PANDERING VS. PERSUASION? PHONETIC ACCOMMODATION IN THE U.S. SUPREME COURT

Daniel Chen, Damian Kozbur, and Alan Yu

1. introduction

Minute changes in pronunciation during conversation are part of our everyday experience. Phonetic accommodation is the subtle changes in vowel quality that can betray the type of identity or persona a speaker might be intentionally or unconsciously projecting. Despite decades of laboratory research, little is known about the practical significance of linguistic adaptation for the individual speaker.

Documenting whether extraneous factors like whether phonetic accommodation predicts judicial decision-making would expand models of how judges decide beyond legal, attitudinal, and rational-choice models. Moreover, the influence of extraneous factors such as phonetic mimicry would suggest also that judges' decisions do not simply reflect motivated cognition, where individuals may come to judgments through initial intuitions and then come up with an explanation to justify their position (Haidt, 2001). Recent laboratory studies find a role for unconscious heuristics, such as anchoring and status quo bias, in decision-making (judges are recruited at judicial conferences to decide on vignettes) (Guthrie et al., 2007).

Nonverbal and verbal mimicry, which have long been studied by social psychologists, have been found to be correlated with consumer behaviors in a real market contexts (Jacob et al., 2011). In one study of verbal cues' potential influence on judges, Schubert et al. (2002) find that in Supreme Court oral arguments, dialect dissimilarity is a cue for ethnolinguistic differences and inspires mistrust and anxiety. Justices tend to challenge Southern dialect counsel more than others, however, dialect is not correlated with win rates.

Verbal and nonverbal cues have also been of interest to economists and legal scholars because of their potential role in explaining differential labor market outcomes (Lang, 1986). Purnell et al. (1999) found evidence of linguistic profiling in the housing market, suggesting that housing administrators might redline prospective clientele by auditory cues (from telephone conversations) alone. In that study, they conducted a series of telephone surveys where housing was requested from the same landlord during a short time period using standard and non-standard dialects. The results demonstrate that landlords discriminate against prospective tenants on the basis of the sound of their voice during telephone conversations. Other studies indicate that masculine voices are preferred in both men and women (Anderson and Klofstad, 2012). Vocal attributes associated with being black have a 12% wage penalty, even controlling for measures of skill and family background (Grogger, 2011).

Recent legal scholarship has advanced the claim that when discrimination directs itself against the subset of a group that fails to assimilate to mainstream norms, such behavior violates civil rights commitments to have equal respect for all races (Yoshino, 2006). Behavioral markers of blacks 'acting white', in which some minorities incur costs for investing in behaviors characteristic of whites (e.g., standard English dialect), have been used to test models of social interactions (Fryer and Torelli, 2010) .

The present study examines whether language accommodation (i.e., linguistic convergence and divergence) extends to a communicative setting as highly stylized and formal as the Supreme Court of the United States. Recent studies find when Supreme Court judges use more unpleasant language toward one side in oral argument, that side is probably going to lose (Black et al., 2011). Judges unfavorable to one side show less linguistic coordination to the disfavored advocate than favorable justices do in the Supreme Court (Danescu-Niculescu-Mizil et al., 2012).

These studies suggest that judges' speech patterns can be a fertile ground to hunt for subtle cues indexing the Justices' hidden preferences and the lawyer's verbal dexterity to gain the Justices' favor. We investigate the hypothesis that a lawyer persuades if the judge's verbal cues move to coordinate with the lawyer's and successfully wins the judge's vote, while a lawyer panders if the lawyer's verbal cues move to coordinate with a judge's and successfully wins the judge's vote.

2. DATA COLLECTION

2.1. *The OYEZ Corpus*

Oral arguments at the Supreme Court of the United States have been recorded since the installation of a recording system in October 1955. The present project draws its data set primarily from the recordings and the associated transcripts made available to the public in electronically downloadable format by the Oyez Project (http://www.oyez.org/), which is a multimedia archive at the Chicago-Kent College of Law devoted to the Supreme Court of the United States and its work. The audio archive contains more than 110 million words in more than 9000 hours of audio synchronized, based on the court transcripts, to the sentence level. Oral arguments are, with rare exceptions, the first occasion in the processing of a case in which the Court meets face-to-face in consideration of the issues. Usually, counsel representing the competing parties of a case each have thirty minutes in which to present their side to the Justices. The Justices may interrupt these presentations with comments and questions, leading to interactions between the Justices, the lawyers and, in some cases, the amici curiae, who are not a party to a case but nonetheless offer information that bears on the case not solicited by any of the parties to assist a court.

