Appendix: From Thin to Thick Representation-
How a Female President Shapes Female Parliamentary Behavior.

Index

Table A1: Main Models

	(1) Number of Speeches	(2) Speeches on the Economy
Negative Binomial		
Banda	-0.054	0.27
	(0.10)	(0.16)
Female	-0.38**	-0.55**
	(0.13)	(0.21)
Banda * Female	0.24	0.31
	(0.20)	(0.25)
Senior MP	0.77**	0.77**
	(0.19)	(0.24)
Newcomer	-0.38**	-0.19
	(0.14)	(0.23)
DPP	0.19	0.22
	(0.14)	(0.32)
PP	0.20	0.55
	(0.24)	(0.55)
MCP	0.28	0.38
	(0.15)	(0.26)
Independent	0.15	0.55
	(0.15)	(0.39)
Month	-0.07**	-0.03
	(0.01)	(0.03)
Month^2	0.00**	0.00
	(0.00)	(0.00)
Finance Committee		0.96*
		(0.42)
Constant	2.90**	0.21
	(0.15)	(0.29)
Logit		
Banda	-0.28	0.13
	(0.16)	(0.28)
Female	0.16	-0.09
	(0.19)	(0.34)
Banda * Female	-0.40	-0.04
	(0.26)	(0.40)
Senior MP	-2.07**	-1.70
	(0.40)	(0.90)
Newcomer	-0.24	-0.29
	(0.26)	(0.44)
DPP	-0.18	-0.01
	(0.32)	(0.49)
PP	-0.61	-0.11
	(0.47)	(0.73)
MCP	-1.13**	-1.30*
	(0.37)	(0.56)
Independent	-23.0**	-25.2**
	(0.37)	(0.70)
Month	-0.02	0.21**
	(0.02)	(0.06)
Month^2	0.00	-0.01**
	(0.00)	(0.00)
Finance Committee		-0.98
		(0.57)
Constant	0.66*	-0.25
	(0.32)	(0.50)
lnalpha	0.30**	1.06**
	(0.09)	(0.24)
BIC	28278.4	13157.1
Observations	5336	5336

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table A2: Robustness checks: Word count as dependent variable

	(3) Total Word Count	(4) Words on the Economy
Negative Binomial		
Banda	0.11	0.33**
	(0.10)	(0.12)
Female	-0.34**	-0.46**
	(0.13)	(0.16)
Banda * Female	0.32	0.42
	(0.21)	(0.23)
Senior MP	0.74**	0.65**
	(0.18)	(0.19)
Newcomer	-0.35**	-0.20
	(0.13)	(0.16)
DPP	0.19	0.23
	(0.14)	(0.19)
PP	0.08	0.38
	(0.24)	(0.38)
MCP	0.23	0.37*
	(0.14)	(0.18)
Independent	0.02	0.36
	(0.15)	(0.20)
Month	-0.05**	0.01
	(0.01)	(0.02)
$Month^2$	0.00**	0.00
	(0.00)	(0.00)
Finance Committee		0.88**
		(0.32)
Constant	7.54**	5.57**
	(0.15)	(0.19)
Logit		
Banda	-0.19	-0.01
	(0.13)	(0.12)
Female	0.19	0.16
	(0.16)	(0.14)
Banda * Female	-0.37	-0.17
	(0.22)	(0.20)
Senior MP	-1.79**	-1.05**
	(0.24)	(0.17)
Newcomer	-0.09	-0.03
	(0.21)	(0.15)
DPP	-0.27	-0.09
	(0.27)	(0.20)
PP	-0.73*	-0.42
	(0.35)	(0.25)
MCP	-1.06**	-0.77**
	(0.32)	(0.23)
Independent	-23.0**	-1.63**
	(0.32)	(0.24)
Month	-0.00	0.12**
	(0.02)	(0.02)
$Month^2$	-0.00	-0.01**
	(0.00)	(0.00)
Finance Committee		-0.75**
		(0.21)
Constant	0.75**	1.19**
	(0.29)	(0.20)
lnalpha	0.13**	0.06
	(0.05)	(0.08)
BIC	55545.5	28068.4
Observations	5336	5336

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table A3: Comparing first Mutharika term (2004) to the 1999 parliament

