The Dynamics of Opinion Expression During Group Discussion

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Overview

- Opinion expression framed in terms of Wilson et al.'s (2022) oscillation model
  - Groups cycle between periods of dissenting and concurring opinions
  - Eventually, groups converge on a product or outcome
- Other plausible explanations include punctuated equilibrium model and dynamic systems theory
- Opinion scores generated with *R* package *sentimentR*
- Analysis based on RDSEM and cross-classified DSEM
- Hypotheses mostly supported

Opinion and Opinion Expression

- *Opinion* as a cognitive construct broadly defined as one's perspective on a issue or matter
- *Opinion expression* contributing one's perspsective to discussion in some form
- Opinions and opinion expression both have polarity and strength
  - One can have a weak or strong opinion for or against something
  - Strength has something to do with the words used to express an opinion
- Regarding opinion expression, overlap in literature among the following:
  - Opinion
  - Argument
  - Information

What is Dynamic About Opinion Expression?

- What does dynamic mean?
  - Based on Ellen's talk from Monday's workshop, dynamism is defined as the state of a system at *Time t* is different than that at *Time t-1*.
    - If autoregression is consistent across time, then the series is consistently dynamic
    - If autoregression varies across time, then the series is inconsistently dynamic
- Dynamism is a function of both local and global factors
  - Local a problem of mutual influence (i.e., what one says is related to what is said prior and what might be said after)
  - Global concerns resources that participants possess prior to interaction (e.g., preferences, arguments, opinions)

Oscillation Model

- Originally addressed idea generation in diverse work groups
- Diversity operationalized as differences in perspective, outlook, opinion, orientation, and so on
    - Harrison and Klein (2007) important here
    - The oscillation model seems to embrace "deep diversity"
    - Surface-level diversity might or might not be related and is irrelevant here
- Model uses the metaphor of "tacking," in which sailboats make progress toward a destination that is into a headwind
    - Model is decidedly "macro" in orientation
    - Tacking requires coordinated effort among crew members to make progress toward the destination

Graph of Oscillation

We don't expect oscillation to look like this.

We aren't sure what it looks like or what the cutoffs might/should be.

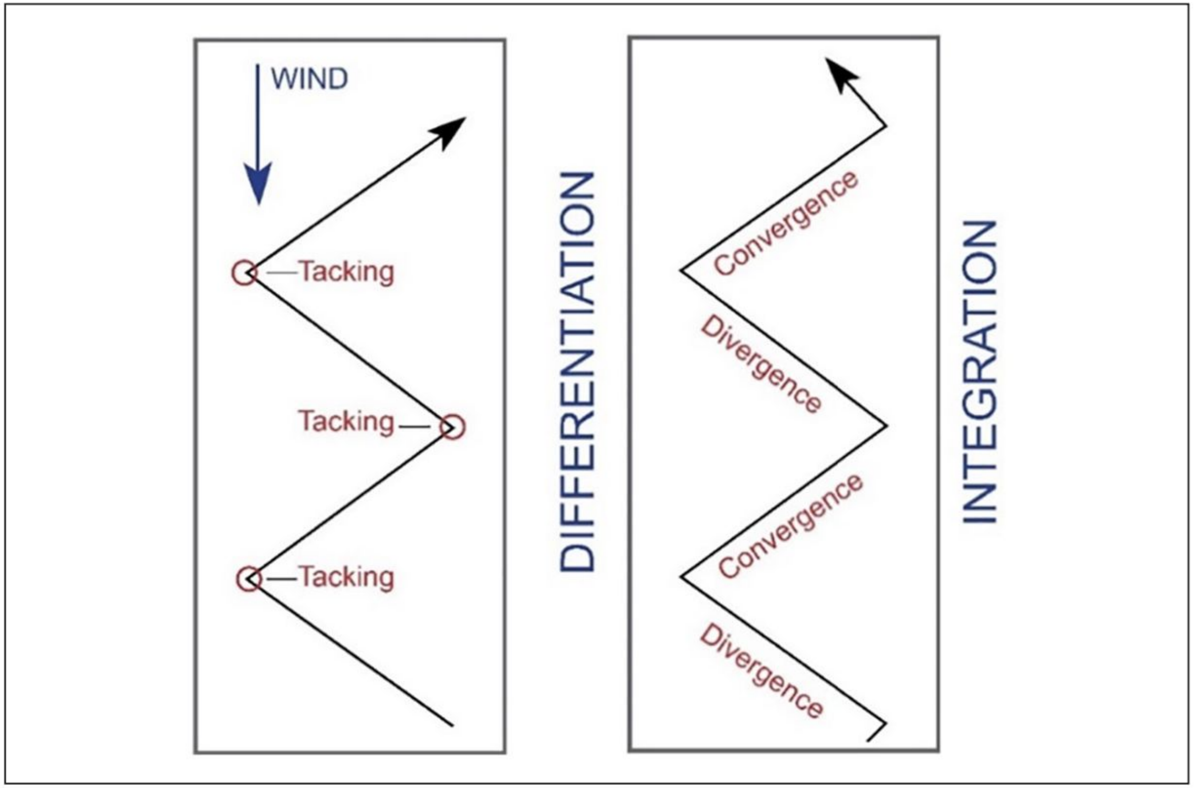


Figure 1. Tacking in a sailboat (left) and the oscillatory procedural framework (right), whereby teams undergo periods of divergence (which emphasize differentiation) and convergence (which emphasize integration)

Opinion Expression as Oscillation

- Group goal is the destination
  - Model seems to apply to many types of groups, including those with a shared or common goal (e.g, juries) and those with distributed goals (e.g., brainstorming, support groups)
- Opinion expression plays a central role in group outcomes
  - The most frequent or common type of group discourse (e.g., Bales)
  - Group outcomes often reflect the option with the most support, in terms of opinion expression (GVM)
  - Or group outcomes reflect the number of members who support a given outcome (DVM)
- Groups "tack" or oscillate from differentiation to integration
- Tacking is managed via communication (i.e., opinion expression) that either diverges or converges

