SR paper analyses for JAPD resubmission

NRG

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Descriptives

Data set descriptives for these analyses:

```
SRALL.data <- dplyr::select(PCSR.data, childAge, sex, matYrsEd, t_income, Snack_avg, FishFlanker_RawScore, # remove empty rows (subjects who consented but never provided any data)
SR.data <- SRALL.data[-c(19, 28, 40, 91, 93),]

desc.data <- dplyr::select(PCSR.data, Snack_avg, FishFlanker_RawScore, ZooGNG_percCorr, FishGNG_percCorr.data <- dplyr::select(PCSR.data, Snack_avg, FishFlanker_RawScore, ChildGNGcomp, Food_RegLCRC, FLA_apa.cor.table(corr.data, filename="corrTable.doc")
```

```
##
##
     3. ChildGNGcomp
                              -0.02 0.91 .18
                                                         .54**
##
                                            [-.03, .38] [.35, .69]
##
                                                         .26*
##
     4. Food_RegLCRC
                              1.74
                                     0.88
                                            .27*
##
                                            [.05, .46] [.02, .47] [-.24, .21]
##
##
     5. FLA_ACC_diffx100
                              -9.70 8.13
                                           .11
                                                         .15
                                                                     .06
##
                                            [-.11, .32] [-.09, .37] [-.17, .28]
##
##
     6. t_momGNG
                              0.67
                                     0.19
                                            .08
                                                         .26*
                                                                     -.05
                                            [-.14, .30] [.02, .47] [-.27, .18]
##
##
                                                         .24*
##
     7. matYrsEd
                              15.15 2.47
                                                                     .30**
                                           . 15
##
                                            [-.06, .35] [.01, .45]
                                                                     [.09, .48]
##
##
                              141.91 44.67 .23*
                                                         .40**
                                                                     .41**
     8. t_income
                                            [.02, .42]
##
                                                        [.18, .58]
                                                                     [.21, .58]
##
                                          7
                 5
                              6
##
##
##
##
##
##
##
##
##
##
##
##
##
     .10
     [-.13, .32]
##
##
##
                  .14
     [-.12, .32] [-.09, .35]
##
##
##
                  .26*
                              .24*
     [-.13, .30] [.04, .45]
##
                              [.02, .44]
##
##
                  .01
                              .24*
                                          .54**
     [-.14, .31] [-.21, .24] [.02, .44] [.38, .68]
##
##
##
## Note. M and SD are used to represent mean and standard deviation, respectively.
## Values in square brackets indicate the 95% confidence interval.
## The confidence interval is a plausible range of population correlations
## that could have caused the sample correlation (Cumming, 2014).
##
    * indicates p < .05. ** indicates p < .01.
stargazer(as.data.frame(desc.data), type = "text",
          title = "Task and Parenting Descriptive Statistics", digits = 2,
          covariate.labels = c("Child appetitive SR (snack delay, score 0-1 x 4 trials)",
```

```
"Child attentional control (Flanker, raw score)",
                           "Child inhibitory control (Zoo GNG, % correct)",
                           "Child inhibitory control (Fish GNG, % correct)",
                           "Mother appetitive SR (Food craving self-regulation, Look Crave - Regula
                           "Mother attentional control (Flanker, % correct incongruent-congruent*",
                           "Mother inhibitory control (GNG, % correct)"),
        omit.summary.stat = c("p25", "p75"), min.max = TRUE, notes = "Raw data shown here; outliers w
## Task and Parenting Descriptive Statistics
## Statistic
                                                                          N Mean St. Dev.
## -----
## Child appetitive SR (snack delay, score 0-1 x 4 trials)
                                                                          88 2.01
                                                                                   1.66
## Child attentional control (Flanker, raw score)
                                                                         73 21.01 12.43
## Child inhibitory control (Zoo GNG, % correct)
                                                                          83 51.68 14.39
## Child inhibitory control (Fish GNG, % correct)
                                                                          66 66.27 16.87
## Mother appetitive SR (Food craving self-regulation, Look Crave - Regulate Crave)* 79 1.74
                                                                                   0.88
## Mother attentional control (Flanker, % correct incongruent-congruent*
                                                                          80 -9.70
                                                                                   8.13
## Mother inhibitory control (GNG, % correct)
                                                                          79 95.50
                                                                                   4.01
## Raw data shown here; outliers were winsorized 3SD from the mean for analyses (marked with an *).
write.csv(SR.data, "SRdata.csv")
```

