bayes_models_diagnostics

January 18, 2023

1 Overview

This is a python notebook to present all the model diagnostics of bayseian models used in Examining the Longitudinal Trajectory of Biopsychosocial Difficulties in Anorexia Nervosa Within a Bayesian Framework paper.

For more information on how the data was pre-processed and how the models where built please see https://github.com/WMDA/BB_data/

1.1 Content

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2 Libraries used in this note book and reading in the data/models

Skip this section if just interested in model diagnostics

[12]:
```
from functions.data_functions import save_pickle, load_pickle, load_data
import seaborn as sns
sns.set_style('darkgrid')
import matplotlib.pyplot as plt
import numpy as np
import arviz as az
```

[2]:
```
models_summary = load_pickle('simpler_saved_models')
fitted_models = load_pickle('simpler_fitted_models')
```

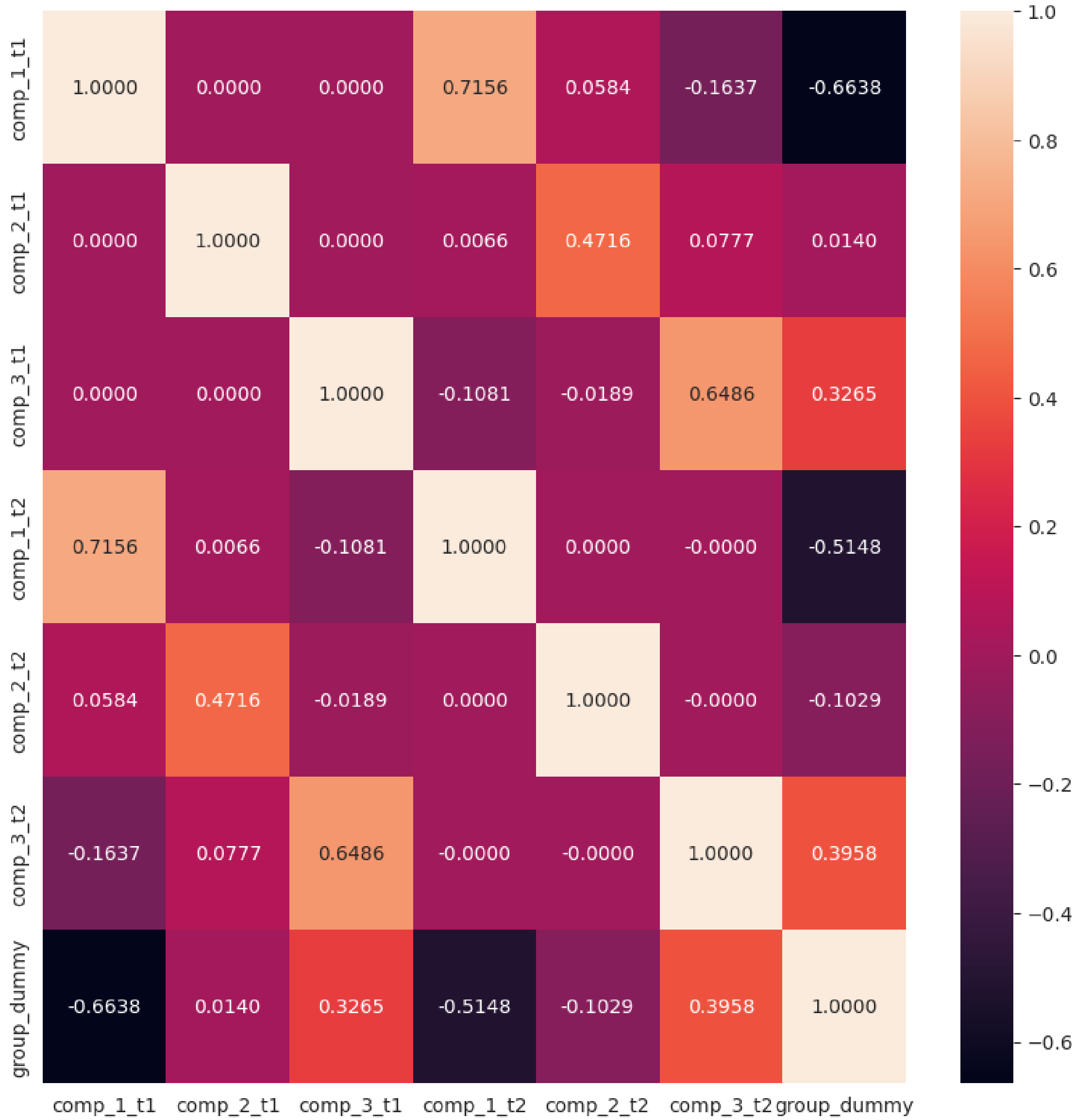
[3]:
```
pca_df = load_data('BEACON', 'pca_df')
#Define number of components to loop over
comp = ['comp_1', 'comp_2','comp_3']
```

3 Heatmap

This is a heatmap of all the variables in the used in the models to check for multicollinearity

[4]:
```
pca_df['group_dummy'] = pca_df['group'].apply(lambda group: 0 if group =='AN' else 1)
plt.figure(figsize=(10, 10))
sns.heatmap(pca_df[['comp_1_t1','comp_2_t1', 'comp_3_t1', 'comp_1_t2', 'comp_2_t2', 'comp_3_t2','group_dummy']].corr(),  annot=True,  fmt=".4f")
```

