

Landmark analyses

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Setup

Load libraries

```
library(tidyverse)
library(broom)
library(knitr)
library(kableExtra)
library(lme4)
library(merTools)
```

Load data

```
learners <- read_csv("./data/landmarks_stress_la_lb_ss.csv")
heritage <- read_csv("./data/landmarks_stress_la_hs_ss.csv")
wm_df_learners <- read_csv("./data/wm.csv")
wm_df_heritage <- read_csv("./data/wm_all.csv")
pstm_df <- read_csv("./data/dur_stress_background_info.csv")
```

Late learners and native controls

Do they predict above chance?

The data analyzed using a linear model with intercept removed. This makes each parameter estimate a two-sided test of independence ($H_a \neq 0$). In order to make this test one-sided ($H_a > 0$) we will take the t-values from the model and calculate the associated probability from the t-distribution for a one-sided test using the model degrees of freedom. In R this can be done with the following function:

```
pt(t_values, mod_df, lower = FALSE)
```

The p-values from the model will now be one-sided tests that the mean difference is greater than 0. Next, we need to put the target fixations (dependent variable) on the same scale. As is, chance = 50%, thus everything will be significant because target fixations are on average at 50% as a minimum. To get around this issue we can subtract 0.5 from each participants mean target fixation at each landmark and test to see if that value is greater than 0. For example, if at the target word onset you are fixating on the target 50% of the time (i.e., at chance), then when we subtract 0.5 from 0.5, we get 0. 0 is not greater than 0 so it wouldn't be significant. We will conduct this test for each group, at each landmark. Then we will add the 0.5 back on to the model estimates and the confidence intervals for plotting purposes.

```
# Model degrees of freedom
learner_mod_df <- 65

learner_mods <- learners %>%
  filter(., !(landmark %in% c('start_sentence', 'word2_c1v1',
                             'end_sentence')))) %>%
  group_by(., participant, group, coda, landmark) %>%
  summarize(., target_fix = mean(targetProp)) %>%
  ungroup(.) %>%
  group_by(., landmark, coda) %>%
  do(tidy(lm(I(target_fix - 0.5) ~ -1 + group, data = .), conf.int = T,
            conf.level = 0.99)) %>%
  mutate(., p_adj = pt(statistic, learner_mod_df, lower = F),
         p_adj = formatC(p_adj, digits = 7, format = "f"),
         sig = if_else(p_adj < 0.05, true = "*", false = " ")) %>%
  ungroup(.) %>%
  mutate(., landmark = fct_relevel(landmark,
                                   'word3_c1v1', 'word3_20msafterv1',
                                   'word3_c2', 'word3_c3', 'word3_suffix')) %>%
  arrange(., coda, landmark)
```

Table 1: Model output

landmark	term	estimate	std.error	statistic	conf.low	conf.high	p_adj	sig
No-coda targets								
word3_c1v1	la	-0.06	0.04	-1.61	-0.17	0.04	0.9438315	
	lb	-0.12	0.05	-2.56	-0.24	0.00	0.9936311	
	ss	-0.10	0.04	-2.26	-0.21	0.02	0.9864650	
word3_20msafterv1	la	-0.02	0.04	-0.52	-0.12	0.08	0.6971842	
	lb	-0.05	0.04	-1.12	-0.17	0.07	0.8671037	
	ss	0.04	0.04	0.93	-0.07	0.15	0.1787654	
word3_c2	la	-0.01	0.04	-0.16	-0.11	0.09	0.5624449	
	lb	-0.04	0.05	-0.84	-0.16	0.08	0.7982615	
	ss	0.09	0.04	2.15	-0.02	0.20	0.0176951	*
word3_suffix	la	0.07	0.04	1.96	-0.03	0.17	0.0274149	*
	lb	0.01	0.04	0.13	-0.11	0.12	0.4496902	
	ss	0.22	0.04	5.46	0.11	0.33	0.0000004	*
word4_c1v1	la	0.21	0.04	5.76	0.11	0.31	0.0000001	*
	lb	0.27	0.04	6.26	0.16	0.39	0.0000000	*
	ss	0.35	0.04	8.71	0.25	0.46	0.0000000	*
Coda targets								
word3_c1v1	la	-0.05	0.03	-1.45	-0.14	0.04	0.9242526	
	lb	-0.04	0.04	-0.96	-0.14	0.07	0.8308077	
	ss	-0.09	0.04	-2.40	-0.18	0.01	0.9902493	
word3_20msafterv1	la	-0.03	0.04	-0.68	-0.13	0.08	0.7508646	
	lb	-0.08	0.05	-1.68	-0.20	0.04	0.9510029	
	ss	0.05	0.04	1.11	-0.07	0.16	0.1353062	
word3_c2	la	-0.01	0.04	-0.15	-0.10	0.09	0.5610294	
	lb	-0.06	0.04	-1.48	-0.18	0.05	0.9281215	
	ss	0.07	0.04	1.72	-0.04	0.18	0.0452329	*
word3_c3	la	0.06	0.04	1.79	-0.03	0.16	0.0390471	*
	lb	-0.05	0.04	-1.24	-0.16	0.06	0.8910685	
	ss	0.20	0.04	5.02	0.09	0.30	0.0000022	*
word3_suffix	la	0.17	0.03	5.57	0.09	0.25	0.0000003	*
	lb	0.04	0.04	1.04	-0.06	0.13	0.1502988	
	ss	0.28	0.03	8.45	0.19	0.37	0.0000000	*
word4_c1v1	la	0.33	0.03	9.68	0.24	0.42	0.0000000	*
	lb	0.25	0.04	6.31	0.15	0.36	0.0000000	*
	ss	0.27	0.04	7.31	0.17	0.37	0.0000000	*

