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HCAP Standardization, Normalization, and Thresholding

(With adjustment for race/ethnicity)

Objective. This document continues analyses of US Health and Retirement Study Harmonized Cognitive Assessment Protocol (HCAP) data.
Sample. The HRS/HCAP sample was stratified into a norming sample and an excluded-from-norming sample (described elsewhere). The norming sample included 1787 persons, the excluded sample 1560 persons.
Measures and procedures. Estimates of cognitive performance, including factor score estimates (plausible values and expected a posteriori scores) assessing memory, executive, language, visuospatial, and global cognitive performance (described elsewhere) were standardized and normalized with respect to the effects seen in the normative sample attributable to age, sex, education level, and race/ethnicity. The age effect was modeled using restricted cubic splines, whereas all others predictors were treated as linear predictors. (We evaluated and rejected alternative parameterizations for education, including a priori defined categorization, restricted cubic splines, and multiple linear spline functions). Adjustment for sociodemographics was accomplished with linear regression. Residuals were normalized to a T score distribution and used as a demographically-adjusted measure of cognitive performance. The resulting scores have a mean of 50 and standard deviation of 10 in a hypothetical population with distribution of similar to our norming sample. As T scores, any participant scoring below 36 has a level of performance about 1.5 standard deviations below what would be expected for someone of their .
Results. We find that 7 % of the norming sample is impaired on a global composite of performance on the HCAP tests (GCP[PV]), and that 30 % of those excluded from the norming sample are so impaired. Overall in the HRS/HCAP sample, 18 % are impaired on this measure of cognition. This prevalence in the norming sample is determined by where we have decided to place the threshold, and the prevalence in the non-norming sample a reflection of how well our selections out of the norming sample identify persons with cognitive impairment. If we take performance on two or more sub-domains (memory, executive functioning, language and fluency, visuospatial, orientation[1]) as a indicator of possible dementia, we have 7 % of the norming sample falling into this category, 26 % of those excluded from the norming sample are in this category, and 16 % are impaired on this measure of cognition in the HRS/HCAP overall. The resulting normalized and standardized scores are only correlated with to the extent that these factors are correlated with membership in the norming sample. Within the norming sample, the normalized and standardized scores are not correlated with these participant characteristics. **Conclusions**. We recommend using normalized factor scores, standardized with respect to sociodemographics, and derived from single domain models. For most applications scores derived as plausible values are preferrable to a posteriori scores.

[1]Orientation was not standardized and normalized, due to extremely skewed distribution. We use just count of 10 orientation to time and place questions as the measure of orientation. Cut-offs for impairment are defined in the norming sample.

Contents

Note on language

Derived scores are **Standardized, adjusted, normalized scores**

Normalized - taking the rank-based percentile normalization transformation (Blom transformation) of HCAP normative sample scores

Adjusted - taking the residuals from regressions of normalized scores on demographics

Standardized - scaling residuals according to the standard error of estimate from the regression model

I may be inconsistent but wanted to get it down one place at least.

1 Source data

Making use of three data files:

Using the factor score estimates from the `CFA-HCAP` workflow, including both Bayesian plausible values and expected a posteriori (EAP) factor score estimates.

Important Note: The norming sample has been modified as provided by Ryan McCammon. It has been modified to exclude persons with a MMSE score of less than 19, or missing. An additional 0 are excluded.

Using an HRS sample data file compiled in the A1 report (February 2019)

Using a data file with HCAP participant's level of education provided by Ryan.

Using weights `hcap2016_weight_20201222.dta` Using a data file with self-reported memory worsening (PD102) from the HRS 2016 Core

2 Normalizing, adjusting, and standardizing cognition scores

The estimated factor scores, from the factor analysis work, are on an arbitrary scale. We desired to produce scores that adjusted for the effect of demographic variables in the norming sample and were on a more interpretable scale.

We accomplish this by placing the scores on a T-score metric. A T-score metric has a mean of 50 and standard deviation of 10. T-score metrics are often used in health research settings.

We use a regression adjustment procedure to account for the effect of demographic variables on test scores.

We use a rank-based normalizing transformation to accomplish two goals. First, the transformation limits the possibility of obtaining out-of-range values from the adjustment procedure. Second, the normalizing transformation makes it easy to identify persons falling below a fixed threshold (in our case, 1.5 SD, or a T score of 35) below the mean in the norming sample.

These are the steps in generating standardized scores:

1. **Raw score is rank-normalized** - Each factor score estimate is subject to a rank-based normalizing transformation (Blom transformation) within the sample of persons selected for generating norms (the norming sample).
    - **Model back-translation of rank-normalized and raw scores in norming sample.** I regress the Blom-transformed score back on to the original factor score estimate using a restricted cubic spline with four knots. This regression model is used to generate Blom transformed factor scores in the norming sample **and** the non-norming sample and any future observation(s). This step is necessary because the Blom transformation is dependent upon the sample in which it is derived. By generating this regression model, I can produce Blom-transformed scores in any future sample that reflect the distribution of scores observed in the norming sample, regardless of the distribution of scores in the new sample. Using restricted cubic splines allows a flexible curve shape and typically very high predictive accuracy (e.g., for memory plausible values the model r-squared is 0.9995, both have means of 0 and standard deviations of 0.999, and the plausible value range is from -3.42 to +3.42 and the predicted range is from -3.48 to 3.30)
    - The reason for the Blom transformation is: In the next step I will be regressing (Blom-transformed) observed score performance on demographic variables. The normalizing transformation helps make sure that the predicted values from this regression model do not lead to implausible values
2. **Regression adjustment**. Regress each Blom-transformed factor score (separately) on age, sex, "race/ethnicity, " and educational attainment.
    - **Age** is modeled as a continuous predictor using restricted cubic splines with knots at 70, 78, 86, 94 (on a range of 65-103). These knots were chosen ad hoc using an empirical process, and fall at the 25th, 60th, 88th, and 99th percentiles of `hcapage`.
        - The somewhat unusual choice of knot locations is driven by the cross-sectional re-

lationship between age and cognitive test score. The shape is distinctly hockey-stick-shaped relationship where a nearly linear performance-age relationship is seen through most of the age range (older people performing worse) but then the direction shifts and older people perform better. Consider the relationship for general cognition: . This effect is likely caused by the retention of only the most cognitively-intact persons among the oldest-old following our exclusions from the norming sample. The knot choice is meant to get more parameters estimated in the region where the age-performance relationship is more dynamic.

- **Sex** is modeled as male and female using a dummy variable
- **Race and ethnicity** is coarsely modeled with two dummy variables, one indicating Black or African-American, the other Hispanic ethnicty.
- **Education** is included as a continuous predcitor (0-17)
  - I compared different ways for controlling for education
    - A continuous variable (0-17)
    - A categorical predictor identifying the following groups defined in terms of years of completed schooling: 0 \1-8 \9-11 \12 \13-15 \16 \17 and higher.
    - A restricted cubic spline with 4 knots placed at default locations
    - A set of models including two linear splines with knots placed from 4 to 15 years
  - I regressed the estimated GCP (EAP), GCP (PV), MEM (EAP), LFL (EAP), `vdori1`, `vdvis1`, and `h1rmseotal` on each of the above representations of education. For all except `vdori1` and `h1rmseotal` the model with the lowest BIC was the continuous linear function of number of years of education. Orientation favored two linear splines with a knot at 13 years of education, and the MMSE preferred the restricted cubic splines.
  - Based on the predominance of evidence, I decided to keep education as a continuous predictor.
- **Main effects and two-way interactions** are included. The only two-way interaction that is not included is `black*hisp`, because in sample there are no persons both Black and Hispanic.

3. **Compute an *expected score*** for every combination of age, sex, education level, and race/ethnicity, using the results of the regression model.
4. **Compute an *adjusted score*** for each person as their observed score minus their expected score given age, sex, education level, and race/ethnicity.
5. **Compute an *adjusted, standardized*** score as their observed minus expected score, all divided by the *standard error of estimate* from the regression model, which is the overall sample standard deviation of the raw score multiplied by $\sqrt{1-R^2}$ where R^2 is the r-squared from the adjustment model in the norming sample.

6. **Compute a *adjusted, standardized, and scaled*** score as their *adjusted, standardized* score multiplied by 10, plus 50, and rounded to the nearest integer. This places the standardized score on a roughly T-score metric.
   - **Rounding** We round all factor scores - after transformation - to the nearest whole number, which provides two digits precision. [2]
7. **The 7.5th percentile** for a T score is a value of 35.6. Since we are rounding to the nearest whole number, a T-score scaled factor score of 36 or higher will be considered above threshold, and a factor score of 35 or below will be considered below threshold.

[2] This should be justified given standard error of measurement for factor scores.

2.1 Key to various scores and tests used in normalization and standardization

Domain	Description
Memory	Memory is a factor score estimated from delayed recall and recognition tasks of episodic memory (10 word delayed recall, 3 word delayed recall, Logical Memory II, story recall (EBMT), 10 word recognition and Logical Memory recognition).
Executive functioning	Executive functioning is a factor score estimated from attention and speed tasks, set shifting tasks, and logical reasoning tasks, including Standard Progressive Matrices, HRS number series, trail making (part A & B), Symbol Digit Modalities Test, Backwards spelling, Backwards counting, and letter cancellation.
Language, fluency	Language, fluency is a factor score estimated from animal naming, object naming (two objects from TICS), two objects from MMSE, objects from the CSI-D, sentence writing, and read and follow command.
Orientation	Orientation is not a factor score, but is the observed performance on 10 orientation to time and place items from the Mini-Mental State Examination. For ease of interpretation the observed score is placed on a T-score metric and standardized in the HCAP normative sample. No Bayesian plausible values are estimated for this score.
Visuospatial	Visuospatial is not a factor score, but is the observed performance on a constructional praxis (immediate) task. For ease of interpretation the observed score is placed on a T-score metric and standardized in the HCAP normative sample. No Bayesian plausible values are estimated for this score.
General cognitive performance	The GCP (General cognitive performance) score is a second order factor score estimate derived from a model with first-order factors for orientation, memory, executive functioning, language/fluency, and visuospatial functioning.

Source estimate	Domain	Source model	Type of estimate
gmemm1	Memory	Second order	PV
memm1		Single factor	PV
gmem		Second order	EAP
mem		Single factor	EAP
gexfm1	Executive Fxn	Second order	PV
exfm1		Single factor	PV
gexf		Second order	EAP
exf		Single factor	EAP
glflm1	Language, fluency	Second order	PV
lflm1		Single factor	PV
glfl		Second order	EAP
lfl		Single factor	EAP
vdori1	Orientation	Sum of correct responses	NA
vdvis1	Visuospatial	CERAD constructional praxis	NA
gcpm1	Global	Second order	PV
gcp		Second order	EAP
h1rmsetotal		MMSE total score	NA

Notes: EAP, Expected a posteriori; NA, Not applicable; PV, Bayesian plausible value.

I will append a `T` to the front of a source estimate (e.g., `Tgmemm1`) to indicate the T-score (mean 50, sd 10) standardized and normalized estimate. These variables have been rank normalized, adjusted for demographics, and standardized on a T-score metric (in the normative sample).

I will append a `IMPAIRED` to the front of a source estimate (e.g., `IMPAIRED_gmemm1`) to identify dummy variables that indicate if a person has scored less than 36 on the normalized, adjusted, and standardized estimate.

