1. Appendix A: Supplementary Tables

Table A1. Keywords by Number of Arrests and Cities with Occupy Arrests, 2009-2015
Table Corresponding to Figure 3 of the Article

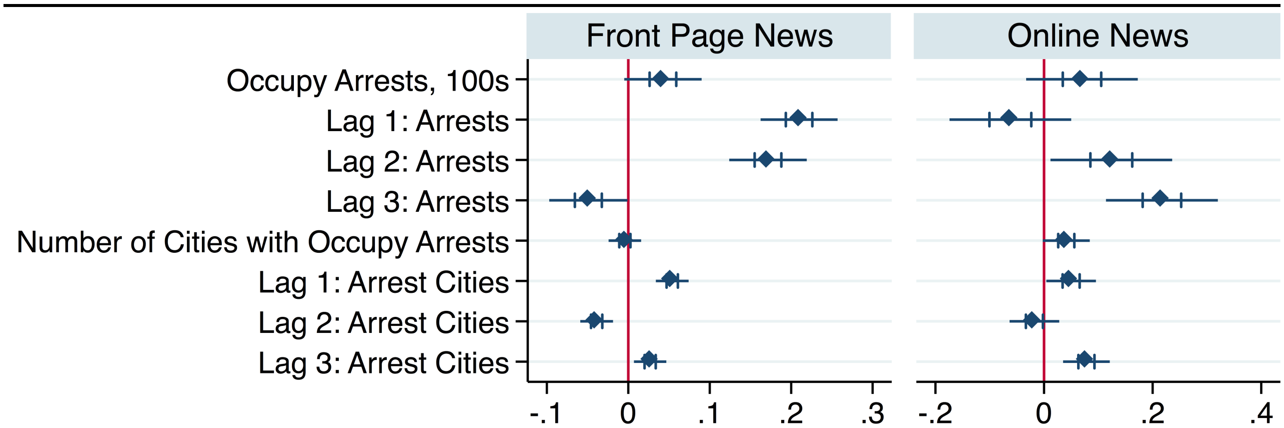
	No Arrests		1-100 Arrests		> 100 Arrests		F-Test	
President Obama	N	Mean	N	Mean	N	Mean	F	Bonferroni
Arrests[1]								
Inequality Count	2323	4.25	172	8.73	15	14.53	28.14***	Pass***
Fair Share Count	2323	0.23	172	1.13	15	2.40	62.28***	Pass***
Arrests – Lag 1 Day								
Inequality Count	2322	4.26	172	9.03	15	9.40	23.79***	Fail
Fair Share Count	2322	0.24	172	1.16	15	1.53	50.27***	Pass***
U.S. Congress								
Arrests[1]								
Inequality Count	2323	103.76	172	128.85	15	205.53	5.23**	Fail
Fair Share Count	2323	0.90	172	2.20	15	2.13	16.18***	Fail
Arrests – Lag 1 Day								
Inequality Count	2322	104.76	172	115.84	15	206.67	3.60*	Fail
Fair Share Count	2322	0.92	172	1.76	15	3.33	10.64***	Pass***

	No Arrest Cities		1-4 Arrest Cities		> 4 Arrest Cities		F-Test	
President Obama	N	Mean	N	Mean	N	Mean	F	Bonferroni
Arrest Cities[1]								
Inequality Count	2323	4.25	155	9.95	32	5.50	28.51***	Fail
Fair Share Count	2323	0.23	155	1.32	32	0.78	57.41***	Pass*
Arrest Cities – Lag 1 Day								
Inequality Count	2322	4.26	155	9.43	32	7.28	24.52***	Fail
Fair Share Count	2322	0.24	155	1.17	32	1.25	50.27***	Pass***
U.S. Congress								
Arrest Cities[1]								
Inequality Count	2323	103.76	155	130.48	32	156.91	3.92*	Fail
Fair Share Count	2323	0.90	155	2.15	32	2.44	16.30***	Pass*
Arrest Cities – Lag 1 Day								
Inequality Count	2322	104.76	155	116.11	32	157.09	2.15	Fail
Fair Share Count	2322	0.92	155	1.81	32	2.22	10.64***	Pass**