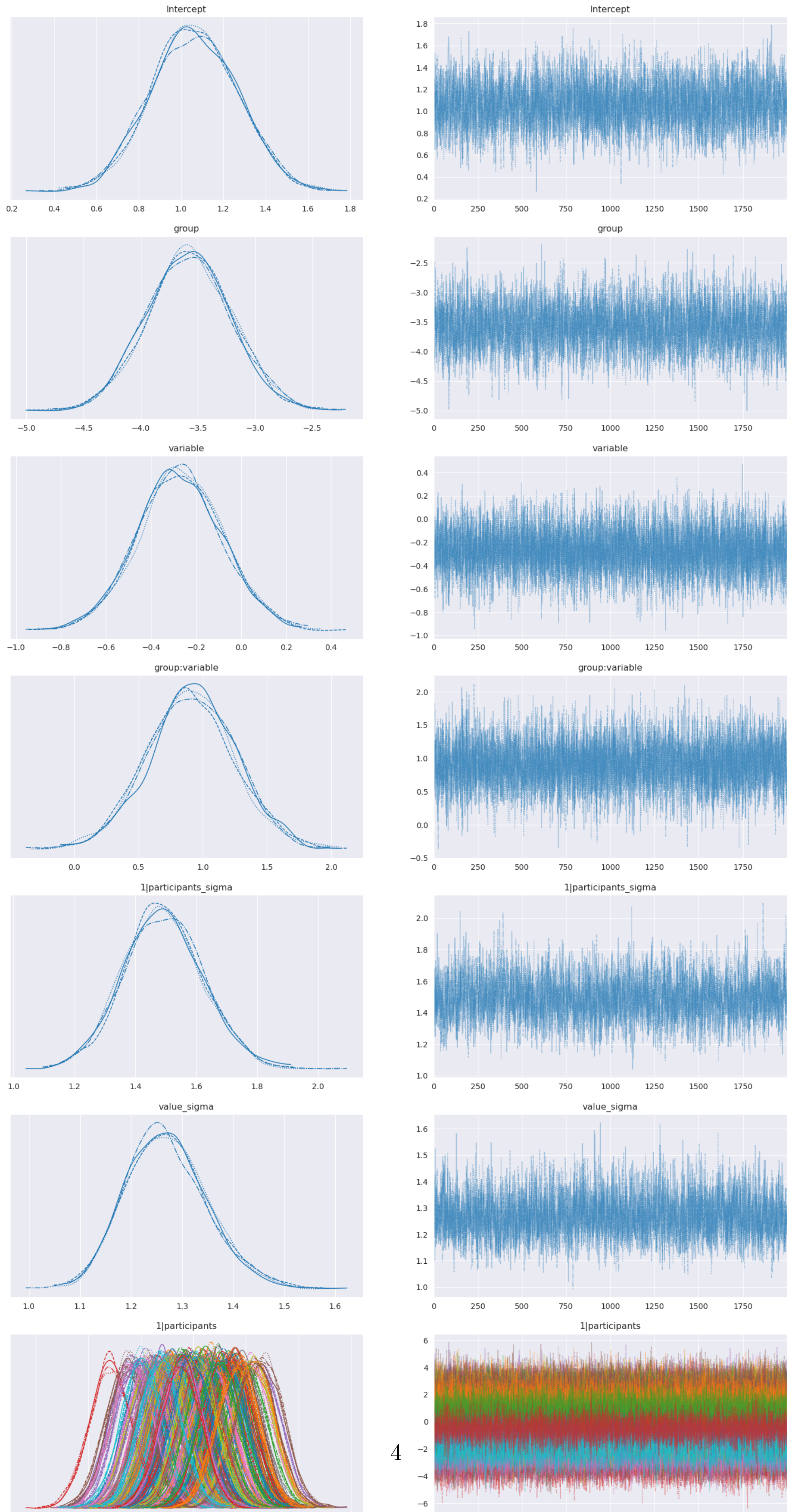
[4]:
```
<AxesSubplot: >
```

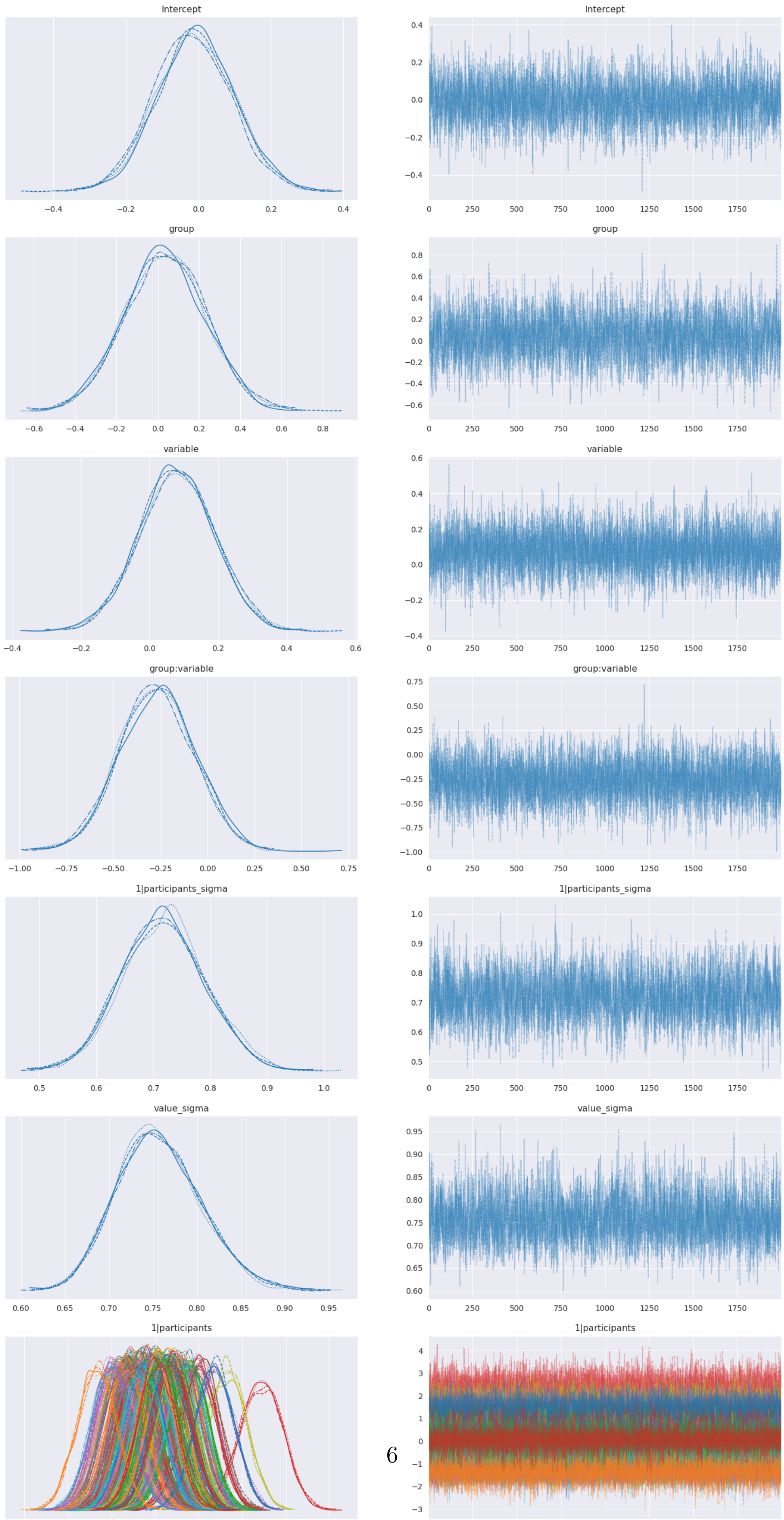


4 KDE and trace plots for the mixed effects models

4.1 Alternative hypothesis models

[5]:
```
for component in comp:
    az.plot_trace(fitted_models['alt'][component], figsize=(18,35))
```


Intercept
Intercept
group
group
variable
variable
group:variable
group:variable
1|participants_sigma
1|participants_sigma
value_sigma
value_sigma
1|participants
1|participants