2.2 Some statistics in the normative sample

```
. su `Tlist´ if normexcl==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Tgmemm1	1,787	49.99236	9.943624	17.29197	82.47731
Tmemm1	1,787	49.88824	9.986352	12.20103	82.92719
Tgmem	1,787	49.81238	9.903523	14.31529	87.08157
Tmem	1,787	49.8853	9.913377	15.51777	81.9619
Tgexfm1	1,787	49.83914	9.949604	12.98327	92.3077
Texfm1	1,786	49.78591	9.903515	15.52633	83.24976
Tgexf	1,787	49.76783	9.870728	12.82936	88.95788
Texf	1,786	49.78573	9.86297	13.62295	88.55615
Tglflm1	1,787	49.65112	9.936679	13.96208	89.29607
Tlflm1	1,787	49.85247	9.972104	16.32137	81.43411
Tglfl	1,787	49.73899	9.915508	16.63568	87.59777
Tlfl	1,787	49.89143	9.922824	17.63156	80.80674
Tvdvis1	1,784	49.60828	10.02776	12.38522	82.22475
Tgcpm1	1,787	49.72299	9.915295	18.03143	82.99464
Tgcp	1,787	49.73131	9.911813	15.53	88.90277
Th1rmsetotal	1,787	49.78532	9.945405	17.58554	83.12962

2.3 Some statistics in both samples

	normexcl=0		normexcl=1	
Estimate	Mean	SD	Mean	SD
`Tgmemm1`	50.0	(9.9)	42.6	(13.5)
`Tmemm1`	50.0	(10.0)	44.1	(12.4)
`Tgmem`	50.0	(9.8)	41.6	(14.0)
`Tmem`	50.0	(9.8)	43.4	(13.0)
`Tgexfm1`	50.0	(9.8)	41.2	(13.2)
`Texfm1`	50.0	(9.8)	42.2	(12.1)
`Tgexf`	50.0	(9.9)	40.6	(13.6)
`Texf`	50.0	(9.9)	41.7	(12.2)
`Tglflm1`	50.0	(9.8)	41.3	(14.4)
`Tlflm1`	50.0	(9.9)	45.5	(12.1)
`Tglfl`	50.0	(9.8)	39.9	(15.5)
`Tlfl`	50.0	(9.9)	44.2	(12.5)
`Tvdvis1`	50.0	(9.6)	46.1	(12.3)
`Tgcpm1`	50.0	(9.8)	41.3	(14.5)
`Tgcp`	50.0	(9.8)	39.8	(15.4)
`Th1rmsetotal`	50.0	(9.8)	41.6	(16.7)

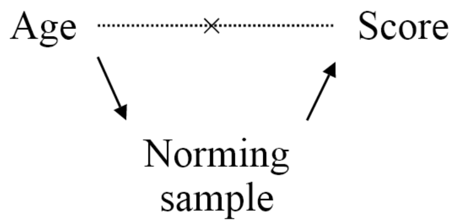
2.3.1 Impairment

Percent impaired (having normalized, adjusted, standardized score less than 36)

Estimate	normexcl=0 %	normexcl=1 %	All HCAP %
IMPAIRED_gmemm1	7.7	28.6	16.2
IMPAIRED_memm1	7.1	24.7	14.2
IMPAIRED_gmem	6.4	30.9	16.3
IMPAIRED_mem	7.3	27.3	15.4
IMPAIRED_gexfm1	6.1	30.0	15.8
IMPAIRED_exfm1	6.3	27.5	14.9
IMPAIRED_gexf	6.5	30.8	16.4
IMPAIRED_exf	6.8	28.3	15.5
IMPAIRED_glflm1	7.0	30.0	16.4
IMPAIRED_lflm1	8.2	21.1	13.4
IMPAIRED_glfl	7.4	32.8	17.7
IMPAIRED_lfl	8.6	22.9	14.4
IMPAIRED_vdvis1	8.0	17.7	11.9
IMPAIRED_gcpm1	6.4	30.2	16.1
IMPAIRED_gcp	7.0	33.3	17.7
IMPAIRED_h1rmsetotal	8.1	30.7	17.3

2.3.2 But are scores related to age?

The normalized, adjusted, and standardized scores is – by construction – not be related to age in the normative sample. This is a consequence of the adjustment procedure. However, the normalized, adjusted and standardized scores may be related to age in the sample excluded from norming, and the HCAP overall. This is because the some correlation of age and test score is caused by the association of age and inclusion in the norming sample. The association between age and test score is indirect, not direct, as a consequence of our design.



Consider that the Spearman correlation of age (limiting to age 65-90) and inclusion in the norming sample is 0.28, and the Spearman correlation of being included in the norming sample and the GCP (plausible value) score (before adjustment, `gcpm1`) is -0.42, then we expect a correlation of the age (and other demographic factor-) adjusted GCP score and age to be no more than $0.28 \times -0.42 =$ -0.12. We actually observe -0.12.

The implication to all this is, if the correlation of the normalized, adjusted, and standardized test scores with age in the overall HCAP sample is lower than what would be desired, the way to increase this is to increase the magnitude of the correlation of age and being included in the norming sample, or increase the magnitude of the correlation of being included in the norming sample and cognitive test performance.

The table below contains means across age group and Spearman rank correlations of the T score and age, but limiting to ages 65 to 90. In parenthesis, I show the Spearman correlation of the unadjusted score with age (also limiting to ages 65-90).

	normexcl=0		normexcl=1		All HCAP	
Estimate	Mean	SD	Mean	SD	Mean	SD
`Tgmemm1`						
1	50	(10)	45	(13)	49	(11)
2	50	(10)	45	(12)	48	(11)
3	50	(10)	43	(14)	47	(12)
4	50	(10)	39	(13)	44	(13)
5	50	(11)	40	(13)	43	(13)
6	51	(7)	40	(15)	41	(14)
7		()	44	(17)	44	(17)
	$r_s = -0.01(-0.23)$		$r_s = -0.17(-0.32)$		$r_s = -0.16(-0.35)$	

`Tmemm1`

1	50 (10)	45 (12)	49 (11)
2	50 (10)	46 (11)	48 (10)
3	50 (10)	45 (11)	48 (11)
4	49 (10)	42 (12)	45 (12)
5	50 (10)	42 (11)	45 (11)
6	52 (11)	42 (15)	44 (15)
7	()	47 (19)	47 (19)
	$r_s = 0.01(-0.22)$	$r_s = -0.13(-0.30)$	$r_s = -0.13(-0.33)$
`Tgmem`			
1	50 (10)	44 (13)	49 (11)
2	50 (9)	44 (12)	48 (11)
3	50 (10)	42 (13)	47 (12)
4	49 (10)	38 (14)	43 (14)
5	51 (11)	39 (13)	42 (14)
6	51 (9)	38 (16)	40 (16)
7	()	44 (19)	44 (19)
	$r_s = 0.00(-0.26)$	$r_s = -0.17(-0.33)$	$r_s = -0.16(-0.37)$
`Tmem`			
1	50 (10)	46 (12)	49 (11)
2	50 (10)	46 (12)	48 (10)
3	50 (10)	44 (12)	48 (11)
4	49 (10)	40 (13)	44 (13)
5	51 (12)	40 (12)	43 (13)
6	51 (10)	41 (15)	42 (15)
7	()	45 (19)	45 (19)
	$r_s = -0.00(-0.23)$	$r_s = -0.17(-0.32)$	$r_s = -0.15(-0.34)$
`Tgexfm1`			
1	50 (10)	43 (12)	49 (11)
2	50 (10)	44 (13)	48 (11)
3	51 (10)	41 (13)	47 (13)
4	50 (9)	39 (13)	44 (13)
5	50 (8)	40 (13)	43 (13)
6	50 (7)	37 (13)	39 (13)
7	()	38 (15)	38 (15)
	$r_s = 0.02(-0.28)$	$r_s = -0.11(-0.31)$	$r_s = -0.14(-0.38)$
`Texfm1`			
1	50 (10)	44 (11)	49 (11)
2	50 (10)	44 (12)	48 (11)
3	50 (10)	42 (13)	47 (12)
4	50 (9)	41 (11)	45 (11)
5	50 (8)	41 (12)	44 (11)

6	50 (9)	39 (13)	40 (13)
7	()	44 (15)	44 (15)
	$r_s = 0.00(-0.27)$	$r_s = -0.09(-0.29)$	$r_s = -0.13(-0.37)$

Tgexf

1	50 (10)	42 (12)	48 (11)
2	50 (10)	43 (13)	48 (11)
3	50 (10)	41 (14)	46 (13)
4	50 (9)	38 (13)	43 (13)
5	50 (8)	39 (13)	42 (13)
6	50 (8)	37 (15)	39 (15)
7	()	41 (15)	41 (15)
	$r_s = 0.01(-0.30)$	$r_s = -0.11(-0.31)$	$r_s = -0.15(-0.39)$

Texf

1	50 (10)	43 (12)	48 (11)
2	50 (10)	44 (13)	48 (11)
3	50 (10)	41 (13)	46 (12)
4	50 (9)	40 (12)	44 (12)
5	50 (8)	41 (12)	44 (11)
6	50 (8)	39 (13)	40 (13)
7	()	45 (11)	45 (11)
	$r_s = 0.01(-0.30)$	$r_s = -0.08(-0.30)$	$r_s = -0.13(-0.39)$

Tglflm1

1	50 (10)	43 (13)	48 (11)
2	50 (10)	44 (13)	48 (11)
3	50 (10)	42 (14)	46 (13)
4	50 (10)	39 (15)	44 (14)
5	51 (9)	40 (15)	43 (14)
6	49 (7)	38 (17)	39 (16)
7	()	41 (17)	41 (17)
	$r_s = 0.03(-0.24)$	$r_s = -0.11(-0.28)$	$r_s = -0.12(-0.34)$

Tlflm1

1	50 (10)	46 (12)	49 (11)
2	50 (9)	46 (11)	48 (10)
3	51 (10)	47 (11)	49 (11)
4	50 (10)	44 (12)	46 (12)
5	50 (9)	44 (12)	46 (11)
6	50 (9)	43 (14)	44 (14)
7	()	50 (16)	50 (16)
	$r_s = 0.02(-0.10)$	$r_s = -0.06(-0.15)$	$r_s = -0.07(-0.18)$

Tglfl

1	50 (10)	42 (14)	48 (11)
2	50 (9)	43 (14)	48 (11)
3	50 (10)	41 (15)	46 (14)
4	50 (10)	36 (16)	42 (15)
5	51 (9)	37 (15)	41 (15)
6	50 (8)	36 (18)	38 (18)
7	()	41 (20)	41 (20)
	$r_s = 0.01(-0.28)$	$r_s = -0.14(-0.31)$	$r_s = -0.15(-0.38)$
Tlfl			
1	50 (10)	45 (12)	49 (11)
2	50 (9)	45 (12)	48 (11)
3	50 (10)	45 (12)	48 (11)
4	50 (10)	42 (12)	46 (12)
5	51 (8)	43 (12)	45 (12)
6	50 (8)	42 (14)	43 (13)
7	()	48 (15)	48 (15)
	$r_s = 0.00(-0.16)$	$r_s = -0.06(-0.19)$	$r_s = -0.09(-0.26)$
Tvdvis1			
1	50 (10)	47 (11)	49 (10)
2	51 (9)	47 (10)	50 (10)
3	50 (10)	47 (13)	48 (12)
4	49 (11)	44 (12)	47 (12)
5	52 (10)	44 (13)	46 (13)
6	48 (10)	45 (14)	45 (14)
7	()	48 (14)	48 (14)
	$r_s = 0.00(-0.09)$	$r_s = -0.08(-0.10)$	$r_s = -0.08(-0.15)$
Tgcpm1			
1	50 (10)	43 (13)	48 (11)
2	50 (10)	44 (12)	48 (11)
3	50 (10)	42 (14)	46 (13)
4	50 (9)	38 (15)	43 (14)
5	50 (9)	39 (15)	43 (14)
6	50 (7)	38 (18)	40 (17)
7	()	42 (21)	42 (21)
	$r_s = 0.03(-0.26)$	$r_s = -0.12(-0.30)$	$r_s = -0.12(-0.36)$
Tgcp			
1	50 (10)	42 (13)	48 (11)
2	50 (9)	43 (14)	48 (11)
3	50 (10)	40 (15)	46 (14)
4	50 (10)	36 (16)	42 (15)
5	51 (9)	37 (15)	41 (15)

6	50 (8)	35 (18)	37 (18)
7	()	41 (20)	41 (20)
	$r_s = 0.01(-0.28)$	$r_s = -0.14(-0.31)$	$r_s = -0.16(-0.38)$
`Th1rmsetotal`			
1	50 (9)	45 (13)	49 (11)
2	50 (10)	46 (12)	48 (11)
3	50 (10)	43 (16)	47 (13)
4	50 (10)	38 (16)	43 (15)
5	51 (10)	38 (16)	42 (16)
6	49 (9)	35 (22)	37 (22)
7	()	33 (30)	33 (30)
	$r_s = -0.01(-0.14)$	$r_s = -0.18(-0.24)$	$r_s = -0.16(-0.26)$

Note: table means reflect weights

2.3.3 But are scores related to education?