Diversity as "Headwinds"

- Original oscillation study used the model to design and implement discussion protocols that create oscillation
- We note that, based on extensive group research, opinions are often developed prior to interaction
- Distributions of opinions within groups (*opinion profile*) function as headwinds in terms of direction and strength
  - *Direction = valence*: the mean or center of the profile can be positive or negative
  - *Strength = variance:* Opinions or perspectives can be hetero- or homogenous
- Discussion often reflects, in some degree, the distribution of initial preferences
- Other features of discusson are "local" or "emergent"

Baseline Hypotheses

- First set of hypotheses examine baseline model characteristics (first sense of "dynamic")
- The issue is whether (a) micro oscillations in opinion expression can be detected, and (b) if micro oscillations provide evidence for macro oscillations
- Also provides a sense of the structure of the random effects, which is of interest
  - H1: Opinion expression at *Time T* is positively associated with opinion expression at *Time T-1*.
  - H2: Mean opinion expression is positively associated with mean opinion profile.
  - H3: Variance of opinion expression is positively associated with opinion profile variance.

Research Questions

- Unclear if and how opinion profile influences autoregression and trend
  - RQ1: Is the association between opinion expression at Time T and T-1 associated with a group's mean opinion profile?
  - RQ2: Is the association between opinion expression at Time T and T-1 associated with a group's opinion profile variance?
  - RQ3: Is a group's opinion expression trend associated with a group's mean opinion profile?
  - RQ4: Is a group's opinion expression trend associated with a group's opinion profile variance?

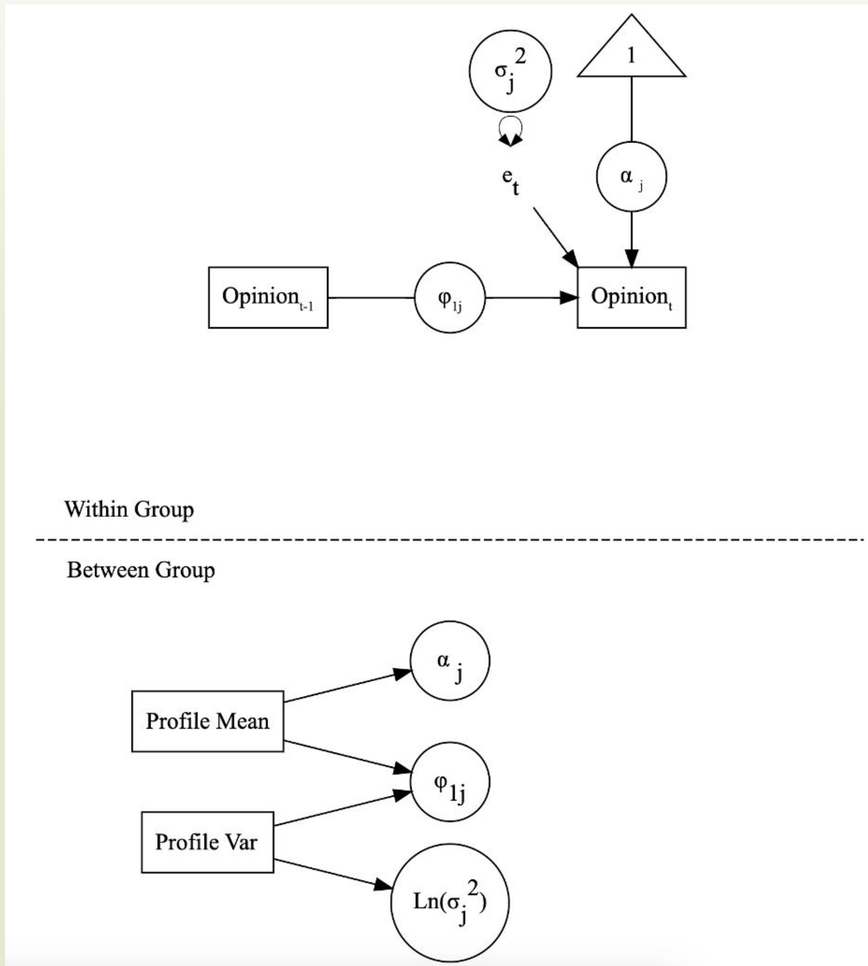
Dynamic Model Hypothesis

- The issue is whether model parameters, especially AR(1), are consistent across speakng turns
- In terms of dynamics, the process is either consistently dynamic or inconsistently dynamic
- Oscillation implies inconsistent dynamics
  - H4: The association between opinion expression at *Time T* and *T-1* varies across discussion.
  - RQ5: What is the pattern of associations among adjacent speaking turns across discussion?

Graph of Theoretical Model

Adapted from McNeish and Hamaker (2020)

Used graphviz within R's *diagrammeR*



Method

- Data from 4 previously published studies that used the same core group task (Groups = 128, N = 434)
  - Participants read 12 statements that described the behaviors of a fictitious person named Jim
  - Participants each wrote, in private, a psychological profile about Jim based on the 12 statements
  - Groups discussed Jim and came to a consenus about him
  - After discussion, members wrote, again in private, their understanding of the group's consensus (not used in this study)
  - Participants also filled out round-robin assessments about discussion
- Discussion data transcribed and unitized
- Analysis here is at the level of the speaking turn, which implies an interpersonal process and dynamic

Opinion Mining

- Private profiles and discussion data scored using Rinker's *sentimentR* package
- An important advance on typical opinion mining in that surrounding words included to better identify unit's direction and magnitude
- Each speaking turn evaluating for opinion expression
- Privately written profiles were evaluated at the sentence level
  - Each person's profile has a mean and standard deviation
  - Each person's mean and standard deviation were used to create the group opinion profile