	(5) Number of Speeches	(6) Speeches on the Economy
Negative Binomial		
Mutharika	0.07	-0.25
	(0.10)	(0.25)
Female	-0.44**	-1.04**
	(0.13)	(0.40)
Mutharika * Female	0.50**	0.89*
	(0.19)	(0.44)
Senior MP	0.58**	-0.08
	(0.11)	(0.15)
Newcomer	-0.27*	-0.08
	(0.11)	(0.18)
Independent	-0.14	-0.27
	(0.15)	(0.21)
Month	0.05**	-0.01
	(0.02)	(0.06)
Month^2	-0.00*	0.00
	(0.00)	(0.00)
Constant	2.74**	0.93*
	(0.13)	(0.40)
Logit		
Mutharika	-0.65**	-0.93**
	(0.13)	(0.20)
Female	-0.10	-0.32
	(0.24)	(0.37)
Mutharika * Female	-0.04	-0.08
	(0.32)	(0.45)
Senior MP	-24.3**	-5.26
	(0.18)	(5.41)
Newcomer	0.11	0.00
	(0.15)	(0.21)
Independent	-24.1**	-19.1**
	(0.22)	(2.90)
Month	-0.13**	-0.23**
	(0.02)	(0.05)
Month^2	0.01**	0.01**
	(0.00)	(0.00)
Constant	1.12**	2.14**
	(0.17)	(0.26)
lnalpha	0.29**	1.05**
	(0.05)	(0.12)
BIC	29793.4	12132.4
Observations	6950	6950

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table A4: Newcomer MPs at second half of parliamentary terms (1999, 2004)

	(7) Number of Speeches	(8) Speeches on the Economy
Negative Binomial		
Second Half	-0.35^{**}	-0.10
	(0.12)	(0.23)
Female	-0.24	-0.54^{*}
	(0.23)	(0.25)
Second Half * Female	-0.45	0.20
	(0.31)	(0.31)
Newcomer	-0.44^{**}	-0.30
	(0.13)	(0.23)
Second Half * Newcomer	0.27^{*}	0.38
	(0.11)	(0.26)
Female * Newcomer	0.42	0.51
	(0.27)	(0.33)
Second Half * Female * Newcomer	0.14	-0.63
	(0.34)	(0.39)
Senior MP	0.60^{**}	-0.12
	(0.11)	(0.13)
Independent	-0.13	-0.26
	(0.14)	(0.22)
Month	0.06^{**}	0.01
	(0.02)	(0.05)
Month^2	-0.00^{*}	-0.00
	(0.00)	(0.00)
Constant	2.84^{**}	0.80^{*}
	(0.13)	(0.34)
Logit		
Second Half	1.48^{**}	1.74^{**}
	(0.16)	(0.32)
Female	-0.74	-0.80
	(0.39)	(0.61)
Second Half * Female	1.14^{*}	1.27
	(0.46)	(1.03)
Newcomer	0.05	-0.01
	(0.20)	(0.28)
Second Half * Newcomer	0.12	0.04
	(0.14)	(0.26)
Female * Newcomer	0.66	0.27
	(0.46)	(0.72)
Second Half * Female * Newcomer	-1.27^{*}	-0.94
	(0.50)	(1.08)
Senior MP	-24.0^{**}	-14.5
	(0.18)	(8.62)
Independent	-23.9^{**}	-3.62^{*}
	(0.22)	(1.74)
Month	-0.29^{**}	-0.38^{**}
	(0.02)	(0.05)
Month^2	0.01^{**}	0.01^{**}
	(0.00)	(0.00)
Constant	1.23^{**}	2.07^{**}
	(0.19)	(0.28)
lnalpha	0.29^{**}	1.02^{**}
	(0.05)	(0.10)
BIC	29694.4	12145.4
Observations	6950	6950

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table A5: Main models without PP members

	(9) Number of Speeches (no PP)	(10) Speeches on the Economy (no PP)
Negative Binomial		
Banda	-0.07	0.24
	(0.10)	(0.14)
Female	-0.38**	-0.53**
	(0.13)	(0.20)
Banda * Female	0.32	0.50
	(0.23)	(0.28)
Senior MP	0.76**	0.81**
	(0.20)	(0.23)
Newcomer	-0.32*	-0.04
	(0.14)	(0.16)
DPP	0.16	0.17
	(0.14)	(0.26)
MCP	0.26	0.42
	(0.16)	(0.24)
Independent	0.13	0.45
	(0.15)	(0.29)
Month	-0.07**	-0.03
	(0.01)	(0.03)
$Month^2$	0.00**	0.00
	(0.00)	(0.00)
Finance Committee		1.00*
		(0.39)
Constant	2.87**	0.17
	(0.15)	(0.28)
Logit		
Banda	-0.28	0.1
	(0.16)	(0.23)
Female	0.15	-0.05
	(0.18)	(0.28)
Banda * Female	-0.35	0.00
	(0.29)	(0.36)
Senior MP	-1.91**	-1.31**
	(0.38)	(0.47)
Newcomer	-0.19	-0.12
	(0.26)	(0.30)
DPP	-0.21	-0.07
	(0.32)	(0.38)
MCP	-1.13**	-1.11**
	(0.37)	(0.42)
Independent	-23.8**	-16.5**
	(0.36)	(0.73)
Month	-0.035	0.16**
	(0.020)	(0.05)
$Month^2$	0.0014	-0.01**
	(0.0012)	(0.00)
Finance Committee		-0.82*
		(0.41)
Constant	0.66*	-0.06
	(0.31)	(0.40)
lnalpha	0.31**	0.93**
	(0.091)	(0.18)
BIC	26264	12156.2
Observations	5059	5059