Multiple Imputation

Correlations with imputed data

```
library(miceadds)

## * miceadds 3.11-6 (2021-01-21 11:48:47)

corr.vars1 <- c("Snack_avg", "FishFlanker_RawScore", "ChildGNGcomp", "Food_RegLCRC", "FLA_ACC_diffx100"
corr.data <- SR.data[corr.vars1]

stargazer(corr.data, type = "text")

##</pre>
```

```
Min Pctl(25) Pctl(75)
                N Mean St. Dev.
                                0
                88 2.011
                                     0
## Snack_avg
                        1.656
## FishFlanker_RawScore 73 21.010
                        12.430 4.000 11.000 36.000 40.000
## ChildGNGcomp 85 -0.017 0.906 -3.000 -0.500 0.640 1.620
## Food_RegLCRC
                79 1.740 0.881 0.104 1.061 2.350 3.750
## FLA_ACC_diffx100
                              -38.380 -14.000 -3.000 0.000
                80 -9.697 8.128
## t_momGNG
                79 0.671 0.194 0.088 0.593 0.801 0.942
```

```
86 141.900 44.670 0.000 110.900 169.600 251.300
## t_income
apa.cor.table(corr.data, filename="Table2.doc", table.number=2)
##
##
## Table 2
## Means, standard deviations, and correlations with confidence intervals
##
##
##
     Variable
                                   SD 1
                                                    2
                                                                3
                            М
##
     1. Snack_avg
                            2.01
                                   1.66
##
     2. FishFlanker_RawScore 21.01 12.43 .25*
##
                                         [.02, .45]
##
##
                            -0.02 0.91 .18
##
     3. ChildGNGcomp
                                                    .54**
##
                                         [-.03, .38] [.35, .69]
##
##
     4. Food_RegLCRC
                            1.74 0.88 .27*
                                                    .26*
                                                              -.02
                                         [.05, .46] [.02, .47] [-.24, .21]
##
##
##
     5. FLA_ACC_diffx100
                            -9.70 8.13 .11
                                                   .15
                                                                .06
                                         [-.11, .32] [-.09, .37] [-.17, .28]
##
##
##
     6. t_momGNG
                            0.67
                                   0.19 .08
                                                    .26*
                                                                -.05
                                         [-.14, .30] [.02, .47] [-.27, .18]
##
##
                            15.15 2.47 .15
                                                    .24*
                                                                .30**
##
    7. matYrsEd
                                         [-.06, .35] [.01, .45] [.09, .48]
##
##
                                                    .40**
     8. t_income
                           141.91 44.67 .23*
                                                                .41**
##
                                         [.02, .42] [.18, .58] [.21, .58]
##
##
##
                5
                          6
                                      7
##
##
##
##
##
##
##
##
##
##
##
##
     .10
##
     [-.13, .32]
##
##
    .10
                .14
     [-.12, .32] [-.09, .35]
##
```

88 15.150 2.466 8 13 16.5

matYrsEd

```
##
                 .26*
                             .24*
##
     .09
     [-.13, .30] [.04, .45] [.02, .44]
##
##
                             .24*
##
                 .01
     [-.14, .31] [-.21, .24] [.02, .44] [.38, .68]
##
##
##
\#\# Note. M and SD are used to represent mean and standard deviation, respectively.
## Values in square brackets indicate the 95% confidence interval.
## The confidence interval is a plausible range of population correlations
## that could have caused the sample correlation (Cumming, 2014).
## * indicates p < .05. ** indicates p < .01.
##
```

micombine.cor(impData, variables = corr.vars1, conf.level = 0.95, method = "pearson", nested = FALSE, p