Sources: (1) Congressional rhetoric taken from the daily U.S. Congressional Record, Jan 01, 2009 to February 12, 2016. (United States, Government Printing Office 2016). The data was downloaded and keyword terms were counted for each category using replicable Python and Bash scripts (Mausolf 2016a-c). (2) Occupy Arrests (2014). Data shown from dates January 1, 2009 to November 15, 2015. Data truncated to show statistics for period of multivariate analysis.
Notes: Significance levels as follows: *p<.05, **p<.01, ***p<.001. F-test compares with Bonferroni pairwise comparisons. Bonferroni pairwise comparisons illustrate the difference between each of the possible pairwise comparisons between the keyword and arrests or arrest cities. In the Bonferroni column, I highlight the three most important pairwise comparisons of the arrests and arrest city categories versus no arrests or no arrest cities. If there was a statistically significant difference between (1) no arrests and 1-100 arrests AND (2) no arrests and > 100 arrests, I denote this condition a "pass." Likewise if there was a statistically significant difference between (1) no arrest cities and 1-4 arrest cities AND (2) no arrest cities and > 4 arrest cities, I denote this condition a "pass." If any of these three failed, I denote a "fail." For passes, I indicate the most conservative probability level of each Bonferroni comparison.

Table A2. ARFIMA Time Series Models of Front-Page and Online Occupy News, 2009-2015

Coefficient Plots Corresponding to Table 3 of the Article

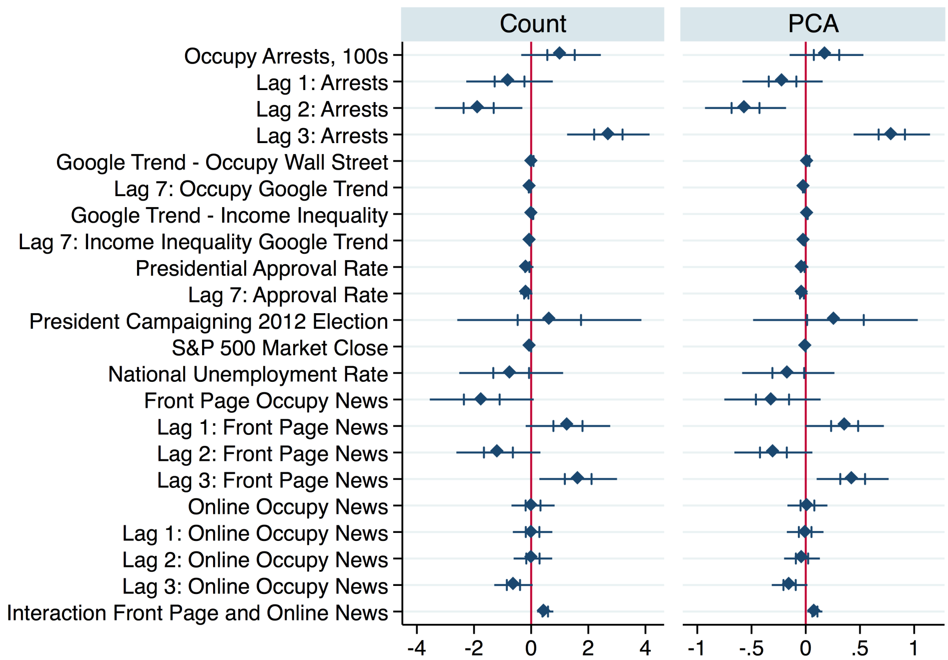


Note: Significance levels using z-test. Confidence bars in coefficient plot represent the 95% confidence intervals around the point estimate. Models 1-2: ARFIMA (2, d, 1) models of count data and PCA of count data with OIM S.E., respectively for inequality and fair share rhetoric. N=2,500. Full model details for these models can be found in Table 3 of the article.

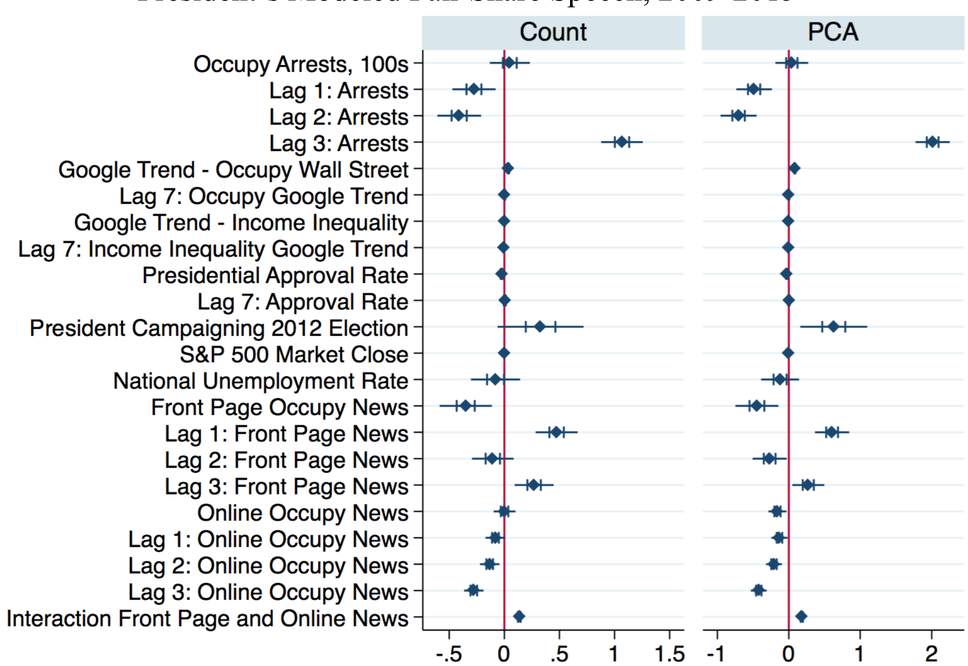
Table A3. ARFIMA Time Series Models of President Obama's Speech, 2009-2015