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table A6: Effects of Democratic Backsliding on MPs' Speech Rate

	(11) Number of Speeches	(12) Speeches on the Economy
Negative Binomial		
Backsliding	-0.85**	-1.01**
	(0.12)	(0.37)
Female	-0.54**	-1.17*
	(0.19)	(0.46)
Backsliding * Female	0.23	0.44
	(0.30)	(0.38)
Senior MP	0.49**	-0.30
	(0.15)	(0.27)
Newcomer	-0.12	-0.14
	(0.14)	(0.23)
Independent	-0.25	-0.45
	(0.18)	(0.38)
Month	0.30**	0.12
	(0.04)	(0.16)
Month^2	-0.021**	-0.01
	(0.00)	(0.01)
Constant	2.50**	1.20
	(0.25)	(0.72)
Logit		
Backsliding	-0.49	-0.00
	(0.11)	(0.25)
Female	0.30	0.19
	(0.28)	(0.72)
Backsliding * Female	-0.77	-1.01
	(0.43)	(0.68)
Senior MP	-23.0**	-4.88
	(0.24)	(4.01)
Newcomer	0.11	0.16
	(0.21)	(0.31)
Independent	-23.0**	-21.2**
	(0.39)	(3.74)
Month	-0.15**	-0.49**
	(0.04)	(0.09)
Month^2	0.01**	0.03**
	(0.00)	(0.01)
Constant	1.20**	2.74**
	(0.22)	(0.41)
lnalpha	0.23**	1.18**
	(0.08)	(0.22)
BIC	10490.7	4026.0
Observations	2880	2880

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table A7: Effects of Cash Gate Scandal on MPs' Speech Rate

	(13) Number of Speeches	(14) Speeches on the Economy
Negative Binomial		
Cash Gate	-1.14**	-2.15**
	(0.16)	(0.31)
Female	-0.23	-0.34
	(0.17)	(0.23)
Cash Gate * Female	0.3	1.14
	(0.21)	(0.7)
Senior MP	0.53**	0.36
	(0.16)	(0.32)
Newcomer	-0.35*	-0.3
	(0.17)	(0.27)
DPP	0.32	0.053
	(0.18)	(0.35)
PP	0.4	0.6
	(0.22)	(0.58)
MCP	0.31	0.18
	(0.18)	(0.32)
Independent	-0.09	0.06
	(0.16)	(0.36)
Month	-0.08	-0.11
	(0.05)	(0.1)
Month^2	0.012	0.02
	(0.01)	(0.01)
Finance Committee		0.02
		(0.21)
Constant	2.88**	1.08**
	(0.21)	(0.36)
Logit		
Cash Gate	-0.08	0.8
	(0.2)	(0.58)
Female	-0.15	-0.13
	(0.28)	(0.38)
Cash Gate * Female	0.36	2.04
	(0.34)	(1.18)
Senior MP	-1.37**	-1.74
	(0.41)	(1.03)
Newcomer	-0.19	-0.24
	(0.28)	(0.46)
DPP	-1.19**	-1.27*
	(0.34)	(0.52)
PP	-1.66**	-1.16
	(0.42)	(0.78)
MCP	-1.81**	-2.22**
	(0.40)	(0.72)
Independent	-23**	-16.3**
	(0.36)	(2.26)
Month	0.10**	0.16**
	(0.28)	(0.06)
Finance Committee		-7.08
		(28.6)
Constant	0.67	0.73
	(0.41)	(0.51)
lnalpha	0.1	0.88**
	(0.09)	(0.18)
BIC	9490.47	4408.8
Observations	1656	1656