variable1	variable2 r	rse f	fisher_r	fisher_rse	e fmi t	p lower9	5 upper95
matYrsEd	t_income 0.5503	0.0761 (0.6189	0.1092	0.0129 5.6687	0.0000 0.3841	0.6820
matYrsEd	$Snack_avg 0.1523$	0.1059 (0.1535	0.1085	$0.0000\ 1.4148$	0.1571 -	0.3505
						0.0591	
matYrsEd	FishFlanker_Ra v\2 7dr?e	0.1048 (0.2787	0.1132	$0.0839\ 2.4616$	$0.0138 \ 0.0567$	0.4627
matYrsEd	ChildGNGcomp 0.2570	0.1046 (0.2629	0.1120	$0.0628\ 2.3476$	$0.0189\ 0.0434$	0.4482
matYrsEd	$Food_RegLCRC0.1212$	0.1173 (0.1218	0.1191	$0.1754\ 1.0232$	0.3062 -	0.3410
						0.1111	
matYrsEd	FLA_ACC_diff x012573	0.1025(0.2633	0.1098	$0.0247\ 2.3971$	$0.0165\ 0.0480$	0.4451
matYrsEd	t_{momGNG} 0.2678	0.1042 (0.2745	0.1123	$0.0678\ 2.4445$	$0.0145\ 0.0544$	0.4578
t_income	$Snack_avg$ 0.2036	0.1049 (0.2065	0.1095	$0.0185\ 1.8863$	0.0593 -	0.3979
						0.0081	
t_income	FishFlanker_Ra v3966	0.0948 (0.4196	0.1125	$0.0712\ 3.7302$	$0.0002\ 0.1965$	0.5649
t_income	ChildGNGcomp 0.4101	0.0917 (0.1102	$0.0318 \ 3.9528$	$0.0001\ 0.2162$	0.5728
t_income	$Food_RegLCRC0.1204$	0.1208 (0.1210	0.1226	$0.2254\ 0.9871$	0.3236 -	0.3464
						0.1187	
t_income	$FLA_ACC_diffx100-$	0.1214	-	0.1214	0.2090 -	0.9137 -	0.2211
	0.0132		0.0132		0.1084		
t_income	t_{momGNG} 0.2983	0.1080 (0.1186	$0.1690\ 2.5937$		
$Snack_avg$	FishFlanker_Ra v S439	0.1038 (0.2489	0.1104	$0.0354\ 2.2538$		0.4344
$Snack_avg$	ChildGNGcomp 0.1778	0.1078 (0.1797	0.1113	$0.0511\ 1.6142$	0.1065 -	0.3781
						0.0385	
$Snack_avg$	${\rm Food_RegLCRC0.2833}$	0.1119 (0.1217	$0.2130\ 2.3935$		
$Snack_avg$	FLA_ACC_diff x 01 09 51	0.1122 (0.0953	0.1132	$0.0832 \ 0.8423$		0.3070
						0.1258	
$Snack_avg$	t_{momGNG} 0.0944	0.1138 (0.0947	0.1148	0.1104 0.8248		0.3094
						0.1296	
_	Raw Suith GNG comp 0.5039	0.1015 (0.1361	$0.3825 \ 4.0759$		0.6758
	RawSodreRegLCRC0.2566	0.1143 (0.1223	$0.2219\ 2.1450$		
FishFlanker_R	Raw ScreACC_diffx010632	0.1084 (0.1647	0.1114	$0.0523\ 1.4789$	0.1392 -	0.3653
						0.0535	
FishFlanker_R		0.1044 (0.2650	0.1119	0.0612 2.3684		
ChildGNGcom	p Food_RegLCRC -	0.1257	-	0.1257	0.2660 -	0.9910 -	0.2402
	0.0014		0.0014		0.0113		
ChildGNGcom	p FLA_ACC_diff x0108 59	0.1093 (0.0359	0.1095	$0.0187 \ 0.3279$	0.7430 -	0.2454
						0.1768	

