Joshua Gary Mausolf



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EDUCATION

2019 expected	Рн.D.	University of Chicago, Department of Sociology Special Field Exams: Survey Research Methods; Inequality in Labor Markets, Wealth, and Social Mobility
2016	M.A.	University of Chicago, Department of Sociology *Preliminary Exams: Stratification and Inequality, Political Sociology, Economic Sociology, Urban and Race, Sex and Gender, Family
2012	B.A.	NEW YORK UNIVERSITY, Department of Sociology Major: Sociology with High Honors, summa cum laude Thesis: "Environmental Hookups: School Social Environment and the College Hookup Scene" (Best Thesis, Departmental Honors)
2010	A.A.	NORTHERN VIRGINIA COMMUNITY COLLEGE Major: Liberal Arts, summa cum laude

PROFESSIONAL EXPERIENCE

2015-Current	University of Chicago, Chicago, IL
	Graduate Research Assistant, XI Song, Dept. of Sociology Graduate Research Assistant, Kathleen Cagney, Dept. of Sociology Graduate Research Assistant, Jenny Trinitapoli, Dept. of Sociology Junior Data Scientist, James Evans Knowledge Lab, Computation Institute
Jun-Aug 2016	DATA SCIENCE FOR THE SOCIAL GOOD, Chicago, IL
	Data Science Fellow, Predicting Adverse Police Incidents, $\it White House Police Data Initiative$
2012-2014	NEW YORK UNIVERSITY, New York, NY
	Research Assistant, Jeff Manza, Dept. of Sociology Research Assistant, Patrick Sharkey, Dept. of Sociology
2011-2012	COLUMBIA UNIVERSITY, New York, NY
	Publishing Assistant: Acquisitions and Subsidiary Rights, $\it Teachers$ $\it College$

RESEARCH EXPERIENCE

Current	University of Chicago, Chicago, IL
2016-2017	Graduate Research Assistant, XI Song, Dept. of Sociology Developing an R-application for a bivariate-locational scale model, which improves on current methods for examining intergenerational mobility.
2016-2017	Graduate Research Assistant, KATHLEEN CAGNEY, Dept. of Sociology (1) Performing research and analysis for a project examining the causal effect of crime on BMI and blood pressure using the Dallas Heart Study. (2) Conducting research on the energy consumption and spending of Chicago residents.
2016	Graduate Research Assistant, Jenny Trinitapoli, <i>Dept. of Sociology</i> Supervising a small team of undergraduate and graduate RA's in cleaning the Tsogolo la Thanzi (TLT) data, a longitudinal study of young people's fertility and reproduction in relation to the AIDS epidemic in Malawi.
2015	Junior Data Scientist, James Evans Knowledge Lab, Computation Institute Analyzing hypergraph network data using NetworkX in Python, visualizing the network in Gephi, and developing dynamic web graphics with Javasript for a project examining the social networks of academics.
Jun-Aug 2016	Data Science for the Social Good, Chicago, IL
	Data Science Fellow, Predicting Adverse Police Incidents, White House Police Data Initiative
	Conducting data science research in collaboration with the Metropolitan Nashville Police Department as part of the White House Police Data Initiative to build a generalizable machine learning model to predict police officers at risk of having an adverse incident.
2012-2014	NEW YORK UNIVERSITY, New York, NY
	Research Assistant, Jeff Manza, Dept. of Sociology
	(1) Conducting original research and writing for a book chapter on Occupy Wall Street and public opinion. (2) Conducting background research for the presentation, "A Broken Public? Americans' Responses to the Great Recession," presented at Harvard's Kennedy School, April 2012.
	Research Assistant, Patrick Sharkey, Dept. of Sociology
	Coding historical, journalistic, and geophysical data to assist a future project examining the cognitive impact of psychological stressors on youth in Chicago Public Schools.
2011-2012	Columbia University, New York, NY
2011-2012	COLUMBIA UNIVERSITY, New TOLK, NT

Publishing Assistant: Acquisitions and Subsidiary Rights, $\mathit{Teachers}$

College

Conference Presentations

2017

Mausolf, Joshua G. "Occupy the Government: Analyzing Presidential and Congressional Response to Disruptive Protest." Presented at the Annual Meeting of the American Sociological Association, *Political Sociology* session, August, Montreal.

Mausolf, Joshua G. "Occupy the Government: Analyzing Presidential and Congressional Response to Disruptive Protest." Presented at the Annual Meeting of the Population Association of America, *Computational Approaches to Dynamic Social Processes* session, April, Chicago.

Mausolf, Joshua G. "The Effect of University Prestige on College Sexual Activity." Presented at the Annual Meeting of the Population Association of America, Sexual Identity, Behavior, and Health session, April, Chicago.

2016

Joshi, Sumedh, Jonathan Keane, Joshua Mausolf, Lin Taylor, Joe Walsh, Jen Helsby, and Allison Weil. "Predicting Adverse Police Incidents." Presented at the 4TH ANNUAL DATA SCIENCE FOR SOCIAL GOOD CONFERENCE, August 24, Chicago.

Mausolf, Joshua G. "Occupy the Government: Presidential and Congressional Rhetorical Response to the Occupy Movement." Presented at the 2ND ANNUAL INTERNATIONAL CONFERENCE ON COMPUTATIONAL SOCIAL SCIENCE, *Collective Action* session, at the Kellogg School of Management, Northwestern University, June 25, Evanston.

2015

Mausolf, Joshua G. "Sexual Privilege: The Effect of Private and Elite Campuses on the College Hookup Scene." Presented at the Annual Meeting of the American Sociological Association *Hookup Culture*, roundtable, August 22, Chicago

Mausolf, Joshua G. "Sexual Privilege: The Effect of Private and Elite Campuses on the College Hookup Scene." Presented at the Engendering Change Conference at the University of Chicago, April 11, Chicago

Grants, Awards, and Fellowships

2016-2017	Marshall Field Fellowship in Sociology ($\$23,000$)
Summer 2016	THE ERIC AND WENDY SCHMIDT DATA SCIENCE FOR THE SOCIAL GOOD SUMMER FELLOWSHIP (\$16,500)
2014-2019	The University of Chicago, Social Science Fellowship (\$107,000)

Honors and Distinctions

2010-2012 New York University

Graduation honors: summa cum laude

Official selection: "Best Honors Thesis" Department of Sociology, nomi-

nated for the Phi Beta Kappa - Albert Borgman Prize.