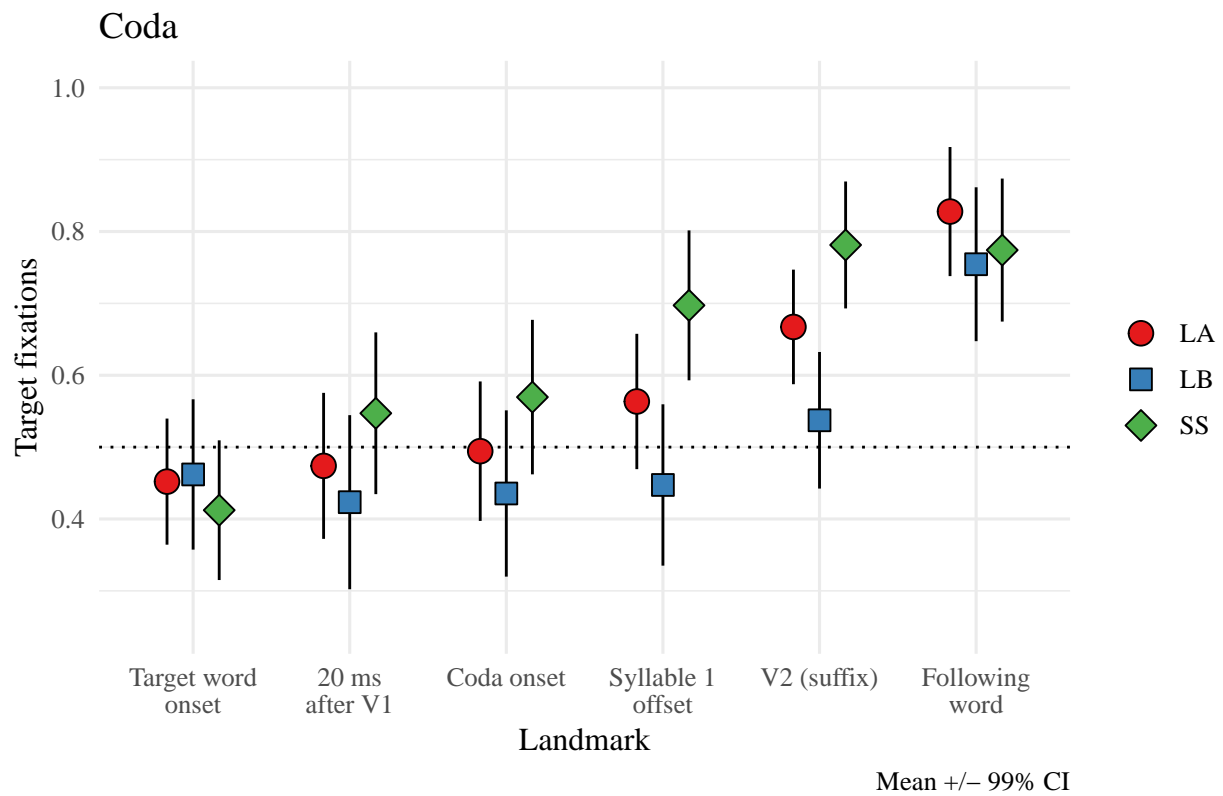
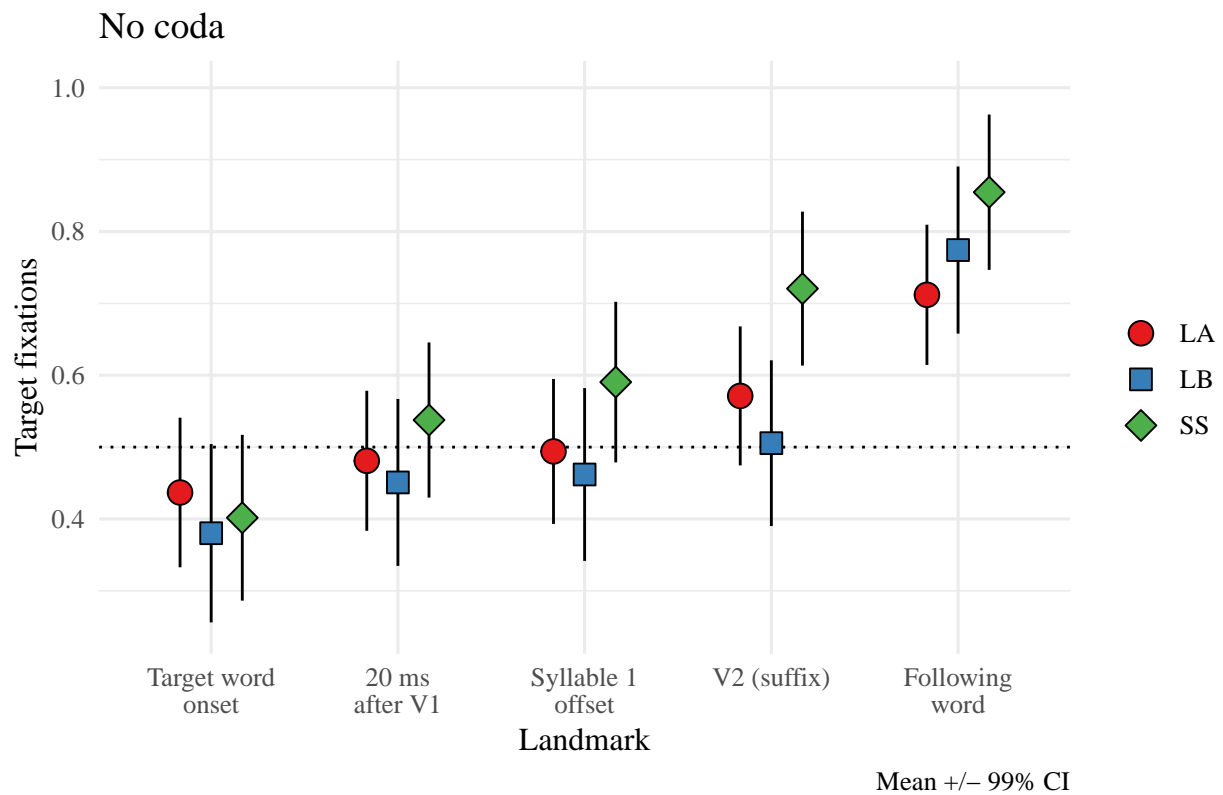
Note:

Parameter estimates show average target fixation minus 0.5.

P-values represent one-sided t-tests.

word3_c2 represents the 2nd syllable onset for no-coda targets and the coda onset for coda targets.

Landmark plots



Is working memory a factor?

```
## Joining, by = "participant"
```

First check for homogeneity of variance.

```
wm_df %>%  
  separate(., participant, into = c('group', 'trash'), sep = 2, remove = F) %>%  
  bartlett.test(wm ~ group, data = .)
```

```
##  
## Bartlett test of homogeneity of variances  
##  
## data:  wm by group  
## Bartlett's K-squared = 2.2443, df = 2, p-value = 0.3256
```

Looks good.

```
## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: cbind(targetCount, distractorCount) ~ (1 + wm_c | participant) +  
## (1 + wm_c | target) + group + group:wm_c - 1  
## Data: learners_no_coda  
## Control: glmerControl(optimizer = "bobyqa")  
##  
##      AIC      BIC    logLik deviance df.resid  
## 6769.9   6823.8  -3373.0   6745.9     644  
##  
## Scaled residuals:  
##      Min       1Q   Median       3Q      Max  
## -10.8543  -2.2048   0.4665   2.1664   6.5376  
##  
## Random effects:  
## Groups      Name      Variance Std.Dev. Corr  
## participant (Intercept) 2.0739192 1.44011  
##           wm_c         0.0008718 0.02953  -1.00  
## target      (Intercept) 0.4367887 0.66090  
##           wm_c         0.0978779 0.31285   0.19  
## Number of obs: 656, groups:  participant, 50; target, 13  
##  
## Fixed effects:  
##              Estimate Std. Error z value Pr(>|z|)  
## groupss      1.120239   0.369304   3.033  0.00242 **  
## groupla      0.276744   0.411122   0.673  0.50086  
## grouplb      0.303418   0.636582   0.477  0.63362  
## groupss:wm_c -0.042576   0.113818  -0.374  0.70835  
## groupla:wm_c  0.002654   0.202578   0.013  0.98955  
## grouplb:wm_c  0.080725   0.210642   0.383  0.70155  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Correlation of Fixed Effects:  
##           gropss groupl grouplb grps:_ grpl:w_  
## groupla      0.225  
## grouplb      0.115  0.127
```