variable1	variable2 r	rse	fisher_r	fisher_rs	e fmi t	p	lower95	upper95
ChildGNGcom	p t_momGNG - 0.0374	0.1132	0.0374	0.1133	0.0857 - 0.330		2 - 0.2539	0.1826
Food_RegLCF	RCFLA_ACC_diff x0109 02			0.1130	0.0802 0.800		5 -	0.3022
Food_RegLCF	RCt_momGNG 0.0917	0.1117	0.0920	0.1127	0.0744 0.816	5 0.4142	0.1303	0.3030
FLA ACC di	iffx <u>10</u> 00.omGNG 0.1352	2 0.1124	L	0.1145	0.1043 1.188	0 0 2349	0.1281	0.3455
							0.0881	
t_income		0.0761		0.1092	$0.0129\ 5.668$		0.3841	0.6820
Snack_avg	matYrsEd 0.1523	0.1059	0.1535	0.1085	0.0000 1.414	8 0.1571	0.0591	0.3505
FishFlanker_F	RawwishdownesEd 0.2717	0.1048	0.2787	0.1132	$0.0839\ 2.461$	6 0.0138	0.0567	0.4627
ChildGNGcom	p matYrsEd 0.2570	0.1046	0.2629	0.1120	$0.0628\ 2.347$	6 0.0189	0.0434	0.4482
Food_RegLCF	RCmatYrsEd 0.1212	0.1173	3 0.1218	0.1191	0.1754 1.023	2 0.3062	2 - 0.1111	0.3410
FLA ACC di	iffxnh00YrsEd 0.257	0.1025	0.2633	0.1098	0.0247 2.397	1 0.016	5 0.0480	0.4451
t_momGNG	$ \text{matYrsEd} \qquad 0.2678 $		2 0.2745	0.1123	0.0678 2.444		5 0.0544	0.4578
Snack_avg		0.1049		0.1095	0.0185 1.886			0.3979
~	<u></u>	012020	0.200	0.200	0.0200 2.000		0.0081	0.00,0
FishFlanker F	RatvSinoreme 0.3966	0.0948	0.4196	0.1125	0.0712 3.730	2 - 0.0002	2 0.1965	0.5649
ChildGNGcom		0.0917	0.4357	0.1102	0.0318 3.952		0.2162	0.5728
Food_RegLCF		0.1208		0.1226	0.2254 0.987			0.3464
FLA_ACC_di	iffxt1000come -	0.1214	l _	0.1214	0.2090	0.913'		0.2211
1 L/1_/100_di	0.0132		0.0132	0.1214	0.108		0.2460	0.2211
t momGNG	t income 0.2983		0.3077	0.1186	0.1690 2.593		5 0.0750	0.4932
FishFlanker_F			0.2489	0.1104	0.0354 2.253		2 0.0324	0.4344
ChildGNGcom	_		0.1797	0.1113	0.0511 1.614			0.3781
	-						0.0385	
Food_RegLCF	_		0.2913	0.1217	0.2130 2.393		7 0.0527	0.4852
FLA_ACC_di	iff: Sh0 0ck_avg 0.0951	0.1122	2 0.0953	0.1132	0.0832 0.842	3 0.3996	0.1258	0.3070
t_{momGNG}	Snack_avg 0.0944	0.1138	3 0.0947	0.1148	0.1104 0.824	8 0.409	5 - 0.1296	0.3094
ChildGNGcom	p FishFlanker Ra v\$03 9	e 0.1015	0.5546	0.1361	0.3825 4.075	9 0.0000		0.6758
	RCFishFlanker_Ra v256 6			0.1223	0.2219 2.145			
	iffxFli90Flanker Ra vS63 2			0.1114	0.0523 1.478			0.3653
		0.200		******	0.00000 0.000	0.1001	0.0535	0.000
t_{momGNG}	FishFlanker Raw Score	e 0.1044	0.2650	0.1119	0.0612 2.368	4 0.0179		0.4497
	RCChildGNGcomp -			0.1257	0.2660			0.2402
_ 0	0.0014		0.0014		0.011		0.2428	
${\rm FLA_ACC_di}$	iff x0101 dGNGcomp 0.0359	0.1093		0.1095	0.0187 0.327			0.2454
							0.1768	
t_momGNG	ChildGNGcomp -			0.1133	0.0857			0.1826
	0.0374		0.0374		0.330		0.2539	
FLA_ACC_di	iffxHood_RegLCRC0.0902	0.1121	0.0905	0.1130	0.0802 0.800	4 0.423		0.3022
	E 1 D 10D000000		. 0 0000	0.110=	0.0544.0.010	F 0 44 **	0.1303	0.0000
t_momGNG	Food_RegLCRC0.0917	0.1117	0.0920	0.1127	0.0744 0.816	5 0.4142		0.3030
CNIC	DIA ACC 1:COMPE	0.110	. 0.1920	0.1145	0.1049.1.100	0 0 00 47	0.1281	0.9455
t_momGNG	FLA_ACC_diffx010052	z U.1124	10.1360	0.1145	0.1043 1.188	υ U.2348	0.0881	0.3455
							0.0001	

Note: these are exactly the same correlations as with the raw data.

