18.76481	79.37591
residlan_w~v	1767	-.0641379	3.440826	-12.32574	14.52148

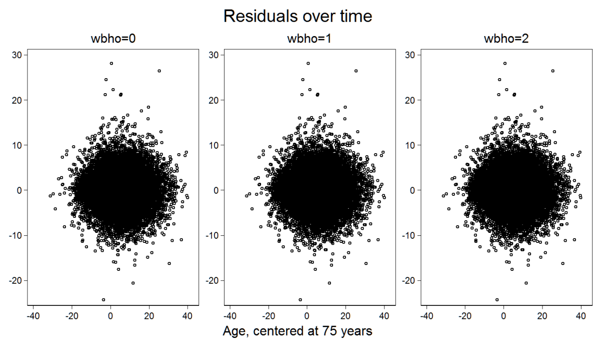
-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_wbho~v	2193	58.36066	7.423685	29.55256	75.88799
residlan_w~v	2193	-.1337629	3.6668	-12.18591	27.0103

Diagnostic distributions for lan model







Pseudo-R2: 0.906

Now here is a multiple groups MLM model for lan, the groups being defined by female: female(0=mal 1=fem). The timescale modeled is time in study. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~t	19637	48.48394	10.41613	8.81539	79.04462
residlan_f~t	19637	-.0000728	3.327288	-22.04156	24.876

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~t	0				
residlan_f~t	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~t	12068	45.16168	9.343869	8.81539	76.82059
residlan_f~t	12068	.1490335	3.406132	-16.34912	24.876

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~t	3505	50.07404	9.291112	13.236	78.46102
residlan_f~t	3505	-.1762936	2.889539	-22.04156	17.2416

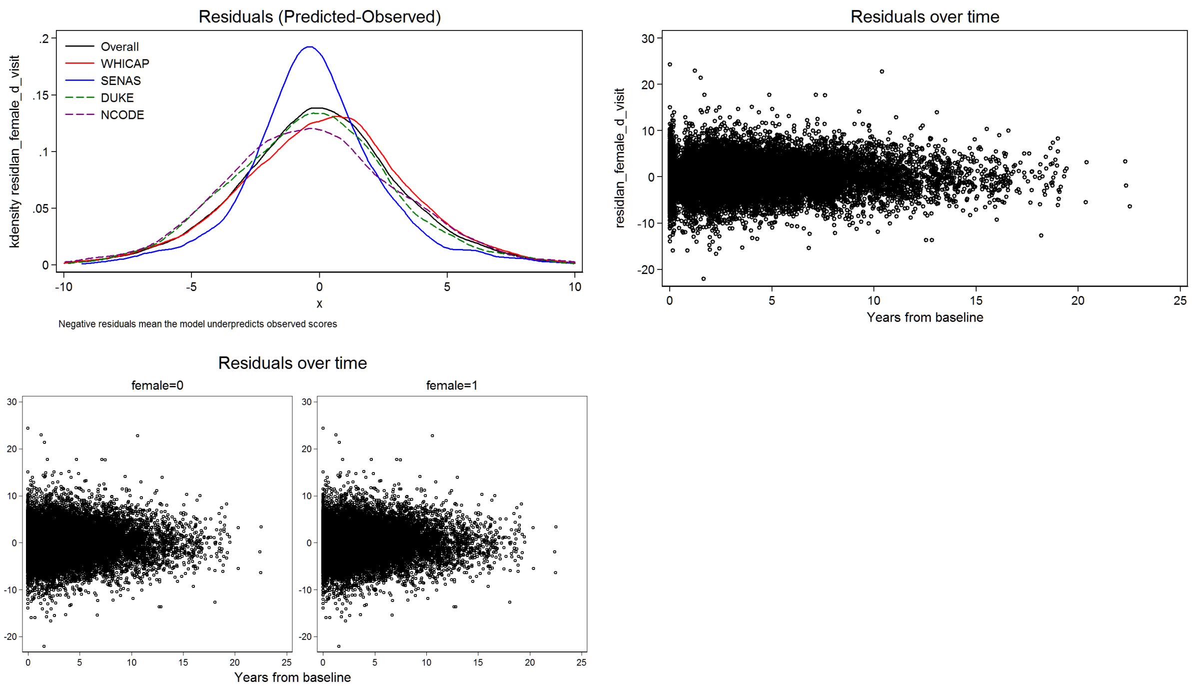
-> data = 11

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~t	1771	55.55564	10.62516	16.13248	79.04462
residlan_f~t	1771	-.309098	3.255304	-11.95966	12.52517

-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~t	2293	58.07652	7.616204	29.04566	75.08044
residlan_f~t	2293	-.276774	3.535784	-12.17993	22.52975

Diagnostic distributions for lan model



Pseudo-R2: 0.920

Now here is a multiple groups MLM model for lan, the groups being defined by female: female(0=mal 1=fem). The timescale modeled is age. Means of random intercepts and slopes are allowed to vary by group. Everything else is the same across group.