Intercept
Intercept
group
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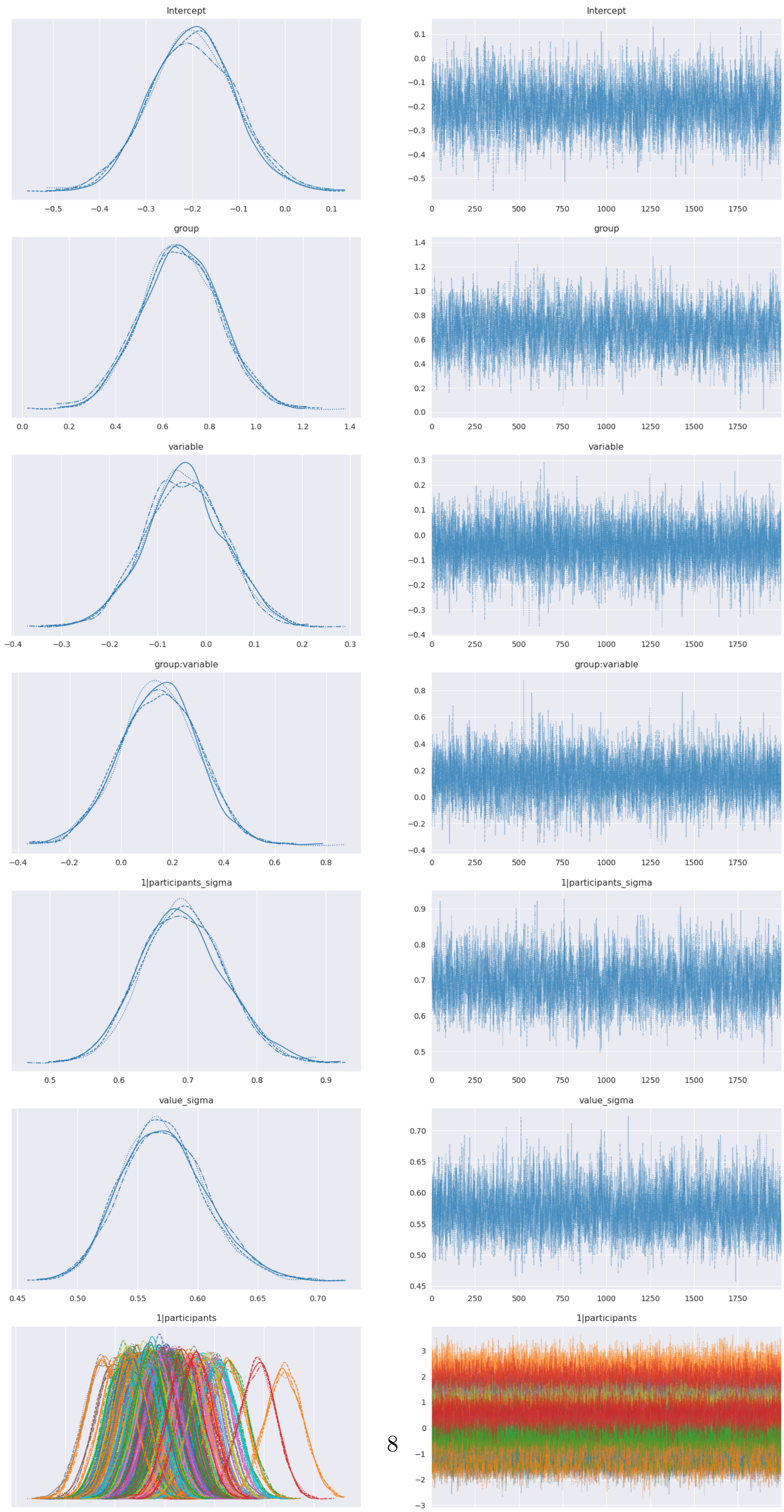
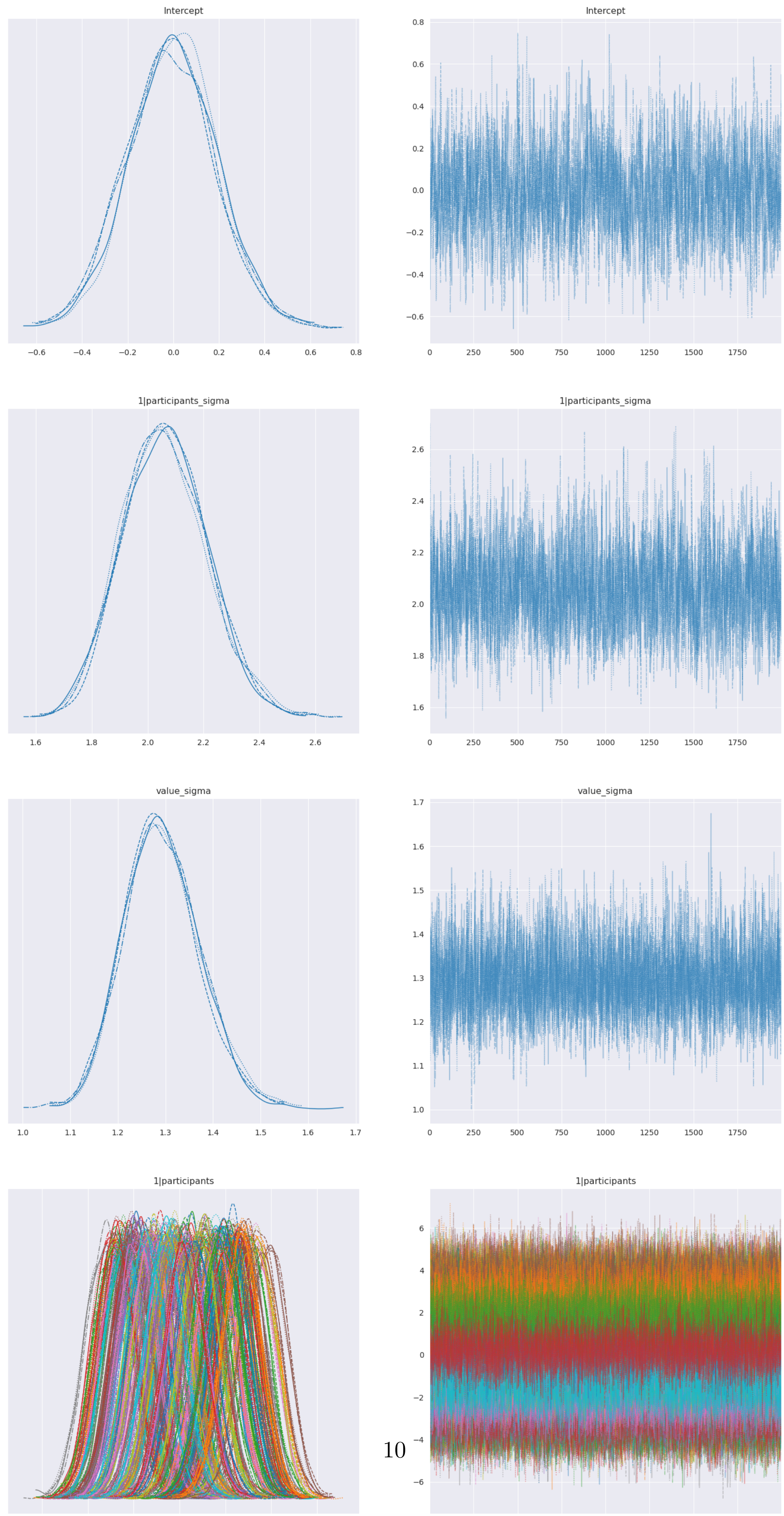