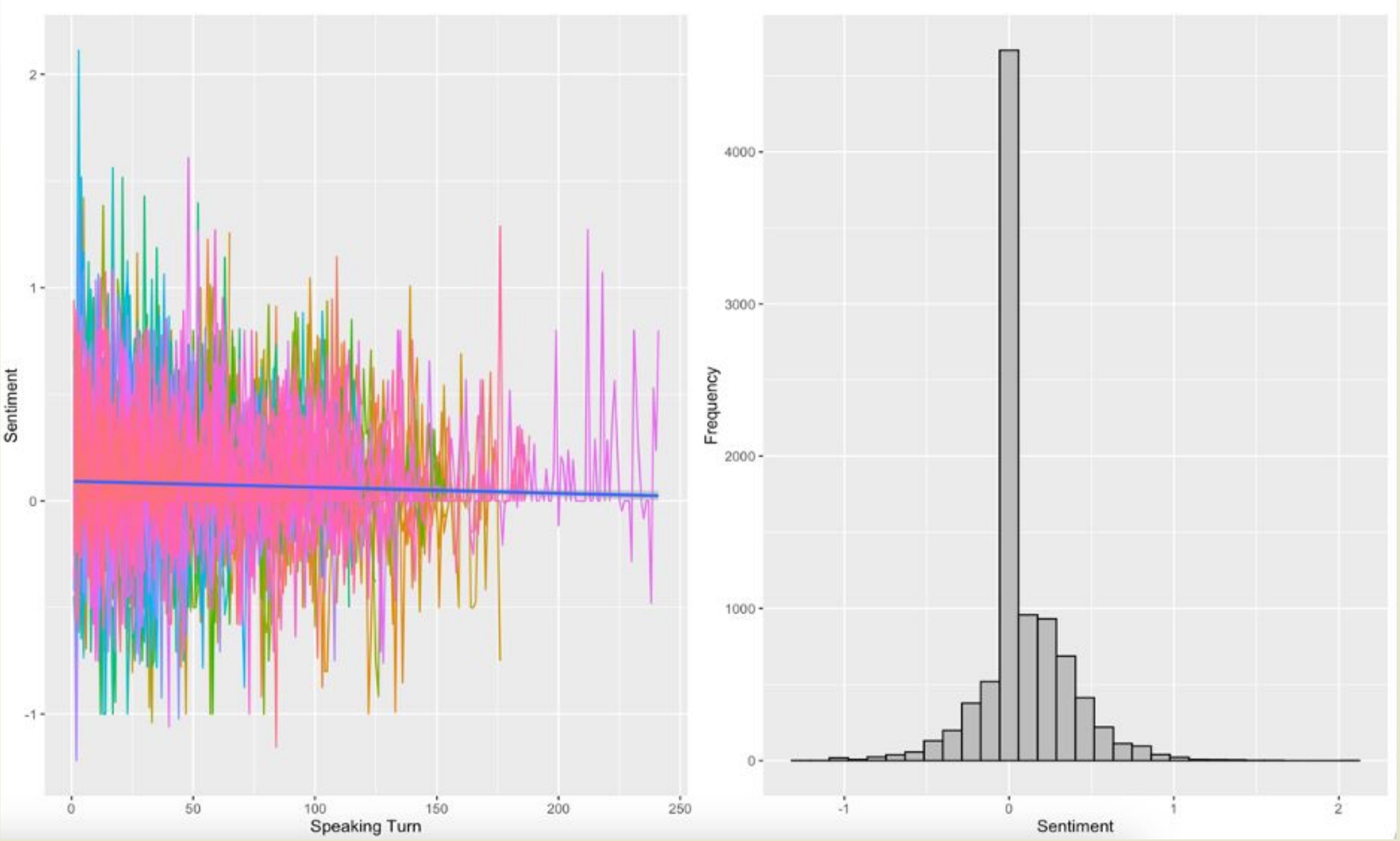
Example Opinion Scores

Text	Word Count	Opinion Score
He is unmotivated	3	-0.577
He is not motivated	4	-0.250
He is not very motivated	5	-0.045
He is somewhat motivated	4	0.050
He is motivated	3	0.289
He is very motivated	4	0.450