Standard errors in parentheses

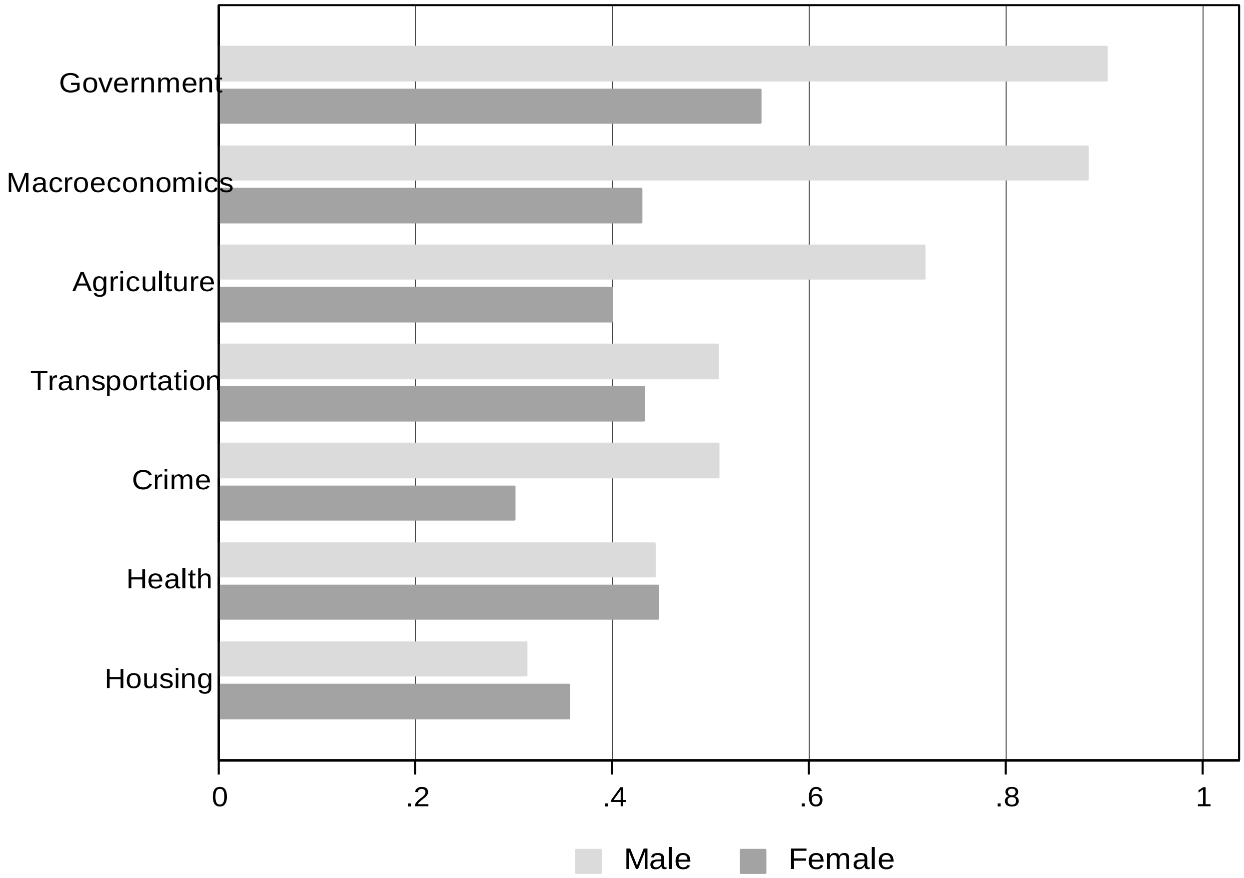
* $p < 0.05$, ** $p < 0.01$

Table A8: The Effect of Banda on the Most Frequent Topics

	(15) Government	(16) Agriculture	(17) Transportation	(18) Crime	(19) Health	(20) Housing
Negative Binomial						
Banda	0.37*	0.24	0.31	-0.36*	0.23	-0.64**
	(0.19)	(0.88)	(0.21)	(0.18)	(0.22)	(0.15)
Female	-0.52	-0.27	-0.27	-0.32	-0.15	-0.39
	(0.29)	(0.85)	(0.22)	(0.30)	(0.30)	(0.25)
Banda * Female	0.24	0.13	-0.45	0.36	-0.06	0.76
	(0.30)	(0.74)	(0.30)	(0.28)	(0.37)	(0.41)
Senior MP	0.88*	1.00**	0.42	0.76**	0.49	0.91**
	(0.39)	(0.37)	(0.31)	(0.26)	(0.32)	(0.23)
Newcomer	-0.63**	0.09	-0.59	-0.53*	-0.06	-0.32
	(0.21)	(1.00)	(0.36)	(0.23)	(0.30)	(0.18)
DPP	0.48	-0.02	0.59	0.24	0.90	0.96**
	(0.29)	(1.76)	(0.35)	(0.35)	(0.58)	(0.21)
PP	0.43	0.16	0.20	0.55	1.30	1.43**
	(0.36)	(1.99)	(0.44)	(0.51)	(0.71)	(0.35)
MCP	0.67	0.39	0.42	0.31	0.71	0.58*
	(0.36)	(1.46)	(0.29)	(0.37)	(0.61)	(0.25)
Independent	0.67	0.002	0.87**	0.23	0.74	0.94**
	(0.43)	(1.18)	(0.31)	(0.43)	(0.70)	(0.24)
Month	-0.01	-0.06	-0.10**	0.04	-0.10*	-0.10**
	(0.03)	(0.09)	(0.03)	(0.03)	(0.04)	(0.03)
Month^2	0.00	0.003	0.01**	-0.00	0.01**	0.00
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.45	-0.48	-0.59*	0.095	-1.42**	-0.89**
	(0.39)	(0.44)	(0.26)	(0.44)	(0.43)	(0.23)
Logit						
Banda	-1.11	0.43	-1.21	-1.09*	0.11	-18.7**
	(1.79)	(2.36)	(1.54)	(0.55)	(0.75)	(2.64)
Female	0.55	-0.53	0.73	0.37	-0.33	-0.23
	(0.54)	(1.94)	(0.91)	(0.30)	(0.53)	(0.60)
Banda * Female	-1.80	0.69	-29.5**	0.42	-0.94	2.93
	(4.01)	(1.78)	(1.65)	(0.52)	(0.88)	(1.75)
Senior MP	-23.2**	-0.43	-33.7**	-1.36*	-0.73	-38.2**
	(1.71)	(0.57)	(1.46)	(0.58)	(0.94)	(2.59)
Newcomer	-1.56	-0.17	-2.97*	-0.26	-0.52	-2.28**
	(1.58)	(1.98)	(1.18)	(0.52)	(1.09)	(0.68)
DPP	2.41	-0.37	4.41	0.31	2.01	5.49
	(3.82)	(3.21)	(4.47)	(0.83)	(4.14)	(7.78)
PP	2.42	-0.19	4.52	0.44	2.89	22.9**
	(4.40)	(3.59)	(4.99)	(1.24)	(4.70)	(8.19)
MCP	-1.06	-1.33	-22.4**	-1.36	-3.16	1.97
	(2.50)	(3.85)	(5.96)	(0.80)	(4.98)	(7.83)
Independent	-36.7**	-22.4**	-26.9**	-22.8**	-25.0**	3.56
	(4.35)	(2.42)	(5.21)	(0.86)	(5.53)	(7.71)
Month	0.03	0.17	-0.08	-0.09	-0.07	-0.06
	(0.14)	(0.14)	(0.15)	(0.07)	(0.09)	(0.11)
Month^2	0.00	-0.01	0.01	0.00	0.01	0.00
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Constant	-1.31	-0.57	-3.28	0.92	-1.57	-3.21
	(2.43)	(2.09)	(4.26)	(0.60)	(3.18)	(7.69)
lnalpha	1.20**	0.92	1.50**	1.29**	1.28**	1.28**
	(0.23)	(0.70)	(0.13)	(0.25)	(0.28)	(0.10)
BIC	10943.6	8805.9	8512	8944.6	6962.5	8087.1
Observations	5336	5336	5336	5336	5336	5336