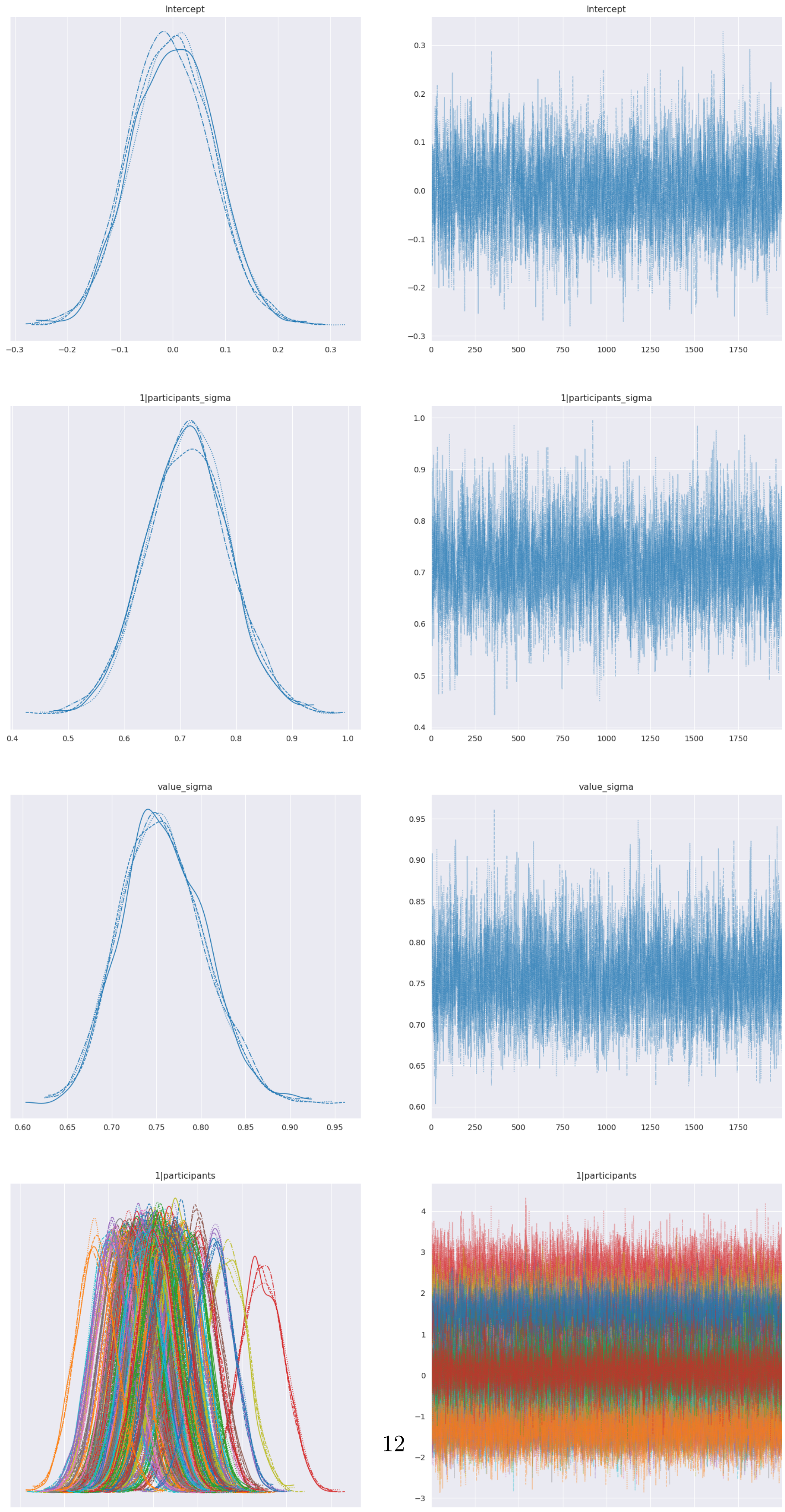
1|participants_sigma
1|participants_sigma
value_sigma
value_sigma
1|participants
1|participants