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~v	19637	48.48379	10.35724	10.485	79.46381
residlan_f~v	19637	-.0002177	3.542846	-25.34446	27.61969

-> data = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~v	0				
residlan_f~v	0				

-> data = 9

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~v	12068	45.13185	9.282789	10.485	76.322
residlan_f~v	12068	.119209	3.611403	-16.98089	27.133

-> data = 10

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~v	3505	50.17761	9.171993	14.809	77.389
residlan_f~v	3505	-.0727206	3.195789	-25.34446	21.06373

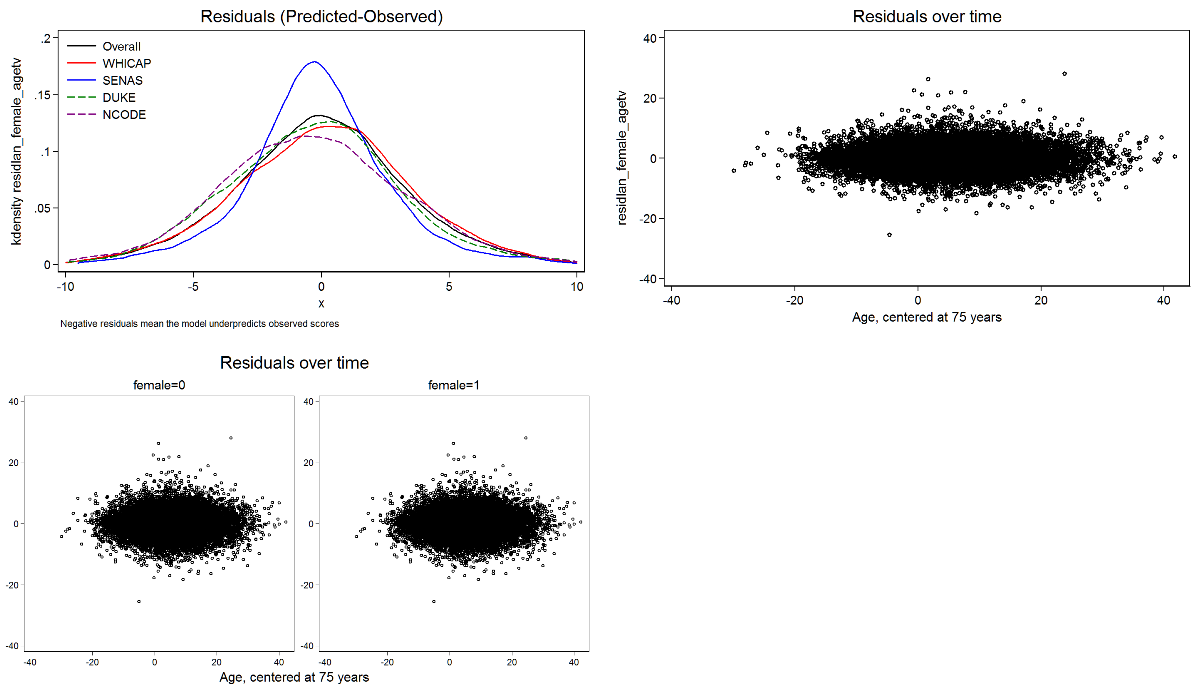
-> data = 11

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~v	1771	55.58378	10.54799	17.30831	79.46381
residlan_f~v	1771	-.2809581	3.473922	-13.59285	14.11732

-> data = 12

Variable	Obs	Mean	Std. Dev.	Min	Max
pylan_fema~v	2293	58.05219	7.531966	29.86362	76.08663
residlan_f~v	2293	-.3011025	3.70137	-12.42631	27.61969

Diagnostic distributions for lan model



Pseudo-R2: 0.909