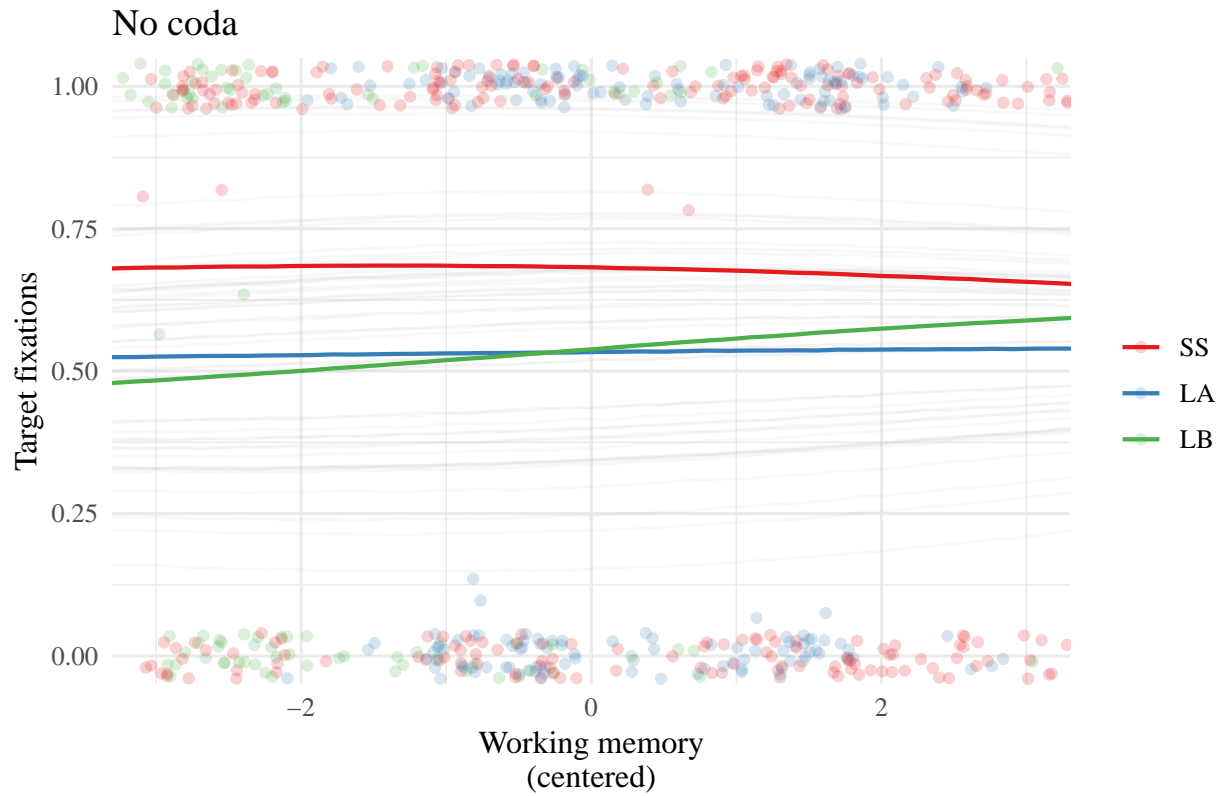
```

## gropss:wm_c -0.056 0.060 0.212
## groupl:wm_c 0.044 0.022 0.004 0.303
## groplb:wm_c 0.001 0.037 0.618 0.541 0.144

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial (logit)
## Formula: cbind(targetCount, distractorCount) ~ (1 + wm_c | participant) +
## (1 + wm_c | target) + group + group:wm_c - 1
## Data: learners_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC    logLik deviance df.resid
##  9438.7   9496.7 -4707.3   9414.7     920
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -11.6794  -2.3284   0.8192   1.9981   6.4440
##
## Random effects:
##      Groups      Name      Variance Std.Dev. Corr
## participant (Intercept) 1.75792  1.3259
##           wm_c         0.03512  0.1874  1.00
## target      (Intercept) 0.46877  0.6847
##           wm_c         0.02595  0.1611  0.53
## Number of obs: 932, groups: participant, 50; target, 19
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## groupss      1.47328    0.33361   4.416 1e-05 ***
## groupla      0.67667    0.38199   1.771 0.0765 .
## groplb       0.06149    0.44972   0.137 0.8912
## groupss:wm_c  0.15546    0.07508   2.070 0.0384 *
## groupla:wm_c -0.17746    0.07178  -2.472 0.0134 *
## groplb:wm_c   0.04160    0.08171   0.509 0.6107
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              gropss groupl groplb grps:_ grpl:w_
## groupla      0.199
## groplb       0.174 0.159
## gropss:wm_c  0.584 0.095 0.067
## groupl:wm_c  0.123 0.672 0.030 0.261
## groplb:wm_c  0.116 0.114 0.837 0.232 0.114

```

Working memory plots



Phonological short-term memory

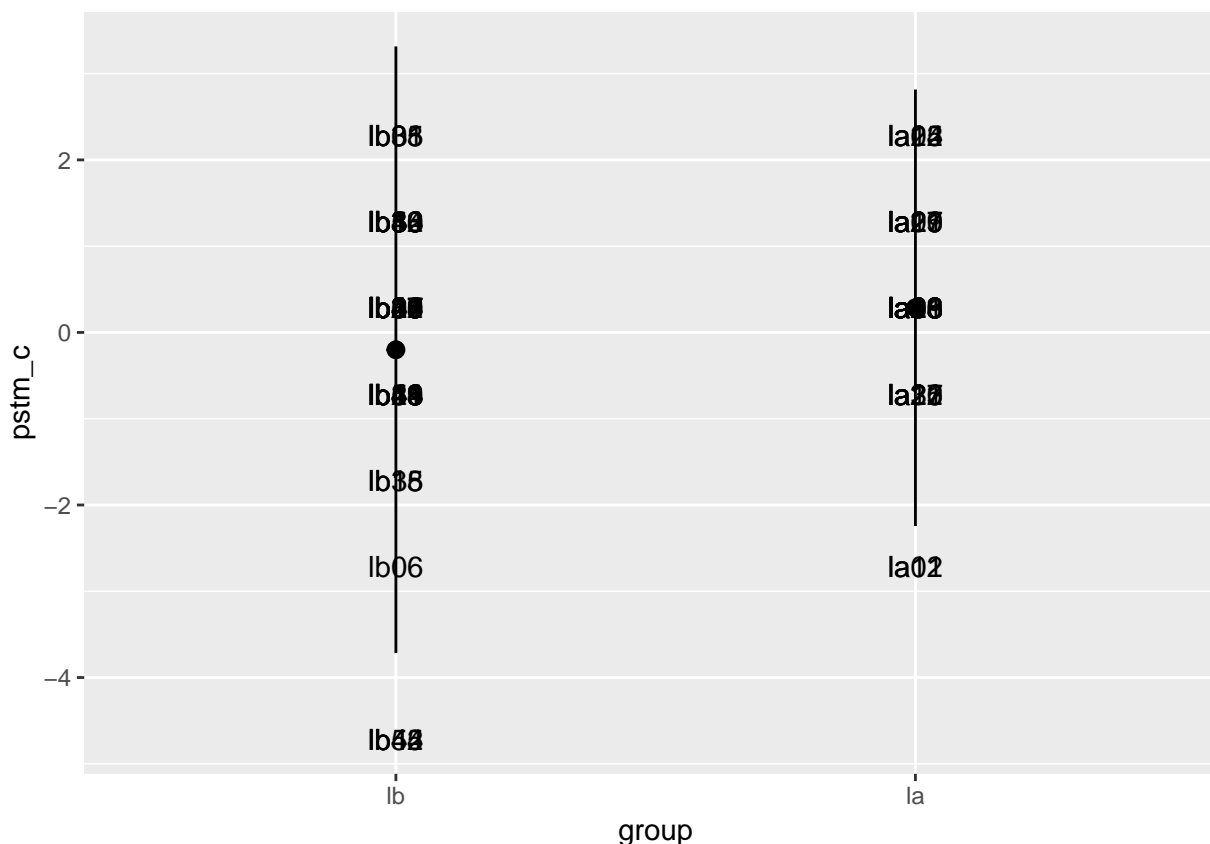
```
## Warning: Column `group` joining factors with different levels, coercing to  
## character vector
```