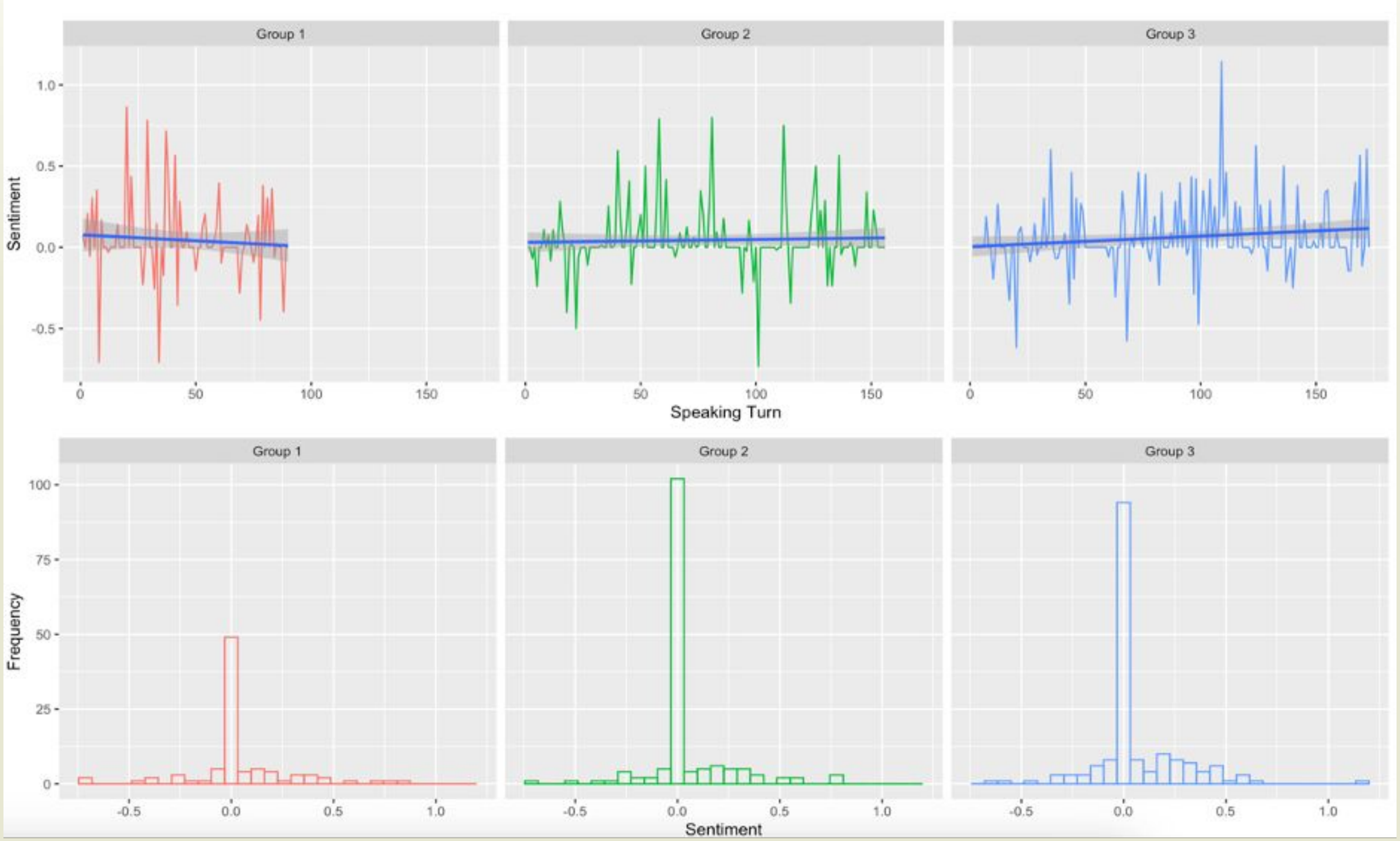
Variables

- *Opinion expression*: the score for any given speaking turn
  - Multiplied by 100 because of too-low variance and CI's that were zeros
- *Lag opinion expression*: opinion score in the previous speaking turn
- *Group opinion profile*: An aggregate of individual profiles written prior to discussion
  - *Mean* group opinion profile
  - *Variance* of the group opinion profile
- Study from which the data were drawn (used as covariates)

Opinion Expression Graph of Series for All Groups



Opinion Expression Graphs for Three Groups



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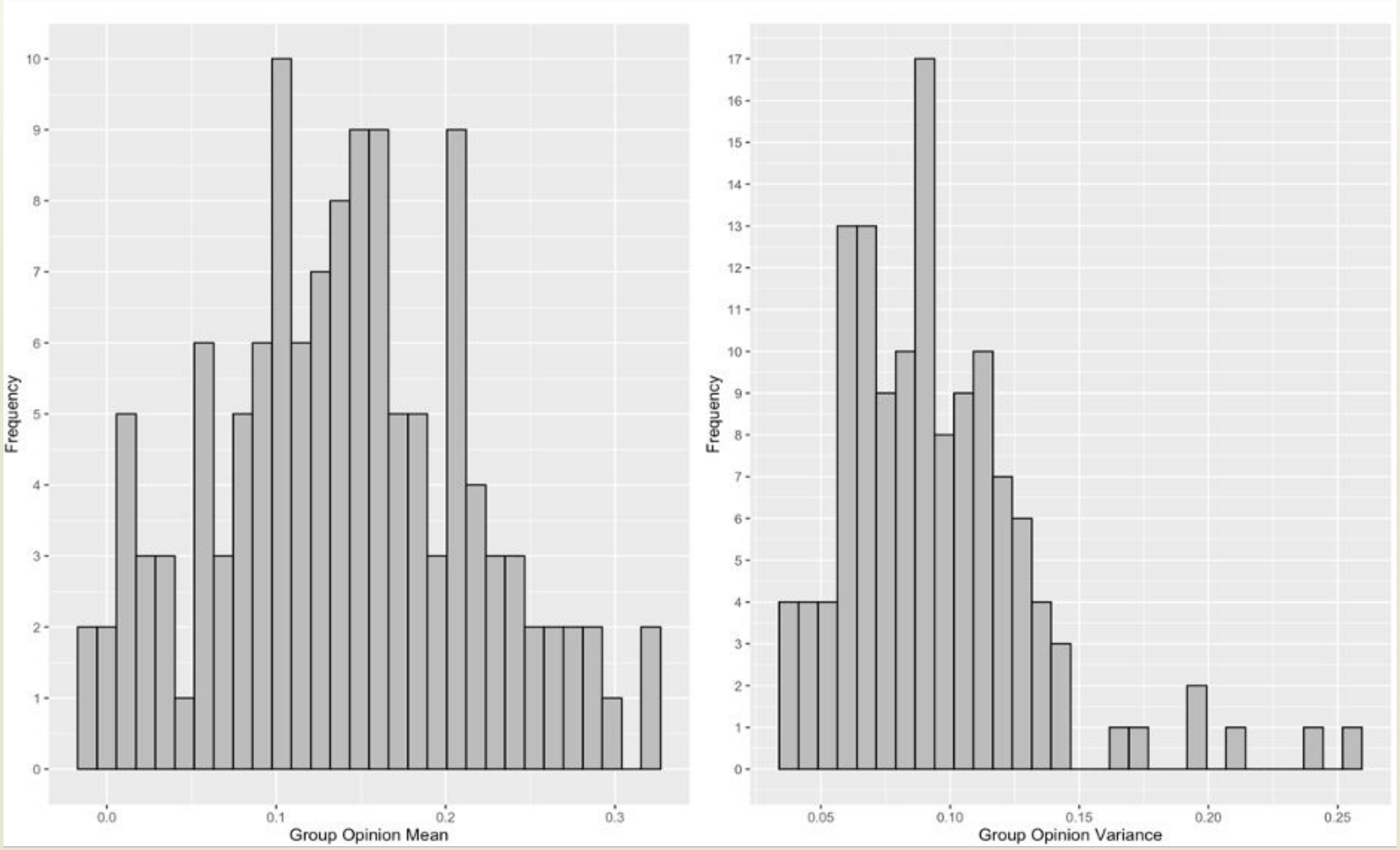
Graph of Opinion Profiles