We linguistically annotate 15 years of oral arguments recorded in the Supreme Court of the United States. While oral arguments have been recorded since the installation of a recording system in October 1955, the transcripts do not identify the speaking turns of individual Justices, referring to them all as "The Court". We focus on audio recordings where all speakers have been identified so far, that is, recordings from 1999 to the 2013 (i.e. fifteen years of oral arguments; approximately 975 hours of audio). The boundaries between words and between individual speech sounds were automatically determined using the Penn Phonetics Lab Forced Aligner (Yuan and Liberman, 2008), whose acoustic models were trained on the same data set using the HTK toolkit (Young and Young, 1994) and the CMU American English Pronouncing Dictionary (Weide, 1995). A subset of the resulting alignment (10%) was manually checked by human labellers to determine the accuracy of the forced aligner as well as across human labellers.

2.2. *Annotation*

We examine the convergence pattern in court cases from 1998 - 2013. Court cases with amicus curiae are excluded since the participation of amicus curiae necessarily leads to a reduction in interaction between the Justices and the lawyer whose side the amicus curiae supports given the duration of each court case is fixed (1 hr total; half an hour for each side). Each court case involved a maximum of ten voices (eight vocal Justices and two lawyers), yielding 16 distinct potential convergence pairs between the lawyers and the Justices. Given the possibility of bi-directional convergence, this yields 32 distinct AXB types and 64 possible distinct trial types, with the order of A and B counterbalanced.

To begin analyzing the phonetic convergence from the perspective of the acoustic signal, the duration, F0 (the acoustic correlate of pitch), and vowel spectra information are measured and converted into scores that reflect the relative difference between the lawyer and the Justice tokens (lawyer − Justices). Following the method developed in Pardo et al. (2013), the differences for a targeted speaker's shadowed items are subtracted from the differences for the baseline items, yielding difference in distance estimates (DID = baseline distance − shadowed distance). Phonetic convergence is suggestive when the DID score is positive (i.e. when differences for the shadowed items to the model items are smaller than those for the baseline items to the model items). A more formal definition follows below.

Duration values are relativized to the speaking rate, operationalized as the duration of an utterance divided by the number of segments within the utterance. F0 values are converted to semitones, while vowel formant values are normalized using the Labov technique in the vowels package for R (Kendall and Thomas, 2010), yielding measures of F1' and F2'. This technique scales raw frequency measures for each talker's vowels against a grand mean, permitting cross-talker comparisons that preserve idiolectal differences in vowel production (Labov et al., 2006).

Voice onset time is measured using a machine learning algorithm described in Sonderegger and Keshet (2012). This algorithm needs a classifier which has been trained on manually-labelled data and the left boundary for the stop's host word, which specifies where the algorithm should begin looking for the burst. We manually label the VOT for one case per year (for 15 years) by two transcribers, following the annotation procedure described in Sonderegger (2012).

Automatic formant measurements for vowels are performed using the FAVE program suite developed at the University of Pennsylvania (Rosenfelder et al., 2011). FAVE takes as input audio files and their orthographic transcriptions. Each transcribed file is forced-aligned using the HTK toolkit (Young and Young, 1994) with sequence of phones corresponding to its canonical pronunication in the CMU American English Pronouncing Dictionary (Weide, 1995), resulting in a predicted start and end time for each phone in the sequence of phones implied by the transcription. FAVE then performs automatic formant measurements for all vowels in each audio file, using the predicted start and end time for each vowel from forced alignment. For each vowel, values of F1, F2, and F3 at ten temporal points is obtained for further analysis. Only vowels with duration of at least 50 msecs is considered to minimize problems in format measurements with reduced vowels.