Founders Day Award

Dean's List

2008-2010 Northern Virginia Community College

Graduation honors: summa cum laude

Award of Academic Achievement in Mathematics

NSCS Special Recognition for "Scholarship, Leadership, and Service"

Presidential Scholar

Dean's List

CURRENT MANUSCRIPTS IN PREPARATION OR UNDER REVIEW

2017 Mausolf, Joshua G. "Occupy the Government: Analyzing Presi-

dential and Congressional Response to Disruptive Protest." (Un-

der Review)

Mausolf, Joshua G. "Sexual Privilege: The Effect of University

Prestige on College Sexual Activity." (Under Review)

Mausolf, Joshua G. "Closing the Gender Gap in Executive Compensation? Reviewing the Evidence, 1992-2015" (In Preparation)

SELECTED SCHOLARLY PAPERS

2015 Mausolf, Joshua, Bridgit Donnelly, and Christine Cook. "Predict-

ing Dropouts in Montgomery County Public Schools: A Machine

Learning Approach to Educational Policy."

2012 Mausolf, Joshua G. "Occupy the Whitehouse: Presidential Poli-

tics and the Efficacy of the 99 Percent."

Mausolf, Joshua G. "Environmental Hookups: School Social En-

vironment and the College Hookup Scene."

Mausolf, Joshua G. "Spatial Enslavement: Mass Incarceration and

the Politics of Disadvantage."

2011 Mausolf, Joshua G. "Ethical Racism and the Obamaian Epoch:

Evaluating White Racial Attitudes in a 'Post Racial' Society."

OTHER PUBLICATIONS AND REVIEWS

2016

Mausolf, Joshua, G. "The Unintended Consequences of Border Patrol: How U.S. Immigration Policy Backfired." *Chicago Policy Review*, April 15.

Research Proposals

2015 Mausolf, Joshua G. "Analyzing Presidential Rhetoric and Occupy

Wall Street: A Computational Approach."

2014 Mausolf, Joshua G. "Mapping Network Effects on Self-Perceived

Life Chances of College Freshmen."

STATISTICAL AND COMPUTATIONAL METHODS

R/STATA

STATISTICAL METHODS

Time-series Models:

Autoregressive Fractionally-Integrated Moving Average (ARFIMA), Autoregressive Moving Average (ARMA), as well as OLS, 2SLS, IV, Poisson, and negative binomial time-series models

LONGITUDINAL MODELS:

Mixed Effect Models (MRM) with and without auto-correlated errors for linear, binary, categorical, and multinomial data; Covariance Pattern Models (CPM); GEE models; and multi-level models

MAXIMUM LIKELIHOOD ESTIMATION:

Logit/Probit, Ordered Logit/Probit, Categorical Data Analysis, Multinomial, Negative Binomial, Poisson, Survival Analysis

HIERARCHICAL LINEAR MODELS:

 HLM for use with linear, binomial, and categorical nested, longitudinal, or cross-classified data

LINEAR REGRESSION MODELS:

Ordinary Least Squares (OLS), 2-Stage Least Squares, Instrumental Variables (IV) Regression, Generalized Least Squares (GLS), and General Linear Models (GLM), Bayesian Linear Regression

DIMENSIONALITY REDUCTION:

Principal Components Analysis (PCA), Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA)

GRAPHICAL:

Time-series and regression plots of model predictions versus observations, Margins Plots, Box Plots, Bar Charts, Histograms, Scatter Plots, Line Plots, Lowess/Lfit/Qfit Lines, and combinations of the above to produce clear and compelling visuals of complex data

OTHER ANALYSES OR TESTS:

Bootstrapping, Bagging, Adjusting Analyses for Survey Sampling Weights, ANOVA, MANOVA MANCOVA, One/Two-Sample T-Tests, F-test, Chi2 Test, Cohen's Kappa Test, A/B Testing, Bayesian Information Criterion (BIC), Akaike information criterion (AIC), and Least Log Likelihood, Likelihood Ratio Testing, Cronbach's Alpha, Regression Diagnostics to Assess Proper Model Fit and Specification

Python/R

Computational Methods

REPRODUCIBLE RESEARCH:

Developing a variety of custom Python applications such as machine learning pipelines, web scrapers, text analysis, data cleanup and preprocessing, regular expressions, statistical analysis and graphs, interfacing with other languages (SQL/Linux), and dynamic web development

MACHINE LEARNING:

Logistic Regression, Random Forest, Decision Trees, Boosting, Bagging, Gradient Boosting, Linear SVM, K-Nearest Neighbors, K-fold Cross Validation, Temporal Cross Validation

DATA MINING AND WEB SCRAPING:

Building complex Python and Bash web-scraping packages to navigate static or dynamic pages, pager/index count pages, or dynamic JavaScript pages; parse specified data text or alternate data; and download and organize this data in a custom database, data frame, or file structure

API/JSON QUERIES:

Utilizing Python API queries: examples: Twitter API, Sunlight Foundation API

SQL

Relational Databases:

Using SQL (MySQL, PostgreSQL, SQL) for data storage and complex queries on remote servers. Experience with database schema design, stored procedures, and ETL process from raw data

HTML/CSS

Web Development:

HTML, CSS, Javascript, to design and customize web pages, developing and embedding dynamic Javascript/XML visual objects, building static webpages with Jeckel and dynamic webpages with Flask using a Python and SQL interface. Using R Shiny Apps and Rmarkdown for webpages.

$\mathrm{Bash}/\mathrm{Git}$

OTHER:

Linux, Mac, and Windows Operating Systems, Shell, SSH protocol, Git, RegEx, Vim, Atom, Sublime

Survey Methods and Research Design

R/STATA

Survey Methods and Design

SURVEY WEIGHTING:

Calculation of base weights, unit non-response weights, item non-response weights, and post-stratification weights under a variety of survey implementations or combinations of simple random sampling, systematic sampling, PPS-sampling, stratified sampling, cluster-sampling, or multi-stage sampling using some combination thereof

SURVEY DESIGN AND OPTIMIZATION:

Designing the appropriate type of survey given a fixed budget or variance, desired sample size, expected response rate, and design factor to maximize results

QUESTIONNAIRE DESIGN:

Design of appropriate survey questions, indexes, and scales that meet cognitive requirements under a variety of implementations such as web (CAWI), phone (CATI), in-person (CAPI), and mail; as well as critically analyzing these questionnaires using pre-testing and cognitive interviewing

OTHER RESEARCH DESIGN COMPETENCIES:

Experimental Design, A/B Tests, Focus Groups, Semi-Structured Interviewing, Unstructured Interviewing, Ethnographic Study

Datasets:

General Social Survey (GSS), American Community Survey (ACS), American National Election Survey (ANES), National Longitudinal Survey of Youth 1997 (NSLY97), Project on Human Development in Chicago Neighborhoods (PHDCN), National Immunization Survey (NIS), NORC Presidential Election Study, Online College Student Life Survey (OCSLS), Montgomery County Public Schools Survey, and Lakeside Neighborhood Survey (2015 PAPI), S&P ExecuComp-Compustat

LANGUAGES

LANGUAGES	ENGLISH (native), FRENCH (proficient), SPANISH (elementary) PYTHON, R, STATA, SQL, POSTGRESQL, MYSQL, LINUX, BASH, GIT, VIM, SSH, MARKDOWN, JSON, HTML, CSS, JAVASCRIPT, LATEX
Libraries	Python: Pandas, Numpy, Scikit-learn, SciPy, NLTK, Beautiful Soup, Flask, NetworkX, Matplotlib, Seaborn, Selenium, Tweepy
	R: Tidyverse, ModelR, Caret, Sparklyr, Ggplot, StringR, Rvest, Shiny, Devtools
OTHER SOFTWARE	MICROSOFT OFFICE SUITE: Word, PowerPoint, Access, Outlook, Excel Adobe Applications: Acrobat Pro, Adobe Photoshop, Lightroom Google Applications: Slides, Sheets, Documents, Gmail, Drive Project Management: SAP, CRM, Trello, Slack Visualization and Analysis: Tableau, Gephi, VosViewer, Atlas.ti Operation Systems: Windows, Apple, and Linux

TEACHING

Spring 2017	Teaching Assistant, Machine Learning for Public Policy (principal instructor: Jens Ludwig)
WINTER 2017	Teaching Assistant, Computing for the Social Sciences (principal instructor: Benjamin Soltoff)
	Teaching Assistant, Social Science Inquiry II (principal instructor: Xi Song)

Fall 2016 Teaching Assistant, Computing for the Social Sciences

(principal instructor: Benjamin Soltoff)

Teaching Assistant, Social Science Inquiry I

(principal instructor: Cheol-Sung Lee)

Spring 2016 Teaching Assistant, Statistical Methods of Research II

(principal instructor: Xi Song)

Teaching Assistant, Principal Components and Factor Analysis

(principal instructor: Kathleen Cagney)

ASSOCIATIONS

American Sociological Association Population Association of America National Society of Collegiate Scholars Phi Theta Kappa International Honor Society The University of Chicago Alumni Association New York University Alumni Association

Statement of Interest in Computational Social Science

RSF Summer Institute in Computational Social Science Application

JOSHUA G. MAUSOLF

THE UNIVERSITY OF CHICAGO 2/17/2017

As a budding computational social scientist, I have taken great strides to develop my computational prowess. In this brief statement, I will cover three primary dimensions of these efforts, namely: (1) academic coursework and teaching, (2) professional experience in computation and quantitative research, and (3) my independent research initiatives.

ACADEMIC INCLINATION TO COMPUTATION

Academically, I have gravitated toward computational and quantitative coursework, taking a raft of courses on topics such as machine learning algorithms and applications, relational databases, natural language processing, web scraping, web-applications, time-series, maximum likelihood, longitudinal analysis, and hierarchical models to name a few. Computational courses used a variety of languages including Python, R, SQL, PostgreSQL, Bash, Git, and Markdown. To a lesser extent, these courses also incorporated JSON, HTML, CSS, JavaScript, and Java. Conversely, most statistical courses utilized R or Stata. Below, I highlight an example project from a course I took, entitled "Machine Learning for Public Policy":

Predicting Dropouts in Montgomery County Public Schools. This project applied a machine learning approach to the problem of high school dropouts in Montgomery County Public Schools (MCPS). I collaborated with fellow students Bridgit Donnelly and Christine Cook. We created a scalable ranking system using machine learning that would allow MCPS to target their interventions to individuals most immediately at risk for dropping out of high school. To detail my involvement in this project, I conducted background research on the school districts and merged this data with the student data using PostgreSQL on a remote AWS server. I wrote the majority of the initial machine-learning pipeline, the feature development, and the classifier initiation and evaluation functions, which can be found on Github. Our team effort resulted in finding an appropriate classifier that improved on current MCPS methods. A copy of the report is available online.

Outside of coursework, I have also sought to bolster my methodological skills by acting as a TA in computational and statistical courses. Courses include both graduate and undergraduate coursework such as "Computing for the Social Sciences," "Machine Learning for Public Policy," and "Statistical Methods for Research," among others. These courses include lectures and lab sessions teaching a variety of topics using Python, R, and Stata.

PROFESSIONAL EXPERIENCE WITH DATA SCIENCE AND QUANTITATIVE RESEARCH

Professionally, I have applied my skills to a variety of data-driven opportunities, including graduate research assistantships and data science fellowships. For example, I picked up several graduate research assistant positions during my time at the University of Chicago. While working for Jenny Trinitapoli, I led a team of junior research assistants in cleaning, recoding, and manipulating longitudinal data on the TLT Project. As a graduate RA for Kathleen Cagney, I create data visualization and analysis for several projects, chiefly (1) examining the effect of localized crime on health, and (2) examining energy consumption and spending in Chicago. Yet, my most computationally intensive projects for faculty include work for James Evans and Xi Song.

Under the guidance of James Evans, I served as a junior data scientist at the Computation Institute's Knowledge Lab at the University of Chicago. I assisted on a project which applied named entity extraction on CV's to build a network of academics connected by edges such as a common university, location, or publication in a given year. My major contributions to the project are twofold. First, I wrote Python code using NetworkX to systematically manipulate and configure the existing hypergraph data. A key issue was that many of the edges reflected data for multiple years, such as "1971-1979." Instead of having nine edges, one for each year, only one edge existed. My code created individual edges for each year between every such node, replacing the initial multiyear edge. My code iterates over this network of 523 nodes and 440,493 edges. Using these results, I helped visualize the network in Gephi, where node size corresponds to an academic's betweenness centrality. The network visuals were rendered using JavaScript for dynamic web interaction. I have put these results on my website, available for years (1941-1982).

Lastly, I am currently working on another computational project for Xi Song to develop an R-application for a new statistical model. The model is a bivariate-locational scale model, which improves on current methods for examining intergenerational mobility. In particular, the model will be allow researches to concurrently model two longitudinal distributions, such as the relationship between parental and child income over the life-course or the relationship between individuals income and wealth distributions over their lifetime.