Coefficient Plots Corresponding to Table 4 of the Article

President's Modeled Inequality Speech, 2009-2015



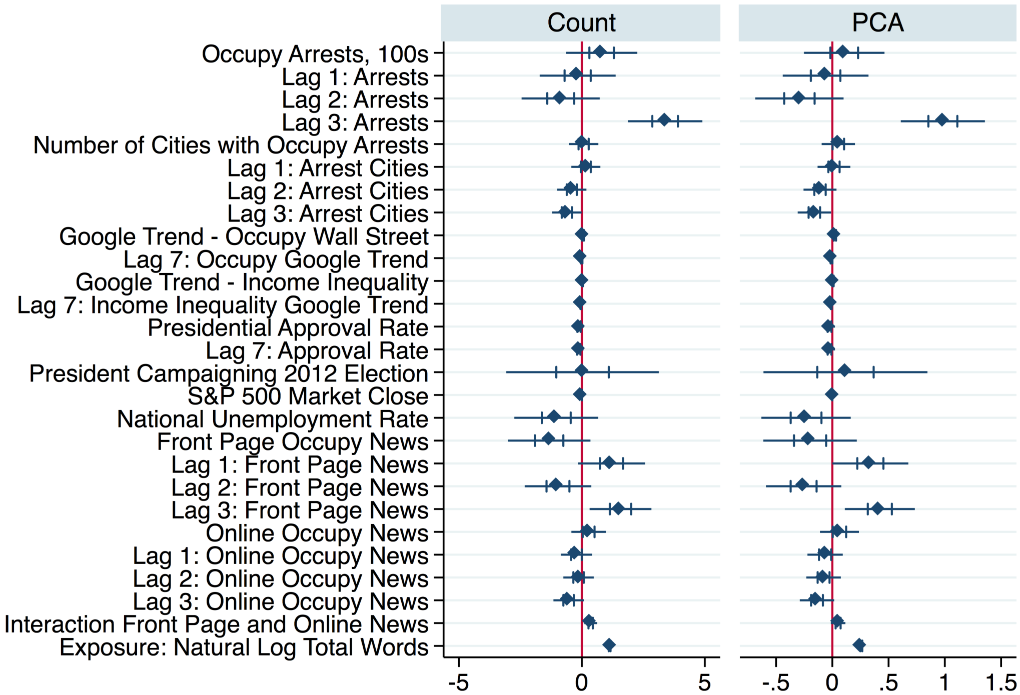
President's Modeled Fair Share Speech, 2009-2015