The normalized, adjusted, and standardized scores should not be related to education in the normative sample, but may be in the non-normative sample and HCAP overall. As with age discussed in the previous section, the correlation of education and test score, in the overall HCAP sample, some correlation of education and test score derives indirectly from the association of education and inclusion in the norming sample.

Consider that the Spearman correlation of education (`schlyrs`) and inclusion in the norming sample is -0.20, and the Spearman correlation of being included in the norming sample and the GCP (plausible value) score (before adjustment, `gcpm1`) is -0.44, then we expect a correlation of the education (and other demographic factor) adjusted GCP score and education to be no more than $-0.20 \times -0.44 =$ 0.09. We actually observe 0.06.

The table below contains means across education groups and Spearman rank correlations of the T score and educational attainment. In parenthesis, I show the Spearman correlation of the unadjusted score with education.

	normexcl=0		normexcl=1		All HCAP	
Estimate	Mean	SD	Mean	SD	Mean	SD
`Tgmemm1`						
schlyrs 0-8	50	(10)	43	(12)	45	(12)
schlyrs 9-11	49	(10)	43	(11)	45	(11)
schlyrs 12	50	(10)	43	(13)	47	(12)
schlyrs 13-15	50	(9)	42	(14)	47	(12)
schlyrs 16	50	(10)	41	(13)	47	(11)
schlyrs 17up	51	(10)	41	(17)	48	(13)
	$r_s = 0.01(0.42)$		$r_s = -0.04(0.29)$		$r_s = 0.04(0.40)$	
`Tmemm1`						
schlyrs 0-8	53	(11)	47	(14)	49	(13)
schlyrs 9-11	49	(10)	45	(10)	47	(10)
schlyrs 12	50	(10)	44	(11)	47	(11)
schlyrs 13-15	50	(10)	43	(13)	47	(12)
schlyrs 16	50	(10)	42	(13)	48	(11)
schlyrs 17up	51	(9)	43	(14)	49	(11)
	$r_s = 0.03(0.35)$		$r_s = -0.07(0.24)$		$r_s = 0.04(0.34)$	
`Tgmem`						
schlyrs 0-8	51	(10)	44	(13)	46	(13)
schlyrs 9-11	48	(9)	42	(11)	45	(11)
schlyrs 12	50	(10)	42	(13)	47	(12)
schlyrs 13-15	50	(10)	41	(15)	46	(13)
schlyrs 16	50	(10)	40	(13)	47	(12)
schlyrs 17up	51	(10)	40	(17)	48	(13)
	$r_s = 0.02(0.46)$		$r_s = -0.07(0.31)$		$r_s = 0.05(0.43)$	

`Tmem`						
schlyrs 0-8	52	(10)	46	(13)	48	(13)
schlyrs 9-11	48	(9)	44	(11)	46	(10)
schlyrs 12	50	(10)	44	(12)	47	(12)
schlyrs 13-15	50	(10)	43	(14)	47	(12)
schlyrs 16	50	(10)	41	(13)	47	(12)
schlyrs 17up	51	(10)	42	(15)	48	(12)
	$r_s = 0.02(0.38)$		$r_s = -0.07(0.25)$		$r_s = 0.03(0.36)$	
`Tgexfm1`						
schlyrs 0-8	48	(11)	40	(12)	43	(12)
schlyrs 9-11	48	(11)	42	(11)	44	(12)
schlyrs 12	51	(10)	42	(13)	47	(12)
schlyrs 13-15	49	(9)	41	(14)	46	(12)
schlyrs 16	50	(10)	41	(13)	47	(12)
schlyrs 17up	50	(9)	40	(16)	47	(13)
	$r_s = 0.02(0.47)$		$r_s = -0.00(0.40)$		$r_s = 0.08(0.47)$	
`Texfm1`						
schlyrs 0-8	48	(10)	44	(12)	46	(12)
schlyrs 9-11	48	(10)	42	(12)	45	(11)
schlyrs 12	51	(10)	43	(12)	48	(11)
schlyrs 13-15	49	(10)	42	(12)	47	(11)
schlyrs 16	50	(9)	40	(12)	47	(11)
schlyrs 17up	50	(10)	39	(14)	47	(12)
	$r_s = 0.02(0.43)$		$r_s = -0.06(0.40)$		$r_s = 0.05(0.45)$	
`Tgexf`						
schlyrs 0-8	48	(11)	42	(12)	44	(12)
schlyrs 9-11	48	(10)	41	(12)	44	(12)
schlyrs 12	51	(10)	41	(13)	47	(13)
schlyrs 13-15	49	(10)	40	(14)	46	(12)
schlyrs 16	50	(9)	39	(13)	47	(12)
schlyrs 17up	50	(9)	38	(17)	47	(13)
	$r_s = 0.03(0.49)$		$r_s = -0.04(0.41)$		$r_s = 0.07(0.48)$	
`Texf`						
schlyrs 0-8	48	(11)	44	(11)	45	(11)
schlyrs 9-11	48	(10)	42	(11)	44	(11)
schlyrs 12	51	(10)	43	(12)	47	(12)
schlyrs 13-15	49	(10)	41	(12)	46	(11)
schlyrs 16	50	(10)	40	(13)	47	(12)
schlyrs 17up	50	(9)	39	(14)	47	(12)
	$r_s = 0.03(0.47)$		$r_s = -0.07(0.42)$		$r_s = 0.05(0.47)$	

`Tglflm1`			
schlyrs 0-8	49 (11)	41 (14)	44 (13)
schlyrs 9-11	48 (9)	41 (13)	44 (12)
schlyrs 12	51 (10)	42 (14)	47 (12)
schlyrs 13-15	50 (10)	41 (15)	47 (12)
schlyrs 16	50 (10)	41 (14)	47 (12)
schlyrs 17up	50 (10)	39 (18)	47 (13)
	$r_s = 0.03(0.45)$	$r_s = -0.02(0.34)$	$r_s = 0.06(0.43)$
`Tlflm1`			
schlyrs 0-8	51 (11)	47 (12)	48 (12)
schlyrs 9-11	50 (11)	46 (11)	48 (11)
schlyrs 12	50 (10)	46 (11)	48 (11)
schlyrs 13-15	49 (9)	46 (13)	48 (11)
schlyrs 16	50 (10)	45 (12)	48 (11)
schlyrs 17up	51 (10)	42 (13)	48 (12)
	$r_s = 0.03(0.28)$	$r_s = -0.06(0.20)$	$r_s = 0.02(0.28)$
`Tglfl`			
schlyrs 0-8	50 (11)	42 (14)	44 (13)
schlyrs 9-11	48 (9)	40 (13)	44 (12)
schlyrs 12	51 (10)	41 (15)	46 (13)
schlyrs 13-15	49 (10)	39 (17)	46 (13)
schlyrs 16	50 (10)	39 (15)	46 (12)
schlyrs 17up	51 (10)	37 (20)	47 (15)
	$r_s = 0.02(0.51)$	$r_s = -0.03(0.38)$	$r_s = 0.07(0.48)$
`Tlfl`			
schlyrs 0-8	51 (10)	45 (11)	47 (11)
schlyrs 9-11	49 (9)	45 (11)	46 (11)
schlyrs 12	50 (10)	45 (11)	48 (11)
schlyrs 13-15	50 (9)	44 (14)	48 (12)
schlyrs 16	50 (10)	44 (12)	48 (11)
schlyrs 17up	51 (11)	41 (16)	48 (13)
	$r_s = 0.03(0.37)$	$r_s = -0.02(0.30)$	$r_s = 0.05(0.38)$
`Tvdvis1`			
schlyrs 0-8	50 (10)	49 (13)	49 (12)
schlyrs 9-11	50 (11)	44 (12)	47 (12)
schlyrs 12	50 (10)	47 (12)	49 (11)
schlyrs 13-15	50 (10)	46 (12)	48 (11)
schlyrs 16	50 (9)	46 (10)	49 (9)
schlyrs 17up	50 (8)	44 (14)	49 (10)
	$r_s = 0.00(0.32)$	$r_s = -0.01(0.30)$	$r_s = 0.03(0.34)$

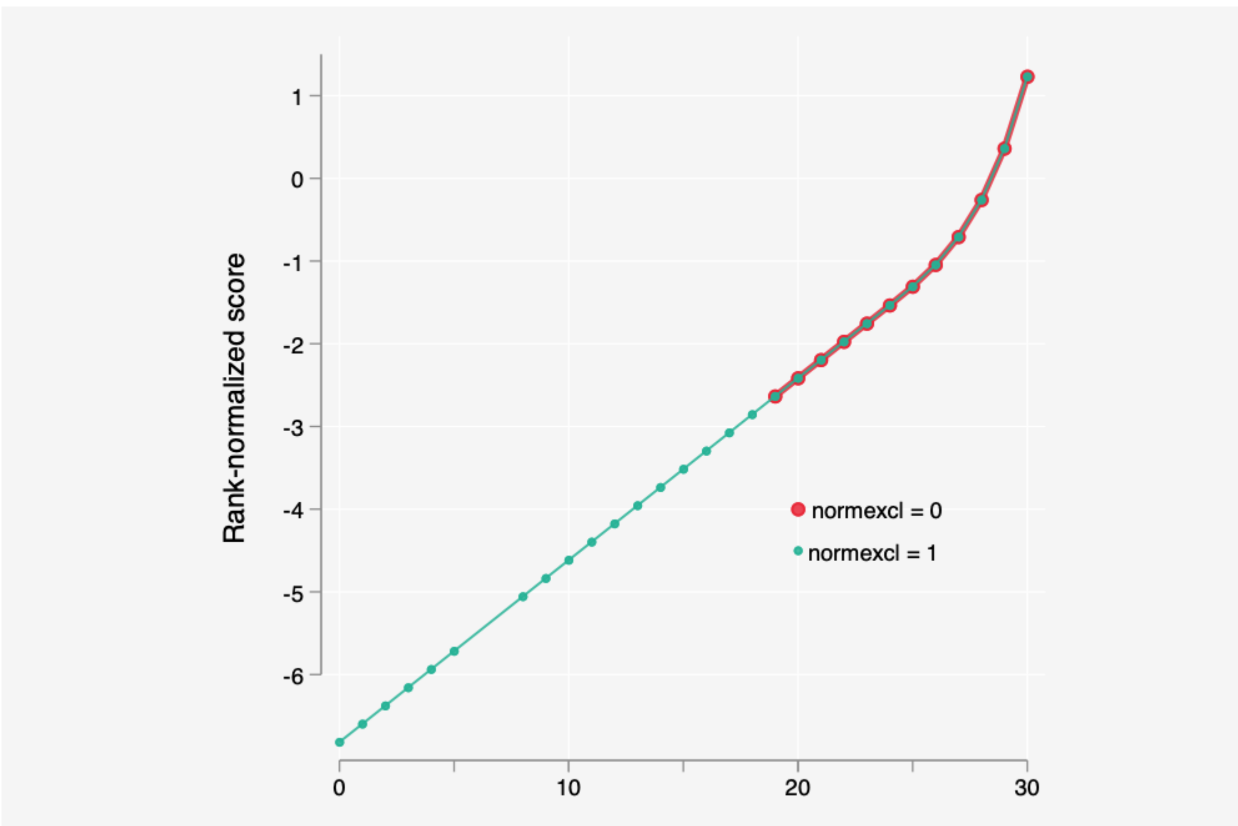
Tgcpm1			
schlyrs 0-8	49 (11)	43 (16)	45 (15)
schlyrs 9-11	48 (10)	41 (12)	44 (12)
schlyrs 12	51 (10)	42 (14)	47 (12)
schlyrs 13-15	50 (10)	41 (15)	47 (12)
schlyrs 16	50 (9)	40 (13)	47 (12)
schlyrs 17up	50 (10)	39 (18)	47 (13)
	$r_s = 0.02(0.47)$	$r_s = -0.03(0.35)$	$r_s = 0.06(0.45)$
Tgcp			
schlyrs 0-8	50 (11)	42 (14)	44 (13)
schlyrs 9-11	48 (9)	40 (13)	43 (12)
schlyrs 12	51 (10)	41 (15)	46 (13)
schlyrs 13-15	49 (10)	39 (16)	46 (13)
schlyrs 16	50 (9)	39 (15)	46 (12)
schlyrs 17up	51 (9)	37 (19)	47 (14)
	$r_s = 0.03(0.51)$	$r_s = -0.04(0.38)$	$r_s = 0.07(0.48)$
Th1rmsetotal			
schlyrs 0-8	47 (14)	42 (18)	44 (17)
schlyrs 9-11	49 (11)	41 (14)	44 (13)
schlyrs 12	51 (10)	42 (17)	47 (14)
schlyrs 13-15	51 (10)	42 (18)	48 (14)
schlyrs 16	51 (9)	40 (15)	47 (12)
schlyrs 17up	49 (9)	40 (18)	46 (13)
	$r_s = 0.00(0.33)$	$r_s = 0.02(0.32)$	$r_s = 0.07(0.37)$

Note: Means (SD) reflect weights

3 Procedure illustrated

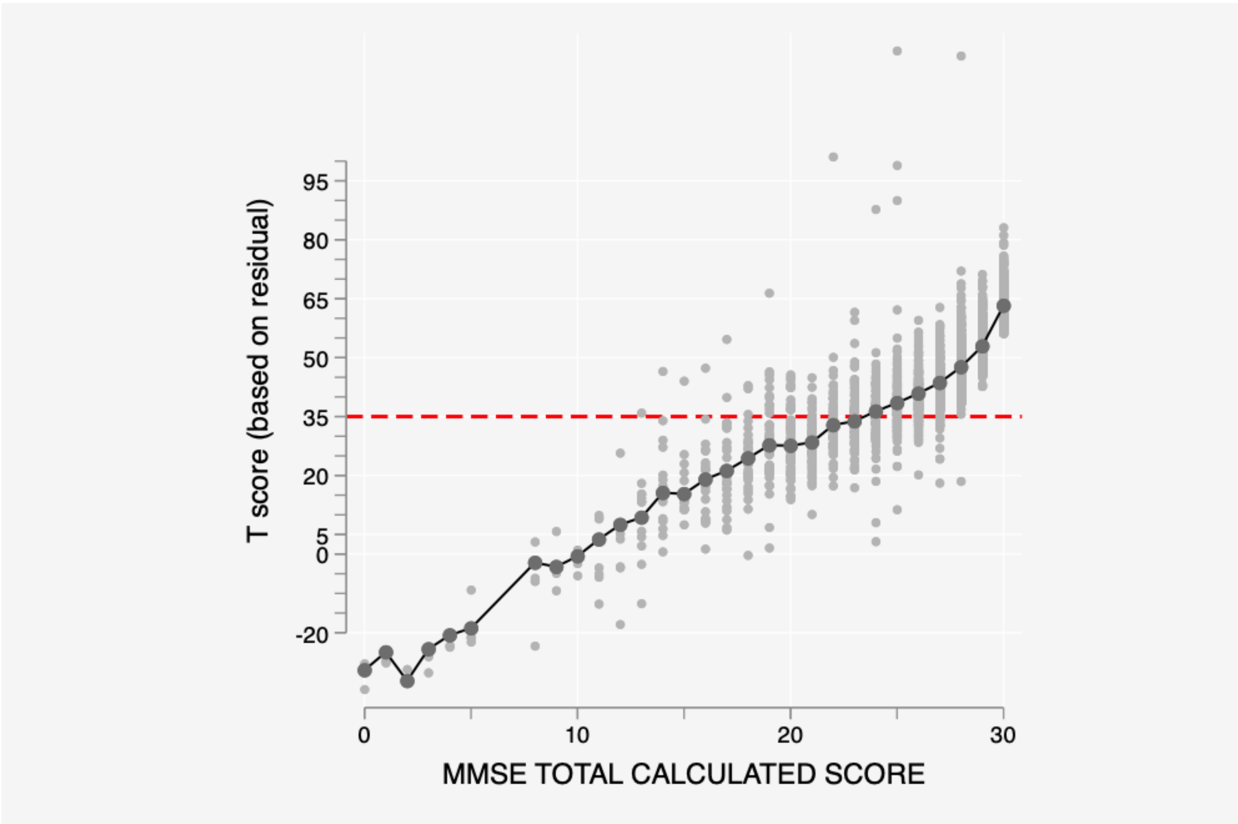
I will illustrate the normalization-adjustment-standardization steps with pictures. For the sake of illustration, I will use the MMSE score as the test score.

Rank-normalized scores vs "raw" scores
This first picture illustrates the modeled relationship between raw scores (x-axis) and rank-normalized scores (y-axis). The red dots illustrate the modeled relationship applied in the normative sample. The green dots illustrate the modeled relationship applied in the non-norm sample. Note that the relationship between the two scores is defined in the norm sample, using linear regression with restricted cubic splines based on the "raw" score. The first spline (and last) spline in a restricted cubic spline is a linear function, so the out-of-range values with respect to the norming sample (MMSE scores between 0 and 10) are related to the Blom-transformed metric using linear regression.

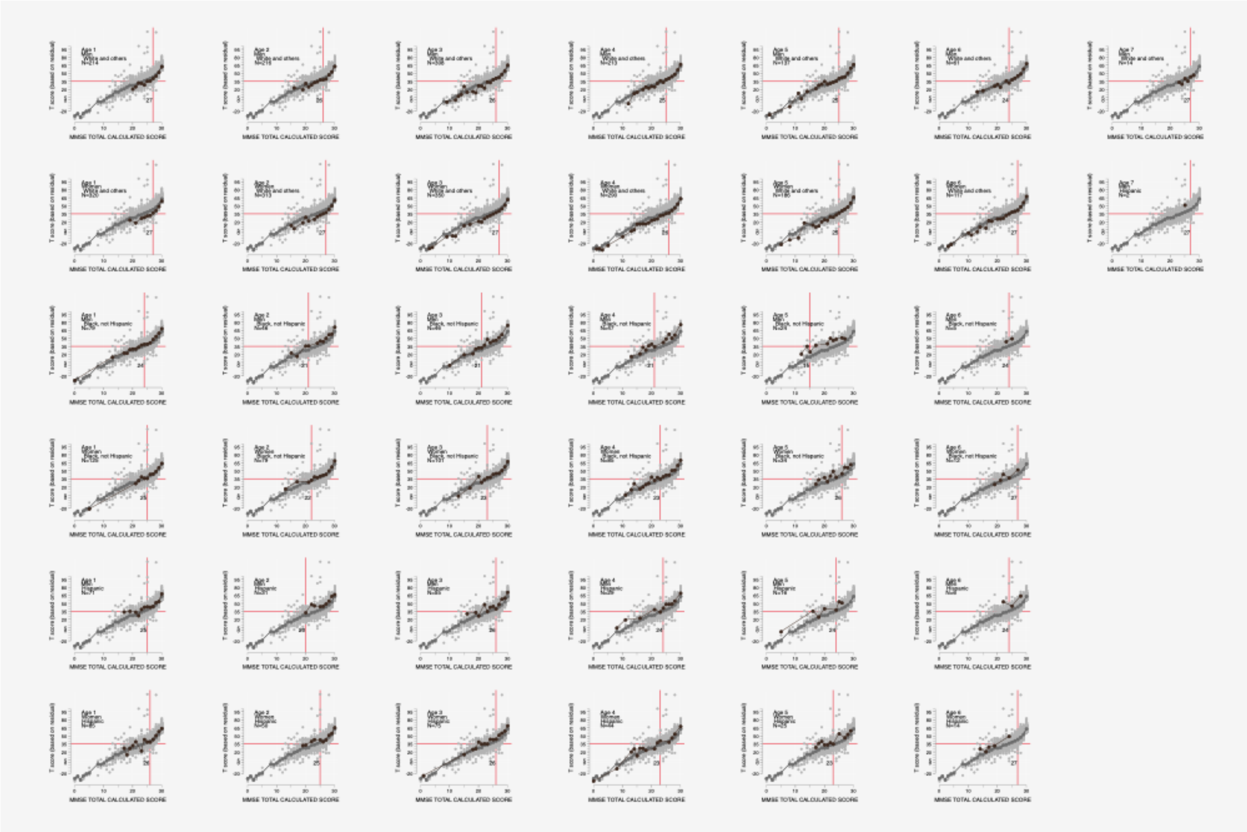


Adjusted and standardized rank-normalized scores vs "raw" scores

The next picture illustrates the scatter of expected T-scores for the MMSE after adjusting for demongraphics (and their two-way interactions) based on model results obtained from the normative sample. The overall mean relationship is shown with connected dots. Each dot on the plot represets a particular expected value for a given combination of MMSE total score and demographic profile.



Adjusted and standardized rank-normalized scores vs "raw" scores by demongraphic group Here is a plot that shows the raw and adjusted scores within major demongraphic groups. Also illustrated and labeled is the cut-point on the "raw" score variable that corresponds to the threshold defined on the adjusted, standardized and normalized test score. NB the effect of education is fixed at 12 years of schooling. This version is too small to get any details, but you can view a high-resolution copy at this link: https://s3.amazonaws.com/hrshcap/explanatory_figure_10k.png.



4 How to generate scores in a new sample

1. **Administer the HCAP** according to the procedures and scoring rules used in the HRS/HCAP.

2. **Collect sociodemographic** information including age at testing, sex (only male/female), whether or not the examinee identifies as Black or African American, whether or not the examinee identifies as Hispanic, and the number of years of schooling the examinee has obtained. The collection of this information should also conform to the procedures used in HRS to maximize comparability.