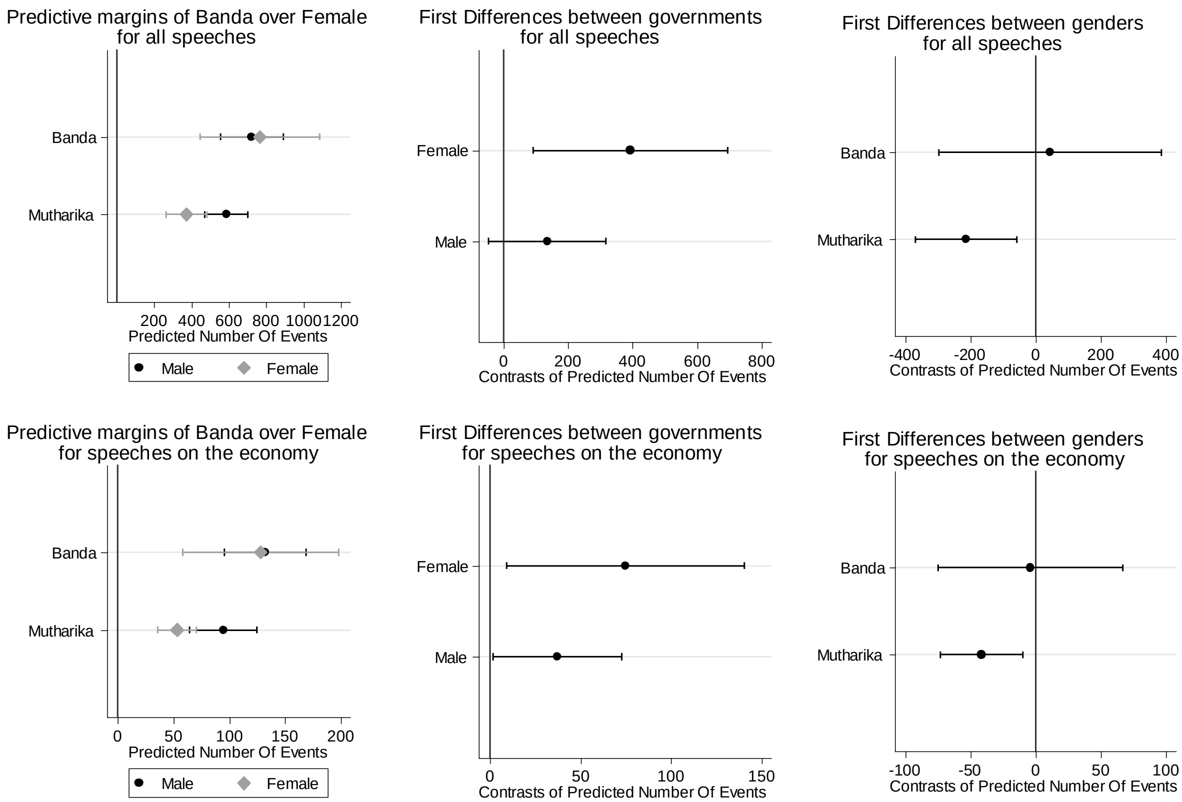
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Figure A1: Speech Topics for Male and Female MPs