Beyond these research positions for faculty, I have sought data science and computational fellowships. Last summer, I enjoyed the opportunity to collaborate with a wonderful team of computational scholars at the Eric and Wendy Schmidt Data Science for Social Good summer fellowship. As a 2016 fellow, I worked with other fellows on a project for the Metropolitan Nashville Police Department. We worked in close collaboration with a second DSSG team working with Charlotte-Mecklenburg police. Collectively, our goal was to develop a comprehensive machine learning pipeline to predict adverse police incidents both at the officer level and dispatch level. A major part of this project was designing a common database schema that would allow reproducible ETL for both departments and any future police departments. In this way, we could create a generalizable machine learning pipeline. My major contributions included generating model evaluation code and database schema using Python and PostgresSQL, launching the Python web app, refining ETL for ACS data, and assisting in the feature generation. The public repository for the project is available on Github. Collectively, our results significantly improved over existing methods of identifying officers at risk of adverse incidents, and both departments are working to implement our models.

INDEPENDENT QUANTITATIVE AND COMPUTATIONAL RESEARCH AGENDAS

Beyond my professional research and fellowship activity in computational and quantitative social science, I have pursued computational and quantitative approaches in my own research, both current and future. Here, I focus on my work to understand the effect of social movements on presidential and congressional discussion of inequality, which I have included as a writing sample.

Analyzing Political Rhetoric of President Obama and Congress. Originally, this paper grew out of several computational courses, wherein I developed Python and Bash web-scrapers to collect all presidential speeches and congressional records from 2009-2015. In sum, the text corpora consisted of 6.62 million and 187.70 million words for President Obama and Congress, respectively. I subsequently created a dataset from those corpora using natural language processing with Python. Using this data, I examined fluctuations in rhetoric on inequality in relation to the number of Occupy Wall Street protesters arrested, media coverage of the Occupy movement, and other covariates controlling for public opinion, political climate, and the economy. I used time-series analysis, particularly ARFIMA models to conduct the study. Theoretically, I challenge the existing paradigm that movements are meaningful only in how they effect legislative or policy gains, suggest that rhetorical gains should instead be considered, and argue that the role of the president should be at the forefront of the analysis of social movements. Ultimately, I demonstrate (1) that the arrests of Occupy protesters not only predict media coverage

but also increased discussion of fairness and inequality by President Obama and Congress, (2) that the president's rhetorical shift influences congressional discussion, (3) that this phenomenon persists after the movement faltered, and (4) that Occupy's use of disruptive protest best predicts this rhetorical response, all else equal. The project is currently under peer review, and I have presented and will present this paper in several computationally focused conference sessions, including a presentation at the 2nd Annual International Conference for Computational Social Science and an upcoming presentation in the "Computational Approaches to Dynamic Social Processes" session at the annual meeting for the *Population Association of America*.

Future Research. Building off the Occupy paper, I plan to expand my emphasis on economic inequality. Although the study of inequality can fundamentally be thought of through the lens of (1) a dichotomy between the poor and affluent or (2) an understanding the conditions engendering the penurious, I propose an alternative perspective. Rather than a distributional or left-tail perspective on inequality, I will examine new empirical boundaries to understanding the maintenance, making, and mobility of American elites as part of a dissertation agenda. In particular, I intend to explore the following topics: (1) Discrimination in Elite Labor Market Entry and Transfers, (2) CEO Networks and Executive Compensation, and (3) Intergenerational Income and Wealth Mobility.

I intend to experimentally examine elite labor markets, namely professional service and technology firms, which are seen as contemporary gateways to top incomes and corporate leadership. In particular, I assess labor market discrimination in terms of race and gender relative to a candidate's university prestige, degree field, and technical skills. In part, the lack of diversity among top firms is blamed on a pipeline problem, which suggests that top firms lack diversity not because they are biased, but rather because of a dearth of qualified diversity candidates from top-four schools. Given perfectly qualified candidates, does discrimination still exist, and at lower levels of prestige, where do differences occur? I intend to see to what degree prestigious qualifications (in university degree, major, and technical skills) create advantage in elite labor markets at different career stages. Methodologically, I intend to utilize online correspondence tests. I will use a variety of computational approaches to assist in generating application materials for job applicants, as well as finding and applying to available jobs. Additionally, I am open to exploring alternate approaches using online experiments for this question.

Next, I will analyze the role of executive network centrality using the concept of N-dimensional interlocks to adjudicate several competing theories of executive compensation, particularly the ways in which benchmarking interacts with interlocks and executive social networks, broadly defined. Currently, I need to collect social network data to match with the executive compensation data I have from ExecuComp Compustat, 1992-2015. Analysis will utilize both network methods and time-series approaches. The collection of network data, if not available from institutional datasets, may include implementing web-scraping and named entity extraction. Beyond exploring the relationship between network centrality and compensation, I envision additional projects such as using machine learning and time-series models to predict executive leadership, promotion, and pay.

Lastly, I seek to assess the life-course accumulation of wealth and its intergenerational transmission, particularly the role of financial literacy, investment behavior, and portfolio composition. Additionally, this work will seek to examine the relation of income versus wealth over the life-course, using the bivariate-locational scale model I am developing with Xi Song. A key process will be simultaneously examining income and wealth distributions, particularly the positive divergence of wealth from personal income, as might occur from regular savings and investment versus high consumption. Here, I envision a twofold process, wherein I first use a temporally validated machine learning model to predict positive wealth divergence, and second utilize the bivariate locational scale model to confirm the statistical significance and causality of top-ranking features. While a variety of survey data exists targeting wealth and income, an ideal solution would be adopting Matthew Salganik's approach of data linkage, a strategy likewise suggested by Russell Sage Foundation's recent call for computational proposals. Ideally, we could connect existing survey datasets with investment portfolio behavior from banking and investment institutions. In this way, we could have more granular data on individual financial decisions and develop more robust models than those that rely solely on survey data.

Occupy the Government:

Analyzing Presidential and Congressional Response to Disruptive Protest

JOSHUA G. MAUSOLF 1

THE UNIVERSITY OF CHICAGO 2/17/2017

Abstract

In this study, I examine the role of Occupy Wall Street in shifting government discussion of economic fairness and inequality. Using data from 4,646 presidential speeches and 1,256 congressional records collected between 2009 and 2015, I test for the mechanisms of disruptive protest, media coverage, public opinion, and presidential agenda setting by applying a novel combination of web scraping, natural language processing, and time series models. I challenge the existing paradigm that movements are meaningful only in how they effect legislative or policy gains, suggest that rhetorical gains should instead be considered, and argue that the role of the president should be at the forefront of the analysis of social movements. Ultimately, I demonstrate (1) that the arrests of Occupy protesters not only predict media coverage but also increased discussion of fairness and inequality by President Obama and Congress, (2) that the president's rhetorical shift influences congressional discussion, (3) that this phenomenon persists after the movement faltered, and (4) that Occupy's use of disruptive protest best predicts this rhetorical response, all else equal.