First check for homogeneity of variance.

```
pstm_learners_clean %>%  
  bartlett.test(pstm_c ~ group, data = .)
```

```
##  
## Bartlett test of homogeneity of variances  
##  
## data: pstm_c by group  
## Bartlett's K-squared = 2.9727, df = 1, p-value = 0.08468
```

```
pstm_learners_clean %>%  
  na.omit(.) %>%  
  ggplot(., aes(x = group, y = pstm_c, label = participant)) +  
    geom_text() +  
    stat_summary(fun.data = mean_sdl, geom = 'pointrange')
```



Groups look ok. Might have to take some out.

```
## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula:  
## cbind(targetCount, distractorCount) ~ (1 + pstm_c | participant) +
```



```

##      (1 + pstm_c | target) + group + group:pstm_c - 1
##      Data: lb_la_pstm_no_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC    logLik deviance df.resid
##    2868.4    2904.1  -1424.2   2848.4     252
##
## Scaled residuals:
##      Min      1Q  Median      3Q      Max
## -8.453 -2.276  0.000  2.269  5.607
##
## Random effects:
##      Groups      Name      Variance Std.Dev. Corr
## participant (Intercept) 0.8337   0.9131
##           pstm_c      0.1759   0.4194   0.72
## target      (Intercept) 0.2559   0.5059
##           pstm_c      0.2587   0.5087  -0.55
## Number of obs: 262, groups: participant, 42; target, 13
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## groupla      0.01772    0.25434   0.070   0.944
## grouplb      0.41125    0.30706   1.339   0.180
## groupla:pstm_c 0.15493    0.23447   0.661   0.509
## grouplb:pstm_c 0.42264    0.31776   1.330   0.184
##
## Correlation of Fixed Effects:
##              groupl groupb grpl:p_
## grouplb      0.198
## grpl:pstm_c -0.110 -0.131
## grplb:pstm_ -0.194  0.137  0.205
##
## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula:
## cbind(targetCount, distractorCount) ~ (1 + pstm_c | participant) +
##      (1 + pstm_c | target) + group + group:pstm_c - 1
##      Data: lb_la_pstm_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC    logLik deviance df.resid
##    4179.5    4218.9  -2079.7   4159.5     372
##
## Scaled residuals:
##      Min      1Q  Median      3Q      Max
## -8.5744 -2.3470  0.6181  2.3402  7.3955
##
## Random effects:
##      Groups      Name      Variance Std.Dev. Corr
## participant (Intercept) 0.6418   0.8011
##           pstm_c      0.2550   0.5050  -0.04
## target      (Intercept) 0.4242   0.6513
##           pstm_c      0.4616   0.6794  -0.41

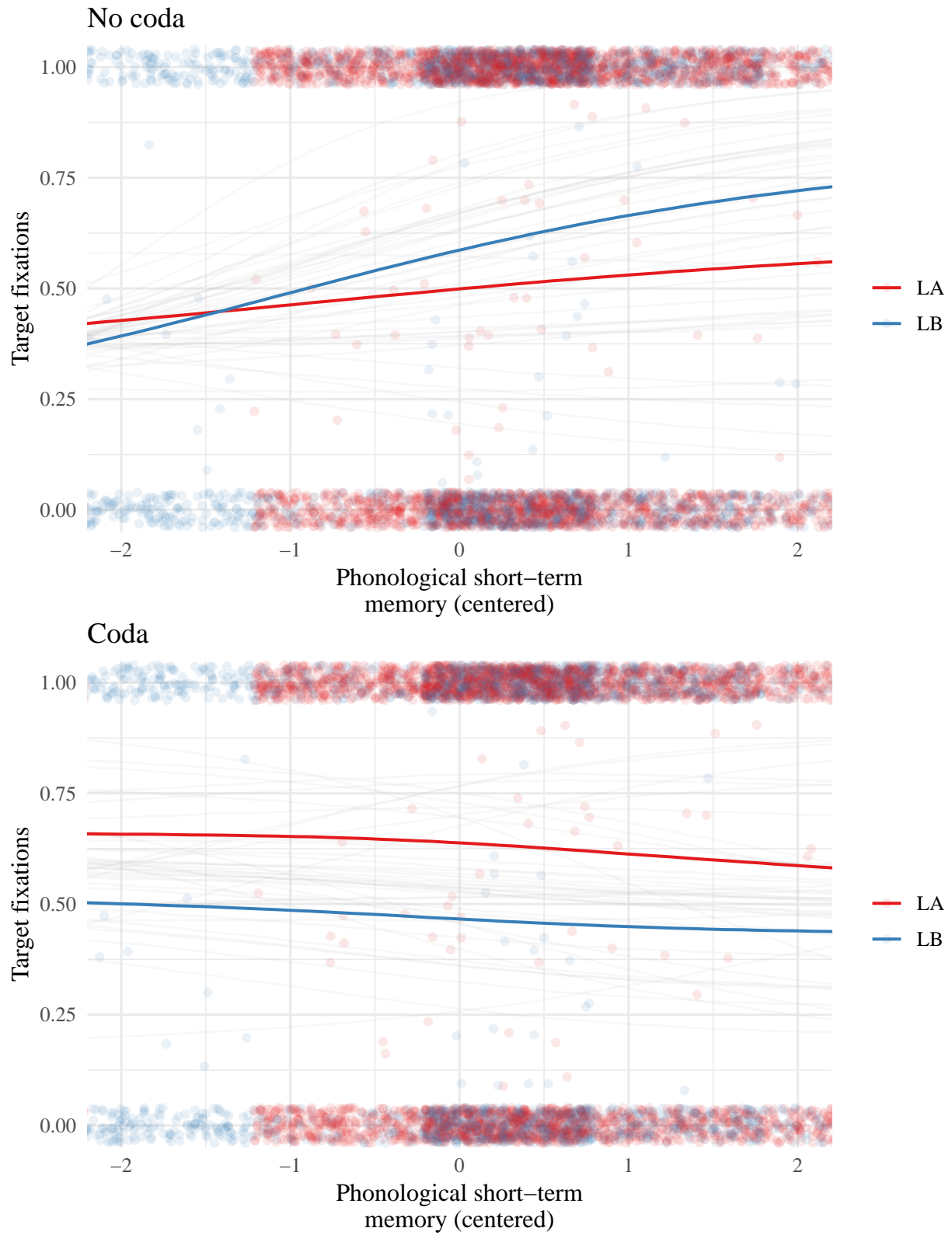
```

```

## Number of obs: 382, groups:  participant, 42; target, 19
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## groupla      0.64642    0.25591   2.526  0.0115 *
## grouplb     -0.15045    0.28920  -0.520  0.6029
## groupla:pstm_c -0.08915    0.26871  -0.332  0.7401
## grouplb:pstm_c -0.06808    0.33013  -0.206  0.8366
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              group1  groupb  grpl:p_
## grouplb      0.305
## grpl:pstm_c -0.355 -0.132
## grplb:pstm_ -0.098 -0.306  0.270

```

PSTM plots



Learners summary

Without coda:

- The native speakers fixate on targets above chance at the offset of the first syllable.
- Advanced learners fixate on targets as well by the time they have heard the target suffix.
- All three groups fixate on targets above chance by the following word.
- No effect of working memory for any groups.
- No effect of phonological short-term memory (very high variability).