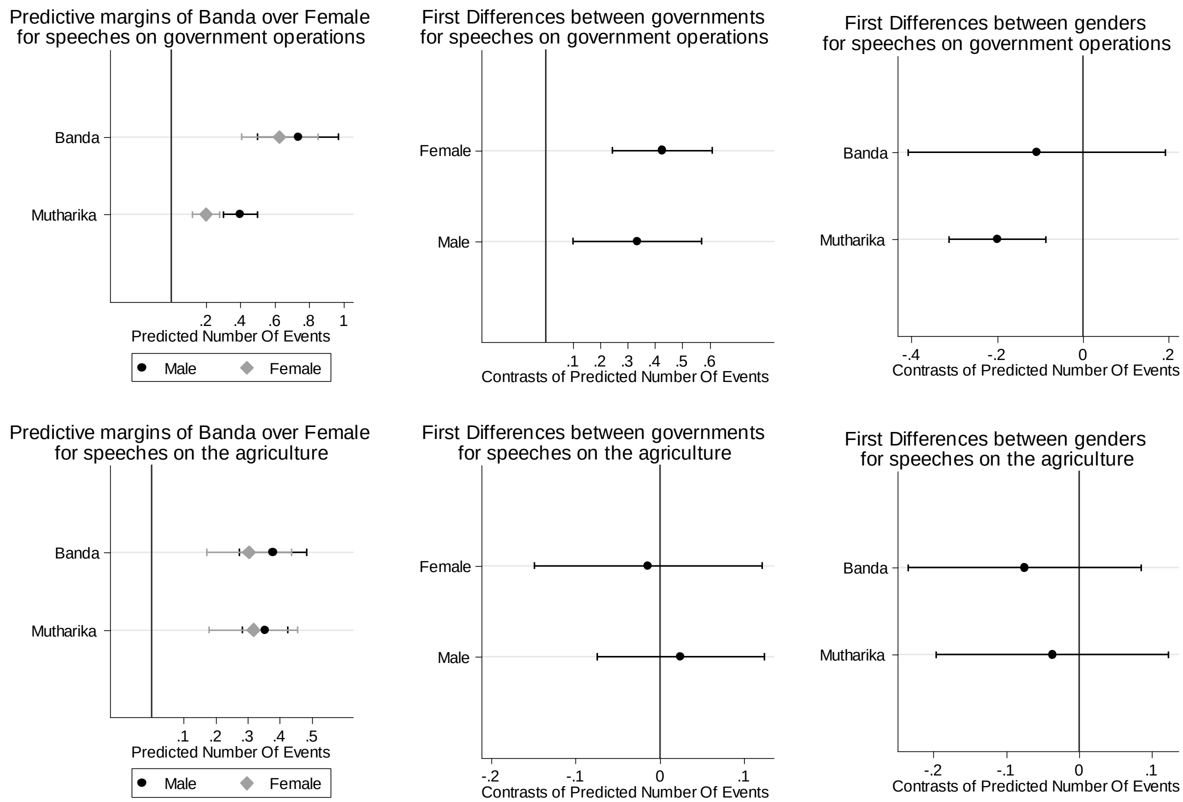
Note: Average number of speeches/month in each topic category for the average male and femal

Figure A2: Predictive Margins for Main Models Using Number of Words as Dependent Variable