Keywords

social movements; disruptive protest; protest efficacy; political mediation/rhetorical response; inequality

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I would like to thank James Allen Evans, Jenny Trinitapoli, John Brehm, John Levi Martin, and Stephen Raudenbush at the University of Chicago and Jeff Manza at New York University for their guidance and support on this project.

¹ The University of Chicago

Occupy the Government: Analyzing Presidential and Congressional Response to Disruptive Protest

Pounding the airwaves with a rhapsodic promise of change, the campaign of Barack Obama resonated with average Americans' political and financial frustrations in the wake of the Great Recession. Yet, change never seemed to transpire, and the roots of discontent that bore the presidency slowly fomented as Wall Street recouped its loss atop the backs of American taxpayers, many of whom still faced harsh economic realities in early 2011 (Gould-Wartofsky 2015; Gitlin 2012). Occupy Wall Street arguably mobilized this discontent and frequently indicted President Obama's commitment to economic equality (Brown 2011; Panagopoulos 2011). With a resounding reframe, "Obama ain't no socialist! We are! We are!"—the protesters not only criticized the president at their rallies, but also heckled the president at his events (Memmott 2011). The president, it seems, has been listening. Since the emergence of Occupy, President Obama amplified his call to equality, arguing that every American deserves a fair shot and all should pay their fair share, a phenomenon duly noted by political commentators (Henninger 2011; Silver 2012). Congress, to a lesser extent, has also joined the fray. Given these observations, I ask (1) what quantifiable role did Occupy have in shifting political rhetoric on economic fairness and inequality by President Obama and Congress, (2) what was the duration of this shift, and (3) how can we best measure the mechanisms of this transformation?

In this paper, I challenge the existing paradigm that movements are meaningful only in how they effect legislative or policy gains. Instead, I argue that a movement's ability to elevate its ideas into the discussion of our nation's highest officials—who have limited words and limited time—reflects a victory and has significant potential to alter the national salience of the movement's cause. Second, my analysis brings the role of the presidency to the forefront, and I challenge the traditional examination of movement efficacy in achieving congressional legislation without also considering the agenda-setting role of the president in effecting change. Third, rather than disambiguating movement activity into particular actor-oriented tactical mechanisms (McAdam and Su 2002), I illustrate how a movement's arrest activity can serve as a singular meaningful measure of disruptive protest and be used to predict rhetorical gains. Lastly, I demonstrate these results by leveraging a novel combination of computational and statistical models in an effort to help pave the groundwork for movements research in the era of big data. Before I dive into the details of the study, I will first outline the theory and hypotheses of my research. Subsequently, I will articulate the methods, present my analysis, and discuss the implications of the work.

SITUATING OCCUPY WALL STREET IN MOVEMENTS RESEARCH

In September 2011, the Occupy Wall Street movement quickly swept the United States and spread across the globe, most infamously with its entrenched encampments in the heart of Wall Street's Zuccotti Park. The protests received extensive media coverage, particularly for their disruptive tactics, arrests, and violent confrontations between protesters and police (Calhoun 2013; DeLuca, Lawson, and Sun 2012; Xu 2013). According to Occupy Wall Street, its purpose is 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

² Quote recorded by the author on November 17, 2011 at the Brooklyn Bridge entrance during an evening rally by Occupy Wall Street after their upheaval from Zuccotti Park.

2011). In short, the movement discursively adapted the widely-circulated worldview of an economic ruling elite, a topic discussed to varying degrees and qualification across sociological and political science research (*c.f.* Bartels 2008; Domhoff 2010; Gilens 2005; Hacker and Pierson 2010; Peters 2013; Picketty and Saez 2007). Some analysts argue that Occupy has had effectively no influence on public opinion even if the plurality are favorable to the "progressive taxation" proposed by the president (Bartels 2012). Yet, other commentators have credited the movement with transforming the nation's awareness and understanding of economic inequality (Berman 2011; Klein 2011; Krugman 2011b). If Occupy shifted awareness of inequality, how was this change achieved and how can we understand its efficacy as a social protest movement?

Toward a New Paradigm of Movement Success

Social protest movements evolve upon a change in consciousness about some transcendent social "issue"—an awakening of Mills "sociological imagination"—coupled with a newfound action upon that change in consciousness that can best be capitalized upon through disruptive action (Mills 1959; Piven and Cloward 1979:3-5; Piven 2006). Under "political mediation theory," we can view social movements as a force that politicians attempt to mediate depending upon how beneficial or detrimental assuaging the protest's request would be to political and business interests (Amenta 2006:14; Giugni 1999). When politicians find little advantage or are opposed to the underlying issues, they introduce new proposals and parallel rhetoric to pacify the movement until the protest inevitably falters (Amenta 2006:26; Piven and Cloward 1979).

Although movement success can be assessed by specific policy gains (Gamson 1990), an alternate approach may offer a more viable solution. We must therefore consider its "collective benefits" which are often unknown, at first undefined, and only later perceptible long after the movement has withered and its goals have faded (Amenta 2006:32; Tilly 1999:268-9). For example, movements frequently generate "unintended social or cultural consequences" such as the demographic changes in the baby boomer generation following the 1960s protests (McAdam 1999:117-8). Fundamentally, the way society perceives a social issue may evolve in the wake of a social movement, and this remains one of the ultimate goals of protest beyond its immediate ends (Giugni 1999:xxx; Goodwin and Jasper 2003:348-9). Therefore, one fundamental measure of movement success is the degree to which it alters the public's awareness and perception about the issue it seeks to change. Contra claims that Occupy was a "moment not a movement" (Calhoun 2013; Gitlin 2013a), I posit that the Occupy Wall Street movement can be thought of not only as an dynamic of exchange and mediation between the protesters, the president, and Congress but also as one having far reaching effects upon both the protesters and American society itself, even if these changes are not yet fully realized in public opinion or public policy. Indeed, some reports already indicate that the lingo of Occupy has permeated our cultural lexicon (Alim 2013; Gitlin 2013a; Stelter 2011). In advocating an issue to the American public, "a president enhances [its] public salience" (Canes-Wrone 2006:23). From this perspective, the president's words—broadcast and re-aired over international wavelengths and extensively quoted and recapitulated in the world's media-serves as a tangible and prominent mechanism by which Occupy's ideas may be disseminated and take on a lasting legacy in American culture. Beyond directly influencing Americans' perception of an issue, the agenda set by the president can likewise influence the debate witnessed in Congress (Edwards and Wood 1999). The conversation by Congress on these issues can further sway Americans understanding of inequality. Analyzing the degree to which Occupy Wall Street may have catalyzed a shift in presidential and congressional rhetoric therefore offers an alternative sociological framework for assessing movement influence.