3. DEFINITION OF CONVERGENCE

In this section we formally outline the data and model that we consider. Supreme Court cases are indexed by Docket ID. For each docket, we observe a series of ABA triplets wherein a speaker (A) makes a statement, followed by a statement from speaker (B), followed again by a statement from speaker (A). Each part of the ABA is called a segment. For each segment, A1 B and A2 of a particular ABA, we observe a sequence of vowels for which we measure context variables as well as linguistic variables. The context variables include the particular word that the vowel is a part of, the vowel's position in the word, the stress of the vowel. The observed linguistic variables include the first and second formants, which we denote $\mathrm{F1}(v)$ and $\mathrm{F2}(v)$ for a vowel v. We say two vowels v, w are comparable, and write $v \sim w$ provided they satisfy a comparability criteria (described below) which is based on the context variables. We write $\overline{\mathrm{F1}}_v(A1)$ to be the average of $F1(w)$ where the average is taken over vowels w which are part of A1 and $w \sim v$ (ie, comparable to v). $\overline{\mathrm{F1}}_v(\mathrm{B})$, $\overline{\mathrm{F2}}_v(\mathrm{A1})$, $\overline{\mathrm{F2}}_v(\mathrm{B})$ are defined similarly. Finally, we allow for additional arbitrary covariates X.

Define convergence, $\mathbf{conv}_{\mathrm{F1}}(\mathrm{A} \to \mathrm{B})$, $\mathbf{conv}_{\mathrm{F2}}(\mathrm{A} \to \mathrm{B})$ so that the following equations hold:

$$\mathbf{Lin.Proj}[\mathrm{F1}(v \in \mathrm{A2})|\mathrm{A1}, \mathrm{B}, \mathrm{X}] = \mathbf{conv}_{\mathrm{F1}}(\mathrm{A} \to \mathrm{B})\overline{\mathrm{F1}}_v(\mathrm{B}) + \beta\overline{\mathrm{F1}}_v(\mathrm{A1}) + \gamma^\top X$$

$$\mathbf{Lin.Proj}[\mathrm{F2}(v \in \mathrm{A2})|\mathrm{A1},\mathrm{B},X] = \mathbf{conv}_{\mathrm{F2}}(\mathrm{A} \to \mathrm{B})\overline{\mathrm{F2}}_v(\mathrm{B}) + \beta\overline{\mathrm{F2}}_v(\mathrm{A1}) + \gamma^\top X$$

The above projections are not observed so we calculate them using linear regression. We denote the estimates by

$$\widehat{\mathbf{conv}}_{\mathrm{F1}}(\mathrm{A} \to \mathrm{B}),\ \widehat{\mathbf{conv}}_{\mathrm{F2}}(\mathrm{A} \to \mathrm{B})$$

To be concrete, we consider observations indexed by the triple (Docket, ABA, vowel). The calculated convergences are estimates and their variability is assessed by clustered standard errors grouped at the ABA level.

This notion of convergence intuitively measures the weight that speaker A put on the vowels sounds of speaker B. The measure is simple to calculate and is easily adjusted depending on the application.

For instance, this convergence can be made to depend only on specific types of vowels, like 'high', 'mid', and 'low', vowels or monopthongs and dipthongs or word-specific variables.

4. RESULTS

In this section we use the data to calcluate the notions of convergence defined above. This allows us to determine whether there is any linguistic accomodation during the Supreme Court oral arguments at all. Next, we calculate the convergence weights for interesting subsets of the data, like judge-lawyer pairs for lawyers with whom the judge votes. This allows us to determine whether the extent of linguistic convergence measured by vowel formants is in any way related to judicial decision making.

We begin with a calculation of the mean overall convergence levels between lawyers and justices as described above. For this measure, we simply use all ABA triples found in the data. For this measure, we simply use the definition that two vowels v and w are comparable precisely if they are the same vowel and have the same stress. The results are reported for F1 in Table 1. We calculate four different convergences weights:

1. Convergence weight defined over all ABA triples where a judge is speaker B to a lawyer for whom the judge voted against.
2. Convergence weight defined over all ABA triples where a judge is speaker B to a lawyer for whom the judge voted.
3. Convergence weight defined over all ABA triples where a judge is speaker A to a lawyer for whom the judge voted against.
4. Convergence weight defined over all ABA triples where a judge is speaker A to a lawyer for whom the judge voted.