3. **Generate factor scores** for processed HCAP data. I use Mplus (version 8.1, Muthen & Muthen, Los Angeles, CA) to generate these factor scores. The factor scores are either means or random draws from a posterior distribution of plausible scores given the previously estimated model in HRS/HCAP. (It may be possible to work out an open source solution to estimating these scores if Mplus is not available.) Snippets of this procedure are contained in the code prepared for the HRS/HCAP factor analysis manuscript, but are **not** currently ready for production. Code for this step will run from Stata, and use a wrapper function to call Mplus, and therefore will not require specialized knowledge of Mplus. Mplus is only used as a ”factor scoring machine”.

4. **Normalization of factor scores.** Factor scores were normalized in the norming sample using a rank-based transformation (the Blom transformation). We have linear functions based on restricted cubic splines that can accomplish the same rescaling in a new sample without making direct use of the HRS/HCAP norming sample. These transformations are available as production-ready Stata code.

5. **Standardization of factor scores** using the regression adjustment results obtained in the HRS/HCAP norming sample. This step involves subtracting a predicted performance score from an observed performance score, and scaling according to the standard error of estimate in the norming sample. This step is available as production-ready Stata code.

5 Appendix 1 - Number of observations by sex, age, race/ethnicity and education

White and others, men

Education level	Age group at HCAP [65-70)	[70-75)	[75-80)	[80-85)	[85-90)	[90-95)	[95-100)
schlyrs 0-8	1	7	12	7	8	3	
schlyrs 9-11	11	8	27	13	13	3	
schlyrs 12	52	66	93	73	35	11	1
schlyrs 13-15	58	49	54	27	19	7	2
schlyrs 16	34	32	40	33	9	9	3
schlyrs 17up	42	35	47	34	25	10	1

White and others, women

Education level	Age group at HCAP [65-70)	[70-75)	[75-80)	[80-85)	[85-90)	[90-95)	[95-100)
schlyrs 0-8	4	4	11	9	7	6	4
schlyrs 9-11	19	28	42	32	20	10	1
schlyrs 12	90	111	124	105	63	31	9
schlyrs 13-15	87	75	80	61	35	19	3
schlyrs 16	44	36	34	27	10	14	2
schlyrs 17up	58	40	38	24	21	4	2

Black or African American, men

Education level	Age group at HCAP [65-70)	[70-75)	[75-80)	[80-85)	[85-90)	[90-95)
schlyrs 0-8	6	2	3	8	4	
schlyrs 9-11	7	7	6	3	5	
schlyrs 12	18	11	14	15	1	2
schlyrs 13-15	18	4	7	2		
schlyrs 16	9	3		3	1	
schlyrs 17up	5	5		2		

Black or African American, women

Education level	Age group at HCAP [65-70)	[70-75)	[75-80)	[80-85)	[85-90)	[90-95)	[95-100)
schlyrs 0-8	6	3	7	9	5	1	2
schlyrs 9-11	21	10	19	10	2	1	1
schlyrs 12	33	24	23	21	6	3	
schlyrs 13-15	27	19	18	16	4	1	
schlyrs 16	16	8	9	3	2	1	
schlyrs 17up	8	2	8	6	1		

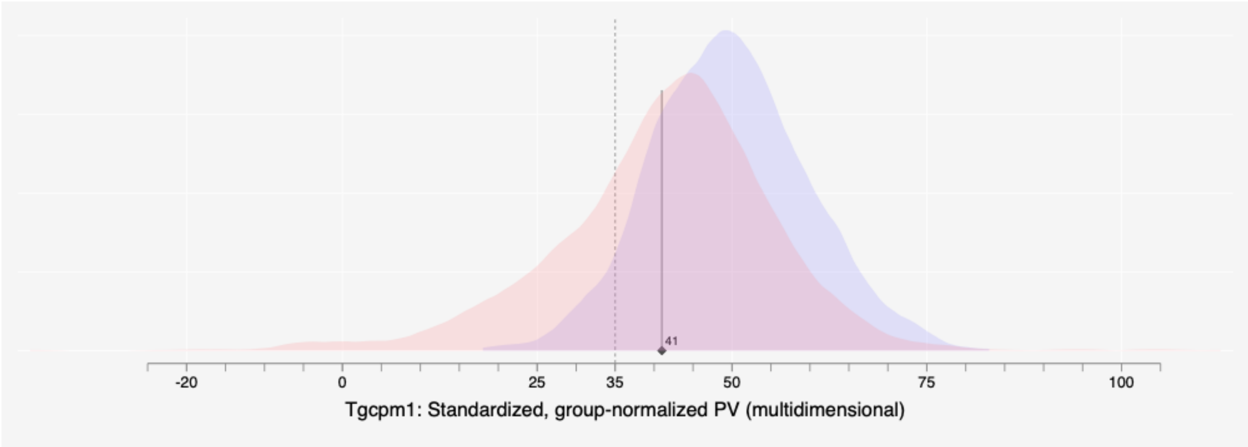
Hispanic, men

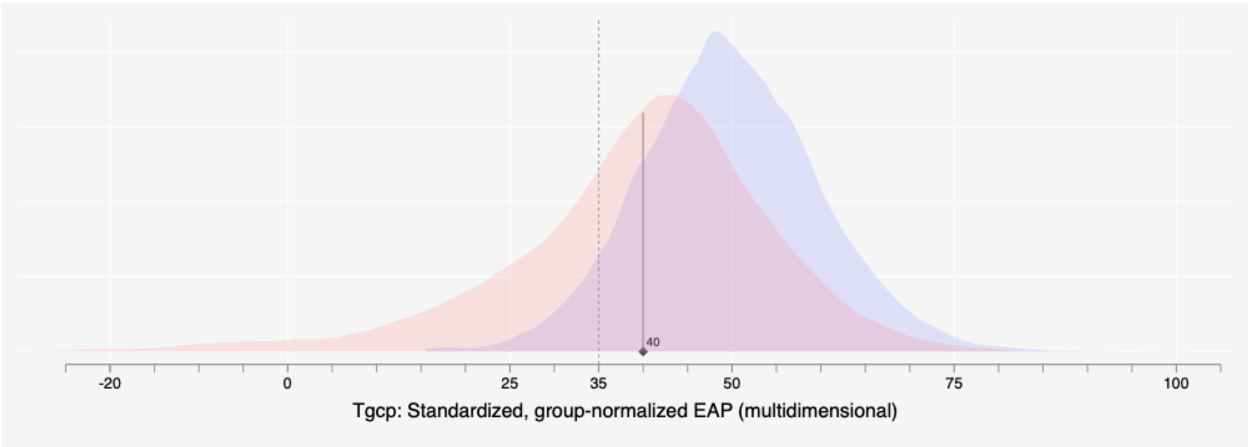
Education level	[65-70)	[70-75)	[75-80)	[80-85)	[85-90)	[90-95)	[95-100)
	Age group at HCAP						
schlyrs 0-8	19	7	16	7	4	2	1
schlyrs 9-11	4	5	4	3	2		
schlyrs 12	7	4	6	3	1	1	
schlyrs 13-15	18	3	7	1			
schlyrs 16	4	2	3	1	1		
schlyrs 17up	4		1	1			

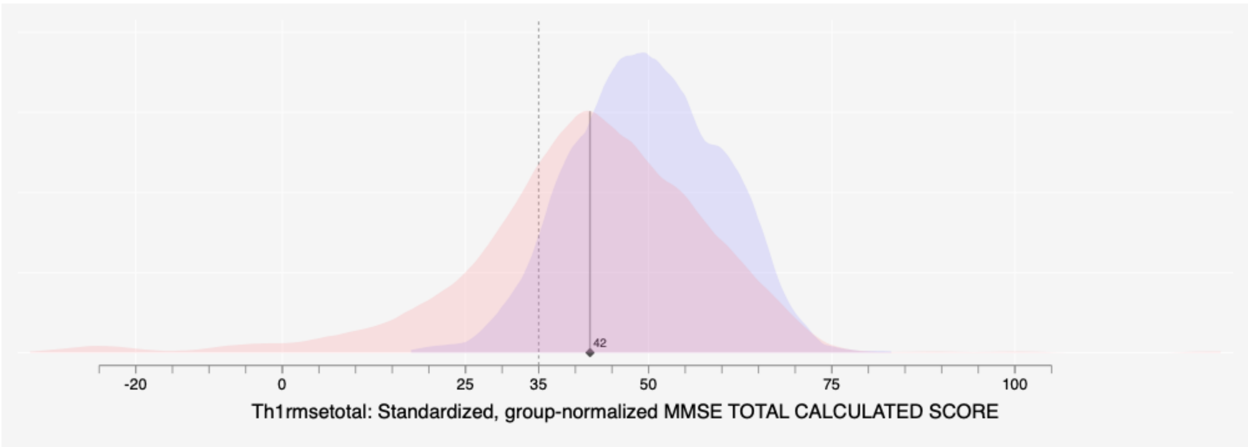
Hispanic, women

Education level	[65-70)	[70-75)	[75-80)	[80-85)	[85-90)	[90-95)	[95-100)
	Age group at HCAP						
schlyrs 0-8	23	16	34	12	9	5	1
schlyrs 9-11	13	2	13	6			
schlyrs 12	20	12	7	6	4		
schlyrs 13-15	9	8	4	3	1		
schlyrs 16	4	1		2			
schlyrs 17up	3	1	1				

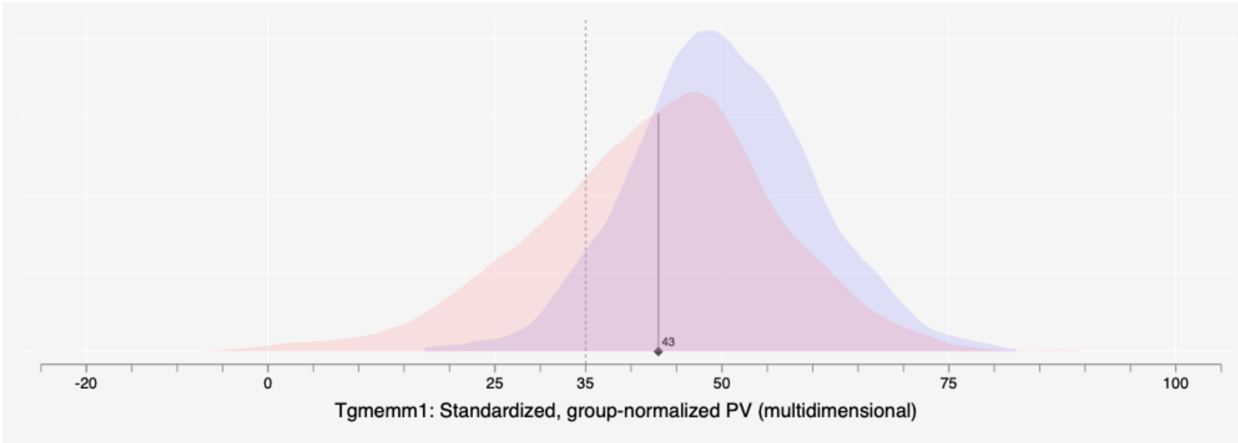
6 Appendix 2 - Density comparisons by norming sample inclusion

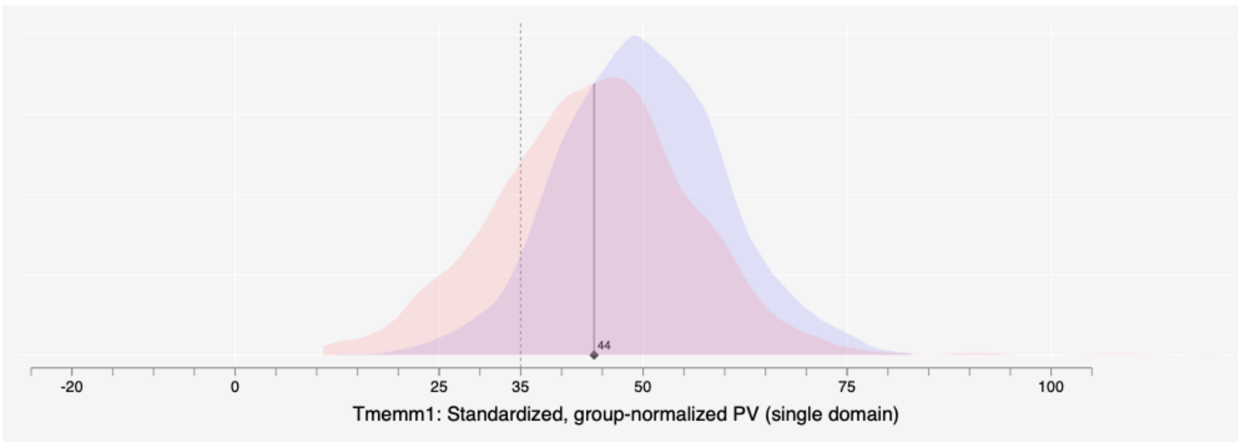


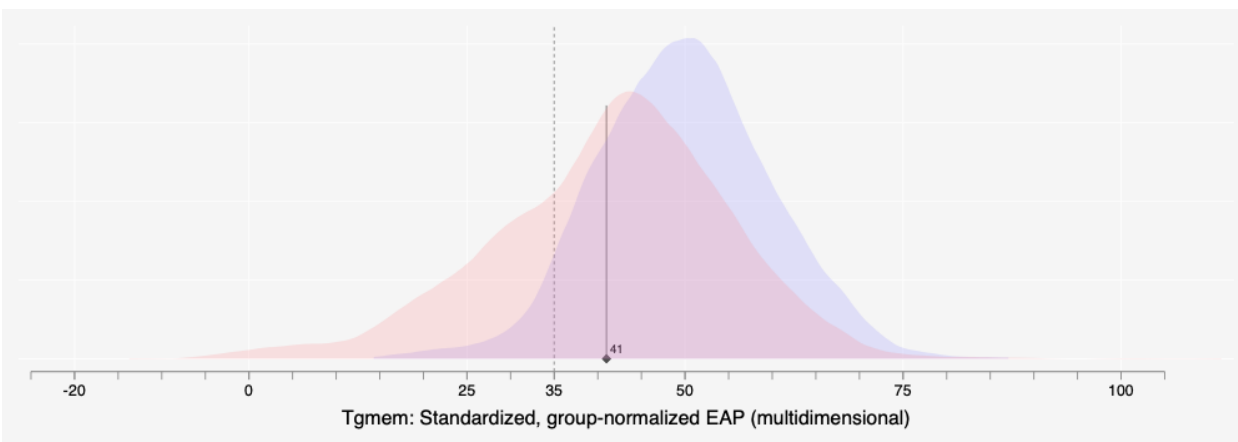




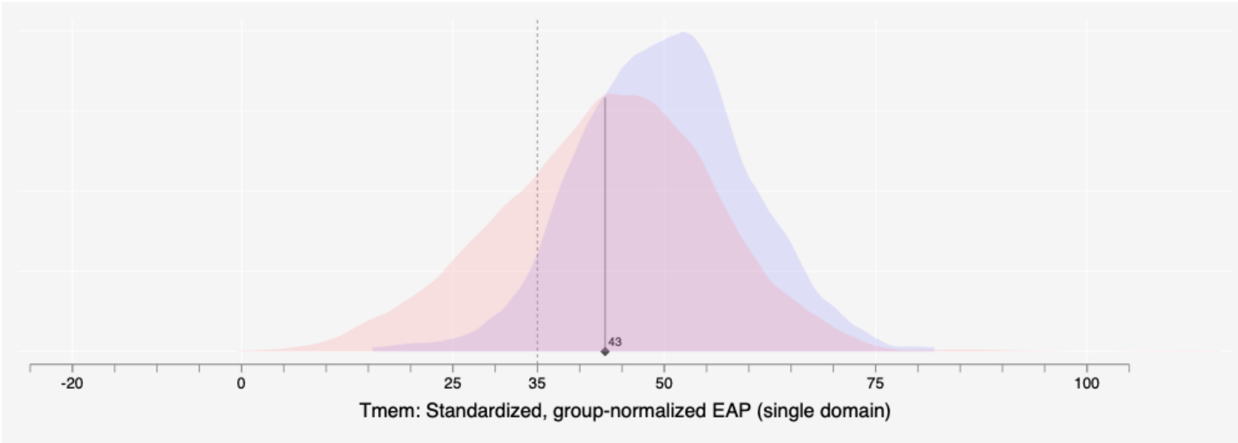
Note: the diamonds mark the mean of the sample excluded from the norming sample.

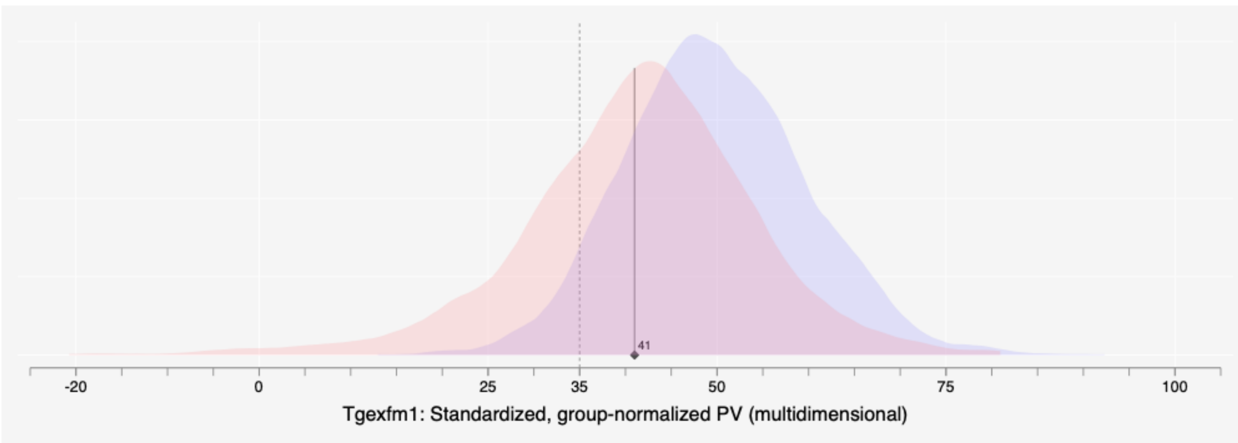


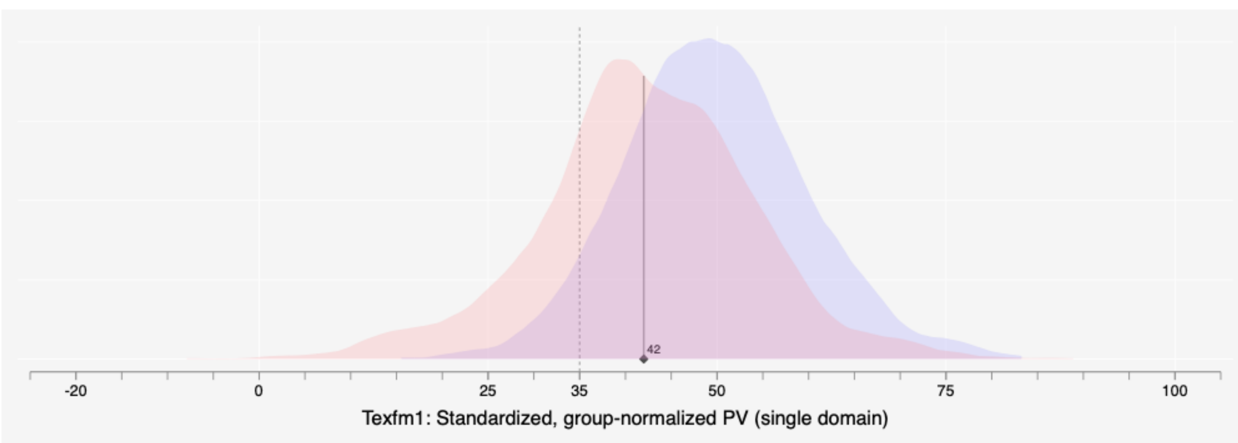




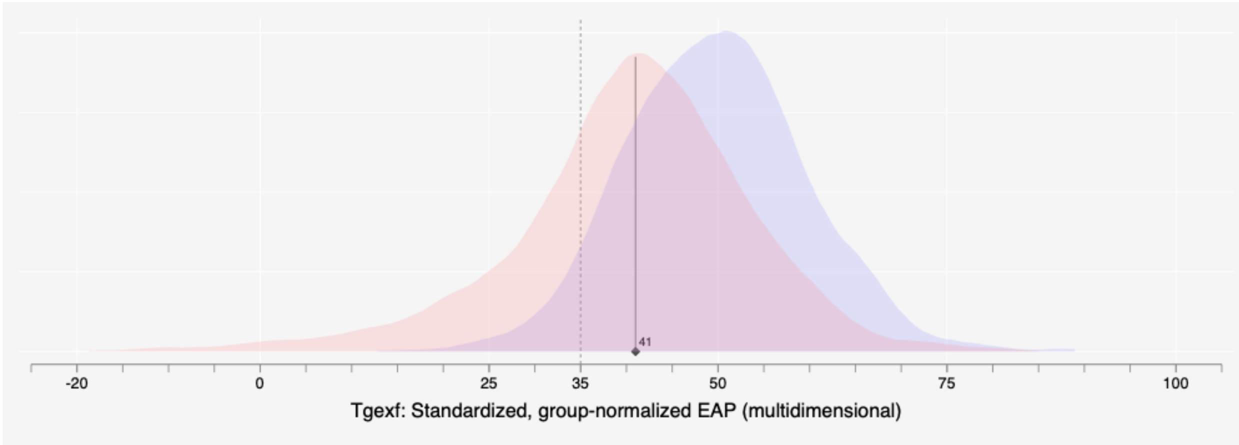
Note: the diamonds mark the mean of the sample excluded from the norming sample.

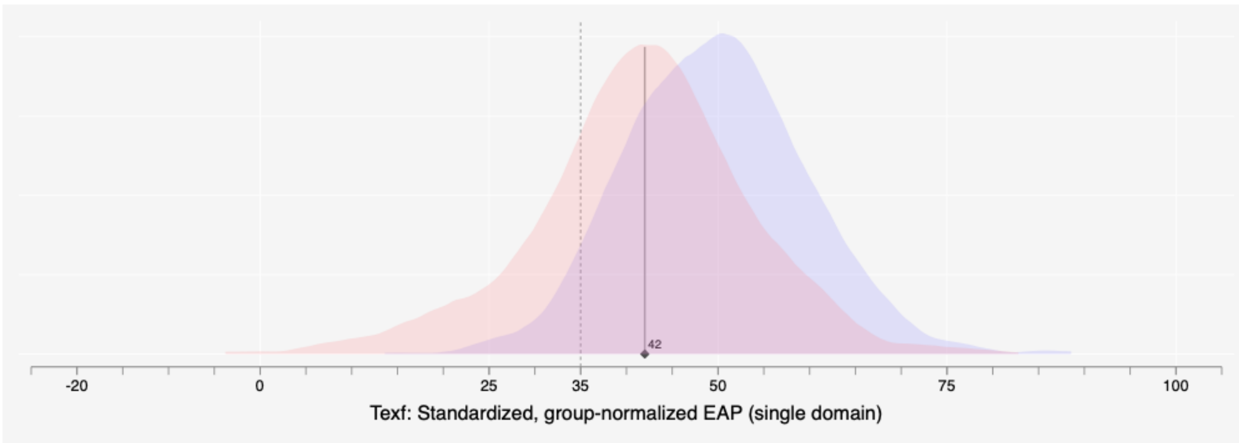


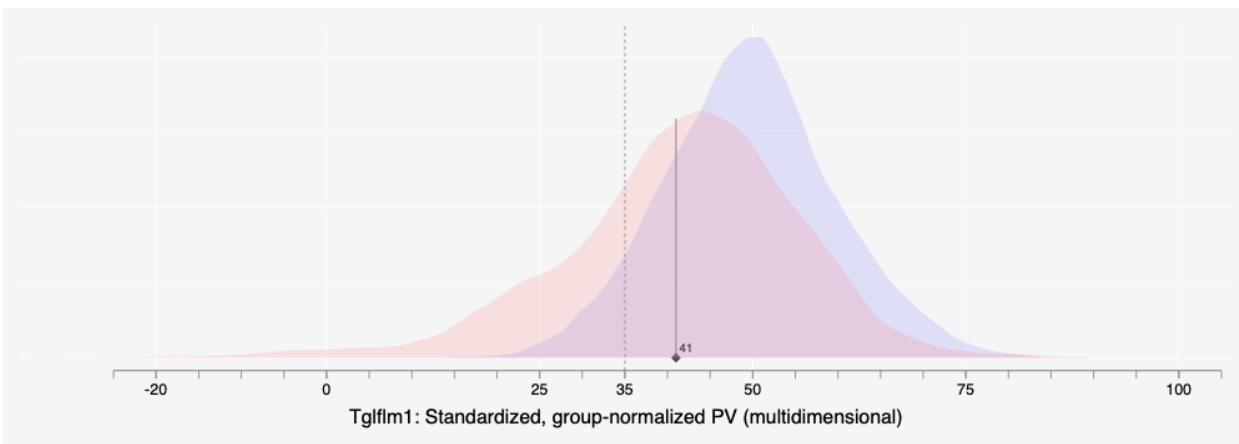




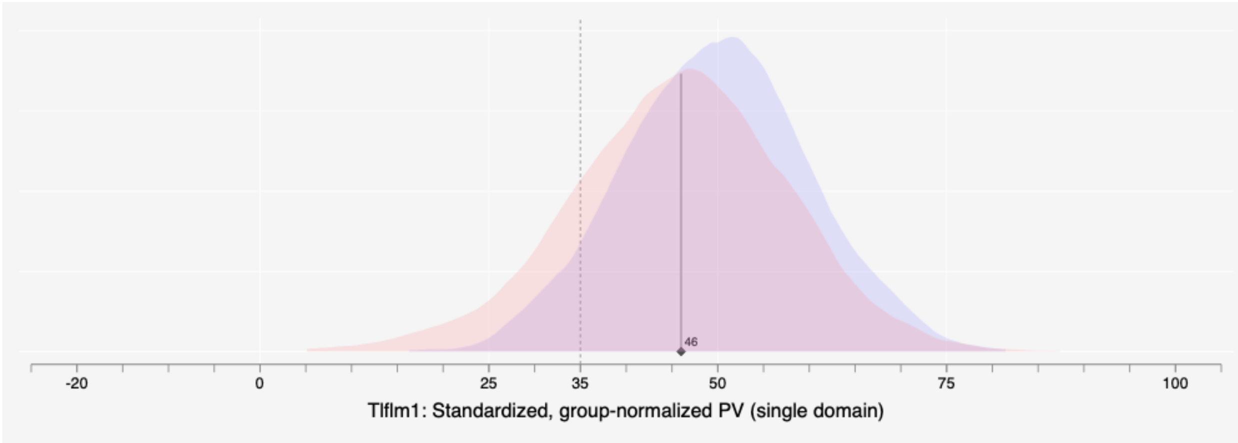
Note: the diamonds mark the mean of the sample excluded from the norming sample.

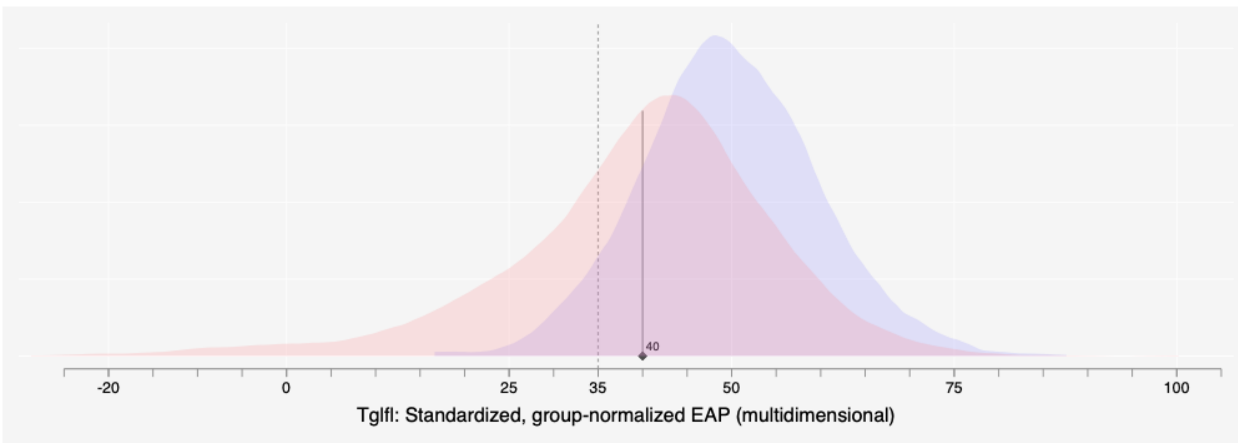


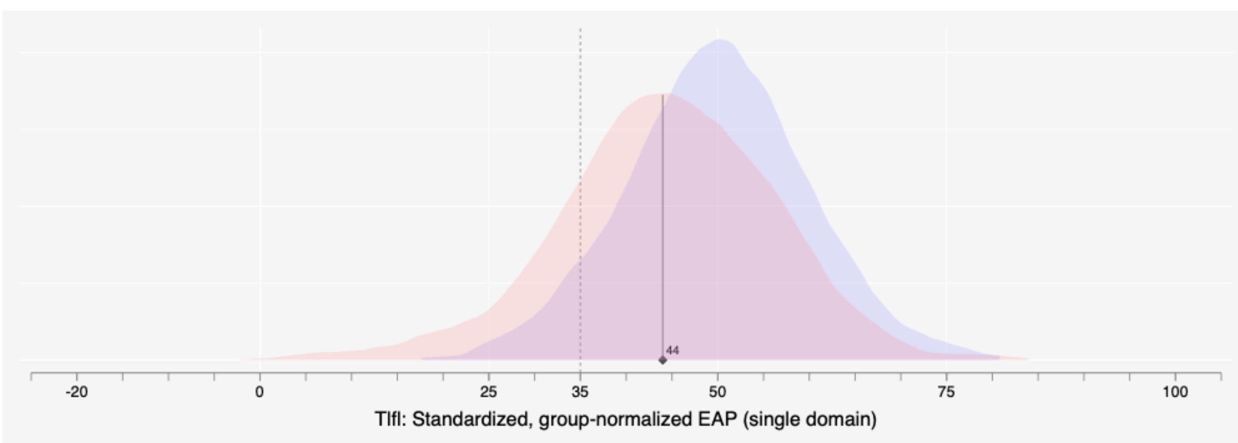




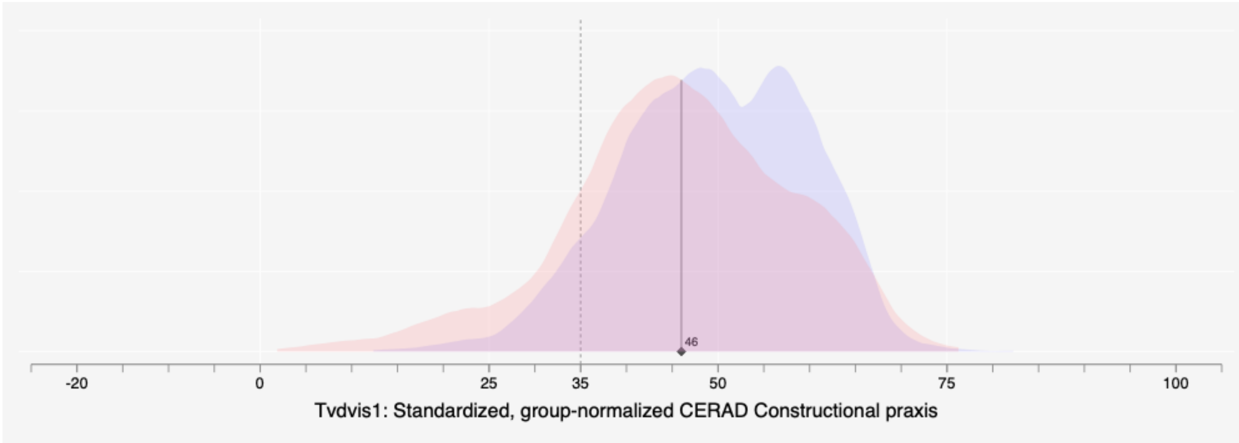
Note: the diamonds mark the mean of the sample excluded from the norming sample.







Note: the diamonds mark the mean of the sample excluded from the norming sample.


46
-20
0
25
35
50
75
100
Tvdvis1: Standardized, group-normalized CERAD Constructional praxis

7 Appendix 3 - Recommended scores

I recommend to users the single domain scores. Either the expected *a posteriori* or plausible values are suitable for use.

Domain	EAP	PV
Memory	mem	memm1
	Tmem	Tmemm1
	IMPAIRED_mem	IMPAIRED_memm1
Executive function	exf	exfm1
	Texf	Texfm1
	IMPAIRED_exf	IMPAIRED_exfm1
Language and fluency	lfl	lflm1
	Tlfl	Tlflm1
	IMPAIRED_lfl	IMPAIRED_lflm1
Orientation	vdori1	NA
Visuospatial	vdvis1	NA
	Tvdvis1	NA
	IMPAIRED_vdvis1	NA
General cognitive performance	gcp	gvpm1
	Tgcp	Tgcpm1
	IMPAIRED_gcp	IMPAIRED_gcpm1

7.1 When to use EAP vs PV

When we estimate a factor score, there is some level of imprecision in that estimate. The imprecision is determined by the number of items used in the factor score, the strength of the correlation between the items and the underlying factor, and the distribution of difficulty levels of the items. Factors with more items, items with strong relationships with the underlying factor, and many and widely dispersed difficulty levels will have less imprecision than factors with only a few items with weak relationships with the underlying factor and coarse and skewed responses. If a factor is measured by all continuous indicators, imprecision is constant across the level of the latent trait. But if a factor is measured with at least one categorical indciator, imprecision will vary across the level of the latent trait, generally being higher at the extremes.

When we generate factor score estimates as plausible values, each person's score is a draw from the posterior distribution of their factor score estimate, whch is determined by the level of imprecision of the factor score. These are analogous to imputations in multiple imputation. In fact, it might be desireable to use multiple plausible values generated for each participant as if they were multiply imputed values in a data analysis.

If we were to take a large number of draws from the posterior for each participant, and then compute the mean of each persons' plausible values - that mean would approach the expected *a posteriori* estimate we obtain for each person.

I recommend using plausible values (or multiple plausible values) in any cirmumstance where population-level parameter estimation and inference is desired. Use of EAP estimates in such circumstances is anti-conservative and may result in biased low standard errors in inflated type-I error levels. In some situations, such as descriptive analysis[3], or in a high-stakes decision making procedure (e.g., selecting participants for a module or sub-study) the EAP estimates would be preferable.

7.2 Why single domain scores of individual domains are preferred to scores derived from multidimensional models

Specific domain factor scores, when derived from a model that only includes more that one latent trait (e.g., a general trait and specific domains), reflect performance in general and on the specific trait. Specific domain factor scores when generated from an item set that only includes items assessing the specific domain are blind to performance on the other domains. It is hard to imagine a situation where the estimates deriving from multidomain models would be preferable to single domain models.

The main purpose of multidomain model-derived factor scores was to explore ways of harmonizing cross-national data where some of the items may differ. This is ongoing work.

Demonstration