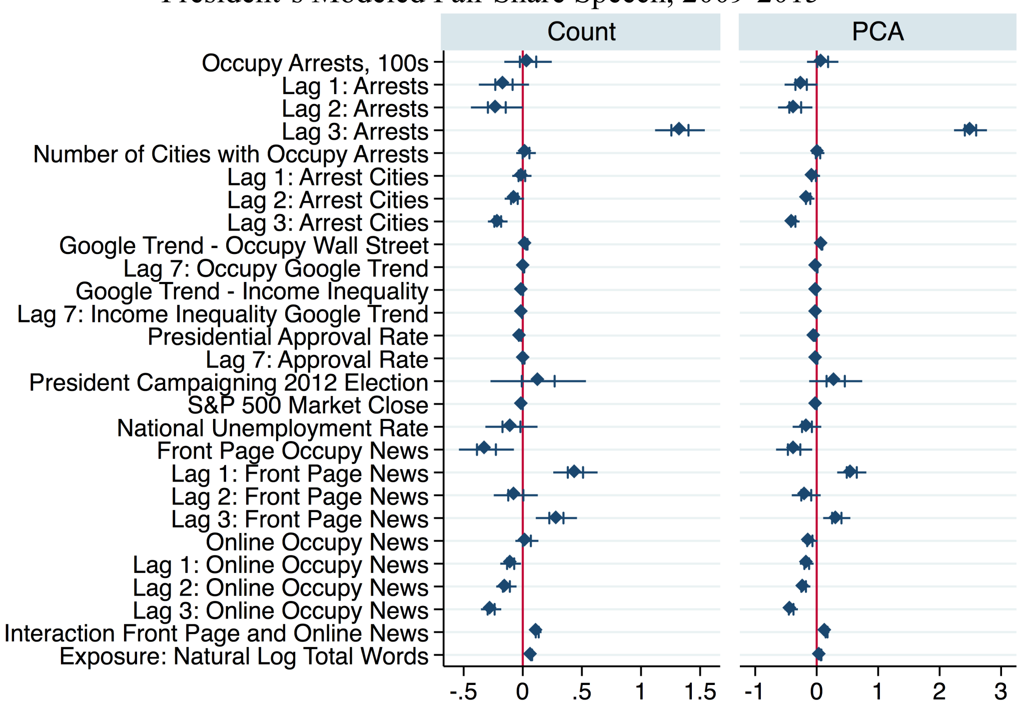
Note: Significance levels using z-test. Confidence bars in coefficient plot represent the 95% confidence intervals around the point estimate. Models 1-4: ARFIMA (2, d, 1) models of count data and PCA of count data with OIM S.E., respectively for inequality and fair share rhetoric. N=2,500. Full model details for these models can be found in Table 4 of the article.

Table A4. ARFIMA Models of Presidential Speech with Exposure Term, 2009-2015

President's Modeled Inequality Speech, 2009-2015



President's Modeled Fair Share Speech, 2009-2015

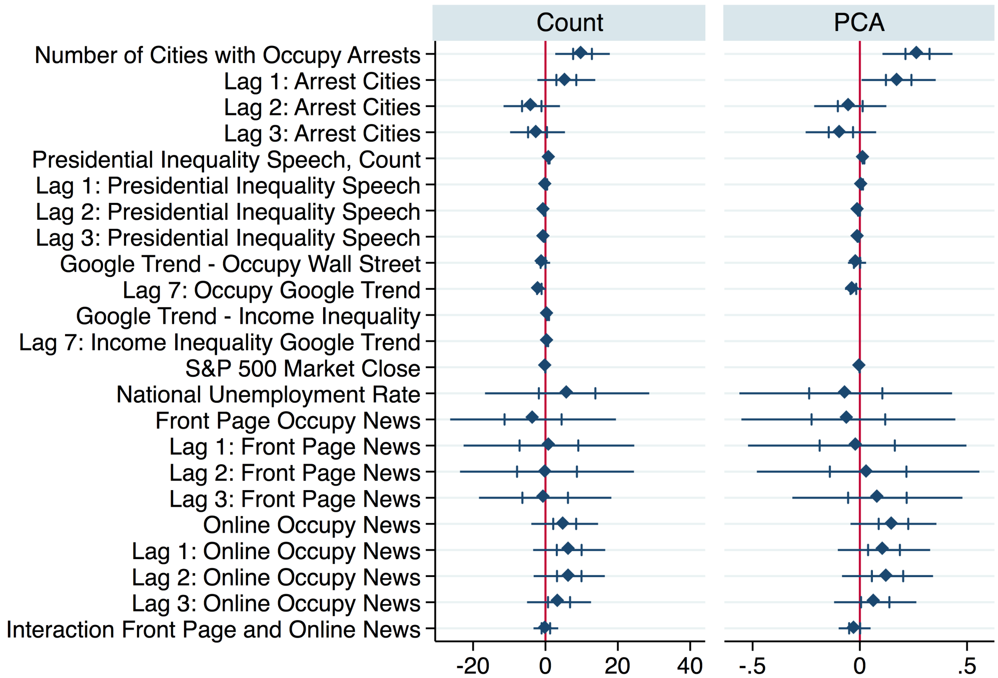


Note: Significance levels using z-test. Confidence bars represent the 95% confidence intervals around the point estimate. Models 1-4: ARFIMA (2, d, 1) models of count data and PCA of count data with OIM S.E., respectively for inequality and fair share rhetoric. N=2,500.