To help facilitate understanding of the complex political dynamics at play, we can situate some of the many possible ties in a field-theoretic framework, as displayed in Figure 1.

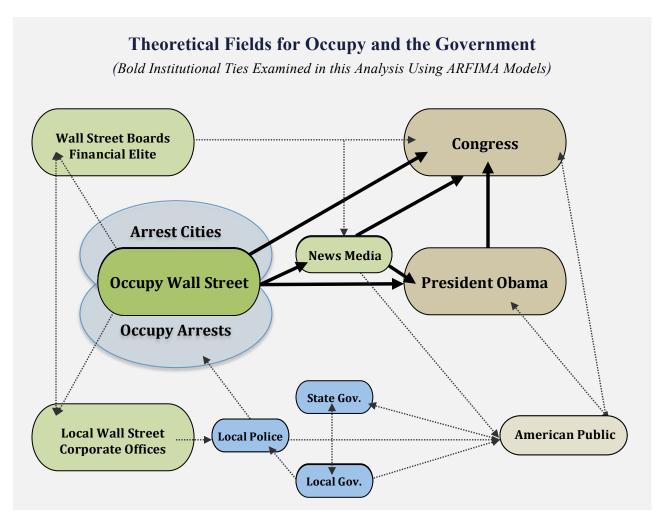


Figure 1. Theoretic Fields for Occupy and the Government (Bold Ties Modeled in Analysis)

Note: Original graphic and application by the author. Figure represents some of the agents and possible directed ties between institutions. In this paper, I focus on the subset of connections designated by bold ties. I return to the modeled results in Figure 5.

For the purposes of this analysis, I focus on the key relationships, designated by bold arrows in the diagram, namely: (1) Occupy \Rightarrow Obama, (2) Occupy \Rightarrow Congress, (3) Occupy \Rightarrow News \Rightarrow Congress, and (4) Occupy \Rightarrow News \Rightarrow Obama \Rightarrow Congress. Although the president can drive congressional discussion, he is believed to react to world events and media attention (Edwards and Wood 1999). Considering media is especially paramount given the amplification it can lend to movement success (Andrews and Caren 2010). Although I model these explicit relationships, I note that these ties are concurrently embedded in a complex field-space where politicians can be conceived as rational agents.

Under this conceptual framework, which borrows from Fligstein and McAdam's (2011) theory of "strategic action fields," a political actor can take on multiple roles depending on the field in question. Relative to Occupy's endgame of balancing economic power, we recognize that the field of interest is in fact ideological. Here, the president implements a strategy of political mediation—one that while

propitiating Occupy Wall Street—simultaneously appeases the ruling elite and benefits President Obama by obviating the inchoate group from forming a powerful political threat in the vein of the Tea Party. In this light, President Obama walks the fine line of maintaining the existing system of economic capitalism benefiting Wall Street while simultaneously espousing an antagonistic rhetoric toward the group whose resources he needs come campaign season (Domhoff 2010:166; Kuttner 2010:15).

In contrast to the acute relationship between Occupy Wall Street and President Obama, the case of Congress differs in ideology and propinquity to Occupy. Whereas Occupy Wall Street directly disparaged and heckled the president on several occasions, any one member of Congress did not equally face the same level of exposure and criticism. Thus, the burden of pacifying unrest and ameliorating criticism unusually befalls the president. His rhetorical response in turn may be viewed as a both a reply to Occupy and also an impetus that any member of Congress may either extol or rebuff depending on their political affiliation. Beyond engaging with the president, legislators may also directly respond to the Occupy movement. Because members of Congress rely on corporate campaign contributions (Hacker and Pierson 2010), Congress faces many of the same political constraints as the president, but for reasons noted, may differ in their response. Understanding how President Obama and Congress navigate complex political space relative to Occupy Wall Street, the ruling elite, the American public, the media, and reelection campaigns illuminates the seemingly paradoxical pattern of presidential and congressional response to Occupy Wall Street. This leads to the first hypothesis:

Hypothesis 1: There will be a statistically significant increase in the discussion of Occupy's objectives by President Obama and Congress in the period after the movement began as compared to the period before Occupy.

In part, this hypothesis stems from the idea that Occupy Wall Street presented a potential threat to both the economic system and President Obama's political solvency in the 2012 election (Oxford Analytica 2011). To a lesser degree, legislators might be expected to respond particularly if their political platform aligns with Occupy or if their district or state is more directly affected by the protests. Political mediation theory suggests that because Occupy Wall Street presented a potential threat, the strategic choice was to mitigate the potential risk by temporarily adopting a parallel rhetoric until the movement faltered (Amenta 2006).

Quelling the Occupy Movement Through Rhetoric

In order to deploy political mediation, politicians must first have some sense of the movement's demands. Ostensibly, Occupy's mission statement exemplifies themes of animus toward Wall Street, the financial collapse, corporate coercion over politics, economic inequality between the top 1% and everyday citizens, and how collectively, those enjoying the benefits of this unfair system should pay their fair share (Occupy 2011). Surveys, interviews, and computational analysis reiterate that these ideas comprise Occupy's key interests (DeTar 2012; DeLuca, Lawson, and Sun 2012; Gould-Wartofsky 2015; Krugman 2011a; Milkman, Luce, and Lewis 2013a-b). If the expected response to disruptive protest is discussion of the movement's objectives, politicians will leverage the best information available, to which point, the movement's mission statement and reports echoing these claims reflect a viable source. I operationalize my work by examining political rhetoric for the discussion of these same topics.