Based on the above comments, when we examine the different kinds of scores, we should see:

- plausible values return *smaller* effect sizes and larger P-values than EAP scores
- Multidomain derived scores return *larger* effect sizes than single domain scores.

Let's use the contrast between those excluded from the norming sample to test these predictions. The table below contains *z* statistics (estimate divided by standard error) for the contrast of `normexcld=1` vs `normexcld=0` on various flavours of factor scores.

	Single domain		Multiple domain	
	EAP	PV	EAP	PV
MEM	-16.9	-15.4	-20.4	-18.4
EXF	-21.7	-20.2	-23.1	-21.6
LFL	-14.6	-11.0	-22.8	-19.5

The table demonstrates the predictions are borne out, and reinforces that **plausible value single domain scores** are the preferred scaling, being the theroretically most appropriate and empirically most conservative set of scores.

[3]Especially describing the limits of resolution of the factor score. EAP estimates will retain floors, ceilings, and discontinuities in measurement due to coarse or sparsely distributed difficulty parameters, whereas Bayesian plausible values will invariably return smoothed and normally distributed factor score estimates. It is important to examine both to be sure that the factor has items that measure underlying ability meaningfully in the region relevant to the research question.

8 APPENDIX 4: Parameter estimates and technical results from regression models

8.1 gmemm1

Source	SS	df	MS			
Model	7900290.32	24	329178.764	Number of obs	=	28365049
Residual	19649753.5	28365024	.69274588	F(24, 28365024)	>	99999.00
				Prob > F	=	0.0000
				R-squared	=	0.2868
				Adj R-squared	=	0.2868
Total	27550043.8	28365048	.971267308	Root MSE	=	.83231

Pgmemm1_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.1031974	.0003102	-332.64	0.000	-.1038055	-.1025894
spage2	.4913836	.0019127	256.90	0.000	.4876348	.4951325
spage3	-1.636708	.0082767	-197.75	0.000	-1.65293	-1.620486
female	-2.063781	.0078499	-262.90	0.000	-2.079167	-2.048395
black	-3.271924	.0147776	-221.41	0.000	-3.300888	-3.242961
hisp	-.1849698	.0167045	-11.07	0.000	-.2177101	-.1522296
schlyrs	-.0968879	.0014693	-65.94	0.000	-.0997676	-.0940081
c.spage1#c.female	.0298274	.0001067	279.53	0.000	.0296183	.0300366
c.spage1#c.black	.0368744	.0002015	183.04	0.000	.0364796	.0372692
c.spage1#c.hisp	.0075602	.0002359	32.05	0.000	.0070978	.0080226
c.spage1#c.schlyrs	.0034891	.000021	165.88	0.000	.0034478	.0035303
c.spage2#c.female	-.1889607	.0006614	-285.70	0.000	-.190257	-.1876643
c.spage2#c.black	-.2238609	.001198	-186.87	0.000	-.2262088	-.2215129
c.spage2#c.hisp	-.0758625	.0019915	-38.09	0.000	-.0797658	-.0719591
c.spage2#c.schlyrs	-.0268863	.0001358	-198.02	0.000	-.0271524	-.0266201
c.spage3#c.female	.7871967	.0028214	279.01	0.000	.7816669	.7927265
c.spage3#c.black	.8178906	.0044121	185.38	0.000	.8092431	.826538
c.spage3#c.hisp	-.1900114	.0123682	-15.36	0.000	-.2142525	-.1657703
c.spage3#c.schlyrs	.0774886	.0006127	126.47	0.000	.0762878	.0786895
c.female#c.black	.0974763	.0012324	79.09	0.000	.0950608	.0998918
c.female#c.hisp	.1843918	.001367	134.89	0.000	.1817126	.187071
c.female#c.schlyrs	.0132103	.0001253	105.40	0.000	.0129646	.0134559
c.schlyrs#c.black	.0006465	.0002428	2.66	0.008	.0001707	.0011224
c.schlyrs#c.hisp	-.0585017	.0001699	-344.39	0.000	-.0588346	-.0581688
_cons	5.39931	.0217487	248.26	0.000	5.356684	5.441937

8.2 memm1

Source	SS	df	MS		
Model	5676277.06	24	236511.544	Number of obs =	28365049
Residual	22416015.3	28365024	.790269568	F(24, 28365024) >	99999.00
				Prob > F =	0.0000
Total	28092292.3	28365048	.990384092	R-squared =	0.2021
				Adj R-squared =	0.2021
				Root MSE =	.88897

Pmemm1_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.0834737	.0003314	-251.92	0.000	-.0841231	-.0828242
spage2	.513895	.0020429	251.55	0.000	.509891	.5178991
spage3	-2.196252	.0088401	-248.44	0.000	-2.213578	-2.178926
female	-1.97525	.0083843	-235.59	0.000	-1.991683	-1.958817
black	-1.272782	.0157835	-80.64	0.000	-1.303717	-1.241847
hisp	1.676438	.0178416	93.96	0.000	1.641469	1.711407
schlyrs	-.0141698	.0015693	-9.03	0.000	-.0172455	-.011094
c.spage1#c.female	.0342602	.000114	300.61	0.000	.0340368	.0344835
c.spage1#c.black	.0184939	.0002152	85.95	0.000	.0180722	.0189156
c.spage1#c.hisp	-.0175313	.000252	-69.58	0.000	-.0180252	-.0170375
c.spage1#c.schlyrs	.0021513	.0000225	95.76	0.000	.0021072	.0021953
c.spage2#c.female	-.2078073	.0007064	-294.17	0.000	-.2091919	-.2064228
c.spage2#c.black	-.237975	.0012795	-185.99	0.000	-.2404828	-.2354672
c.spage2#c.hisp	.0785884	.0021271	36.95	0.000	.0744194	.0827575
c.spage2#c.schlyrs	-.0285424	.000145	-196.82	0.000	-.0288266	-.0282581
c.spage3#c.female	.8656184	.0030134	287.25	0.000	.8597122	.8715246
c.spage3#c.black	1.020663	.0047124	216.59	0.000	1.011427	1.0299
c.spage3#c.hisp	-.9765704	.0132101	-73.93	0.000	-1.002462	-.9506791
c.spage3#c.schlyrs	.1222347	.0006544	186.79	0.000	.1209521	.1235172
c.female#c.black	.2918041	.0013163	221.69	0.000	.2892242	.2943839
c.female#c.hisp	-.0517383	.00146	-35.44	0.000	-.0545998	-.0488767
c.female#c.schlyrs	-.0104487	.0001339	-78.05	0.000	-.010711	-.0101863
c.schlyrs#c.black	-.0413511	.0002593	-159.46	0.000	-.0418593	-.0408428
c.schlyrs#c.hisp	-.0500944	.0001814	-276.10	0.000	-.05045	-.0497388
_cons	4.061674	.0232292	174.85	0.000	4.016146	4.107202

8.3 gmem

Source	SS	df	MS			
Model	9334976.6	24	388957.358			
Residual	17900834.2	28365024	.631088278			
Total	27235810.8	28365048	.96018913			

Number of obs	=	28365049
F(24, 28365024)	>	99999.00
Prob > F	=	0.0000
R-squared	=	0.3427
Adj R-squared	=	0.3427
Root MSE	=	.79441

Pgmem_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.120461	.0002961	-406.81	0.000	-.1210413	-.1198806
spage2	.6556234	.0018256	359.13	0.000	.6520452	.6592015
spage3	-2.493959	.0078998	-315.70	0.000	-2.509442	-2.478476
female	-1.356235	.0074925	-181.01	0.000	-1.37092	-1.34155
black	-3.259475	.0141046	-231.09	0.000	-3.28712	-3.231831
hisp	-.3322354	.0159438	-20.84	0.000	-.3634847	-.3009861
schlyrs	-.1721454	.0014024	-122.75	0.000	-.174894	-.1693968
c.spage1#c.female	.0198536	.0001018	194.94	0.000	.019654	.0200532
c.spage1#c.black	.0382031	.0001923	198.69	0.000	.0378263	.03858
c.spage1#c.hisp	.0103286	.0002252	45.87	0.000	.0098873	.0107699
c.spage1#c.schlyrs	.0046898	.0000201	233.60	0.000	.0046504	.0047291
c.spage2#c.female	-.1500977	.0006313	-237.77	0.000	-.1513349	-.1488604
c.spage2#c.black	-.2864608	.0011434	-250.53	0.000	-.2887019	-.2842197
c.spage2#c.hisp	-.0455015	.0019008	-23.94	0.000	-.0492271	-.0417759
c.spage2#c.schlyrs	-.0404283	.0001296	-311.96	0.000	-.0406823	-.0401743
c.spage3#c.female	.6700106	.0026929	248.81	0.000	.6647326	.6752886
c.spage3#c.black	1.084879	.0042111	257.62	0.000	1.076625	1.093133
c.spage3#c.hisp	-.4076282	.0118049	-34.53	0.000	-.4307654	-.384491
c.spage3#c.schlyrs	.1480778	.0005848	253.22	0.000	.1469316	.1492239
c.female#c.black	.1311229	.0011763	111.47	0.000	.1288175	.1334284
c.female#c.hisp	.1070127	.0013047	82.02	0.000	.1044555	.1095699
c.female#c.schlyrs	.0205817	.0001196	172.04	0.000	.0203472	.0208162
c.schlyrs#c.black	-.0080748	.0002317	-34.85	0.000	-.008529	-.0076206
c.schlyrs#c.hisp	-.0643847	.0001621	-397.11	0.000	-.0647025	-.0640669
_cons	6.467142	.0207583	311.55	0.000	6.426457	6.507828

8.4 mem

Source	SS	df	MS			
Model	6739517.56	24	280813.232	Number of obs	=	28365049
Residual	20558064.2	28365024	.724768088	F(24, 28365024)	>	99999.00
Total	27297581.8	28365048	.962366846	Prob > F	=	0.0000
				R-squared	=	0.2469
				Adj R-squared	=	0.2469
				Root MSE	=	.85133

Pmem_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.1199879	.0003173	-378.12	0.000	-.1206099	-.119366
spage2	.6391496	.0019564	326.69	0.000	.6353151	.6429841
spage3	-2.40761	.0084658	-284.39	0.000	-2.424203	-2.391018
female	-1.155198	.0080293	-143.87	0.000	-1.170935	-1.139461
black	-2.540253	.0151153	-168.06	0.000	-2.569878	-2.510627
hisp	-.2371293	.0170862	-13.88	0.000	-.2706177	-.2036408
schlyrs	-.2462246	.0015029	-163.84	0.000	-.2491702	-.2432791
c.spage1#c.female	.0166599	.0001091	152.64	0.000	.016446	.0168738
c.spage1#c.black	.0322208	.0002061	156.37	0.000	.031817	.0326247