For each subset (1) - (4), Tables 1 and 2 display the calculated convergences weights for F1 and F2. The results from the table suggest that the typical 'convergence weights' are on the order of 1-2%. Next we perform an analysis by judge. For each judge, we first simply calculate average convergence weights defined over ABA triples where the judge in question interacts with any lawyer, irrespecitve to the direction of the interaction, or the win/loss result for the lawyer. These estimates are presented in Table 2 for F1 and Table 3 for F2. Finally, we calculate separate convergence weights by judge depending on whether the judge is speaker A and whether the lawyer recieved the judge's vote. These results are shown in Table 3 and Table 4 (split in two for readability). The results are presented using the same format as Table 1, only expanded by judge.

5. DISCUSSION

Table I shows that the Justices do generally converge to the lawyers. The Justices' F1 convergence weights to lawyers are estimated at .0109 (+/- .0031 std. err), .0113 (+/- .0038 std. err.) depending on if the lawyer was on the winning side. The F2 convergence weights are estimated at .0076 (+/- .0024 std. err.) and .0126 (+/- .0033 std. err.). Table I also demonstrates that lawyers tend exhibit higher convergence to Justices: the F1 convergence weights are .0166 (+/- .0022 std. err.) .0172 (+/- .0022 std. err.); the F2 convergence weights are .0197 (+/- std. err. .0016) .0179 (+/- std. err. .0019). With the estimates of convergence rates presented in Table I, there is not enough precision to determine whether Justices systematically exhibit higher convergence to the lawyers on the winning side, nor do the lawyers on the winning side exhibit higher levels of convergence to the Justices.

Tables II-III show that the Justices seem to have measurably differing levels of linguistic convergence. For example, Justice O'Connor exhibits almost no convergence weight (F1 estimate: .0005 +/-.0059 std. err., F2 estimate: .0037 +/- .0052 std. err.) while Justice Breyer has the highest convergence (F1 estimate: .0317 +/- .0044 std. err. F2 estimate: .0218 +/- .0039 std. err.).

Tables IV - VII examine these patterns for each judge individually. A few patterns emerge from the analysis. Lawyers always move away from Justice Rehnquist. For most judges, the greatest gradient of convergence is when the judge converges to the lawyer and the lawyer loses the judge's vote. Justice Kagan displays the overall judge response more strongly than the other judges. The convergence magnitudes are atypically large. Also, when she speaks first, the lawyers converge a lot to her; and the more they do, the more they lose her vote.

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TABLE I

Court-Wide F1 and F2 Convergence Patterns

Convergence Direction, Lawyer Outcome	Convergence	St Err	95% lower	95% upper
Court-Wide F1 Convergence Patterns				
Lawyer → Judge, Lawyer Loses	0.0166	0.0022	0.0122	0.0210
Lawyer → Judge, Lawyer Wins	0.0172	0.0022	0.0130	0.0215
Judge → Lawyer, Lawyer Loses	0.0109	0.0031	0.0048	0.0170
Judge → Lawyer, Lawyer Wins	0.0113	0.0038	0.0038	0.0188
Court-Wide F2 Convergence Patterns				
Lawyer → Judge, Lawyer Loses	0.0197	0.0016	0.0165	0.0229
Lawyer → Judge, Lawyer Wins	0.0179	0.0019	0.0142	0.0216
Judge → Lawyer, Lawyer Loses	0.0076	0.0024	0.0029	0.0123
Judge → Lawyer, Lawyer Wins	0.0126	0.0033	0.0061	0.0190

TABLE II

Overall F1 Convergence Patterns by Justice

Justice	Convergence	St Err	95% lower	95% upper
Anthony M. Kennedy	0.0213	0.0037	0.0139	0.0286
Antonin Scalia	0.0203	0.0029	0.0146	0.0260
David H. Souter	0.0217	0.0044	0.01294	0.0304
Elena Kagan	0.0189	0.0079	0.0034	0.0344
John G. Roberts, Jr.	0.0137	0.0037	0.0064	0.0210
John Paul Stevens	0.0162	0.0046	0.0071	0.0252
Ruth Bader Ginsburg	0.0171	0.0037	0.0099	0.0243
Samuel A. Alito , Jr.	0.0164	0.0064	0.0038	0.0289
Sandra Day O'Connor	0.0005	0.0059	-0.0111	0.0121
Sonya Sotomayor	0.0054	0.0068	-0.0081	0.0189
Stephan G. Breyer	0.0317	0.0044	0.0231	0.0403
William H. Rehnquist	-0.0029	0.0067	-0.0162	0.0103