With coda:

- Native speakers fixate on targets above chance at the onset of the coda.
- Advanced learners fixate on targets above chance by the offset of the target syllable.
- All three groups fixate on targets above chance by the following word.
- There is an effect of working memory for natives. Increased WM equals increased target fixations at the offset of the target syllable.
- WM is negatively correlated with target fixations for the advanced learners (I can't think of an explanation for this).
- No effect of phonological short-term memory.

Late vs. early bilinguals and native (monolingual) controls

Do they predict above chance?

Same analysis as previously described.

```
# Model degrees of freedom
heritage_mod_df <- 72

heritage_mods <- heritage %>%
  filter(., !(landmark %in% c('start_sentence', 'word2_c1v1',
                             'end_sentence')))) %>%
  group_by(., participant, group, coda, landmark) %>%
  summarize(., target_fix = mean(targetProp)) %>%
  ungroup(.) %>%
  group_by(., landmark, coda) %>%
  do(tidy(lm(I(target_fix - 0.5) ~ -1 + group, data = .), conf.int = T,
            conf.level = 0.99)) %>%
  mutate(., p_adj = pt(statistic, heritage_mod_df, lower = F),
         p_adj = formatC(p_adj, digits = 7, format = "f"),
         sig = if_else(p_adj < 0.05, true = "*", false = " ")) %>%
  ungroup(.) %>%
  mutate(., landmark = fct_relevel(landmark,
                                   'word3_c1v1', 'word3_20msafterv1',
                                   'word3_c2', 'word3_c3', 'word3_suffix')) %>%
  arrange(., coda, landmark)
```

Table 2: Model output

landmark	term	estimate	std.error	statistic	conf.low	conf.high	p_adj	sig
No-coda targets								
word3_c1v1	hs	-0.09	0.04	-2.14	-0.21	0.02	0.9819752	
	la	-0.06	0.04	-1.46	-0.18	0.05	0.9257015	
	ss	-0.10	0.05	-2.05	-0.23	0.03	0.9780822	
word3_20msafterv1	hs	-0.05	0.04	-1.41	-0.15	0.05	0.9188499	
	la	-0.02	0.04	-0.52	-0.12	0.08	0.6965797	
	ss	0.04	0.04	0.92	-0.07	0.15	0.1795164	
word3_c2	hs	-0.03	0.04	-0.83	-0.14	0.07	0.7965654	
	la	-0.01	0.04	-0.16	-0.11	0.10	0.5615723	
	ss	0.09	0.04	2.12	-0.02	0.20	0.0188317	*
word3_suffix	hs	0.07	0.04	1.84	-0.03	0.18	0.0348610	*
	la	0.07	0.04	1.80	-0.03	0.18	0.0381995	*
	ss	0.22	0.04	5.02	0.10	0.34	0.0000018	*
word4_c1v1	hs	0.29	0.04	7.55	0.19	0.40	0.0000000	*
	la	0.21	0.04	5.53	0.11	0.31	0.0000002	*
	ss	0.35	0.04	8.36	0.24	0.47	0.0000000	*
Coda targets								
word3_c1v1	hs	-0.04	0.03	-1.46	-0.12	0.04	0.9259936	
	la	-0.05	0.03	-1.61	-0.13	0.03	0.9441519	
	ss	-0.09	0.03	-2.66	-0.18	0.00	0.9951562	
word3_20msafterv1	hs	-0.04	0.04	-0.99	-0.13	0.06	0.8372537	
	la	-0.03	0.04	-0.72	-0.12	0.07	0.7627565	
	ss	0.05	0.04	1.17	-0.06	0.15	0.1223290	
word3_c2	hs	-0.04	0.04	-0.99	-0.14	0.06	0.8383116	
	la	-0.01	0.04	-0.15	-0.10	0.09	0.5607754	
	ss	0.07	0.04	1.71	-0.04	0.18	0.0457271	*
word3_c3	hs	0.08	0.04	1.96	-0.03	0.19	0.0271484	*
	la	0.07	0.04	1.79	-0.03	0.18	0.0390024	*
	ss	0.20	0.04	4.56	0.08	0.32	0.0000104	*
word3_suffix	hs	0.21	0.04	5.71	0.11	0.30	0.0000001	*
	la	0.17	0.04	4.72	0.07	0.26	0.0000057	*
	ss	0.28	0.04	7.16	0.18	0.39	0.0000000	*
word4_c1v1	hs	0.30	0.04	8.48	0.21	0.40	0.0000000	*
	la	0.33	0.04	9.35	0.23	0.42	0.0000000	*
	ss	0.27	0.04	7.06	0.17	0.38	0.0000000	*