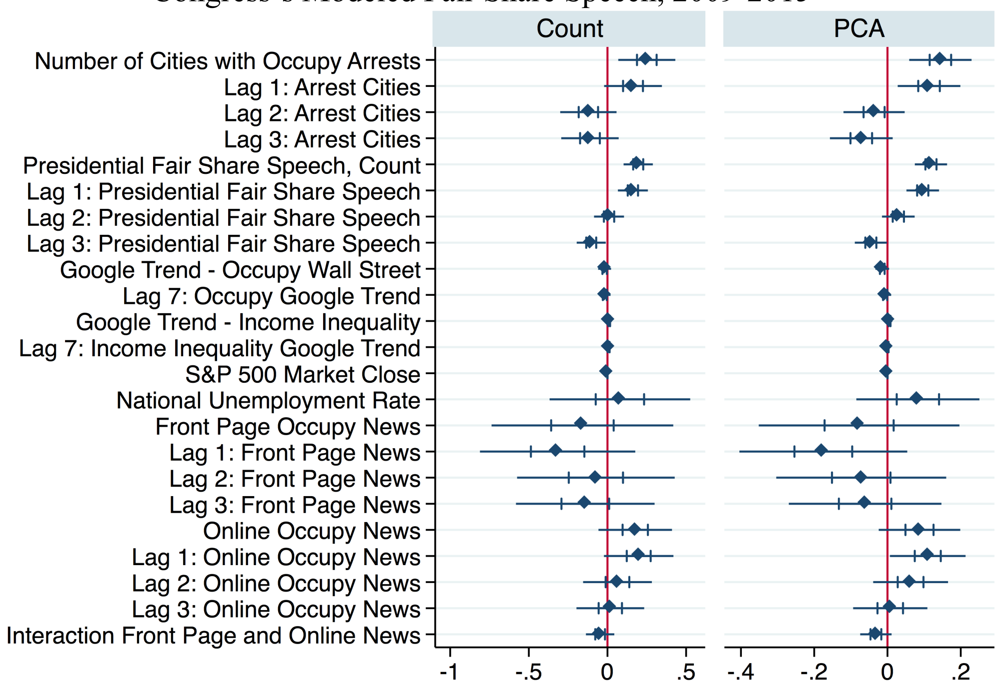
Table A5. ARFIMA Time Series Models of Congress's Speech, 2009-2015

Coefficient Plots Corresponding to Table 5 of the Article

Congress's Modeled Inequality Speech, 2009-2015



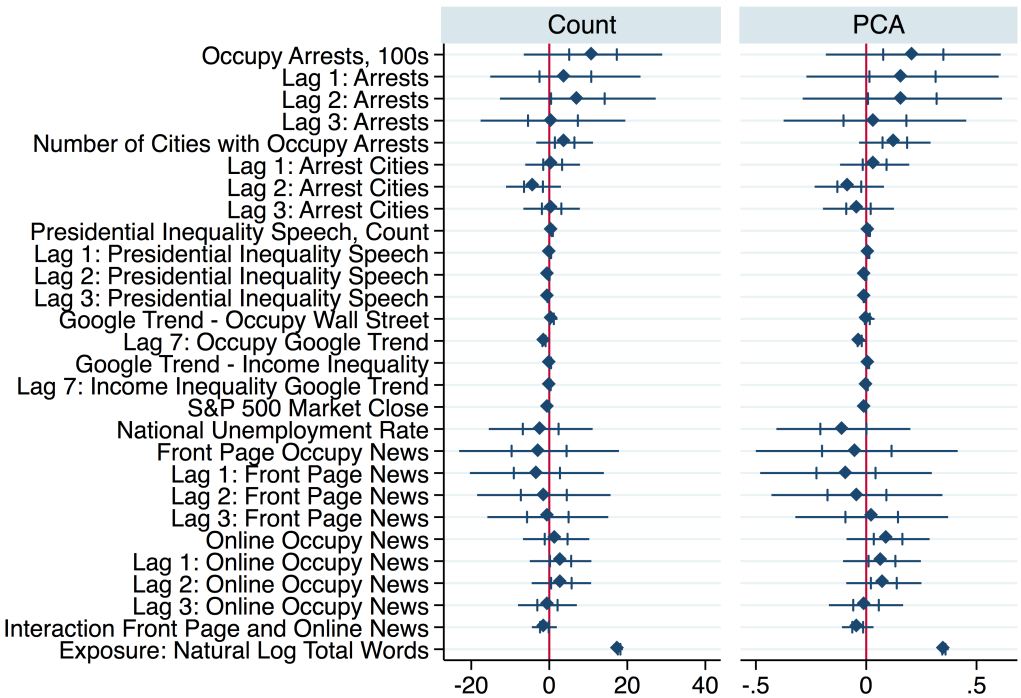
Congress's Modeled Fair Share Speech, 2009-2015