c.spage1#c.hisp	.0090163	.0002413	37.37	0.000	.0085433	.0094892
c.spage1#c.schlyrs	.0053353	.0000215	247.98	0.000	.0052931	.0053775
c.spage2#c.female	-.1310511	.0006765	-193.71	0.000	-.1323771	-.1297252
c.spage2#c.black	-.3113285	.0012253	-254.07	0.000	-.3137302	-.3089269
c.spage2#c.hisp	-.0331562	.002037	-16.28	0.000	-.0371488	-.0291637
c.spage2#c.schlyrs	-.0396184	.0001389	-285.27	0.000	-.0398906	-.0393462
c.spage3#c.female	.6139799	.0028858	212.76	0.000	.6083237	.619636
c.spage3#c.black	1.20124	.0045129	266.18	0.000	1.192395	1.210085
c.spage3#c.hisp	-.5742524	.0126508	-45.39	0.000	-.5990475	-.5494573
c.spage3#c.schlyrs	.1423717	.0006267	227.18	0.000	.1411434	.1435999
c.female#c.black	.1764663	.0012606	139.99	0.000	.1739957	.178937
c.female#c.hisp	.1350902	.0013982	96.62	0.000	.1323497	.1378306
c.female#c.schlyrs	.0259471	.0001282	202.39	0.000	.0256959	.0261984
c.schlyrs#c.black	-.0173489	.0002483	-69.86	0.000	-.0178356	-.0168621
c.schlyrs#c.hisp	-.0605713	.0001738	-348.61	0.000	-.0609118	-.0602307
_cons	6.720366	.0222457	302.10	0.000	6.676765	6.763967

8.5 gexfm1

Source	SS	df	MS			
Model	11002479.1	24	458436.63	Number of obs	=	28365049
Residual	16212210.8	28365024	.571556393	F(24, 28365024)	>	99999.00
Total	27214689.9	28365048	.959444523	Prob > F	=	0.0000
				R-squared	=	0.4043
				Adj R-squared	=	0.4043
				Root MSE	=	.75601

Pgexfm1_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.0408112	.0002818	-144.82	0.000	-.0413635	-.0402588
spage2	.0982091	.0017374	56.53	0.000	.0948039	.1016142
spage3	-.18457	.0075179	-24.55	0.000	-.1993049	-.1698351
female	-1.533899	.0071303	-215.12	0.000	-1.547874	-1.519923
black	-4.753945	.0134229	-354.17	0.000	-4.780253	-4.727636
hisp	.5797154	.0151732	38.21	0.000	.5499765	.6094543
schlyrs	.3430804	.0013346	257.07	0.000	.3404646	.3456961
c.spage1#c.female	.0270902	.0000969	279.50	0.000	.0269002	.0272801
c.spage1#c.black	.0477834	.000183	261.14	0.000	.0474248	.0481421
c.spage1#c.hisp	-.0072419	.0002143	-33.80	0.000	-.0076619	-.0068219
c.spage1#c.schlyrs	-.0026127	.0000191	-136.75	0.000	-.0026501	-.0025752
c.spage2#c.female	-.1521661	.0006008	-253.28	0.000	-.1533436	-.1509886
c.spage2#c.black	-.2135324	.0010881	-196.23	0.000	-.2156652	-.2113997
c.spage2#c.hisp	.0280186	.001809	15.49	0.000	.0244731	.0315642
c.spage2#c.schlyrs	.002593	.0001233	21.02	0.000	.0023513	.0028347
c.spage3#c.female	.5669732	.0025627	221.24	0.000	.5619503	.571996
c.spage3#c.black	.6040192	.0040076	150.72	0.000	.5961644	.6118739
c.spage3#c.hisp	-.2883583	.0112343	-25.67	0.000	-.3103772	-.2663394
c.spage3#c.schlyrs	-.0198882	.0005565	-35.74	0.000	-.0209789	-.0187974
c.female#c.black	.0471912	.0011194	42.16	0.000	.0449972	.0493853
c.female#c.hisp	-.0073411	.0012417	-5.91	0.000	-.0097747	-.0049075
c.female#c.schlyrs	-.0126809	.0001138	-111.38	0.000	-.012904	-.0124577
c.schlyrs#c.black	.0361442	.0002205	163.89	0.000	.035712	.0365764
c.schlyrs#c.hisp	-.0426134	.0001543	-276.18	0.000	-.0429159	-.042311
_cons	.9839422	.019755	49.81	0.000	.9452232	1.022661

8.6 exfm1

Source	SS	df	MS			
				Number of obs	=	28351380
				F(24, 28351355)	>	99999.00
Model	9502663	24	395944.292	Prob > F	=	0.0000
Residual	17526847.4	28351355	.618201403	R-squared	=	0.3516
				Adj R-squared	=	0.3516
Total	27029510.4	28351379	.953375511	Root MSE	=	.78626

Pexfm1_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.0505826	.000294	-172.05	0.000	-.0511588	-.0500063
spage2	.1551794	.0018134	85.57	0.000	.1516252	.1587336
spage3	-.663201	.0078396	-84.60	0.000	-.6785664	-.6478356
female	-.7804782	.0074163	-105.24	0.000	-.7950139	-.7659426
black	-4.502196	.0139609	-322.49	0.000	-4.529559	-4.474833
hisp	1.853086	.0157842	117.40	0.000	1.82215	1.884023
schlyrs	.2126255	.0013919	152.76	0.000	.2098974	.2153537
c.spage1#c.female	.0171473	.0001008	170.04	0.000	.0169496	.0173449
c.spage1#c.black	.0414537	.0001908	217.27	0.000	.0410798	.0418277
c.spage1#c.hisp	-.0244312	.0002229	-109.60	0.000	-.0248681	-.0239942
c.spage1#c.schlyrs	-.0008588	.0000199	-43.09	0.000	-.0008978	-.0008197
c.spage2#c.female	-.0668816	.0006251	-106.99	0.000	-.0681068	-.0656564
c.spage2#c.black	-.2012664	.0011351	-177.31	0.000	-.2034913	-.1990416
c.spage2#c.hisp	.1098918	.0018815	58.41	0.000	.106204	.1135795
c.spage2#c.schlyrs	-.0080828	.0001287	-62.81	0.000	-.008335	-.0078306
c.spage3#c.female	.0871636	.002666	32.69	0.000	.0819383	.0923889
c.spage3#c.black	.7395861	.0041758	177.11	0.000	.7314017	.7477706
c.spage3#c.hisp	-.7150899	.0116841	-61.20	0.000	-.7379902	-.6921895
c.spage3#c.schlyrs	.0495614	.0005801	85.43	0.000	.0484244	.0506985
c.female#c.black	.1537353	.0011687	131.55	0.000	.1514448	.1560259
c.female#c.hisp	-.0799054	.0012916	-61.87	0.000	-.0824369	-.077374
c.female#c.schlyrs	-.0212018	.0001186	-178.76	0.000	-.0214343	-.0209694
c.schlyrs#c.black	.0473748	.0002347	201.84	0.000	.0469148	.0478349
c.schlyrs#c.hisp	-.0484552	.0001605	-301.96	0.000	-.0487698	-.0481407
_cons	1.797081	.020605	87.22	0.000	1.756696	1.837466

8.7 gexf

Source	SS	df	MS			
				Number of obs	=	28365049
				F(24, 28365024)	>	99999.00
Model	11976278.9	24	499011.623	Prob > F	=	0.0000
Residual	15592795.4	28365024	.549719097	R-squared	=	0.4344
				Adj R-squared	=	0.4344
Total	27569074.3	28365048	.971938222	Root MSE	=	.74143

Pgexf_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.0625662	.0002764	-226.39	0.000	-.0631078	-.0620245
spage2	.241432	.0017039	141.70	0.000	.2380926	.2447715
spage3	-1.049644	.0073729	-142.36	0.000	-1.064095	-1.035194
female	-1.065188	.0069928	-152.33	0.000	-1.078894	-1.051482
black	-5.251982	.013164	-398.97	0.000	-5.277783	-5.226181
hisp	-.0209791	.0148805	-1.41	0.159	-.0501444	.0081861
schlyrs	.2292907	.0013089	175.18	0.000	.2267254	.231856
c.spage1#c.female	.0201808	.0000951	212.31	0.000	.0199945	.0203671
c.spage1#c.black	.0554846	.0001795	309.19	0.000	.0551329	.0558363
c.spage1#c.hisp	.0008509	.0002101	4.05	0.000	.000439	.0012628
c.spage1#c.schlyrs	-.0008446	.0000187	-45.07	0.000	-.0008813	-.0008079
c.spage2#c.female	-.1126206	.0005892	-191.15	0.000	-.1137754	-.1114659
c.spage2#c.black	-.2646592	.0010672	-248.00	0.000	-.2667508	-.2625676
c.spage2#c.hisp	-.007068	.0017741	-3.98	0.000	-.0105451	-.0035909
c.spage2#c.schlyrs	-.0103863	.000121	-85.87	0.000	-.0106234	-.0101492
c.spage3#c.female	.4055802	.0025133	161.37	0.000	.4006542	.4105062
c.spage3#c.black	.9044079	.0039303	230.11	0.000	.8967047	.9121112
c.spage3#c.hisp	-.2429699	.0110176	-22.05	0.000	-.264564	-.2213757
c.spage3#c.schlyrs	.0546653	.0005458	100.16	0.000	.0535956	.055735
c.female#c.black	.0949485	.0010978	86.49	0.000	.0927968	.0971002
c.female#c.hisp	-.0454941	.0012177	-37.36	0.000	-.0478808	-.0431074
c.female#c.schlyrs	-.0145117	.0001117	-129.97	0.000	-.0147305	-.0142929
c.schlyrs#c.black	.0293755	.0002163	135.82	0.000	.0289516	.0297994
c.schlyrs#c.hisp	-.0419418	.0001513	-277.17	0.000	-.0422384	-.0416452
_cons	2.421745	.0193739	125.00	0.000	2.383773	2.459717

8.8 exf

Source	SS	df	MS			
				Number of obs	=	28351380
				F(24, 28351355)	>	99999.00
Model	11181050.2	24	465877.092	Prob > F	=	0.0000
Residual	16348293.6	28351355	.576631827	R-squared	=	0.4062
				Adj R-squared	=	0.4061
Total	27529343.8	28351379	.971005461	Root MSE	=	.75936

Pexf_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.0501831	.0002839	-176.73	0.000	-.0507396	-.0496266
spage2	.1421182	.0017514	81.15	0.000	.1386856	.1455508
spage3	-.7371062	.0075715	-97.35	0.000	-.7519459	-.7222664
female	-.9092469	.0071626	-126.94	0.000	-.9232854	-.8952085
black	-5.539214	.0134834	-410.82	0.000	-5.565641	-5.512787
hisp	-.0012951	.0152443	-0.08	0.932	-.0311733	.0285832
schlyrs	.2856882	.0013443	212.52	0.000	.2830533	.288323
c.spage1#c.female	.0188531	.0000974	193.58	0.000	.0186622	.019044
c.spage1#c.black	.0574992	.0001843	312.05	0.000	.057138	.0578603
c.spage1#c.hisp	-.0011769	.0002153	-5.47	0.000	-.0015989	-.000755
c.spage1#c.schlyrs	-.0018081	.0000192	-93.93	0.000	-.0018458	-.0017704
c.spage2#c.female	-.0952632	.0006037	-157.79	0.000	-.0964465	-.0940799
c.spage2#c.black	-.2767469	.0010963	-252.43	0.000	-.2788956	-.2745981
c.spage2#c.hisp	-.0000458	.0018172	-0.03	0.980	-.0036074	.0035158