Analysis Part 1

- Hypothesis 1, 2, and 3 and the first four research questions analyzed with DSEM, but…
- A regression analysis of the discussion data, with opinion expression regressed on speaking turn, showed a slight, negative trend
- DSEM assumes trendless data
- RDSEM to the rescue
    - Residuals, rather than raw scores, used in the analysis.
    - Interpretation remains roughly the same
- The study from which the data were drawn was included as a series of dummy variables
- Chose model building approach here to examine random variance terms

DSEM Parameters

$$Y_{tj} = \alpha_j + \varphi_{(t-1)j} + e_{tj}$$

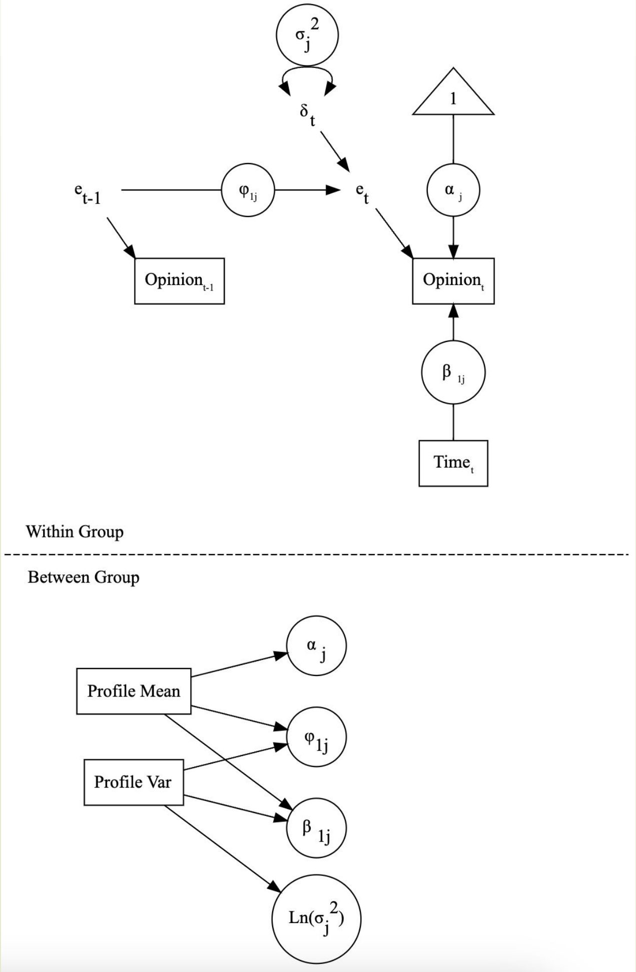
$$\alpha_j = \lambda_{00} + u_{0j}$$

$$\varphi_j = \lambda_{10} + u_{1j}$$

Where

- The predicted value of *Y* (opinion expression) for group *j* at time *t* is equal to a group-level intercept α_j plus a group-level autoregressive (i.e., opinion is regressed on itself at the previous lag) term φ_j.
- The lambdas (λ_{00} and λ_{10}) are the intercepts for the mean and autoregression of the series, respectively, with their respective variances, μ_{0j} and μ_{1j}.
- Finally, e_{ij} is the error term that represents the distribution of scores around the mean of the series for each time point.

RDSEM Graph


σj2
δt
1
et-1
φ1j
et
α j
Opiniont-1
Opiniont
β 1j
Timet
Within Group
Between Group
α j
Profile Mean
φ1j
Profile Var
β 1j
Ln(σj2)

RDSEM Model 2 Mplus Code

```
TITLE: Rdsem Model 2--Random Covariances
 DATA:
 FILE = "rdsem1a.dat";
VARIABLE:
 NAMES = group resent linenum study2 study3 study4;
 MISSING=.;
  CLUSTER is Group;
            WITHIN is linenum;
            BETWEEN is study2 study3 study4;
            LAGGED is resent(1);
 ANALYSIS:
 TYPE = TWOLEVEL RANDOM; ESTIMATOR = BAYES; BITERATIONS = 1000;
 MODEL:
         %WITHIN%
         ar1 | resent^ ON resent^1; !latent AR sent
         logv | resent; !within level variance sent
         trend | resent on linenum; !captures trend

         %BETWEEN%
         resent ON study2 study3 study4; !study covariates
         ar1 trend logv WITH ar1 trend logv ;
 PLOT:
         TYPE=PLOT3;
        FACTORS=ALL;
```

McNeish and Hamaker (2020)

RDSEM Model 2 Output

MODEL	RESULTS						
			Posterior	One-Tailed	95%	C.I.	
		Estimate	S.D.	P-Value	Lower	Upper	Significance
Between	Level						
	AR1	WITH					
	TREND	0	0.001	0.454	-0.002	0.002	
	LOGV	**0.013**	**0.006**	**0.014**	**0.002**	**0.025**	*
	TREND	WITH					
	LOGV	-0.002	0.004	0.248	-0.009	0.007	
	Means						
	AR1	0.045	0.014	0	0.02	0.07	*
	LOGV	6.44	0.037	0	6.362	6.51	*
	TREND	-0.031	0.011	0	-0.052	-0.008	*
	Variances						
	AR1	**0.009**	**0.003**	**0**	**0.004**	**0.017**	*
	LOGV	**0.139**	**0.025**	**0**	**0.102**	**0.198**	*
	TREND	**0.001**	**0.001**	**0**	**0**	**0.002**	*
	Residual	Variances					
	RESENT	10.983	3.089	0	5.942	17.365	*