TABLE III
Overall F2 Convergence Patterns by Justice

Justice	Convergence	St Err	95% lower	95% upper
Anthony M. Kennedy	0.0126	0.0035	0.0058	0.0195
Antonin Scalia	0.0277	0.0030	0.0219	0.0336
David H. Souter	0.0181	0.0044	0.0095	0.0268
Elena Kagan	0.0178	0.0055	0.0070	0.0287
John G. Roberts, Jr.	0.0291	0.0034	0.0223	0.0358
John Paul Stevens	0.0300	0.0048	0.0206	0.0395
Ruth Bader Ginsburg	0.0080	0.0019	0.0043	0.0118
Samuel A. Alito , Jr.	0.0058	0.0051	-0.0043	0.0158
Sandra Day O'Connor	0.0037	0.0052	-0.0066	0.0140
Sonya Sotomayor	0.0192	0.0041	0.0112	0.0272
Stephan G. Breyer	0.0218	0.0039	0.0141	0.0294
William H. Rehnquist	0.0135	0.0064	0.0009	0.0261

TABLE IV

Outcome and Direction Specific F1 Convergence Patterns by Justice - Part 1

Convergence Direction, Lawyer Outcome	Convergence	St Err	95% lower	95% upper
Anthony M. Kennedy				
Lawyer → Judge, Lawyer Loses	0.0225	0.0079	0.0068	0.0381
Lawyer → Judge, Lawyer Wins	0.0315	0.0072	0.0172	0.0456
Judge → Lawyer, Lawyer Loses	0.0015	0.0126	-0.0233	0.0263
Judge → Lawyer, Lawyer Wins	0.0212	0.0108	-0.0000	0.0425
Antonin Scalia				
Lawyer → Judge, Lawyer Loses	0.0204	0.0064	0.0078	0.0330
Lawyer → Judge, Lawyer Wins	0.0356	0.0082	0.0194	0.0518
Judge → Lawyer, Lawyer Loses	-0.0082	0.0097	-0.02727	0.0108
Judge → Lawyer, Lawyer Wins	-0.0005	0.0105	-0.0212	0.0202
David H. Souter				
Lawyer → Judge, Lawyer Loses	0.0365	0.0108	0.0152	0.0578
Lawyer → Judge, Lawyer Wins	0.0182	0.0103	-0.0021	0.0385
Judge → Lawyer, Lawyer Loses	0.0324	0.0090	0.0147	0.0500
Judge → Lawyer, Lawyer Wins	-0.0222	0.0126	-0.0471	0.0027
Elena Kagan				
Lawyer → Judge, Lawyer Loses	0.0356	0.0124	0.0111	0.0600
Lawyer → Judge, Lawyer Wins	0.0125	0.0114	-0.0101	0.0351
Judge → Lawyer, Lawyer Loses	0.0456	0.0287	-0.0112	0.1025
Judge → Lawyer, Lawyer Wins	0.0279	0.0254	-0.0225	0.0782
John G. Roberts, Jr.				
Lawyer → Judge, Lawyer Loses	0.0132	0.0071	-0.0009	0.0272
Lawyer → Judge, Lawyer Wins	0.0242	0.0076	0.0092	0.0393
Judge → Lawyer, Lawyer Loses	0.0188	0.0129	-0.0065	0.0442
Judge → Lawyer, Lawyer Wins	0.0182	0.0130	-0.0074	0.0438
John Paul Stevens				
Lawyer → Judge, Lawyer Loses	0.0195	0.0100	-0.0002	0.0393
Lawyer → Judge, Lawyer Wins	0.0250	0.0135	-0.0017	0.0516
Judge → Lawyer, Lawyer Loses	0.0216	0.0089	0.0040	0.0392
Judge → Lawyer, Lawyer Wins	0.0018	0.0144	-0.0266	0.0303