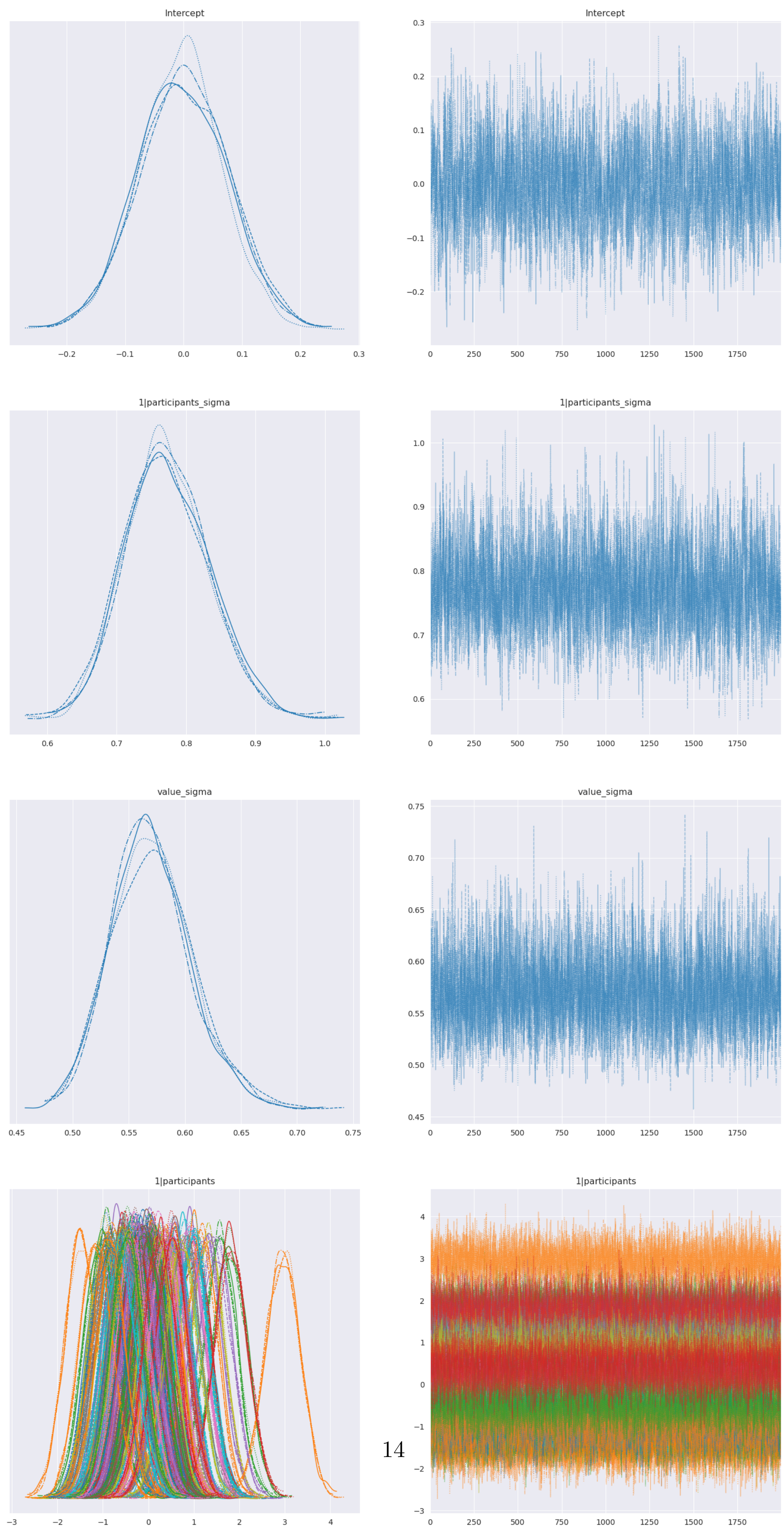

Intercept
Intercept
group
group
variable
variable
group:variable
group:variable
1|participants_sigma
1|participants_sigma
value_sigma
value_sigma
1|participants
1|participants

4.2 For the null hypothesis models

[6]:
```
for component in comp:
    az.plot_trace(fitted_models['null'][component], figsize=(18,35))
```


Intercept
Intercept
1|participants_sigma
1|participants_sigma
value_sigma
value_sigma
1|participants
1|participants


Intercept
Intercept
1|participants_sigma
1|participants_sigma
value_sigma
value_sigma
1|participants
1|participants


Intercept
Intercept
1|participants_sigma
1|participants_sigma
value_sigma
value_sigma
1|participants
1|participants