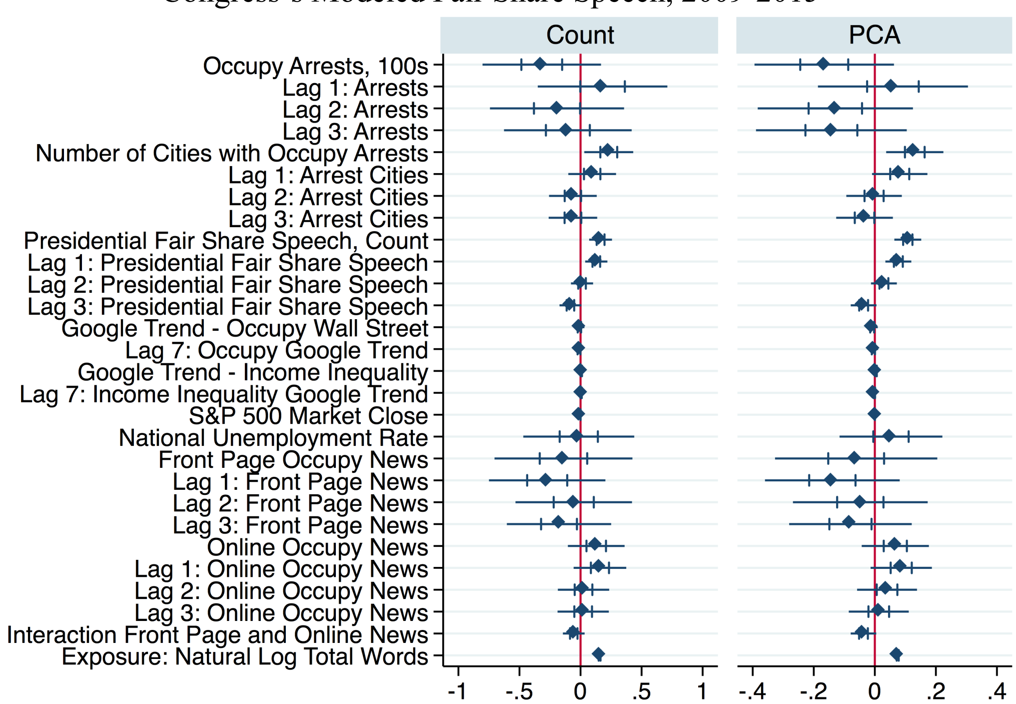
Note: Significance levels using z-test. Confidence bars in coefficient plot represent the 95% confidence intervals around the point estimate. Models 1-4: ARFIMA (2, d, 1) models of count data and PCA of count data with OIM S.E., respectively for inequality and fair share rhetoric. N=2,500. Full model details for these models can be found in Table 5 of the article.

Table A6. ARFIMA Models of Congressional Speech with Exposure Term, 2009-2015

Congress's Modeled Inequality Speech, 2009-2015



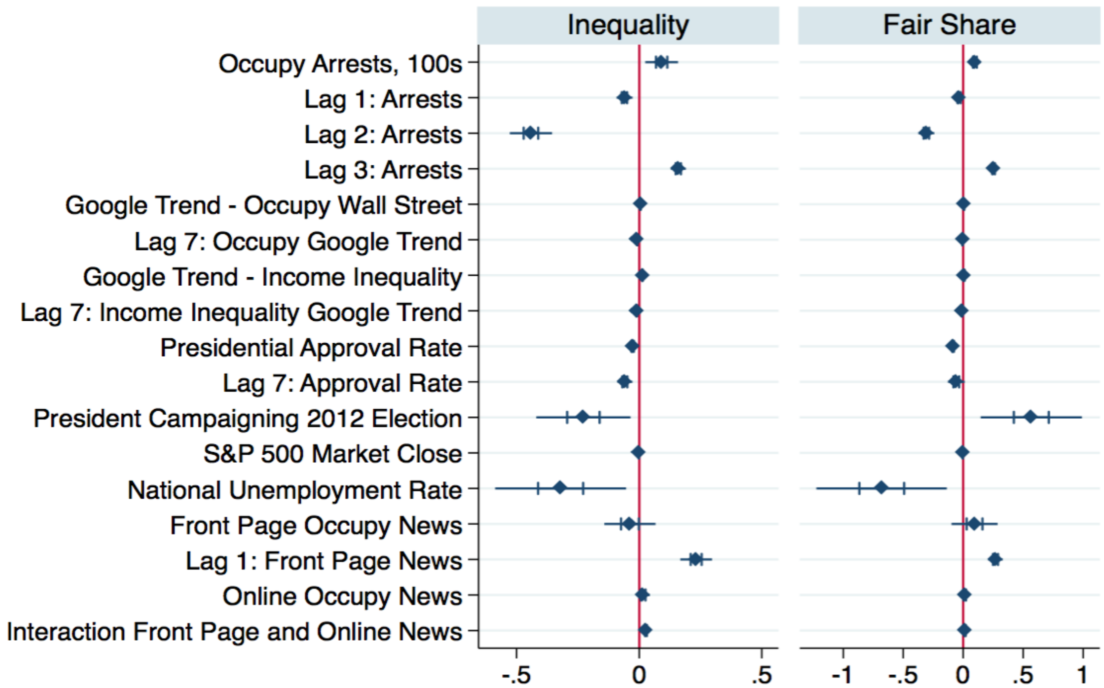
Congress's Modeled Fair Share Speech, 2009-2015