Hypothesis 1

Testing associations between mom and child SR controlling for child age and sex.

hot SR hotSR <- with(data = impData, exp = lm(Snack_avg ~ Food_RegLCRC + sex + childAge)) summary(pool(hotSR))</pre>

term	estimate	std.error	statistic	df	p.value
(Intercept)	0.1790	0.9575	0.1869	81.30	0.8522
$Food_RegLCRC$	0.5266	0.2239	2.3513	48.61	0.0228
sex	0.4402	0.3480	1.2650	79.37	0.2096
$\operatorname{childAge}$	0.1765	0.2350	0.7509	77.29	0.4550

pool.r.squared(hotSR)

```
## est lo 95 hi 95 fmi
## R^2 0.1056 0.01057 0.2665 NaN
```

GNG

```
GNG <- with(data = impData, exp = lm(ChildGNGcomp ~ t_momGNG + sex + childAge))
summary(pool(GNG))</pre>
```

term	estimate	std.error	statistic	df	p.value
(Intercept)	-2.5747	0.5250	-4.9045	79.22	0.0000
t_momGNG	-0.3843	0.4498	-0.8544	63.00	0.3961
sex	0.1290	0.1685	0.7657	78.38	0.4461
$\operatorname{childAge}$	0.6716	0.1119	6.0032	76.88	0.0000

pool.r.squared(GNG)

```
## est lo 95 hi 95 fmi
## R^2 0.3148 0.157 0.4773 NaN
```

```
# Flanker
```

```
FLA <- with(data = impData, exp = lm(FishFlanker_RawScore ~ FLA_ACC_diffx100 + sex + childAge))
summary(pool(FLA))
```

term	estimate	std.error	statistic	df	p.value
(Intercept)	-19.6306	5.9826	-3.281	77.26	0.0016
FLA_ACC_diffx100	0.1494	0.1326	1.127	71.16	0.2637
sex	2.9987	2.0899	1.435	74.49	0.1555
$\operatorname{childAge}$	9.7773	1.3514	7.235	79.88	0.0000

pool.r.squared(FLA)

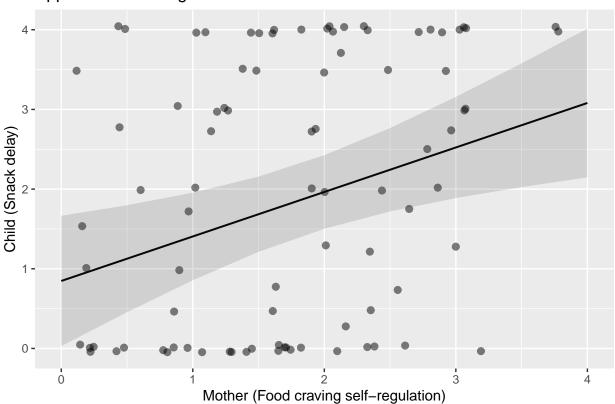
```
## est lo 95 hi 95 fmi
## R^2 0.4144 0.2486 0.5682 NaN
```

Plot all three models in one figure

Package 'effects' is not available, but needed for 'ggeffect()'. Either install package 'effects', or