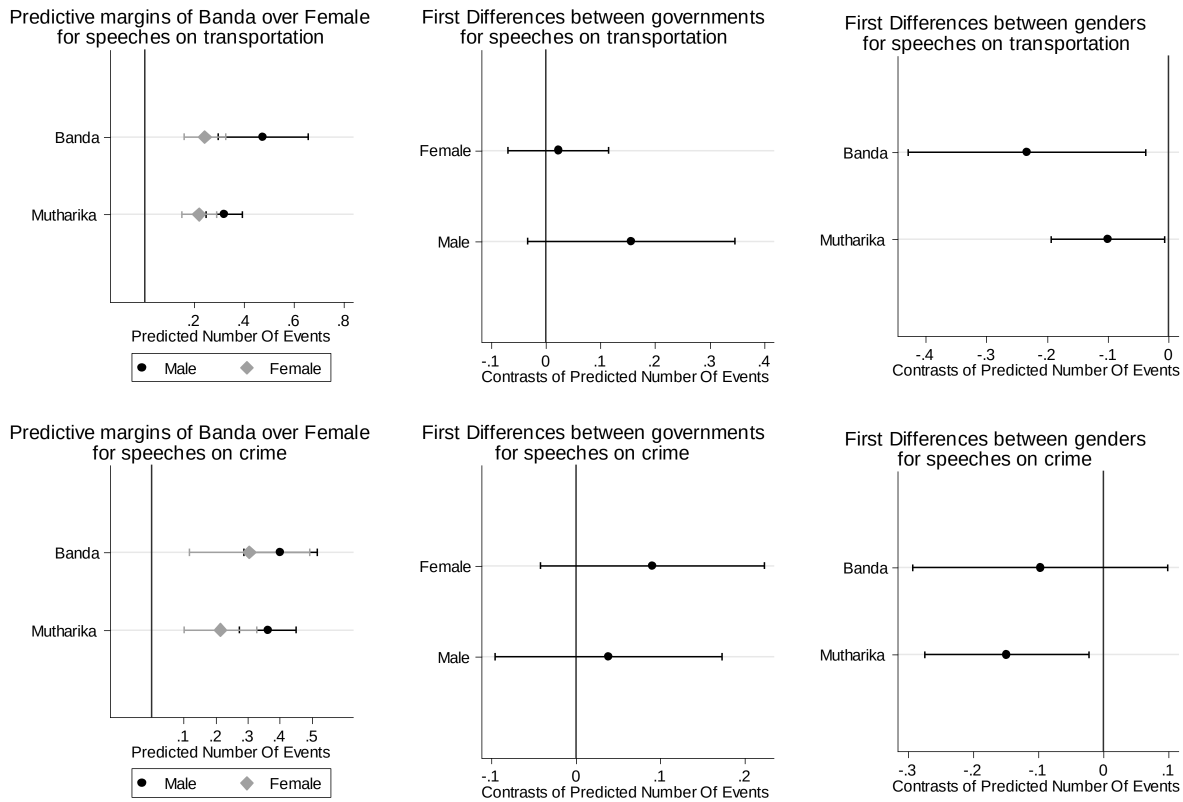
Note: The 95% confidence intervals are included

Figure A3: Predictive Margins for the topics of Government Operations and Agriculture



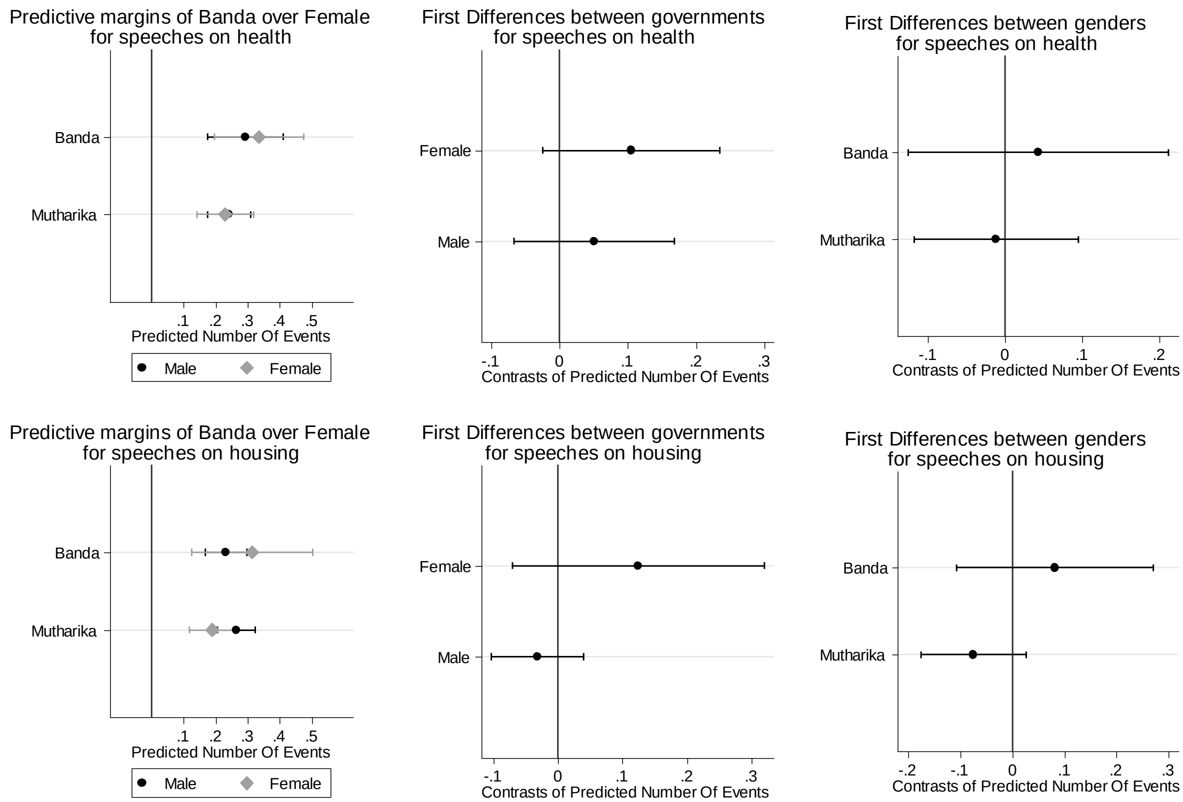
Note: The 95% confidence intervals are included