Note: Significance levels using z-test. Confidence bars represent the 95% confidence intervals around the point estimate. Models 1-4: ARFIMA (2, d, 1) models of count data and PCA of count data with OIM S.E., respectively for inequality and fair share rhetoric. N=2,500.

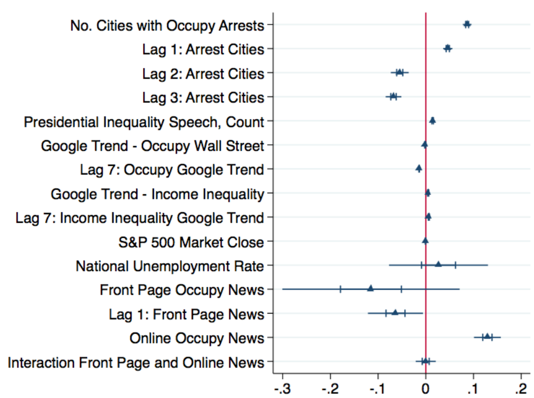
Table A7. Negative Binomial Models of Presidential and Congressional Speech, 2009-2015

President's Modeled Speech, 2009-2015

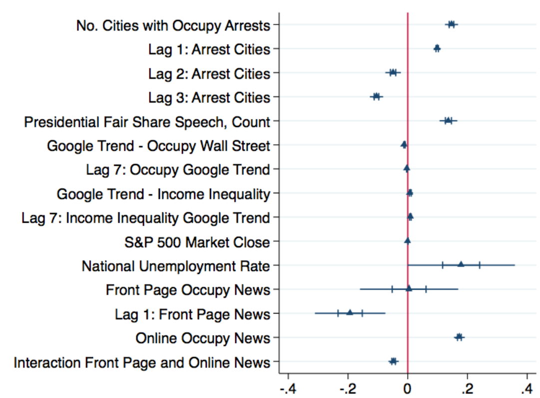


Congress's Modeled Speech, 2009-2015

Inequality



Fair Share



Note: Significance levels using z-test. Confidence bars in coefficient plot represent the 95% confidence intervals around the point estimate. Generalized negative binomial models of count data using (HAC), Newey-West S.E., respectively for inequality and fair share rhetoric. N=2,500.

2. Appendix B: Counting Keywords and Phrases

Full code for the project can be found online (Mausolf 2016c). The following terms were used in the text keyword counter script. Not all categories were fully utilized. As previously indicated, the keyword categories follow Occupy's purpose to fight "the corrosive power of major banks and multinational corporations over the democratic process,…the role of Wall Street in creating an economic collapse,…[and] the richest 1% of people that are writing the rules of an unfair global economy" (Occupy 2011). Research using surveys, qualitative assessments, and computational techniques reiterates these essential ideas (DeTar 2012; DeLuca et al. 2012; Gould-Wartofsky 2015; Krugman 2011a; Milkman et al. 2013a-b). For example, the Occupy Wall Street survey (DeTar 2012) asked protest participants to list the top three keywords that motivated them to participate. The terms "income inequality, "inequality, "corporate influence in politics," and "corporate greed" were all top responses. Through these ideas we can see the central tenant that *the top 1% are writing their rules to the unfair world economy, and should like everyone else pay their fair share and play by the same rules*. In an alternate survey by Milkman, Luce, and Lewis (2013a), 47.5% of Occupy participants indicated that "Inequality/the 1%" was a top motivating concern in supporting Occupy. Similarly, 25.5% and 18.5% indicated that "money in politics/frustration with D.C." and "corporate greed" were top reasons for support. I operationalize my work by examining political rhetoric for discussion of these same topics. The keywords used for categories are as follows:

Table B1. Discrete Keywords by Speech Category Used by Python NLP Script (Mausolf 2016c)

Inequality Keywords and Phrases
inequality = ["wealth", "wealthy", "income equality", "income inequality", "inequality", "privileged", "rich", "1%", "1 percent", "one percent", "99%", "99 percent", "ninety-nine percent", "ninety nine percent", "fair", "unfair", "fairness", "unfairness", "middle-class", "middle class", "working class", "working-class", "lower class", "poor", "poverty", "rich", "upper class", "equity", "inequity", "egalitarian", "disparity", "unequal", "average American", "average Americans", "Wall Street", "Main Street", "main street", "50 million", " Warren Buffet", "Warren Buffett's secretary", "secretary", "class warfare", "class warefare", "warrior for the middle class", "Giving everybody a shot", "giving everybody a shot", "everybody a fair shot", "work your way up", "working your way up", "starting at the bottom", "blood, sweat and tears", "blood sweat and tears", "blood, sweat, and tears", "willing to work hard", "fair and just", "everybody is included", " folks at the top", "folks at the bottom"]

Fair Share Keywords and Phrases
fair_share = ["fair shot", "fair shake", "gets a fair shake", "pay their fair share", "our fair share", "fair share"]

Wall Street Keywords and Phrases
wall_street = ["lobby", "lobbying", "lobbies", "special interest", "special interests", "revolving door", "campaign donor", "campaign donation", "campaign donations", "bidder", "highest bidder", "campaign contributions", "loophole", "loopholes", "tax shelter", "tax evasion", "write their own rules", "own rules", "Wall Street", "bailout", "bailouts"]

Corporate Greed Keywords and Phrases
corporate_greed = ["cheat", "cheating", "stacked against", "stacked up against", " stacked against", "good benefits", "decent salary", "stack the deck", "deck got stacked against", "exploit", "exploiting", "protect workers", "protecting workers", "protect laborers", "protecting laborers", "protect Americans", "protecting Americans", "protect employee", "protect employees", "protecting employees", "work safe", "working safely", "safe at work", "work conditions", "innocent", "minimum wage", "pollute", "polluting", "regulate", "regulating", "federal oversight", "financial reform", "gambling", "derivative", "derivatives", "sub-prime", "risky investment", "risky investments", "bust unions", "union", "unions", "labor unions", "dirtiest air", "cheapest labor", "wages", "workplace safety", "Consumer Finance Protection Bureau", "consumer protection", "unions", "union label", "union workers", "CEO", "CEO's", "corporation", "corporations"]

Top Results from the Occupy Wall Street Survey of Keywords and Phrases (DeTar 2012)[1]
OWS_survey = ["income inequality", "inequality", "economic conditions", "corruption", "justice", "corporate influence in politics", "corporations", "corporate personhood", "injustice", "social justice", "corporate greed", "anti-capitalism", "greed", "unemployment", "citizens united", "equality", "money in politics", "government corruption", "poverty", "environmental concerns", "democracy", "fairness", "freedom", "change", "inequity", "jobs", "money out of politics", "health care", "financial reform", "solidarity", "war", "movement building", "foreclosures", "frustration", "banks", "politics", "curiosity", "money", "campaign finance reform", "climate change", "education", "disparity", "bailouts", "future", "anger", "hope", "revolution", "humanity", "equity", "children", "police brutality", "rights", "community", "Oligarchy", "0.99", "fascism", "freedom of speech", "food", "civil liberties", "taxes", "peace", "plutocracy", "love", "corporate corruption", "joblessness", "campaign finance", "fraud", "Wall Street", "human rights", "compassion", "accountability", "NDAA", "debt", "tax the rich", "lobbyists", "broken political system", "agreement", "inequality", "corruption", "economy", "justice", "environment", "income inequality", "economic inequality", "healthcare", "capitalism", "corporatism", "economics", "social injustice", "income disparity", "political corruption", "government", "economic justice", "economic disparity", "economic injustice", "civil rights", "wealth disparity", "oppression", "racism", "patriarchy", "sustainability", "homelessness", "corporate power", "workers rights", "student loans", "wall street", "corrupt government", "exploitation", "accountability", "housing", "patriotism", "apathy", "responsibility", "corporations"]

[1] *Note:* These specific terms are those indicated by Occupy Wall Street protesters in a survey as the top motivating keywords driving them to participate in the OWS protest. Respondents were offered a 1st, 2nd, and 3rd choice. This group reflects the pooled terms from the 1st, 2nd, and 3rd choice keywords or phrases listed that had greater than or equal to five respondents enter the keyword (DeTar 2012).