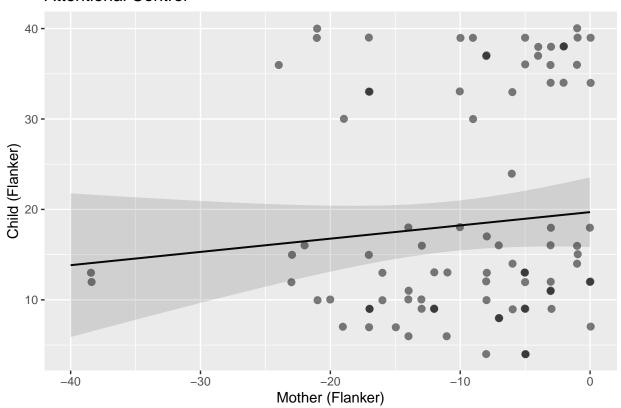
as

Appetitive Self-Regulation



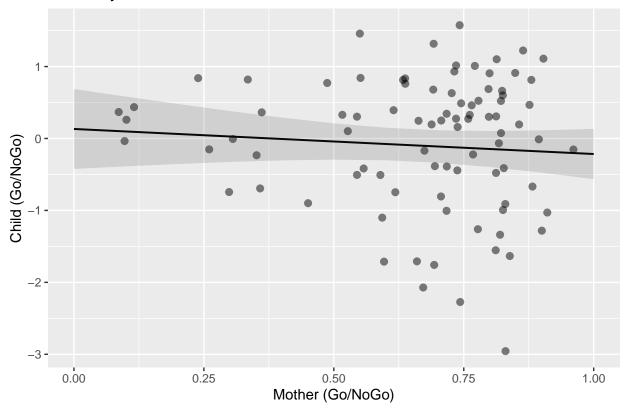
Package 'effects' is not available, but needed for 'ggeffect()'. Either install package 'effects', or

Attentional Control



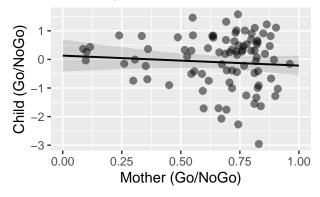
Package 'effects' is not available, but needed for 'ggeffect()'. Either install package 'effects', or
ic

Inhibitory Control



Appetitive Self–Regulation Attentional Control (very supplication) Attentional Control (very supplication) Attentional Control (very supplication) (very supplication) (very supplication) (very supplication) Attentional Control (very supplication) (v

c Inhibitory Control



Compare models

```
# use multiply imputed data set 3 for plotting
# z-score all variables since raw regression parameters are in the units of the DV
cData3$Mom_appSR <- c(scale(cData3$Food_RegLCRC, center=TRUE, scale=TRUE))
cData3$Mom_GNG <- c(scale(cData3$Snack_avg, center=TRUE, scale=TRUE))
cData3$Mom_GNG <- c(scale(cData3$ChildGNGcomp, center=TRUE, scale=TRUE))
cData3$Mom_FLA <- c(scale(cData3$FLA_ACC_diffx100, center=TRUE, scale=TRUE))
cData3$Child_FLA <- c(scale(cData3$FishFlanker_RawScore, center=TRUE, scale=TRUE))
cData3$Child_FLA <- c(scale(cData3$FishFlanker_RawScore, center=TRUE, scale=TRUE))
hotSRz <- lm(Child_appSR ~ Mom_appSR + sex + childAge, data = cData3)
GNGz <- lm(Child_GNG ~ Mom_GNG + sex + childAge, data = cData3)
FLAz <- lm(Child_FLA ~ Mom_FLA + sex + childAge, data = cData3)

# create CIs around the regression parameters (with robust SEs)
summ(hotSRz, robust = "HC1", confint = TRUE, digits = 3)</pre>
```

Observations	88
Dependent variable	$Child_appSR$
Type	OLS linear regression

F(3,84)	3.812
\mathbb{R}^2	0.120
$Adj. R^2$	0.088

	Est.	2.5%	97.5%	t val.	р
(Intercept)	-0.546	-1.713	0.620	-0.932	0.354
Mom_appSR	0.309	0.123	0.494	3.314	0.001
sex	0.249	-0.159	0.658	1.212	0.229
$\operatorname{childAge}$	0.106	-0.176	0.387	0.746	0.458

Standard errors: Robust, type = HC1

summ(GNGz, robust = "HC1", confint = TRUE, digits = 3)

Observations	88
Dependent variable	$Child_GNG$
Type	OLS linear regression

F(3,84)	13.189
\mathbb{R}^2	0.320
$Adj. R^2$	0.296

	Est.	2.5%	97.5%	t val.	p
(Intercept)	-3.028	-3.982	-2.074	-6.312	0.000
Mom_GNG	-0.079	-0.222	0.064	-1.099	0.275
sex	0.120	-0.240	0.480	0.662	0.510
$\operatorname{childAge}$	0.733	0.513	0.953	6.631	0.000

Standard errors: Robust, type = HC1

summ(FLAz, robust = "HC1", confint = TRUE, digits = 3)

Observations	88
Dependent variable	$Child_FLA$
Type	OLS linear regression

F(3,84)	19.906
\mathbb{R}^2	0.416
$Adj. R^2$	0.395

create CIs around the regression parameters
confint(hotSRz)

```
## 2.5 % 97.5 %
## (Intercept) -1.6858 0.5929
## Mom_appSR 0.0995 0.5178
```