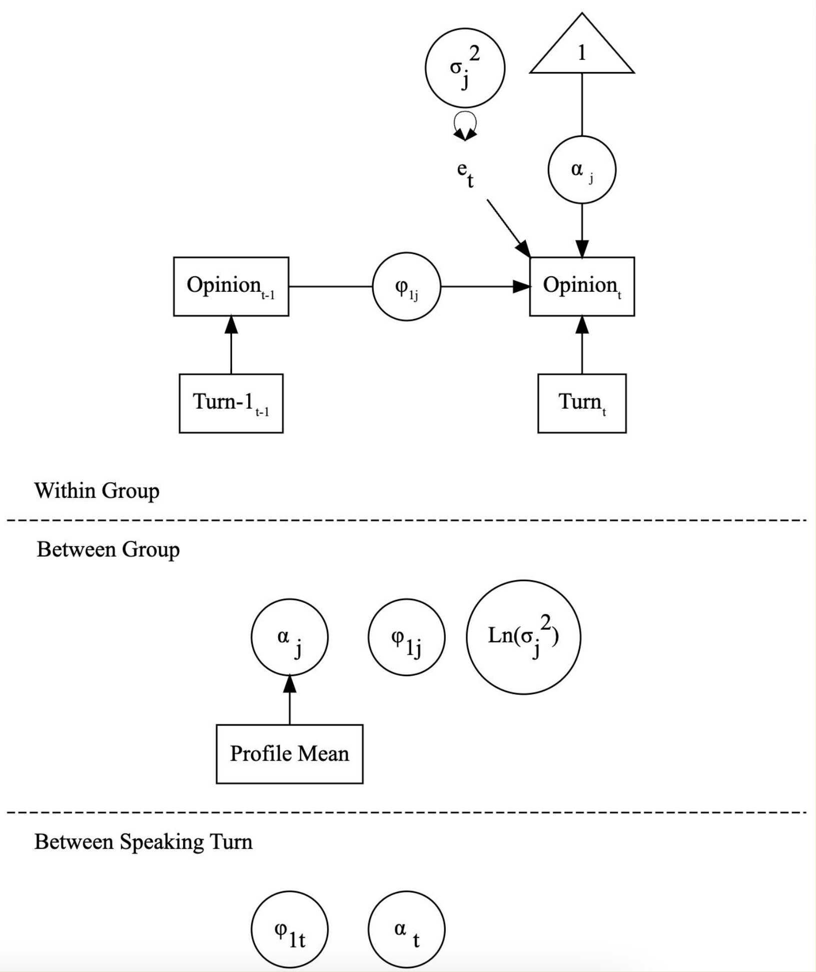
Findings: H1-H4 and RQs

- H1: Positive autoregressive parameter is *supported*
- H2: Positive association between mean group opinion profile and opining expression *supported*
- H3: Positive association between group profile variance and opinion expression *not supported*
- *None* of the associations specified in the research questions was significant

Anaysis Part 2

- Hypothesis 4 and RQ 5 analyized with cross-classified DSEM (no RDSEM for this)
- Speaking turn is added at the between level, along with group
- The model tests the presumption that the autoregressive parameter is consistent across speaking turns while preserving between-group variation
- Study covariates included as before in the between-groups section of the model
- Did not uses model building approach here because convergence issues with more complicated models

Cross-classified DSEM



Cross-Classifed DSEM Mplus Code

```
CLUSTER is group linenum;
          LAGGED is resent(1);
          BETWEEN IS (group) jim_mean study2 study3 study4 (linenum) timet;
          WITHIN is timew;
          USEVARIABLES = jim_mean study2 study3 study4 resent timet timew ;
DEFINE:
timew = linenum;  timet = linenum;
ANALYSIS:
TYPE = CROSSCLASSIFIED RANDOM; ESTIMATOR = BAYES; BITERATIONS = 5000;
MODEL:
      %WITHIN%
            ar1 | resent ON resent&1; !latent autogression estimate
            trend | resent ON timew;
            logv | resent; !random residual variance
      %BETWEEN Group%
            resent ON jim_mean study2 study3 study4;
            logv trend ar1 resent; !random residual variance
       %BETWEEN linenum%
            resent trend ar1; !no logv at this level
PLOT:
TYPE=PLOT3;
       FACTORS=ALL;
```

See UG examples 9.39a and 9.39b, McNeish & Hamaker (2020), and McNeish (2021)

