# Supplemental Analysis

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In the current study (removed for blinding) we chose the Bayesian approach to compare different nonnested models for which model including caregiver behaviors best predicts children's gains in processing speed (reaction time, RT) and vocabulary size (measured using the MacArthur Inventarios del Desarrollo de Habilidades Comunicativas, CDI). This approach allowed us to compare the predictive power of different models against each other and quantify these differences. Thus, we could examine whether all predictors lead to similar findings or if they diverge.

In contrast to the Bayesian model comparison, standard frequentist regression models require nested models for comparison. This document includes exploratory analyses to illustrate model comparisons using a frequentist approach.

For each dependent variables of RT and CDI, we tested if models with each of the predictors of AWC, labels, or gestures performed better than the baseline model (with covariates of SES and children's earlier language skills). We compared them in the following manner:

- 1) Baseline (child covariates only) vs. Model 1 (caregiver AWC)
- 2) Baseline (child covariates only) vs. Model 2 (caregiver referential labels)
- 3) Baseline (child covariates only) vs. Model 3 (caregiver referential gestures)

## Standard Hierarchical Regression

#### Comparing models - RT

For RT, none of the models with the predictors (models 2, 3, and 4) added significant variance above the covariates (model 1). This finding is different from what we are able to see with the Bayesian comparisons, where we found that either models with labels or AWC seem to perform better than the baseline model.

```
## Analysis of Variance Table
##
## Model 1: rt_25m ~ ses_18m + rt_18m
## Model 2: rt_25m ~ ses_18m + rt_18m + awc_phr_18m
## Res.Df RSS Df Sum of Sq F Pr(>F)
## 1 39 1098966
## 2 38 1051057 1 47909 1.7321 0.196
```

```
## Analysis of Variance Table
##
## Model 1: rt_25m ~ ses_18m + rt_18m
## Model 2: rt_25m ~ ses_18m + rt_18m + labels
## Res.Df
             RSS Df Sum of Sq F Pr(>F)
## 1 39 1098966
## 2
      38 1034250 1 64717 2.3778 0.1314
## Analysis of Variance Table
## Model 1: rt_25m ~ ses_18m + rt_18m
## Model 2: rt_25m ~ ses_18m + rt_18m + gestures
## Res.Df
             RSS Df Sum of Sq F Pr(>F)
## 1
     39 1098966
      38 1095485 1 3481.1 0.1208 0.7301
## 2
```

### Regression table - RT

# #		Dependent variable:				
# #	(1)	25m Spanish Language (2)	Processing Speed (R'	г) (4)		
# # 18m SES #	-29.065 (26.371)	-27.980 (26.140)	-27.661 (25.933)	-29.786 (26.754)		
# # 18m RT #	50.441. (26.371)	47.561. (26.218)	52.711* (25.959)	50.869. (26.701)		
.# # 18m AWC #	(20.0, 2)	-34.312 (26.071)	(201000)	(2011-02)		
# # 18m Labels #		(2010) 17	-39.828 (25.829)			
# # 18m Gestures #				-9.249 (26.616)		
# # Constant # #	850.680*** (25.902)	850.680*** (25.662)	850.680*** (25.456)	850.680*** (26.199)		
•	42	 42	42	42		
# R2 # Adjusted R2	0.103 0.057	0.142 0.074	0.156 0.089	0.106 0.035		
# F Statistic	Error 167.865 (df = 39) 2.235 (df = 2; 39)	) 2.095 (df = 3; 38)	2.335. (df = 3; 38)	1.497 (df = 3; 38		

#### Comparing models - CDI

For CDI, we actually see similar findings to what we see with the model comparisons where AWC and labels significantly predicted children's vocabulary, though labels may yield more predictive power. Model 2 with AWC significantly added 11.6% additional variance above the baseline model, and Model 3 with labels significantly added 16.7% additional variance to the baseline model.

```
## Analysis of Variance Table
##
## Model 1: cdi_25m ~ ses_18m + cdi_18m
## Model 2: cdi_25m ~ ses_18m + cdi_18m + awc_phr_18m
     Res.Df
              RSS Df Sum of Sq
                                    F Pr(>F)
##
## 1
        34 898037
## 2
        33 768018 1
                        130019 5.5866 0.02414 *
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Analysis of Variance Table
##
## Model 1: cdi_25m ~ ses_18m + cdi_18m
## Model 2: cdi_25m ~ ses_18m + cdi_18m + labels
##
    Res.Df
              RSS Df Sum of Sq
                                    F
                                         Pr(>F)
## 1
        34 898037
        33 710965 1
                        187072 8.6831 0.005854 **
## 2
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Analysis of Variance Table
##
## Model 1: cdi_25m ~ ses_18m + cdi_18m
## Model 2: cdi_25m ~ ses_18m + cdi_18m + gestures
    Res.Df
              RSS Df Sum of Sq
## 1
         34 898037
## 2
         33 851998
                   1
                         46039 1.7832 0.1909
```

#### Regression table - CDI

##						
##	=======================================					
##						
##						
##			25m Spanish Vocal	oulary Size (CDI)		
##		(1)	(2)	(3)	(4)	
##						
##	18m SES	-18.650	-23.195	-20.289	-14.264	
##		(27.201)	(25.606)	(24.573)	(27.093)	
##						
##	18m CDI	77.688**	74.012**	83.697**	89.854**	
##		(27.201)	(25.581)	(24.651)	(28.394)	
##						
##	18m AWC		60.406*			
##			(25.557)			

##					
##	18m Labels			72.342**	
##				(24.550)	
##					
##	18m Gestures				38.156
##					(28.573)
##					
##	Constant	273.649***	273.649***	273.649***	273.649***
##		(26.718)	(25.080)	(24.131)	(26.416)
##					
##					
##	Observations	37	37	37	37
##	R2	0.197	0.313	0.364	0.238
##	Adjusted R2	0.150	0.251	0.306	0.169
##	Residual Std. Error	162.520 (df = 34)	152.556 (df = 33)	146.780 (df = 33)	160.680 (df = 33)
##	F Statistic	4.169* (df = 2; 34)	5.017** (df = 3; 33)	6.302** (df = 3; 33)	3.438* (df = 3; 33)
##					
##	Note:	*p<0.05; **p<0.01; *	***p<0.001		

Based on these findings, we believe that the Bayesian model comparisons reported in the current study provide a similar bottom line in that caregivers' use of labels are predictive of children's vocabulary, but we also gain an additional understanding in our interpretation by quantifying the relative weight of different non-nested models. Thus, we can make conclusions that assess to what extent models differ from each other. In a standard regression approach, we are limited in our ability to quantify the difference between non-nested models.