5 Diagnostic Summaries of the mixed effects models

5.1 Alternative Hypothesis

[7]:
```
alt_variables = ['Intercept', 'group', 'group:variable', 'value_sigma',␣
↪'1|participants_sigma']
null_variables = ['value_sigma', '1|participants_sigma']
```

[8]:
```
az.summary(fitted_models['alt']['comp_1'], kind='diagnostics',␣
↪var_names=alt_variables )
```

[8]:

	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
Intercept	0.004	0.003	3194.0	4645.0	1.0
group[HC]	0.006	0.005	3311.0	5059.0	1.0
group:variable[HC, t2]	0.004	0.003	6509.0	5701.0	1.0
value_sigma	0.002	0.001	2697.0	4278.0	1.0
1|participants_sigma	0.003	0.002	2101.0	3993.0	1.0

[9]:
```
az.summary(fitted_models['alt']['comp_2'], kind='diagnostics',␣
↪var_names=alt_variables)
```

[9]:

	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
Intercept	0.002	0.001	2852.0	4230.0	1.0
group[HC]	0.004	0.003	2847.0	4499.0	1.0
group:variable[HC, t2]	0.003	0.002	5177.0	6231.0	1.0
value_sigma	0.001	0.001	2708.0	4788.0	1.0
1|participants_sigma	0.002	0.001	2341.0	4528.0	1.0

[10]:
```
az.summary(fitted_models['alt']['comp_3'], kind='diagnostics',␣
↪var_names=alt_variables)
```

[10]:

	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
Intercept	0.002	0.001	2229.0	3852.0	1.0
group[HC]	0.003	0.002	2557.0	3974.0	1.0
group:variable[HC, t2]	0.002	0.002	5459.0	5436.0	1.0
value_sigma	0.001	0.000	2866.0	5044.0	1.0
1|participants_sigma	0.001	0.001	2333.0	4097.0	1.0

Extracting the number of divergences, tree depth, energy steps and acceptance rate.

[13]:
```
for component in comp:
    print(f'Number of divergences for {component} alt model:', int(np.
↪sum(fitted_models['alt'][component].sample_stats.diverging))
```

```
    print(f'Number of times tree depth hit 10 for {component} alt model:',␣
↪int(np.sum(fitted_models['alt'][component].sample_stats.tree_depth == 10)))
    print(f'Number of energy steps > 0.3 for {component} alt model:', int(np.
↪sum(fitted_models['alt'][component].sample_stats.energy < 0.3)))
    print(f'Number of steps where acceptance rate < 0.95 for {component} alt␣
↪model:', int(np.sum(fitted_models['alt'][component].sample_stats.
↪acceptance_rate < 0.95)))
    print('\n\n')
```

```
Number of divergences for comp_1 alt model: 0
Number of times tree depth hit 10 for comp_1 alt model: 0
Number of energy steps > 0.3 for comp_1 alt model: 0
Number of steps where acceptance rate < 0.95 for comp_1 alt model: 3074



Number of divergences for comp_2 alt model: 0
Number of times tree depth hit 10 for comp_2 alt model: 0
Number of energy steps > 0.3 for comp_2 alt model: 0
Number of steps where acceptance rate < 0.95 for comp_2 alt model: 3213



Number of divergences for comp_3 alt model: 0
Number of times tree depth hit 10 for comp_3 alt model: 0
Number of energy steps > 0.3 for comp_3 alt model: 0
Number of steps where acceptance rate < 0.95 for comp_3 alt model: 3186
```

5.2 Null Hypothesis

[14]:
```
az.summary(fitted_models['null']['comp_1'], kind='diagnostics',␣
↪var_names=null_variables)
```

[14]:

	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
value_sigma	0.001	0.001	3209.0	4753.0	1.0
1|participants_sigma	0.004	0.003	1427.0	2394.0	1.0

[15]:
```
az.summary(fitted_models['null']['comp_2'], kind='diagnostics',␣
↪var_names=null_variables)
```

[15]:

	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
value_sigma	0.001	0.001	2821.0	4512.0	1.0
1|participants_sigma	0.002	0.001	2411.0	4181.0	1.0

[16]:
```python
az.summary(fitted_models['null']['comp_3'], kind='diagnostics',␣
↪var_names=null_variables)
```

[16]:

	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
value_sigma	0.001	0.000	3160.0	4755.0	1.0
1|participants_sigma	0.001	0.001	2353.0	4323.0	1.0

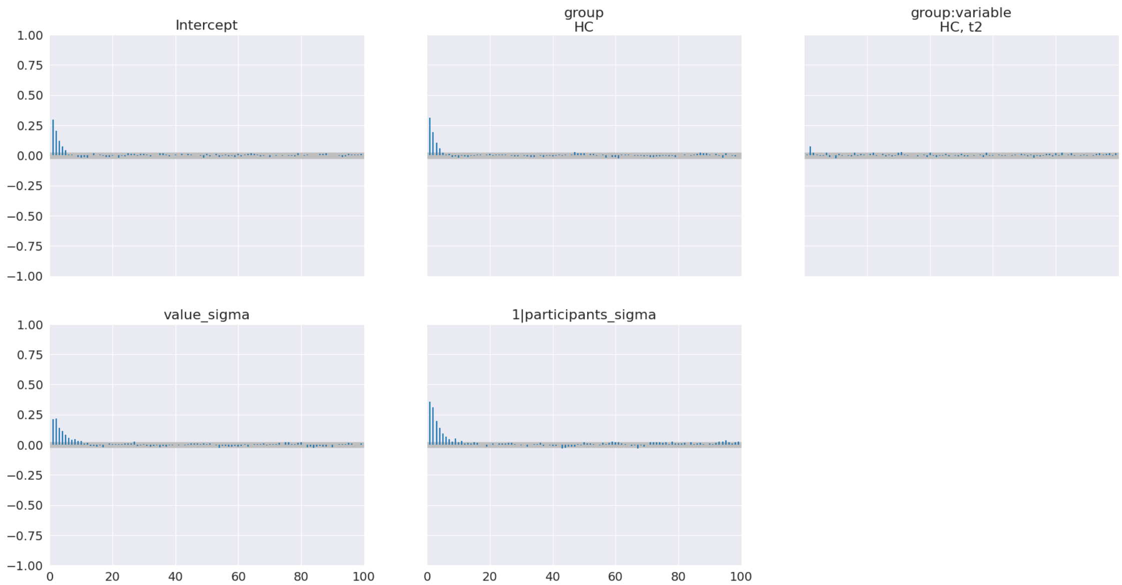
Extracting the number of divergences, tree depth, energy steps and acceptance rate.