TABLE V

Outcome and Direction Specific F1 Convergence Patterns by Justice - Part 2

Convergence Direction, Lawyer Outcome	Convergence	St Err	95% lower	95% upper
Ruth Bader Ginsberg				
Lawyer → Judge, Lawyer Loses	0.0210	0.0054	0.0104	0.0316
Lawyer → Judge, Lawyer Wins	0.0244	0.0067	0.0112	0.0375
Judge → Lawyer, Lawyer Loses	-0.0072	0.0087	-0.0244	0.0100
Judge → Lawyer, Lawyer Wins	0.0200	0.0141	-0.0078	0.0478
Samuel A. Alito , Jr.				
Lawyer → Judge, Lawyer Loses	0.0325	0.0094	0.0139	0.0510
Lawyer → Judge, Lawyer Wins	-0.0006	0.0085	-0.0174	0.0162
Judge → Lawyer, Lawyer Loses	0.0109	0.0164	-0.0215	0.0432
Judge → Lawyer, Lawyer Wins	0.0138	0.0216	-0.0290	0.0566
Sandra Day O'Connor				
Lawyer → Judge, Lawyer Loses	0.0026	0.0097	-0.0165	0.0217
Lawyer → Judge, Lawyer Wins	0.0000	0.0079	-0.0156	0.0156
Judge → Lawyer, Lawyer Loses	0.0174	0.0315	-0.0449	0.0798
Judge → Lawyer, Lawyer Wins	-0.0481	0.0283	-0.1039	0.0078
Sonya Sotomayor				
Lawyer → Judge, Lawyer Loses	0.0067	0.0096	-0.0123	0.0257
Lawyer → Judge, Lawyer Wins	-0.0062	0.0091	-0.0241	0.0117
Judge → Lawyer, Lawyer Loses	0.0135	0.0172	-0.0205	0.0474
Judge → Lawyer, Lawyer Wins	0.0181	0.0248	-0.0308	0.0669
Stephan G. Breyer				
Lawyer → Judge, Lawyer Loses	0.0243	0.0079	0.0087	0.0399
Lawyer → Judge, Lawyer Wins	0.0184	0.0094	-0.0002	0.0370
Judge → Lawyer, Lawyer Loses	0.0318	0.0083	0.0154	0.0482
Judge → Lawyer, Lawyer Wins	0.0455	0.0130	0.0198	0.0711
William H. Rehnquist				
Lawyer → Judge, Lawyer Loses	0.0123	0.0113	-0.0099	0.0345
Lawyer → Judge, Lawyer Wins	0.0157	0.0171	-0.0181	0.0495
Judge → Lawyer, Lawyer Loses	-0.0088	0.0200	-0.0482	0.0306
Judge → Lawyer, Lawyer Wins	-0.0000	0.0368	-0.0729	0.0728