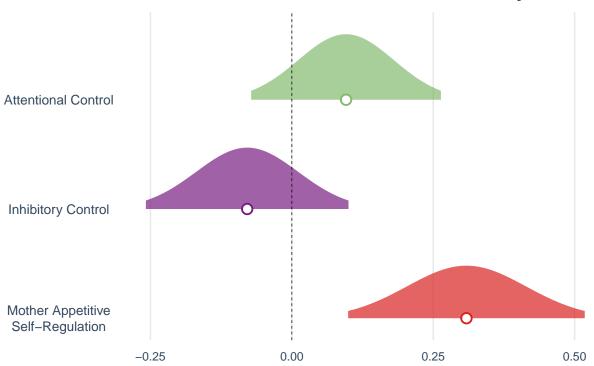
	Est.	2.5%	97.5%	t val.	р
(Intercept)	-3.392	-4.167	-2.617	-8.703	0.000
Mom_FLA	0.096	-0.059	0.251	1.228	0.223
sex	0.248	-0.084	0.580	1.487	0.141
$\operatorname{childAge}$	0.808	0.606	1.010	7.955	0.000

Standard errors: Robust, type = HC1

```
## sex
              -0.1582 0.6564
## childAge
              -0.1676 0.3787
confint(GNGz)
                2.5 % 97.5 %
## (Intercept) -4.0126 -2.0442
## Mom_GNG
              -0.2581 0.1002
              -0.2368 0.4765
## sex
              0.4986 0.9682
## childAge
confint(FLAz)
                 2.5 % 97.5 %
## (Intercept) -4.30956 -2.4742
## Mom_FLA
             -0.07191 0.2635
## sex
              -0.08441 0.5808
## childAge
              0.58939 1.0265
# plot
s <- plot_summs(GNGz, FLAz, hotSRz, ci_level = 0.95, coefs = c("Mother Appetitive\nSelf-Regulation" = "
## Loading required namespace: broom.mixed
## Loading required namespace: broom.mixed
## Loading required namespace: broom.mixed
s + theme(legend.position = "none") + ggtitle("Association Between Mother and Child SR by Domain") +
```

xlab("Parameter Estimate of Child SR Controlling for Child Age and Sex")

Association Between Mother and Child SR by Domain



Parameter Estimate of Child SR Controlling for Child Age and Sex

Explore moderation by SES

```
# moderated by mother education?
hotSR_ed <- with(data = impData, exp = lm(Snack_avg ~ Food_RegLCRC * matYrsEd + sex + childAge))
summary(pool(hotSR_ed))</pre>
```

term	estimate	std.error	statistic	df	p.value
(Intercept)	3.8610	3.1200	1.238	38.77	0.2233
Food_RegLCRC	-2.1867	1.6174	-1.352	26.25	0.1879
matYrsEd	-0.2569	0.2029	-1.266	35.67	0.2137
sex	0.4374	0.3390	1.290	78.69	0.2007
$\operatorname{childAge}$	0.2351	0.2327	1.010	73.63	0.3156
$Food_RegLCRC:matYrsEd$	0.1764	0.1030	1.712	28.22	0.0978

pool.r.squared(hotSR_ed)

```
## est lo 95 hi 95 fmi
## R^2 0.1696 0.04733 0.3303 NaN
```

```
GNG_ed <- with(data = impData, exp = lm(ChildGNGcomp ~ t_momGNG * matYrsEd + sex + childAge))
summary(pool(GNG_ed))</pre>
```

term	estimate	$\operatorname{std.error}$	statistic	df	p.value
(Intercept)	-5.8814	2.1014	-2.7988	69.11	0.0066
t_momGNG	1.5976	2.8558	0.5594	68.93	0.5777
matYrsEd	0.2355	0.1406	1.6751	70.06	0.0984
sex	0.1198	0.1585	0.7559	75.09	0.4521
$\operatorname{childAge}$	0.6957	0.1050	6.6237	74.33	0.0000
$t_momGNG:matYrsEd$	-0.1637	0.1932	-0.8471	69.26	0.3999

pool.r.squared(GNG_ed)

```
## est lo 95 hi 95 fmi
## R^2 0.4167 0.2512 0.5698 NaN
```