c.spage2#c.schlyrs	-.0035431	.0001243	-28.51	0.000	-.0037867	-.0032995
c.spage3#c.female	.3051345	.0025748	118.51	0.000	.300088	.3101811
c.spage3#c.black	.9826382	.004033	243.65	0.000	.9747337	.9905427
c.spage3#c.hisp	-.1848035	.0112844	-16.38	0.000	-.2069206	-.1626865
c.spage3#c.schlyrs	.0363499	.0005603	64.88	0.000	.0352517	.0374481
c.female#c.black	.1095416	.0011287	97.05	0.000	.1073294	.1117538
c.female#c.hisp	-.0733102	.0012474	-58.77	0.000	-.075755	-.0708653
c.female#c.schlyrs	-.0205477	.0001145	-179.38	0.000	-.0207722	-.0203231
c.schlyrs#c.black	.0401819	.0002267	177.26	0.000	.0397376	.0406262
c.schlyrs#c.hisp	-.0323893	.000155	-208.99	0.000	-.0326931	-.0320856
_cons	1.714832	.0199002	86.17	0.000	1.675828	1.753835

8.9 glflm1

Source	SS	df	MS			
				Number of obs	=	28365049
				F(24, 28365024)	>	99999.00
Model	8846983.63	24	368624.318	Prob > F	=	0.0000
Residual	18254935.4	28365024	.643572005	R-squared	=	0.3264
				Adj R-squared	=	0.3264
Total	27101919	28365048	.955468822	Root MSE	=	.80223

Pglflm1_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.1054098	.000299	-352.51	0.000	-.1059959	-.1048238
spage2	.4040249	.0018436	219.15	0.000	.4004116	.4076382
spage3	-1.316438	.0079775	-165.02	0.000	-1.332073	-1.300802
female	-1.113778	.0075662	-147.20	0.000	-1.128608	-1.098949
black	-4.868154	.0142434	-341.78	0.000	-4.896071	-4.840238
hisp	2.164125	.0161007	134.41	0.000	2.132569	2.195682
schlyrs	-.0879259	.0014162	-62.09	0.000	-.0907015	-.0851502
c.spage1#c.female	.0221873	.0001028	215.73	0.000	.0219857	.0223889
c.spage1#c.black	.0559207	.0001942	288.00	0.000	.0555401	.0563012
c.spage1#c.hisp	-.02393	.0002274	-105.24	0.000	-.0243757	-.0234843
c.spage1#c.schlyrs	.0035789	.0000203	176.53	0.000	.0035392	.0036187
c.spage2#c.female	-.1234317	.0006375	-193.62	0.000	-.1246812	-.1221822
c.spage2#c.black	-.3053356	.0011547	-264.44	0.000	-.3075987	-.3030725
c.spage2#c.hisp	.1301727	.0019196	67.81	0.000	.1264105	.133935
c.spage2#c.schlyrs	-.0237378	.0001309	-181.39	0.000	-.0239943	-.0234813
c.spage3#c.female	.544327	.0027194	200.16	0.000	.5389971	.5496569
c.spage3#c.black	1.032707	.0042526	242.84	0.000	1.024372	1.041042
c.spage3#c.hisp	-.7835758	.0119211	-65.73	0.000	-.8069408	-.7602109
c.spage3#c.schlyrs	.0699214	.0005905	118.40	0.000	.0687639	.0710788
c.female#c.black	.0163297	.0011879	13.75	0.000	.0140016	.0186579
c.female#c.hisp	-.2267412	.0013176	-172.09	0.000	-.2293236	-.2241589
c.female#c.schlyrs	-.0153869	.0001208	-127.37	0.000	-.0156236	-.0151501
c.schlyrs#c.black	.0165878	.000234	70.88	0.000	.0161292	.0170465
c.schlyrs#c.hisp	-.0502598	.0001637	-306.97	0.000	-.0505807	-.0499389
_cons	5.389931	.0209626	257.12	0.000	5.348845	5.431017

8.10 lflm1

Source	SS	df	MS
Model	3216487.07	24	134020.295
Residual	24778493.7	28365024	.873558002
Total	27994980.8	28365048	.986953407

Number of obs	=	28365049
F(24, 28365024)	>	99999.00
Prob > F	=	0.0000
R-squared	=	0.1149
Adj R-squared	=	0.1149
Root MSE	=	.93464

Plflm1_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.107895	.0003484	-309.70	0.000	-.1085778	-.1072122
spage2	.5083149	.0021479	236.66	0.000	.5041051	.5125246
spage3	-2.068015	.0092943	-222.50	0.000	-2.086231	-2.049798
female	-1.548043	.0088151	-175.61	0.000	-1.56532	-1.530766
black	-1.709069	.0165944	-102.99	0.000	-1.741593	-1.676544
hisp	1.413332	.0187583	75.34	0.000	1.376567	1.450098
schlyrs	-.2888694	.0016499	-175.08	0.000	-.2921032	-.2856356
c.spage1#c.female	.0218721	.0001198	182.54	0.000	.0216373	.022107
c.spage1#c.black	.0233829	.0002262	103.36	0.000	.0229395	.0238263
c.spage1#c.hisp	-.0046855	.0002649	-17.69	0.000	-.0052048	-.0041663
c.spage1#c.schlyrs	.0055924	.0000236	236.77	0.000	.0055461	.0056387
c.spage2#c.female	-.1456416	.0007427	-196.09	0.000	-.1470973	-.1441859
c.spage2#c.black	-.1385531	.0013453	-102.99	0.000	-.1411897	-.1359164
c.spage2#c.hisp	-.0196856	.0022364	-8.80	0.000	-.0240688	-.0153024
c.spage2#c.schlyrs	-.0296052	.0001525	-194.17	0.000	-.029904	-.0293063
c.spage3#c.female	.6477903	.0031682	204.46	0.000	.6415806	.6539999
c.spage3#c.black	.4989451	.0049545	100.71	0.000	.4892345	.5086558
c.spage3#c.hisp	.0325743	.0138888	2.35	0.019	.0053528	.0597958
c.spage3#c.schlyrs	.1154655	.000688	167.82	0.000	.114117	.116814
c.female#c.black	-.1941089	.0013839	-140.26	0.000	-.1968213	-.1913964
c.female#c.hisp	.1401454	.001535	91.30	0.000	.1371368	.143154
c.female#c.schlyrs	.0132834	.0001407	94.38	0.000	.0130075	.0135593
c.schlyrs#c.black	-.0171989	.0002726	-63.08	0.000	-.0177332	-.0166645
c.schlyrs#c.hisp	-.0991172	.0001908	-519.61	0.000	-.0994911	-.0987434
_cons	6.226239	.0244226	254.94	0.000	6.178372	6.274107

8.11 glfl

Source	SS	df	MS			
Model	11655174.7	24	485632.277	Number of obs	=	28365049
Residual	15459442	28365024	.545017764	F(24, 28365024)	>	99999.00
				Prob > F	=	0.0000
Total	27114616.6	28365048	.955916472	R-squared	=	0.4298
				Adj R-squared	=	0.4298
				Root MSE	=	.73825

Pglfl_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.1155555	.0002752	-419.93	0.000	-.1160949	-.1150162
spage2	.6130749	.0016965	361.37	0.000	.6097497	.6164001
spage3	-2.306798	.0073413	-314.22	0.000	-2.321187	-2.292409
female	-1.387136	.0069628	-199.22	0.000	-1.400783	-1.37349
black	-4.275594	.0131076	-326.19	0.000	-4.301285	-4.249904
hisp	-.5032181	.0148167	-33.96	0.000	-.5322584	-.4741779
schlyrs	-.0873129	.0013032	-67.00	0.000	-.0898672	-.0847586
c.spage1#c.female	.0226533	.0000946	239.35	0.000	.0224678	.0228388
c.spage1#c.black	.0480693	.0001787	269.02	0.000	.0477191	.0484195
c.spage1#c.hisp	.0127669	.0002092	61.01	0.000	.0123568	.0131771
c.spage1#c.schlyrs	.0038681	.0000187	207.33	0.000	.0038316	.0039047
c.spage2#c.female	-.1620402	.0005867	-276.21	0.000	-.16319	-.1608903
c.spage2#c.black	-.2528096	.0010626	-237.92	0.000	-.2548922	-.250727
c.spage2#c.hisp	-.0745357	.0017665	-42.19	0.000	-.0779979	-.0710735
c.spage2#c.schlyrs	-.0374724	.0001204	-311.15	0.000	-.0377085	-.0372364
c.spage3#c.female	.6777792	.0025025	270.84	0.000	.6728743	.6826841
c.spage3#c.black	.8769273	.0039135	224.08	0.000	.869257	.8845975
c.spage3#c.hisp	-.1366647	.0109704	-12.46	0.000	-.1581663	-.1151631
c.spage3#c.schlyrs	.137413	.0005434	252.85	0.000	.1363478	.1384781
c.female#c.black	.0224229	.0010931	20.51	0.000	.0202804	.0245653
c.female#c.hisp	.0368015	.0012125	30.35	0.000	.0344251	.0391779
c.female#c.schlyrs	.0017613	.0001112	15.84	0.000	.0015434	.0019792
c.schlyrs#c.black	.0052001	.0002154	24.15	0.000	.0047781	.0056222
c.schlyrs#c.hisp	-.0634951	.0001507	-421.41	0.000	-.0637904	-.0631998
_cons	5.867085	.0192909	304.14	0.000	5.829275	5.904894

8.12 lfl

Source	SS	df	MS			
				Number of obs	=	28365049
				F(24, 28365024)	>	99999.00
Model	5784253.24	24	241010.552	Prob > F	=	0.0000
Residual	21829452.3	28365024	.769590475	R-squared	=	0.2095
				Adj R-squared	=	0.2095
Total	27613705.5	28365048	.97351168	Root MSE	=	.87726

Plfl_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.1536011	.000327	-469.74	0.000	-.154242	-.1529602
spage2	.8223383	.002016	407.91	0.000	.818387	.8262896
spage3	-2.906114	.0087237	-333.13	0.000	-2.923212	-2.889016
female	-.9505854	.0082739	-114.89	0.000	-.9668019	-.9343689
black	-2.684374	.0155756	-172.34	0.000	-2.714902	-2.653847
hisp	-1.504869	.0176067	-85.47	0.000	-1.539377	-1.47036
schlyrs	-.4848041	.0015486	-313.05	0.000	-.4878394	-.4817688
c.spage1#c.female	.0171649	.0001125	152.62	0.000	.0169445	.0173853
c.spage1#c.black	.0325793	.0002123	153.44	0.000	.0321631	.0329954
c.spage1#c.hisp	.0340818	.0002486	137.07	0.000	.0335944	.0345691
c.spage1#c.schlyrs	.0090404	.0000222	407.77	0.000	.0089969	.0090838
c.spage2#c.female	-.1461474	.0006971	-209.64	0.000	-.1475137	-.1447811
c.spage2#c.black	-.1415904	.0012627	-112.14	0.000	-.1440652	-.1391156
c.spage2#c.hisp	-.2108412	.0020991	-100.44	0.000	-.2149554	-.2067271
c.spage2#c.schlyrs	-.0573263	.0001431	-400.58	0.000	-.0576068	-.0570458
c.spage3#c.female	.6072431	.0029737	204.20	0.000	.6014146	.6130715
c.spage3#c.black	.3770192	.0046503	81.07	0.000	.3679047	.3861337
c.spage3#c.hisp	.5248574	.0130361	40.26	0.000	.4993071	.5504077
c.spage3#c.schlyrs	.1953794	.0006458	302.55	0.000	.1941137	.1966451
c.female#c.black	-.1639605	.001299	-126.23	0.000	-.1665064	-.1614146