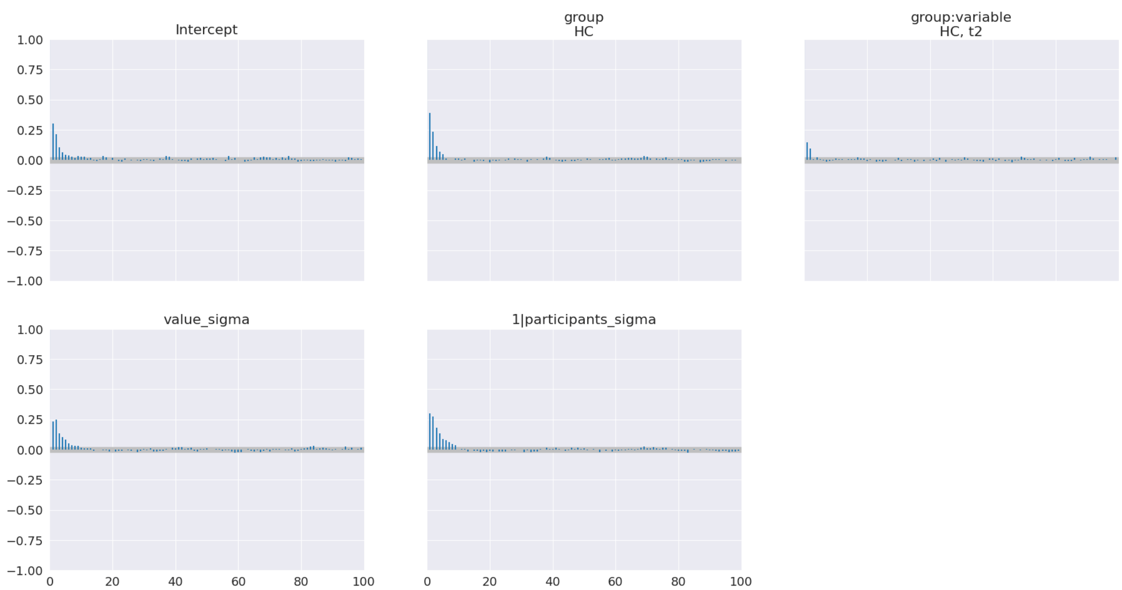
[17]:
```python
for component in comp:
    print(f'Number of divergences for {component} alt model:', int(np.
↪sum(fitted_models['null'][component].sample_stats.diverging)))
    print(f'Number of times tree depth hit 10 for {component} alt model:',␣
↪int(np.sum(fitted_models['null'][component].sample_stats.tree_depth == 10)))
    print(f'Number of energy steps > 0.3 for {component} alt model:', int(np.
↪sum(fitted_models['null'][component].sample_stats.energy < 0.3)))
    print(f'Number of steps where acceptance rate < 0.95 for {component} alt␣
↪model:', int(np.sum(fitted_models['null'][component].sample_stats.
↪acceptance_rate < 0.95)))
    print('\n\n')
```

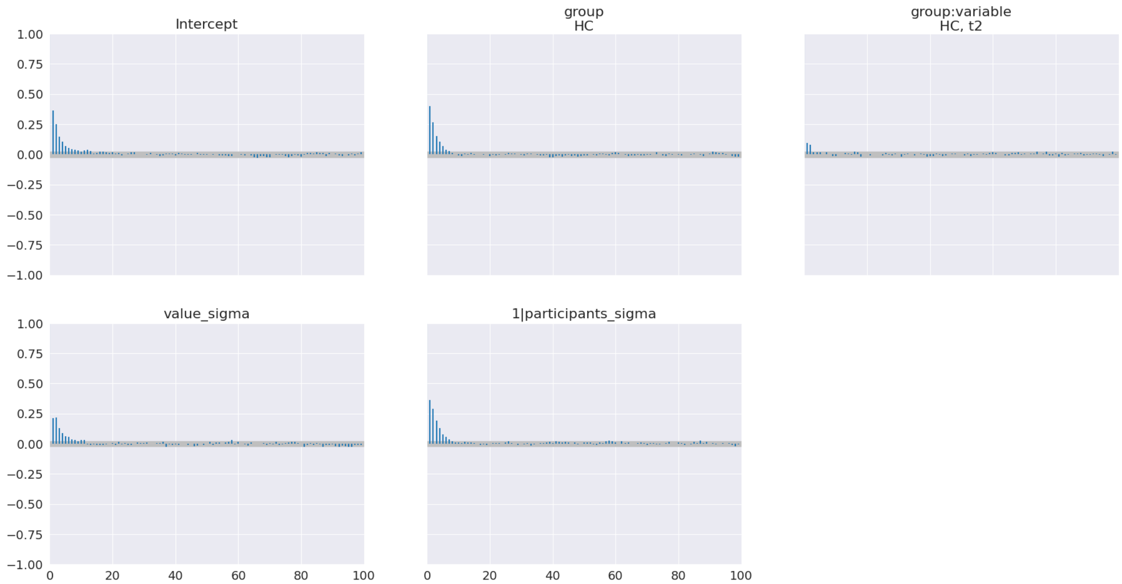
```
Number of divergences for comp_1 alt model: 0
Number of times tree depth hit 10 for comp_1 alt model: 0
Number of energy steps > 0.3 for comp_1 alt model: 0
Number of steps where acceptance rate < 0.95 for comp_1 alt model: 3319



Number of divergences for comp_2 alt model: 0
Number of times tree depth hit 10 for comp_2 alt model: 0
Number of energy steps > 0.3 for comp_2 alt model: 0
Number of steps where acceptance rate < 0.95 for comp_2 alt model: 3123



Number of divergences for comp_3 alt model: 0
Number of times tree depth hit 10 for comp_3 alt model: 0
Number of energy steps > 0.3 for comp_3 alt model: 0
Number of steps where acceptance rate < 0.95 for comp_3 alt model: 3150
```