FLA_ed <- with(data = impData, exp = lm(FishFlanker_RawScore ~ FLA_ACC_diffx100 * matYrsEd + sex + chilesummary(pool(FLA_ed))

term	estimate	std.error	statistic	df	p.value
(Intercept)	-44.8196	11.0060	-4.0723	64.83	0.0001
FLA_ACC_diffx100	-0.1339	0.5551	-0.2413	73.50	0.8100
matYrsEd	1.5249	0.6059	2.5168	56.42	0.0147
sex	2.9706	1.9961	1.4882	71.82	0.1411
$\operatorname{childAge}$	10.0379	1.2783	7.8527	77.89	0.0000
$FLA_ACC_diffx100:matYrsEd$	0.0118	0.0376	0.3147	71.91	0.7539

pool.r.squared(FLA_ed)

```
## est lo 95 hi 95 fmi
## R^2 0.4914 0.3292 0.6323 NaN
```

```
# moderated by family income?
```

hotSR_inc <- with(data = impData, exp = lm(Snack_avg ~ Food_RegLCRC * t_income + sex + childAge))
summary(pool(hotSR_inc))</pre>

estimate	$\operatorname{std.error}$	statistic	df	p.value
0.4211	1.5488	0.2719	72.09	0.7865
0.1136	0.7183	0.1582	65.09	0.8748
0.0011	0.0096	0.1116	69.26	0.9114
0.4789	0.3467	1.3810	77.64	0.1712
0.0845	0.2438	0.3466	75.53	0.7299
0.0027	0.0046	0.5937	71.62	0.5546
	0.4211 0.1136 0.0011 0.4789 0.0845	0.4211 1.5488 0.1136 0.7183 0.0011 0.0096 0.4789 0.3467 0.0845 0.2438	0.4211 1.5488 0.2719 0.1136 0.7183 0.1582 0.0011 0.0096 0.1116 0.4789 0.3467 1.3810 0.0845 0.2438 0.3466	0.4211 1.5488 0.2719 72.09 0.1136 0.7183 0.1582 65.09 0.0011 0.0096 0.1116 69.26 0.4789 0.3467 1.3810 77.64 0.0845 0.2438 0.3466 75.53

pool.r.squared(hotSR_inc)

```
## est lo 95 hi 95 fmi
## R^2 0.1369 0.02561 0.3003 NaN
```

```
GNG_inc <- with(data = impData, exp = lm(ChildGNGcomp ~ t_momGNG * t_income + sex + childAge))
summary(pool(GNG_inc))</pre>
```

term	estimate	std.error	statistic	df	p.value
(Intercept)	-2.8955	1.1357	-2.5496	39.78	0.0147
t_momGNG	-0.7484	1.5041	-0.4976	32.97	0.6221
t_income	0.0073	0.0079	0.9249	40.17	0.3605
sex	0.1768	0.1606	1.1005	74.82	0.2746
$\operatorname{childAge}$	0.5648	0.1105	5.1093	74.23	0.0000
$t_momGNG:t_income$	-0.0005	0.0110	-0.0494	36.81	0.9608

pool.r.squared(GNG_inc)

```
## est lo 95 hi 95 fmi
## R^2 0.4086 0.2435 0.5627 NaN
```

```
FLA_inc <- with(data = impData, exp = lm(FishFlanker_RawScore ~ FLA_ACC_diffx100 * t_income + sex + chi summary(pool(FLA_inc))
```

		. 1		1.0	1
term	estimate	std.error	statistic	df	p.value
(Intercept)	-26.7695	7.2074	-3.7142	77.73	0.0004
FLA_ACC_diffx100	-0.0778	0.4404	-0.1766	71.45	0.8603
t_income	0.0836	0.0381	2.1909	67.54	0.0319
sex	3.5231	2.0647	1.7064	69.40	0.0924
$\operatorname{childAge}$	8.5907	1.3720	6.2612	75.77	0.0000
$FLA_ACC_diffx100:t_income$	0.0017	0.0030	0.5664	67.88	0.5730

pool.r.squared(FLA_inc)

```
## est lo 95 hi 95 fmi
## R^2 0.4728 0.3097 0.6167 NaN
```