TABLE VI

Outcome and Direction Specific F2 Convergence Patterns by Justice - Part 1

Convergence Direction, Lawyer Outcome	Convergence	St Err	95% lower	95% upper
Anthony M. Kennedy				
Lawyer → Judge, Lawyer Loses	0.0194	0.0063	0.0070	0.0319
Lawyer → Judge, Lawyer Wins	0.0339	0.0064	0.0213	0.0465
Judge → Lawyer, Lawyer Loses	-0.0138	0.0105	-0.0345	0.0069
Judge → Lawyer, Lawyer Wins	-0.0017	0.0098	-0.0211	0.0178
Antonin Scalia				
Lawyer → Judge, Lawyer Loses	0.0221	0.0047	0.0127	0.0314
Lawyer → Judge, Lawyer Wins	0.0372	0.0062	0.0250	0.0495
Judge → Lawyer, Lawyer Loses	0.0171	0.0078	0.0017	0.0324
Judge → Lawyer, Lawyer Wins	0.0322	0.0089	0.0147	0.0497
David H. Souter				
Lawyer → Judge, Lawyer Loses	0.0238	0.0081	0.0077	0.0398
Lawyer → Judge, Lawyer Wins	0.0255	0.0076	0.0105	0.0405
Judge → Lawyer, Lawyer Loses	0.0150	0.0079	-0.0004	0.0303
Judge → Lawyer, Lawyer Wins	0.0201	0.0133	-0.0062	0.0464
Elena Kagan				
Lawyer → Judge, Lawyer Loses	0.0120	0.0103	-0.0082	0.0323
Lawyer → Judge, Lawyer Wins	-0.0007	0.0111	-0.0227	0.0212
Judge → Lawyer, Lawyer Loses	0.0128	0.0220	-0.0307	0.0563
Judge → Lawyer, Lawyer Wins	-0.0183	0.0241	-0.0661	0.0295
John G. Roberts, Jr.				
Lawyer → Judge, Lawyer Loses	0.0330	0.0058	0.0217	0.0444
Lawyer → Judge, Lawyer Wins	0.0367	0.0068	0.0234	0.0500
Judge → Lawyer, Lawyer Loses	0.0077	0.0086	-0.0092	0.0246
Judge → Lawyer, Lawyer Wins	0.0234	0.0103	0.0030	0.0438
John Paul Stevens				
Lawyer → Judge, Lawyer Loses	0.0526	0.0074	0.0380	0.0671
Lawyer → Judge, Lawyer Wins	0.0178	0.0095	-0.0009	0.0367
Judge → Lawyer, Lawyer Loses	0.0116	0.0104	-0.0090	0.0321
Judge → Lawyer, Lawyer Wins	0.0106	0.0122	-0.0135	0.0348

TABLE VII

Outcome and Direction Specific F2 Convergence Patterns by Justice - Part 2

Convergence Direction, Lawyer Outcome	Convergence	St Err	95% lower	95% upper
Ruth Bader Ginsburg				
Lawyer → Judge, Lawyer Loses	0.0190	0.0038	0.0116	0.0264
Lawyer → Judge, Lawyer Wins	0.0124	0.0039	0.0047	0.0202
Judge → Lawyer, Lawyer Loses	0.0032	0.0083	-0.0131	0.0195
Judge → Lawyer, Lawyer Wins	0.0035	0.0120	-0.0201	0.0271
Samuel A. Alito , Jr.				
Lawyer → Judge, Lawyer Loses	0.0178	0.0075	0.0030	0.0327
Lawyer → Judge, Lawyer Wins	0.0128	0.0089	-0.0048	0.0303
Judge → Lawyer, Lawyer Loses	-0.0032	0.0132	-0.0292	0.0228
Judge → Lawyer, Lawyer Wins	-0.0246	0.0204	-0.0649	0.0156
Sandra Day O'Connor				
Lawyer → Judge, Lawyer Loses	0.0283	0.0106	0.0075	0.0491
Lawyer → Judge, Lawyer Wins	0.0052	0.0080	-0.0106	0.0210
Judge → Lawyer, Lawyer Loses	0.0034	0.0203	-0.0366	0.0434
Judge → Lawyer, Lawyer Wins	0.0388	0.0212	-0.0032	0.0807
Sonya Sotomayor				
Lawyer → Judge, Lawyer Loses	0.0240	0.0077	0.0088	0.0392
Lawyer → Judge, Lawyer Wins	0.0279	0.0082	0.0117	0.0441
Judge → Lawyer, Lawyer Loses	0.0046	0.0114	-0.0178	0.0271
Judge → Lawyer, Lawyer Wins	0.0204	0.0138	-0.0068	0.0475
Stephan G. Breyer				
Lawyer → Judge, Lawyer Loses	0.0241	0.0060	0.0122	0.0360
Lawyer → Judge, Lawyer Wins	0.0313	0.0090	0.0136	0.0491
Judge → Lawyer, Lawyer Loses	0.0139	0.0064	0.0012	0.0266
Judge → Lawyer, Lawyer Wins	0.0274	0.0102	0.0073	0.0474
William H. Rehnquist				
Lawyer → Judge, Lawyer Loses	0.0161	0.0095	-0.0026	0.0349
Lawyer → Judge, Lawyer Wins	0.0123	0.0122	-0.0118	0.0364
Judge → Lawyer, Lawyer Loses	0.0036	0.0149	-0.0257	0.0330
Judge → Lawyer, Lawyer Wins	0.0056	0.0326	-0.0588	0.0700