c.female#c.hisp	-.0069198	.0014408	-4.80	0.000	-.0097437	-.0040959
c.female#c.schlyrs	-.0051282	.0001321	-38.82	0.000	-.0053872	-.0048693
c.schlyrs#c.black	-.0051796	.0002559	-20.24	0.000	-.0056812	-.0046781
c.schlyrs#c.hisp	-.0800688	.000179	-447.20	0.000	-.0804197	-.0797178
_cons	8.883129	.0229233	387.52	0.000	8.838201	8.928058

8.13 vdvis1

Source	SS	df	MS
Model	3613355.42	24	150556.476
Residual	18013071.8	28345792	.635476045
Total	21626427.2	28345816	.762949537

Number of obs	=	28345817
F(24, 28345792)	>	99999.00
Prob > F	=	0.0000
R-squared	=	0.1671
Adj R-squared	=	0.1671
Root MSE	=	.79717

Pvdvis1_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.040513	.0002972	-136.32	0.000	-.0410955	-.0399305
spage2	.2739882	.0018325	149.52	0.000	.2703966	.2775798
spage3	-.7356267	.0079297	-92.77	0.000	-.7511686	-.7200849
female	-.920054	.0075208	-122.33	0.000	-.9347945	-.9053135
black	-1.261813	.0141787	-88.99	0.000	-1.289603	-1.234023
hisp	.4425547	.0159993	27.66	0.000	.4111966	.4739128
schlyrs	-.0204586	.0014076	-14.53	0.000	-.0232175	-.0176997
c.spage1#c.female	.0095893	.0001022	93.80	0.000	.0093889	.0097896
c.spage1#c.black	.0056738	.0001934	29.33	0.000	.0052947	.0060529
c.spage1#c.hisp	-.0089268	.0002259	-39.51	0.000	-.0093696	-.0084839
c.spage1#c.schlyrs	.0017165	.0000202	85.18	0.000	.001677	.001756
c.spage2#c.female	-.0676531	.0006337	-106.76	0.000	-.0688951	-.0664111
c.spage2#c.black	.1099702	.0011491	95.70	0.000	.1077181	.1122224
c.spage2#c.hisp	.1150039	.0019075	60.29	0.000	.1112653	.1187425
c.spage2#c.schlyrs	-.0182956	.0001301	-140.64	0.000	-.0185506	-.0180406
c.spage3#c.female	.1014087	.0027032	37.51	0.000	.0961106	.1067067
c.spage3#c.black	-.6210063	.0042298	-146.82	0.000	-.6292965	-.6127161
c.spage3#c.hisp	-.7470169	.0118461	-63.06	0.000	-.7702347	-.723799
c.spage3#c.schlyrs	.0514886	.000587	87.71	0.000	.050338	.0526391
c.female#c.black	-.0254295	.0011811	-21.53	0.000	-.0277444	-.0231145
c.female#c.hisp	.0155488	.0013093	11.88	0.000	.0129827	.0181149
c.female#c.schlyrs	.0126261	.0001201	105.15	0.000	.0123907	.0128614
c.schlyrs#c.black	.0228329	.0002327	98.12	0.000	.0223768	.0232889
c.schlyrs#c.hisp	.0109985	.0001627	67.60	0.000	.0106796	.0113174
_cons	1.694443	.0208349	81.33	0.000	1.653607	1.735278

8.14 gcpm1

Source	SS	df	MS			
				Number of obs	=	28365049
				F(24, 28365024)	>	99999.00
Model	9990264.99	24	416261.041	Prob > F	=	0.0000
Residual	17317855.5	28365024	.610535547	R-squared	=	0.3658
				Adj R-squared	=	0.3658
Total	27308120.4	28365048	.962738383	Root MSE	=	.78137

Pgcpm1_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.0810651	.0002912	-278.34	0.000	-.081636	-.0804943
spage2	.2892764	.0017956	161.10	0.000	.285757	.2927957
spage3	-.8936572	.0077701	-115.01	0.000	-.9088863	-.8784282
female	-.4334176	.0073694	-58.81	0.000	-.4478614	-.4189738
black	-4.378705	.013873	-315.63	0.000	-4.405896	-4.351515
hisp	2.336685	.015682	149.00	0.000	2.305949	2.367421
schlyrs	.0445203	.0013794	32.28	0.000	.0418169	.0472238
c.spage1#c.female	.0109097	.0001002	108.91	0.000	.0107134	.0111061
c.spage1#c.black	.0470365	.0001891	248.71	0.000	.0466659	.0474072
c.spage1#c.hisp	-.0284917	.0002215	-128.65	0.000	-.0289257	-.0280576
c.spage1#c.schlyrs	.0016884	.0000197	85.50	0.000	.0016497	.0017271
c.spage2#c.female	-.0873775	.0006209	-140.72	0.000	-.0885945	-.0861605
c.spage2#c.black	-.2264965	.0011246	-201.39	0.000	-.2287007	-.2242922
c.spage2#c.hisp	.2300752	.0018696	123.06	0.000	.2264107	.2337396
c.spage2#c.schlyrs	-.0154071	.0001275	-120.87	0.000	-.0156569	-.0151572
c.spage3#c.female	.4533211	.0026487	171.15	0.000	.4481298	.4585124
c.spage3#c.black	.7048116	.004142	170.16	0.000	.6966935	.7129298
c.spage3#c.hisp	-1.582442	.0116111	-136.29	0.000	-1.605199	-1.559684
c.spage3#c.schlyrs	.0382811	.0005752	66.55	0.000	.0371537	.0394084
c.female#c.black	-.044085	.001157	-38.10	0.000	-.0463526	-.0418174
c.female#c.hisp	-.156757	.0012833	-122.15	0.000	-.1592722	-.1542418
c.female#c.schlyrs	-.0077451	.0001177	-65.82	0.000	-.0079758	-.0075145
c.schlyrs#c.black	.0233819	.0002279	102.58	0.000	.0229351	.0238286
c.schlyrs#c.hisp	-.0497206	.0001595	-311.78	0.000	-.0500331	-.049408
_cons	3.715046	.0204175	181.95	0.000	3.675029	3.755064

8.15 gcp

Source	SS	df	MS			
Model	11887183.2	24	495299.302	Number of obs	=	28365049
Residual	15293477.8	28365024	.53916675	F(24, 28365024)	>	99999.00
				Prob > F	=	0.0000
Total	27180661.1	28365048	.958244846	R-squared	=	0.4373
				Adj R-squared	=	0.4373
				Root MSE	=	.73428

Pgcp_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.1061269	.0002737	-387.75	0.000	-.1066633	-.1055905
spage2	.5664878	.0016874	335.71	0.000	.5631805	.5697951
spage3	-2.160239	.0073018	-295.85	0.000	-2.17455	-2.145927
female	-1.353748	.0069253	-195.48	0.000	-1.367321	-1.340174
black	-4.366507	.013037	-334.93	0.000	-4.392059	-4.340955
hisp	-.3940637	.014737	-26.74	0.000	-.4229476	-.3651797
schlyrs	-.0277726	.0012962	-21.43	0.000	-.0303132	-.0252321
c.spage1#c.female	.0220659	.0000941	234.40	0.000	.0218814	.0222504
c.spage1#c.black	.0489213	.0001777	275.27	0.000	.0485729	.0492696
c.spage1#c.hisp	.010399	.0002081	49.97	0.000	.0099911	.0108069
c.spage1#c.schlyrs	.003009	.0000186	162.15	0.000	.0029726	.0030454
c.spage2#c.female	-.1555431	.0005835	-266.57	0.000	-.1566868	-.1543995
c.spage2#c.black	-.2580044	.0010569	-244.12	0.000	-.2600758	-.255933
c.spage2#c.hisp	-.0567184	.001757	-32.28	0.000	-.060162	-.0532748
c.spage2#c.schlyrs	-.0337061	.0001198	-281.39	0.000	-.0339408	-.0334713
c.spage3#c.female	.6508438	.0024891	261.48	0.000	.6459653	.6557222
c.spage3#c.black	.906269	.0038924	232.83	0.000	.89864	.9138979
c.spage3#c.hisp	-.2150439	.0109114	-19.71	0.000	-.2364298	-.193658
c.spage3#c.schlyrs	.1258863	.0005405	232.90	0.000	.1248269	.1269457
c.female#c.black	.0415605	.0010872	38.23	0.000	.0394295	.0436914
c.female#c.hisp	.0341505	.001206	28.32	0.000	.0317868	.0365141
c.female#c.schlyrs	.0023326	.0001106	21.10	0.000	.0021159	.0025493
c.schlyrs#c.black	.0059763	.0002142	27.90	0.000	.0055565	.0063961
c.schlyrs#c.hisp	-.0607339	.0001499	-405.27	0.000	-.0610276	-.0604401
_cons	5.222462	.019187	272.19	0.000	5.184857	5.260068

8.16 h1rmsetotal

Source	SS	df	MS			
				Number of obs	=	28365049
				F(24, 28365024)	>	99999.00
Model	4838901.27	24	201620.886	Prob > F	=	0.0000
Residual	18314169.1	28365024	.645660271	R-squared	=	0.2090
				Adj R-squared	=	0.2090
Total	23153070.4	28365048	.816253523	Root MSE	=	.80353

Ph1rmsetotal_blom	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
spage1	-.1110934	.0002995	-370.92	0.000	-.1116804	-.1105064
spage2	.5111354	.0018466	276.80	0.000	.5075162	.5147546
spage3	-2.226211	.0079904	-278.61	0.000	-2.241872	-2.21055
female	-2.699219	.0075785	-356.17	0.000	-2.714072	-2.684365
black	-3.221603	.0142665	-225.82	0.000	-3.249565	-3.193641
hisp	-2.406037	.0161268	-149.19	0.000	-2.437645	-2.374429
schlyrs	-.2358848	.0014185	-166.29	0.000	-.238665	-.2331047
c.spage1#c.female	.0426963	.000103	414.47	0.000	.0424944	.0428982
c.spage1#c.black	.0256938	.0001945	132.11	0.000	.0253126	.0260749
c.spage1#c.hisp	.0334116	.0002277	146.70	0.000	.0329652	.033858
c.spage1#c.schlyrs	.004905	.0000203	241.55	0.000	.0048652	.0049448
c.spage2#c.female	-.2696516	.0006385	-422.30	0.000	-.2709031	-.2684001
c.spage2#c.black	-.1029399	.0011565	-89.01	0.000	-.1052067	-.1006731
c.spage2#c.hisp	.0475146	.0019227	24.71	0.000	.0437462	.0512829
c.spage2#c.schlyrs	-.0286959	.0001311	-218.92	0.000	-.0289529	-.028439
c.spage3#c.female	1.302694	.0027238	478.26	0.000	1.297356	1.308033
c.spage3#c.black	.5401369	.0042595	126.81	0.000	.5317885	.5484854
c.spage3#c.hisp	-.938091	.0119404	-78.56	0.000	-.9614938	-.9146882
c.spage3#c.schlyrs	.1189913	.0005915	201.17	0.000	.117832	.1201506
c.female#c.black	.0362123	.0011898	30.44	0.000	.0338804	.0385443
c.female#c.hisp	-.2061054	.0013197	-156.18	0.000	-.2086919	-.2035188
c.female#c.schlyrs	-.0019314	.000121	-15.96	0.000	-.0021685	-.0016942
c.schlyrs#c.black	.0614217	.0002344	262.04	0.000	.0609623	.0618811
c.schlyrs#c.hisp	-.0022363	.000164	-13.64	0.000	-.0025577	-.0019149
_cons	6.381657	.0209966	303.94	0.000	6.340505	6.42281