6 Autocorrelation plots

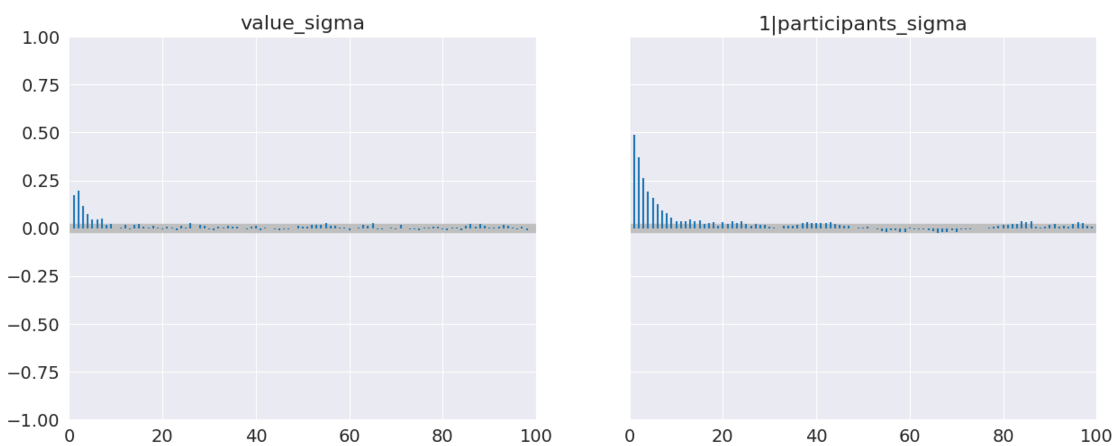
[ ]:
```
for component in comp:
    az.plot_autocorr(fitted_models['alt'][component] ,combined=True,␣
↪var_names=alt_variables)
```

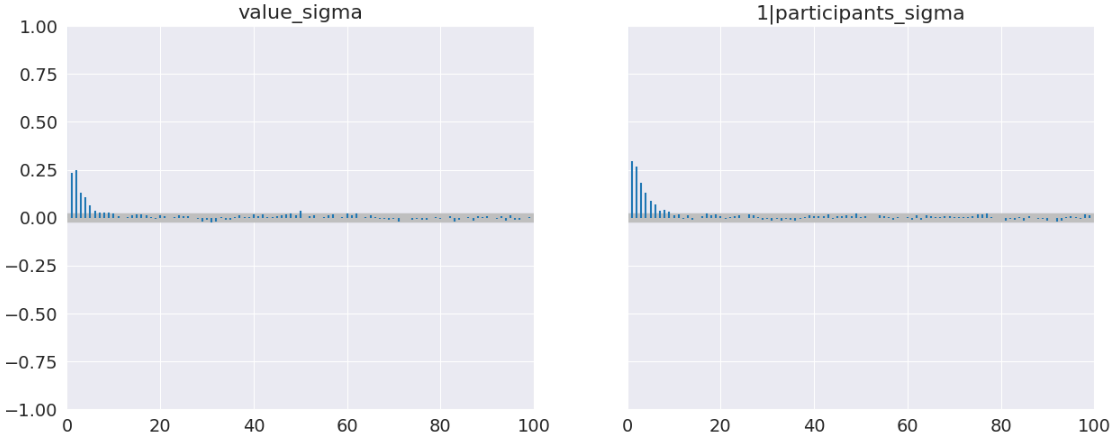


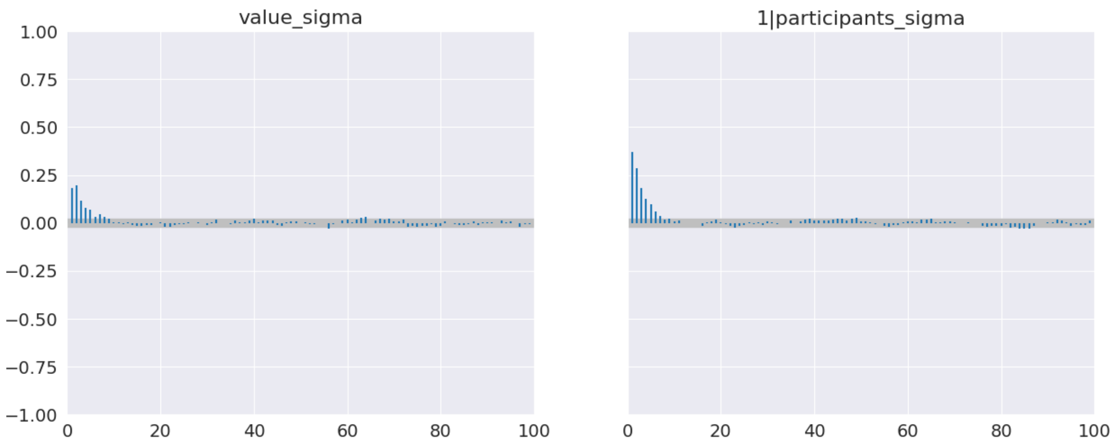





```
[ ]: for component in comp:
         az.plot_autocorr(fitted_models['null'][component] ,combined=True,␣
     ↪var_names=null_variables)
```




value_sigma
1|participants_sigma
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
20
40
60
80
100


value_sigma
1|participants_sigma
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
20
40
60
80
100