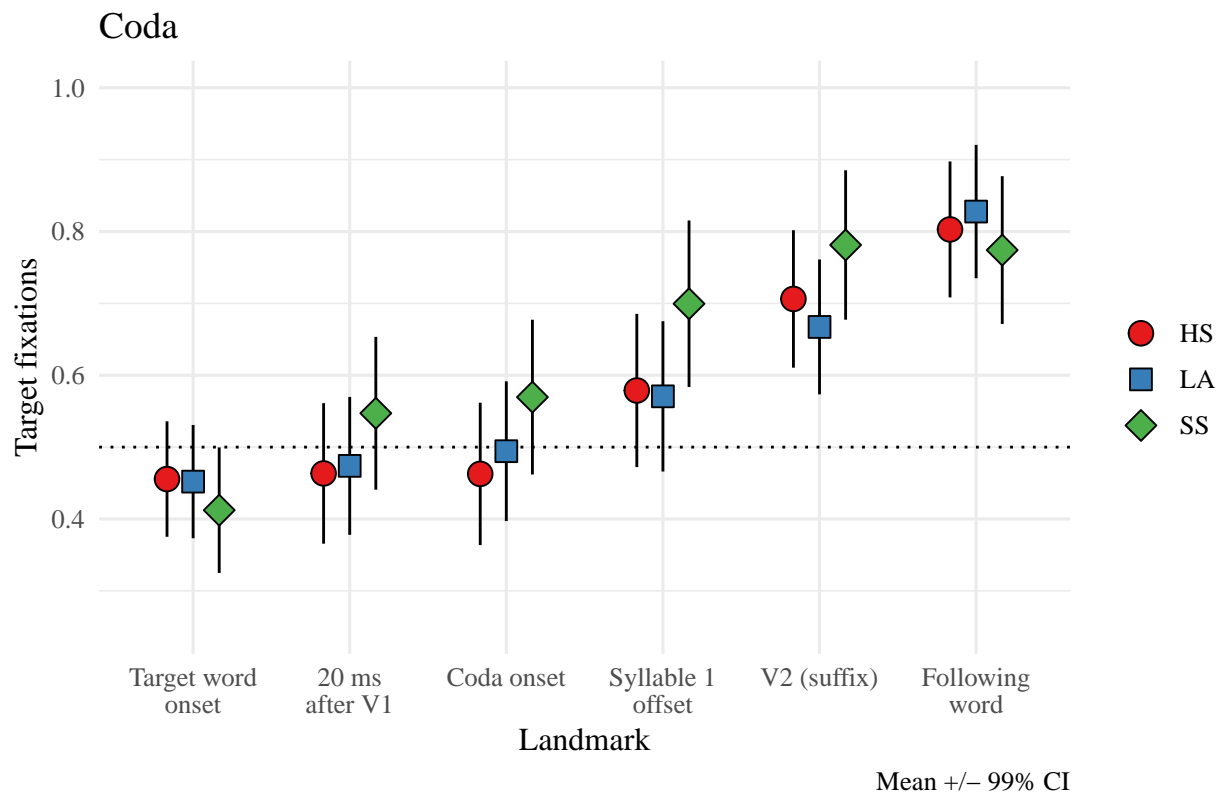
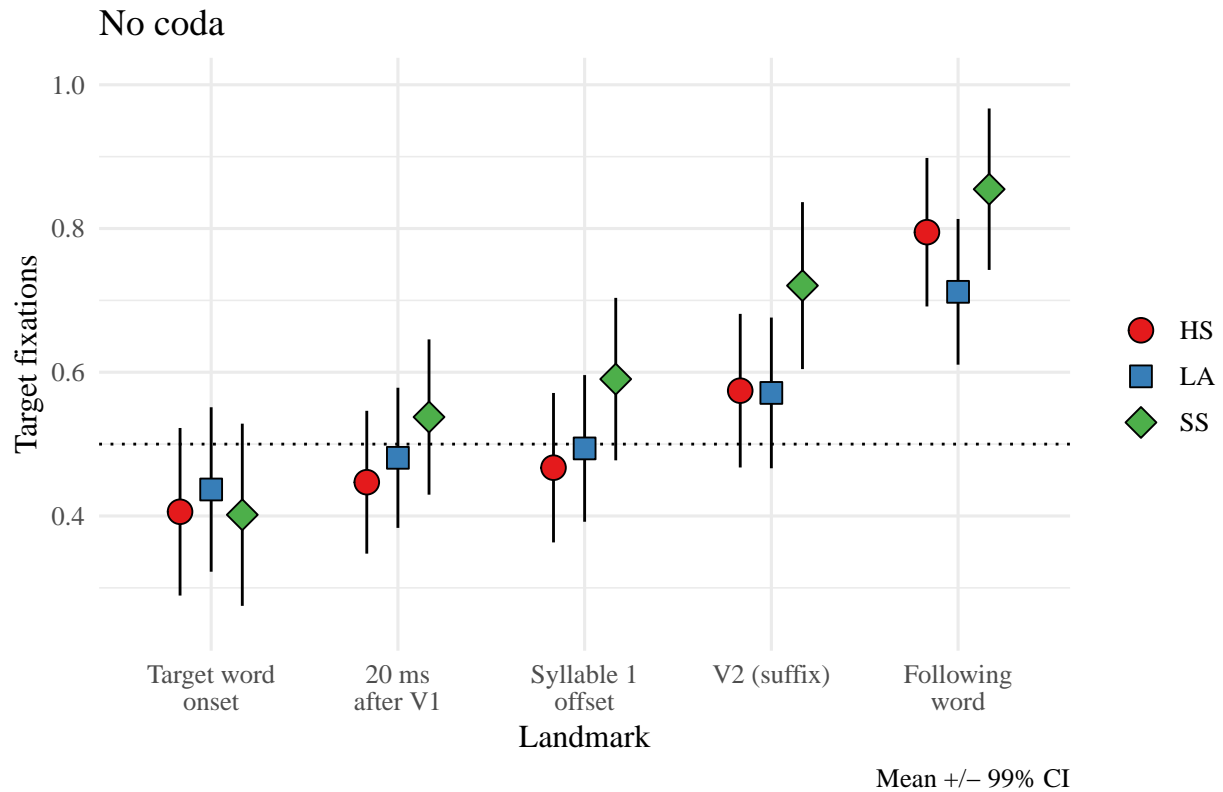
Note:

Parameter estimates show average target fixation minus 0.5.

P-values represent one-sided t-tests.

word3_c2 represents the 2nd syllable onset for no-coda targets and the coda onset for coda targets.

Landmark plots



Is working memory a factor?

```
## Joining, by = c("participant", "group")
## Warning: Column `group` joining character vector and factor, coercing into
## character vector
```

Check for homogeneity of variance.

```
wm_df_heritage %>%
  filter(., group %in% c("LA", "HS", "S")) %>%
  bartlett.test(WM ~ group, data = .)
```

```
##
## Bartlett test of homogeneity of variances
##
## data: WM by group
## Bartlett's K-squared = 1.9167, df = 2, p-value = 0.3835
```

Looks good.

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: cbind(targetCount, distractorCount) ~ (1 + wm_c | participant) +
## (1 + wm_c | target) + group + group:wm_c - 1
## Data: heritage_no_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC    logLik deviance df.resid
##  4464.7   4513.4  -2220.3   4440.7      418
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -11.818  -2.084   0.000    2.157   8.608
##
## Random effects:
##   Groups      Name      Variance Std.Dev. Corr
## participant (Intercept) 0.78649  0.8868
##           wm_c         0.09341  0.3056   0.28
## target      (Intercept) 0.56189  0.7496
##           wm_c         0.08844  0.2974  -0.19
## Number of obs: 430, groups: participant, 67; target, 13
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## groupss      1.1378486  0.3295983   3.452 0.000556 ***
## grouphs     -0.0621776  0.3202746  -0.194 0.846067
## groupla      0.1093136  0.2888496   0.378 0.705100
## groupss:wm_c  0.0005255  0.1716472   0.003 0.997557
## grouphs:wm_c -0.2246620  0.1707950  -1.315 0.188379
## groupla:wm_c  0.0390305  0.1783353   0.219 0.826759
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##      gropss grouphs groupl grps:_ grph:_
```



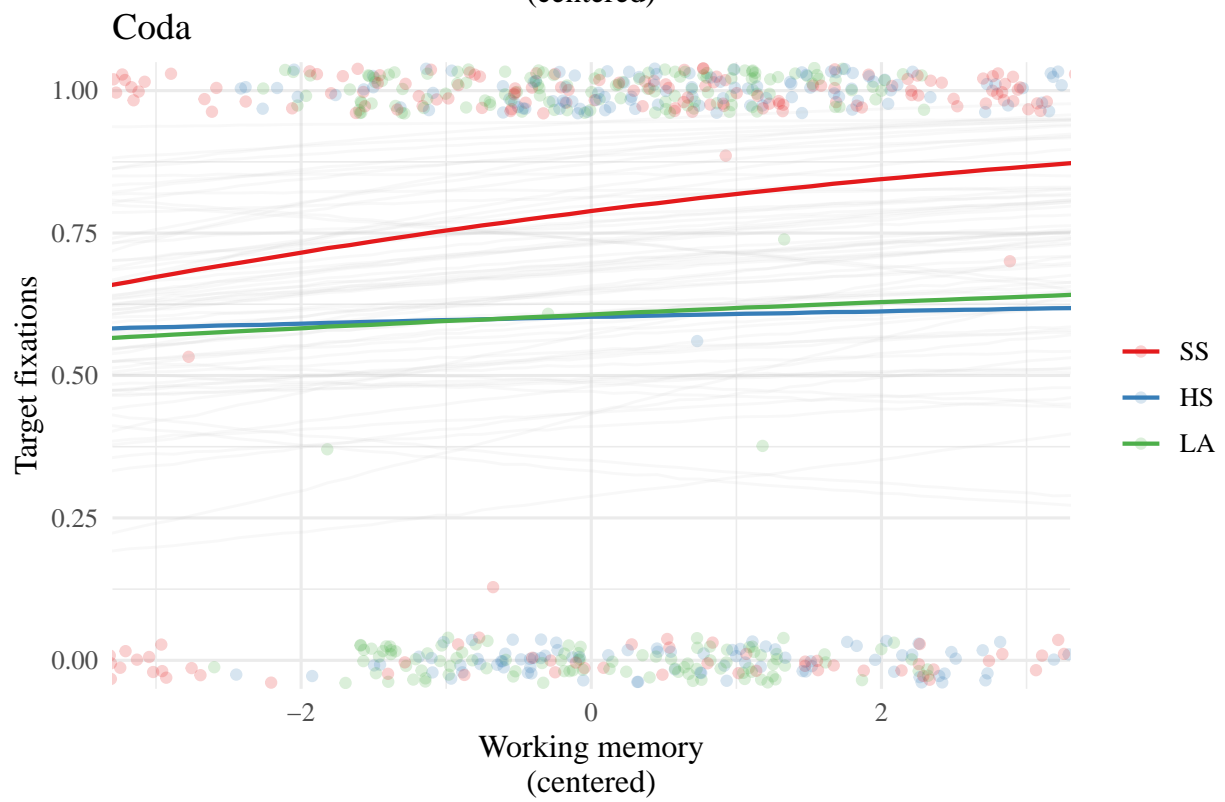
```