Linking Occupy's ideological goals to a framework of political mediation, we must also weigh how the tactics used by Occupy lend further credence to Hypothesis 1. Consider the highly volatile protests, which included devastating police brutality that spanned both coasts; mass arrests of hundreds of protesters; disruptive obstruction of businesses, mass transportation, and highways; as well as violence instigated by the protesters against police (Associated Press 2011; Cherkis 2011; New York Times 2012;

Nir 2011). In sociological literature, particularly violent or threatening mobilizations have been more successful in garnering favorable outcomes, including legislative votes (McAdam and Su 2002; Steedly and Foley 1979). Similarly, *disruptive* protests and *violence by police* against protesters yield increased congressional voting to address the concerns of protesters (McAdam and Su 2002). In the case of Occupy, the protests largely adopted the latter pattern by using disruption such as obstructing the Brooklyn Bridge or conducting sit-ins inside or in front of multinational banks. Police were repeatedly criticized for brutality against protesters including excessive use of force (DeLuca, Lawson, and Sun 2012; Gitlin 2013a-b). Although McAdam and Su's (2002) study pertains to congressional voting and action rather than rhetoric, we can infer that if there is an increased likelihood of favorable roll call votes, there will also be an increased likelihood of favorable rhetoric preceding those votes. In general, the debate surrounding the protests increases. Collectively, the same mechanisms that McAdam and Su (2002) identify as efficacious for Congress suggest that disruptive protests by Occupy will also be more likely to achieve increased presidential discussion of the movement's objectives, formally:

Hypothesis 2: There will be a positive chronological association between Occupy arrest activity and discussion of Occupy's objectives by President Obama and Congress in the hours and days following the event.

This hypothesis draws much of its sociological veracity from the above discussion, particularly when we view the protests-violent or otherwise-as a form of communication with the status quo-of which, President Obama is part and parcel. Effectively, the interchange between a social protest movement is a constant "dialogue" of exchange, wherein the actions of politicians can influence social movements, and protesters can conversely challenge and influence state actors (Meyer, Jenness, and Ingram 2005:302). Thus, both the protests and government rhetoric can be understood as communication. We would expect this communication to increase—just as any response—in the hours and days following a protest event, especially if the protest were marked by extreme disruption or violence. Scholars have coined the term "tactical innovation" - a sort of arms war of protest theatrics where protesters evolve in evermore extreme ways to gain leverage and provoke progress while the powers at be evolve to enervate the escalating disruption (McAdam 1983). Tactical innovation and movement mobilization are particularly acute for multi-issue or "hybrid" movements (Wang and Soule 2016; Heaney and Rojas 2014), as was the case for Occupy, which fought for many specific ideas within the domains of economic and political inequality (DeTar 2012; Krugman 2011b; Milkman, Luce, and Lewis 2013a). Furthermore, a movement's ability to be flexible, spontaneous, inventive, and collaborative is integral to their success (McCammon 2012; Snow and Moss 2014; Wang and Soule 2012). In part, Occupy's use of social media such as Twitter and Facebook helped facilitate the spontaneous collective action and disruptive mass mobilization that engendered widespread arrests across the country (DeLuca, Lawson, and Sun 2012; Gaby and Caren 2012; Gamson and Sifry 2013; Snow and Moss 2014).

In turn, political mediation theory suggests that politicians will orient their rhetoric toward the movement's objectives (Amenta 2006). These dynamic responses to mobilization inevitably follow cyclical chronological patterns wherein increases in favorable outcomes ensue escalating protest events—as was the case in the Civil Rights Movement, the Vietnam War movement, or the Women's Suffrage Movement (McAdam 1983; McAdam and Su 2002; McCammon 2003). While these studies do not apply this logic to presidential rhetoric, I submit that the observed "reactive relationship vis-à-vis the movement" pattern of "tactical innovation" evident between the federal government and these protesters similarly unfolds between Occupy Wall Street, the president, and Congress (McAdam 1983:746). Considering the complex political dynamics at play, we understand that the reciprocal dynamism between government and the movement may not only reflect a strategic vitiation of Occupy's political

threat but also a tactic of maximizing the president's political gains by channeling progressive rhetoric at heightened periods of public awareness.

If we consider the high-profile dramatism of the protests splashed across major news networks and print, we can see how strategic framing of progressive rhetorical response garners greater traction when deployed in the immediate aftermath of the day's event. Occupy Wall Street, therefore, also presented President Obama with a newfound opportunity (Krugman 2011a). According to presidential historians such as David M. Kennedy and Douglas Brinkley, President Obama strategically vied throughout his first term to write his place in history as a "transformative figure" (Kantor 2012). But between the summer of 2010 and 2011, President Obama was vexed by public opposition, the nettlesome thorn of the Tea Party Movement, and the debt ceiling debate (Kantor 2012). During a dinner in July 2011, these historians, fully aware of President Obama's historical goals, adjured the president to adopt a progressive model of attack against republicans in the spirit of Theodore Roosevelt (Kantor 2012). I argue that Occupy Wall Street presented the ideal opportunity for President Obama to capitalize on this recommendation. Thus, while political mediation presents one potential explanation to Hypotheses 1 and 2, these hypotheses can also be seen as an act of political opportunism. Traditionally, shifts in favorable rhetoric—and especially policy—are most likely to transpire when it is expedient for the political interests at hand-in this case, for President Obama's legacy and reelection campaign (Amenta 2006; Piven and Cloward 1979). This leads to the following:

Hypothesis 3: If Hypotheses 1-2 are true, the increase in President Obama and Congress's rhetoric will be causal to the Occupy Wall Street movement, namely:

*H*3_{*A*}: The rhetorical shift followed the onset of Occupy Wall Street.

*H*3_{*R*}: The rhetorical shift lingered after the decline of Occupy Wall Street.

*H*3_{*c*}: The rhetorical shift is best explained by the onset of Occupy Wall Street versus the controls.

If historians are correct in chronicling the president's—at least partial motive—to cast himself in the role of a transformative president (Kantor 2012)—then echoing the rhetoric of the movement in its immediate aftermath maximizes the speeches' utility. Theoretically, these hypotheses draw a salient point. If the president and Congress simply wish to appease the movement through political mediation, debate about inequality should also cease with the movement. If however, the president has a vested interest in the movement's ideology and wishes to curate his legacy, those ideas should persist even if somewhat abetted for the duration of the presidency.

Collectively, this study builds on the framework of social movements in the context of political mediation and rhetorical response to disruptive protest, which I operationalize using Occupy arrest activity. I hypothesize that Occupy arrest activity will predict presidential and congressional discussion of economic fairness and inequality, especially when considering the role of Occupy in news coverage and secondary impacts of these changes. Through this analysis, I challenge the paradigm that movement success is meaningful only in policy gains. I instead argue that rhetorical gains deserve equal consideration, particularly with respect to the role of the president, who has unparalleled potential to elevate the national salience of an issue. I posit that a presidential rhetorical shift will not only exemplify a dynamic response of political mediation to Occupy but also reflect President Obama's capitalization on a political opportunity to recast the economic dialogue and thereby help him craft his historical legacy as president.

DATA AND METHODS

To evaluate these hypotheses, I employ several data sources including text data from the president's speeches and remarks and the congressional record. I analyze the discussion of inequality in these texts relative to the number of Occupy Wall Street protesters arrested and alternatively, the number of cities with Occupy arrests. Below, I specify these measures.