Figure A4: Predictive Margins for the topics of Transportation and Crime



Note: The 95% confidence intervals are included

Figure A5: Predictive Margins for the topics of Health and Housing



Note: The 95% confidence intervals are included

Coding Parliamentary Speeches via a Neural Network Approach

All parliamentary transcripts were obtained directly from the parliamentary library in Lilongwe, with generous assistance from the parliamentary librarian. Some of these transcripts had previously been digitized and stored in the library's computers, while some transcripts were scanned and digitized specifically for this project. Given the large volume of speeches, we opted to use machine learning to code their content. We particularly needed to assign each speech to an individual MP and also code each speech's primary content (the speech topic). Prior research on parliamentary debates, particularly in Europe and North America, provides a reliable framework for us to categorize speeches using widely established speech categories (eg. Martin 2011, Jennings et al. 2011). For the purpose of this project, we opted for the widely used Comparative Agendas Project (CAP) coding scheme (Baumgartner et al., 2006) to sort the speeches into categories. The benefit of using an existing scheme is to maximize the comparability between our data and data from other, more researched, cases. CAP sorts speeches into 21 main speech categories, we also decided to add one additional category for procedural speeches.

Since the set of categories was pre-defined by CAP, we followed a supervised machine learning approach. This necessitates the existence of a hand-coded training dataset on which to train our classifier.[1] We trained three undergraduate Research Assistants (RAs) to perform hand-coding of randomly selected speeches from the entire parliamentary period under investigation (1999-2014). In the hand-coding, the RAs identified the speaker and categorized each speech in accordance with the CAP classification scheme. In cases where RAs recorded the categorization as ambiguous, the speech was forwarded to one of the authors for classification. In total, 2,500 speeches were hand-coded for training purposes.

Our machine learning classifier is an artificial neutral network. There has been a recent uptick in the use of supervised machine learning approaches for text analysis tasks in political science applications. Examples of widely used approaches include support vector machines (eg. D'Ortazio et al., 2014) and

[1] For our application, where we have well defined concepts of interest and labels that will allow us to explicitly measure them, a supervised approach, is preferable compared to unsupervised approaches, like structural topic modeling, which are most useful when we do not have labeled data for the outcome that we are interested in (Cranmer, 2019).

random forests (Montgomery and Olivella, 2016). Artificial neutral networks, however, are a rather novel approach, that offers important advantages to other alternative approaches. Neural networks have been shown to be highly effective in Natural Language Processing (NLP) tasks (Popov, 2016) and are particularly well suited for text classification (Mirończuk and Protasiewicz, 2018). Neural networks are a form of machine learning in which a computer learns to perform some task by analyzing training examples. Neural networks tend to be organized into layers of nodes. Each node is connected to one or several nodes located in the previous and subsequent layer, hence creating the architecture of the network. Adding layers increases the depth of the network. The data pass through the layers in succession via the nodes.

Rather than training the network from scratch, we fine-tuned the pre-trained network BERT (Bidirectional Encoder Representations from Transformers), which is made available by Google (Devlin, 2018). This method, commonly referred to as transfer learning, has been shown to improve classification accuracy, especially when the available hand-coded training data are limited (Howard and Ruder, 2018). While underutilized in the social sciences, BERT, is one of the most advanced publicly available neural networks trained for NLP tasks. In simple terms, BERT is capable of "comprehending" a text in terms of sentences rather than simply in term of words. As a result, it is better equipped to identify words, phrases, or other kinds of sequences that are used most often when someone is speaking about a specific topic. By associating different speech characteristics with each topic, it can then classify new texts in one of these categories. In addition, due to the use of word embeddings[2], the network's learning through the hand-coded training data is not limited to the words used within these examples. Due to the existence of these word vectors that accompany each word, it generalizes the aforementioned associations to the words semantically close to the words it meets in the training examples. To summarize, due to its ability to read text in terms of sentences, through the attention mechanism, and to generalize to a wider vocabulary, through the word

[2] Word embeddings map words in a continuous numeric vector. Words with similar meanings are mapped closer to each other. Therefore, it becomes possible for the model to "learn" more efficiently by being able to find which words have similar (or opposite) meanings via vector arithmetic.

embeddings, BERT is well equipped to handle complex NLP tasks like categorizing parliamentary speeches in pre-selected topic categories.

To deploy BERT, we use *ktrain* (Maiya, 2018), a Python library that allows users to easily modify and fine-tune the original model. Through *ktrain* we use the base version of BERT, which is 12 layers deep, with hidden layer size of 768 nodes, 12 self-attention heads, and 110M total parameters. We fine-tuned the network using 80% of our hand-coded data and validated using the remaining 20%. After the training, the network coded the validation set with an F1 score of 80.91%, with precision at 82.43% and recall at 80.48%.[3]

[3] As a point of reference, Burscher et al. 2015, who use a different kind of supervised machine learning approach to code Dutch Parliamentary Questions based on the same CAP coding scheme, get an F1 score of 68%.

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