## groups      0.412
## groupla     0.454  0.477
## gropss:wm_c 0.068 -0.076 -0.076
## groups:wm_c -0.055 -0.144 -0.084  0.274
## group1:wm_c -0.045 -0.019 -0.006  0.213  0.176

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: cbind(targetCount, distractorCount) ~ (1 + wm_c | participant) +
## (1 + wm_c | target) + group + group:wm_c - 1
## Data: heritage_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC    logLik deviance df.resid
##  6320.1   6373.3  -3148.1   6296.1     611
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -14.4393  -2.3485   0.9542   1.9974   5.9255
##
## Random effects:
##   Groups      Name      Variance Std.Dev. Corr
## participant (Intercept) 1.02946  1.0146
##           wm_c         0.06093  0.2468  0.20
## target      (Intercept) 0.24227  0.4922
##           wm_c         0.05640  0.2375 -0.35
## Number of obs: 623, groups: participant, 67; target, 19
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## groupss      1.53689    0.30076   5.110 3.22e-07 ***
## groups       0.50761    0.27925   1.818  0.0691 .
## groupla      0.52173    0.25059   2.082  0.0373 *
## groupss:wm_c 0.23605    0.18356   1.286  0.1984
## groups:wm_c  0.04100    0.16652   0.246  0.8055
## groupla:wm_c 0.06045    0.18699   0.323  0.7465
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           gropss groups group1 grps:_ grph:_
## groups      0.105
## groupla     0.129  0.229
## gropss:wm_c 0.039  0.002 -0.013
## groups:wm_c 0.023 -0.216 -0.126 -0.108
## group1:wm_c 0.006 -0.117 -0.092 -0.161  0.333

```

Working memory plots



Phonological short-term memory

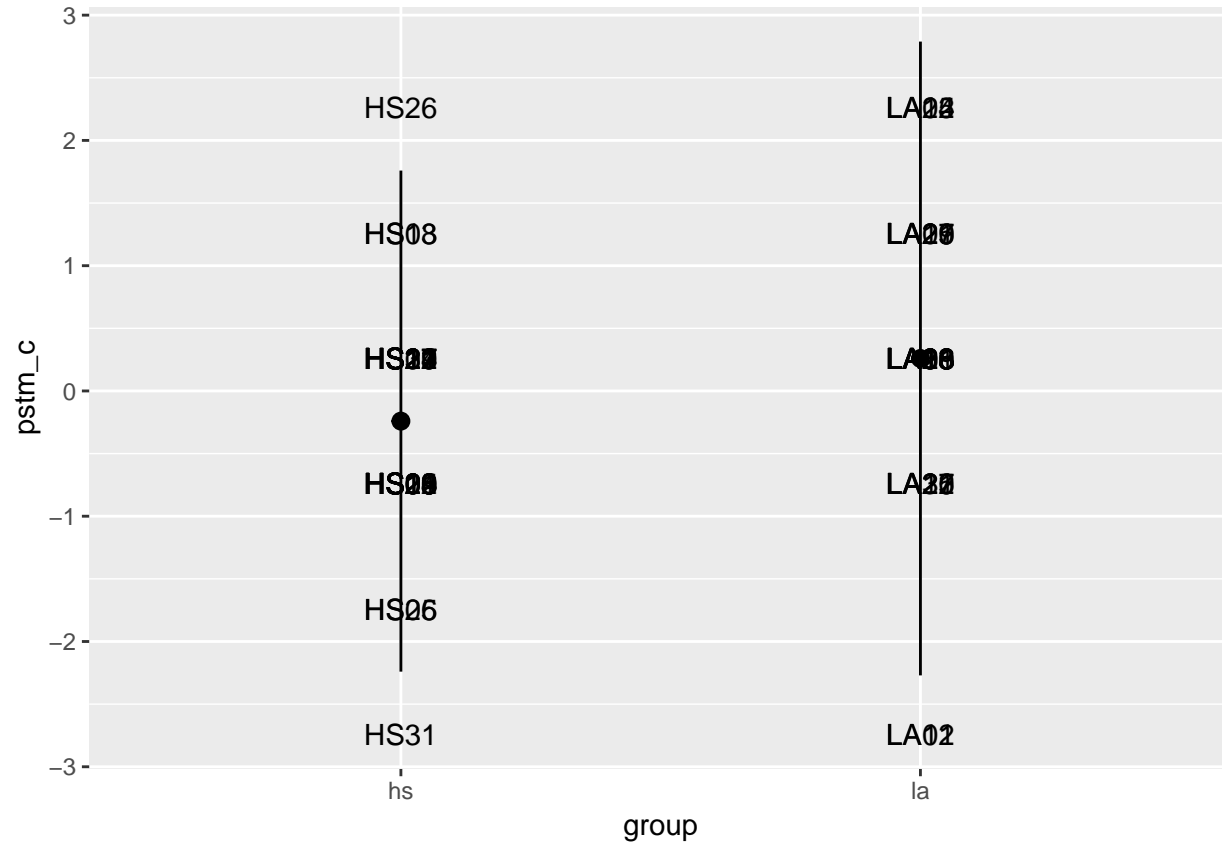
```
## Joining, by = c("participant", "group")
```

First check for homogeneity of variance.