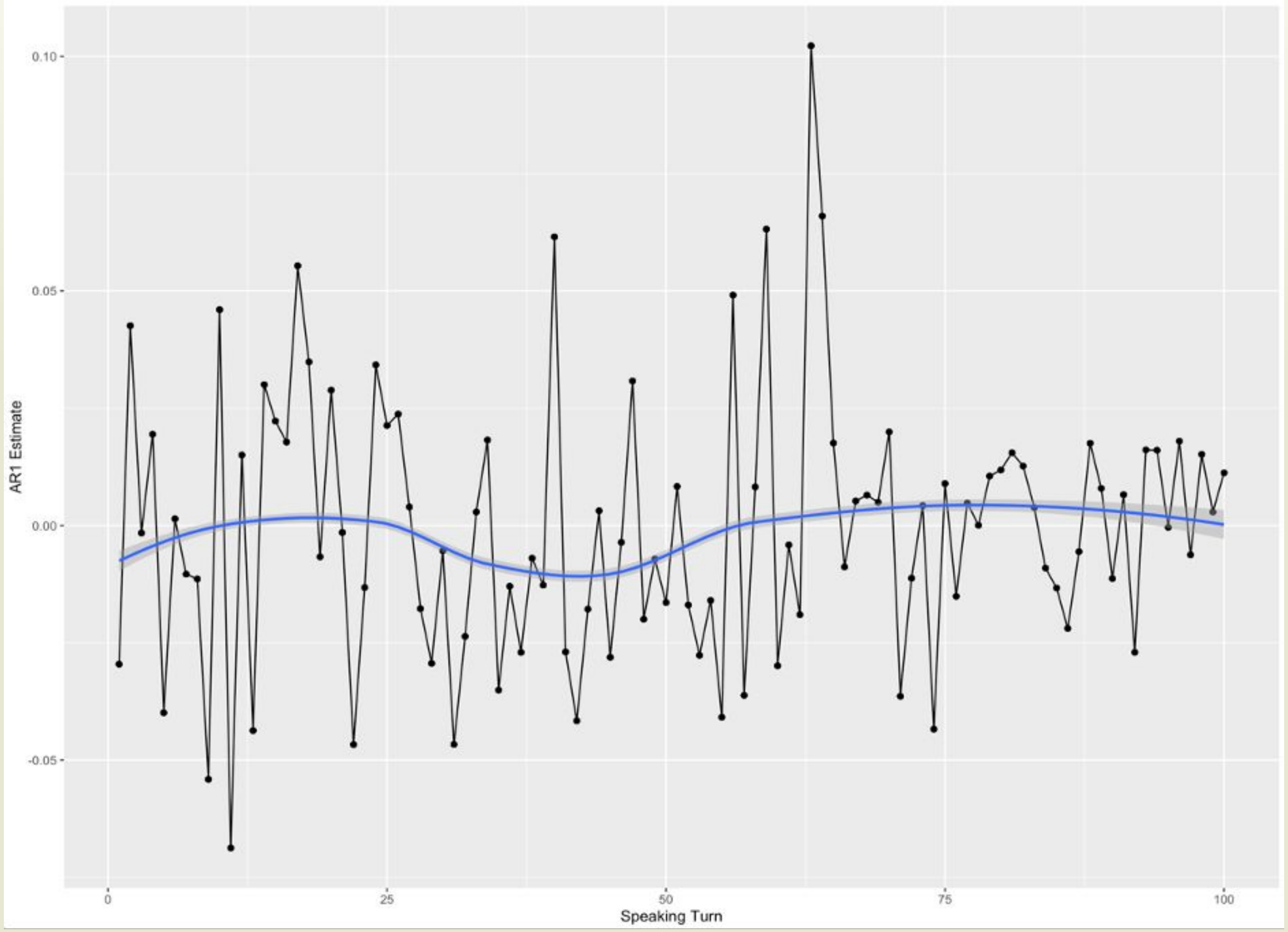
Relevent Out for CC-DSEM

			Posterior	One-Tailed	95% C.I.		
		Estimate	S.D.	P-Value	Lower 2.5%	Upper 2.5%	Significance
Within	Level						
Between	**LINENUM**	**Level**					
	Variances						
	TIMET	4852.814	473.112	0	4060.52	5909.157	*
	RESENT	0.85	0.63	0	0.319	2.49	*
	AR1	**0.005**	**0.002**	**0**	**0.001**	**0.01**	*
	TREND	**0**	**0**	**0**	**0**	**0**	*
Between	**GROUP**	**Level**					
	RESENT	ON					
	JIM_MEAN	15.537	6.212	0.002	4.034	28.385	*
	Intercepts						
	RESENT	4.711	1.194	0	2.423	7.102	*
	Variances						
	AR1	**0.008**	**0.003**	**0**	**0.003**	**0.013**	*
	TREND	**0.001**	**0**	**0**	**0**	**0.002**	*
	LOGV	0.124	0.02	0	0.088	0.166	*
	Residual Variances						
	RESENT	8.488	3.422	0	3.89	17.642	*

Findings: H4 and RQ5

- H4: Variation in the AR(1) parameter across speaking turns supported
- RQ5: What is the shape or distribution of the AR(1) parameter across discussion? See next slide
  - Fun fact about dealing with Mplus' gh5 files
- Point made by Ellen on Monday about what makes a model dynamic
  - Her take is that the state of the system at *T+1* is different from that at *T*
  - Assuming the AR(1) does not change, the model seems predictably or consistently dynamic
  - If it does change, then the model is inconsistently dynamic

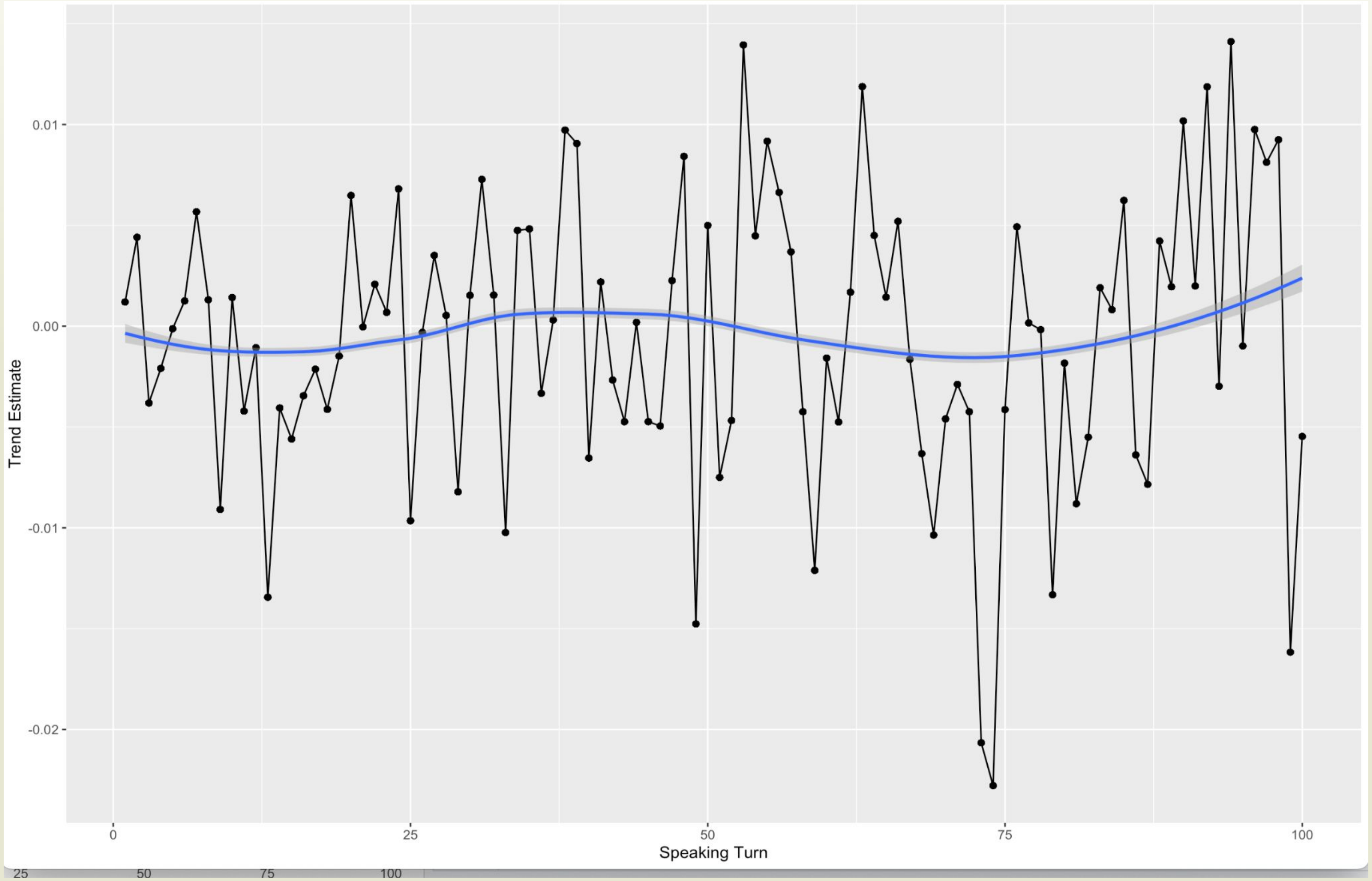
Opinion Expression AR(1) Graph for CC-DSEM



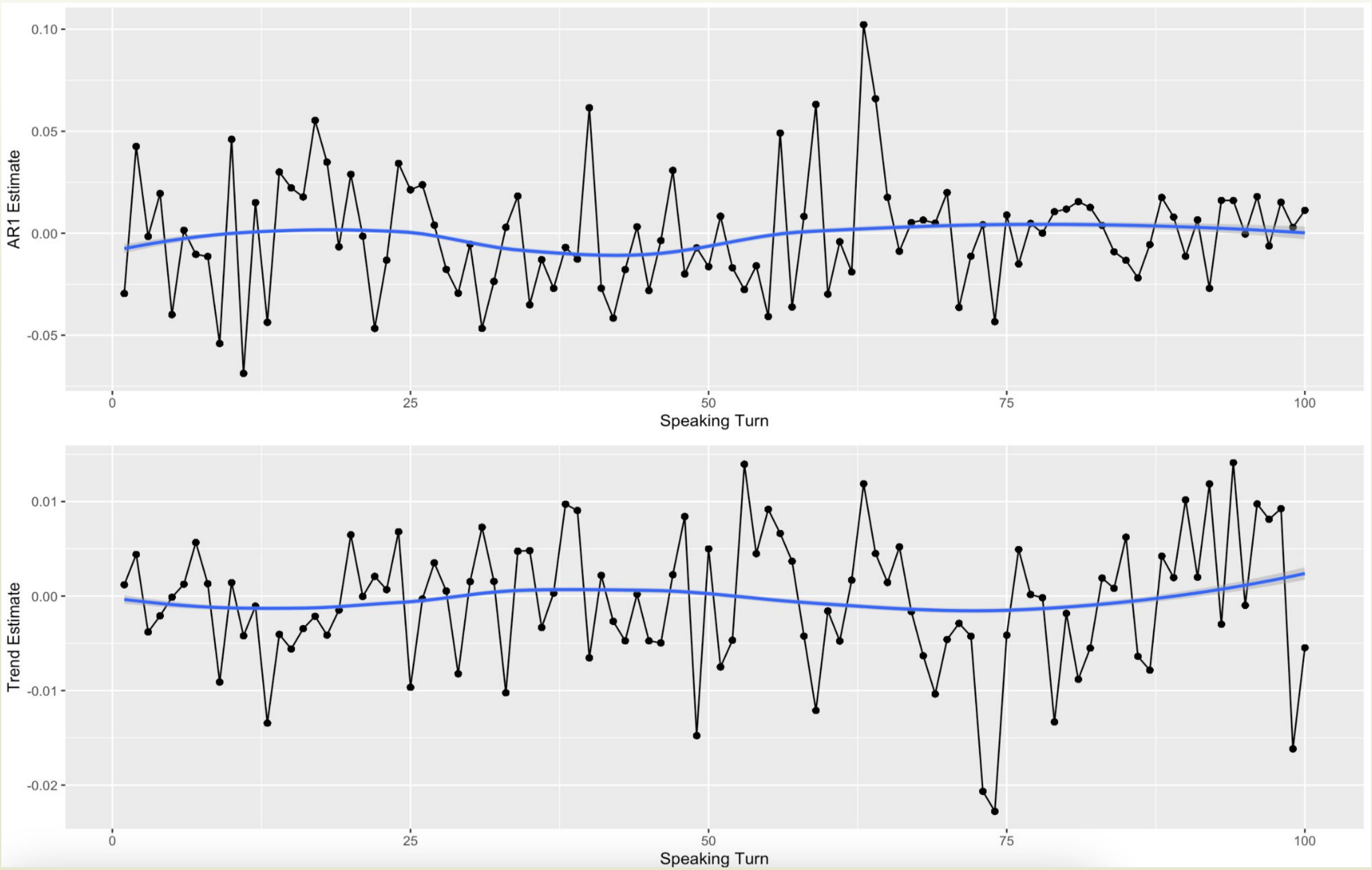
About That Previous Slide

- Following Bengt's talk on Tuesday, there might be a way to model the cycles seen in the graph
- Without a TVC, the question concerns how to model time/transitons in meaningful ways
- Bengt mentioned cosines, splines, and other options, all of which require exploration

Graphing Dynamic Trends



Comparing AR(1) and Trend Graphs



In Closing

- Process of opinion expression seems inconsistely dynamic
- Process seems a form of oscillation
  - Maybe cut points present themselves when considering trend estimates?
- Speaking turns not consistent across discussions
  - How much inconsistency is too much?
  - What is the cut point (speaking turns) to evaluate the data
- DSEM handles only 2 levels, which means within person variation not examined