```
pstm_clean %>%  
  bartlett.test(pstm_c ~ group, data = .)
```

```
##  
## Bartlett test of homogeneity of variances  
##  
## data: pstm_c by group  
## Bartlett's K-squared = 1.4022, df = 1, p-value = 0.2364
```

```
pstm_clean %>%  
  na.omit(.) %>%  
  ggplot(., aes(x = group, y = pstm_c, label = participant)) +  
    geom_text() +  
    stat_summary(fun.data = mean_sdl, geom = 'pointrange')
```



Groups look good.

```
## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula:  
## cbind(targetCount, distractorCount) ~ (1 + pstm_c | participant) +  
## (1 + pstm_c | target) + group + group:pstm_c - 1
```

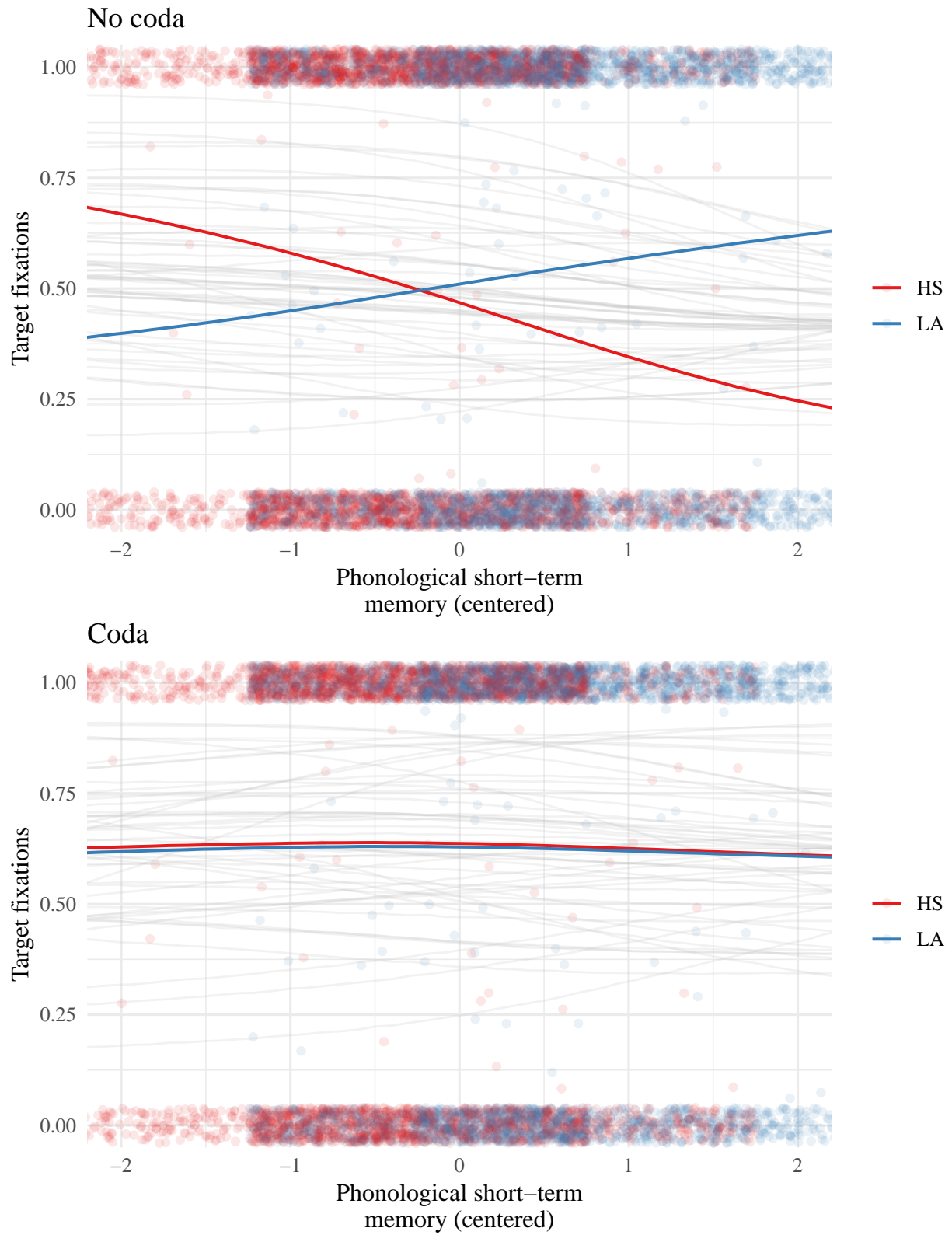
```

## Data: hs_la_pstm_no_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC    logLik deviance df.resid
##  3201.9   3239.4  -1590.9   3181.9     306
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -16.069  -2.063   0.000    2.119   8.489
##
## Random effects:
##  Groups      Name      Variance Std.Dev. Corr
## participant (Intercept) 0.8138   0.9021
##           pstm_c      0.1735   0.4165  -0.35
## target      (Intercept) 0.9015   0.9495
##           pstm_c      0.7006   0.8370  -0.33
## Number of obs: 316, groups: participant, 50; target, 13
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## groupla      0.05001    0.34025   0.147   0.883
## grouphs     -0.14185    0.35263  -0.402   0.687
## groupla:pstm_c 0.28958    0.30913   0.937   0.349
## grouphs:pstm_c -0.56678    0.40755  -1.391   0.164
##
## Correlation of Fixed Effects:
##           groupl grouphs grpl:_
## grouphs      0.580
## grpl:pstm_c -0.362 -0.182
## grphs:pstm_ -0.144 -0.046  0.399
##
## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula:
## cbind(targetCount, distractorCount) ~ (1 + pstm_c | participant) +
## (1 + pstm_c | target) + group + group:pstm_c - 1
## Data: hs_la_pstm_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC    logLik deviance df.resid
##  4703.6   4744.8  -2341.8   4683.6     445
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -14.2457  -2.2282   0.9312   2.0076   6.6046
##
## Random effects:
##  Groups      Name      Variance Std.Dev. Corr
## participant (Intercept) 0.8588   0.9267
##           pstm_c      0.2576   0.5076  -0.01
## target      (Intercept) 0.2289   0.4785
##           pstm_c      0.5546   0.7447  -0.18
## Number of obs: 455, groups: participant, 50; target, 19

```

```
##
## Fixed effects:
##           Estimate Std. Error z value Pr(>|z|)
## groups      0.66125    0.25831   2.560  0.0105 *
## groupla      0.61823    0.25580   2.417  0.0157 *
## groups:pstm_c -0.03598    0.33682  -0.107  0.9149
## groupla:pstm_c -0.02879    0.29049  -0.099  0.9211
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           grophs groupl grph:_
## groupla      0.151
## grphs:pstm_  0.216 -0.003
## grpl:pstm_c -0.029 -0.267  0.258
```

PSTM plots



Early/late bilinguals summary

Learners summary

Without coda:

- Only monolinguals fixate on target above chance at the offset of the first syllable.
- All three groups fixate on target above chance by the suffix.
- No effect of working memory (a lot of variability for heritage).
- No effect of PSTM.

With coda:

- Only monolinguals fixate on targets above chance at the coda.
- All three groups fixate on targets above chance at the offset of the first syllable.
- No effect of working memory. This is different for monolinguals and advanced learners if compared to the 'learner' analysis above (because the two analyses don't involve the exact same participants because of the homogeneity of variance issue).
- No effect of PSTM.