Dependent Variable Data Collection – Presidential and Congressional Speeches

President Obama's speeches and remarks were collected from the White House, Office of the Press Secretary's public website. As a matter of notation, I use the terms "speeches" or "speeches and remarks" to designate the dependent variable. Although the White House has an explicit definition of "speeches and remarks" (White House 2016a); I use the term more broadly to also include weekly addresses (2016b); statements, letters, memos, op-eds (2016c); and select press briefings (2016d). In all categories, I restrict the speeches to that content publicly spoken or attributed to the President. I do not include speeches and remarks by other parties such as the First Lady, Vice President, or members of the administration.

To collect these speeches and remarks, I developed a web-scraping application written in *Python* and *Shell* (Author 2016a).³⁻⁴ In short, web scraping is a computational method to automate the selective extraction and download of internet content. With respect to President Obama, this yields 4,646 speeches between January 21, 2009 and November 15, 2015. This package has multiple quality control measures to ensure proper content. For example, when trying to parse each speech URL, the package evaluates the resulting word and paragraph length to determine if the content was properly extracted from *HTML*. It also checks the date and other metadata characteristics. If errors occur, a series of alternate parser specifications recursively attempt to collect the data and reevaluate for proper content. Where errors cannot be automatically resolved, the errant URLs are added to a separate file, which I collected manually. Although the president is often the sole speaker during a speech, in many cases he shares the floor with another foreign diplomat, the Vice President, the First Lady, reporters, or audience members who, at times, speak at length or ask directed questions. To avoid conflating these lines of text with the president's, I examined each of the president's speeches by hand, removing lines and paragraphs not spoken by the president. The results reflect a high quality corpus of speech data for the entire Obama presidency.

Similarly, I collected the Congressional Record, which documents all the speeches and proceedings of Congress (both House and Senate) on days where Congress is in session (United States, Government Printing Office 2016). For each day of the congressional record, a PDF exists. To download and convert these files to raw text, I developed and executed a second web-scraping application (Author 2016b).⁵

Keyword Extraction

Subsequently, I implemented code to analyze each presidential and congressional record for specific keywords and phrases related to my research question and Occupy's interests (Author 2016c).⁶

 $^{^3}$ This package automatically opens a web-browser, navigates the various White House primary domains (2016a-d), saves every speech URL in a spreadsheet (N \approx 15,900 URLs); sorts these URLs based on primary speaker; and then parses that speech, saving it with a unique filename in designated folders.

⁴ The code is open source and will be linked upon publication. It is omitted for the purposes of blinded peer review.

⁵ Ibid.

⁶ Ibid.

This package builds a dataset consisting of a speech ID, speech date, summary statistics for the speech, and numerous keyword counts per speech for pre-specified, theoretically-driven words and phrases expected to change in response to Occupy Wall Street (Appendix B). After running this script, the resulting dataset has the following specifications:

Table 1. Descriptive Statistics of Text Data, 2009-2015

	Total Speeches	Total Files	Total Words	
Presidential Speeches	2053	4646	6.62 million	
Congressional Record	1256	1256	187.70 million	

Sources: Speech terms taken from the U.S. congressional records and the White House records (United States, Government Printing Office 2016; White House 2016a-d) The data was downloaded and keyword terms were counted for each category using replicable Python and Bash scripts (Author 2016a-c).

Measuring Occupy Wall Street Arrests

Data on Occupy Wall Street arrests came from an online database (OccupyArrests 2014). The dataset details the number, date, and city of arrests, with a description and linked source. In total, 7,775 arrests are included across 452 incidents. For the analysis, I employ both the number of protesters arrested and the number of cities with arrests, which while related, are theoretically and numerically discrete.⁷ To validate the data, I selected a random subsample of 45 incidents, investigating the links to corroborate both the date of arrest and the number arrested. I further substantiated the results by verifying this data from multiple sources. In terms of accuracy, 91% of the cases matched perfectly in date and number arrested. In no cases were the numbers overestimated. The only errors were in the date of arrest, which differed by only one day where the four errors occurred. Theses errors reflect disparities between when the news reports were published versus when the arrests transpired. Beyond 91% accuracy, the data subsample and my results are highly correlated (r = 0.994, p<0.001) and have a Cronbach's Alpha, $\alpha = 0.997$. In terms of inter-coder reliability, my analysis reveals a Cohen's Kappa, $\kappa = 0.881$ (p < 0.0001) between my collected arrest sample and the random subsample of original data. In sum, these metrics illustrate the high quality of the arrest data.

Data Preprocessing and Control Variables

Prior to analysis, I compiled the full dataset to include the extracted keywords of the presidential and congressional speeches. Because multiple presidential speeches often occur on a given date, presidential data was collapsed onto a daily scale and was merged with the other covariates. Other covariates include metrics of U.S. public awareness or interest in (a) Occupy Wall Street and (b) income inequality (provided via Google Trends); political factors such as the president's approval rate and whether the president was campaigning in the 2012 election; economic indicators (namely the S&P 500 index and the national unemployment rate); and lastly media coverage of Occupy Wall Street, chiefly (a) the number of front-page news articles from major world newspapers about Occupy, and (b) the number of select online news articles featuring Occupy Wall Street (see Table 2 for further details). While some covariate data was on a daily scale, the remaining data was converted to a daily scale using the last known value.

 $^{^{7}}$ Although significantly correlated ($\rho = 0.58^{***}$, p < 0.001), arrests versus arrest cities are discrete variables and have different event histories. For example, Occupy arrests peaked on October 1, 2011 with the occupation of the Brooklyn Bridge (700 arrests) whereas the number of arrest cities peaked on November 17, with 514 arrests transpiring across 14 American cities.

⁸ The use of newspapers in movement research is frequent (c.f. Earl et al. 2004; Kim and McCarthy 2016; McAdam and Su 2002).

Table 2. Descriptive Statistics of Study Variables, 2009-2015

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Sources: (1) Speech terms taken from the U.S. congressional records and the White House records (United States, Government Printing Office 2016; White House 2016a-d) The data was downloaded and keyword terms were counted for each category using replicable Python and Bash scripts (Author 2016a-c). (2) Occupy Arrests (2014). (3) Google Trends (2015a), search term "Occupy Wall Street". (4) Google Trends (2015b), search term "Income Inequality". (5) Rasmussen Reports (2016). (6) Date President declared 2012 Campaign through Election Day, November 6, 2012. (7) S&P Dow Jones Indices (2015). (9) United States, Department of Labor (2016). (10) LexisNexis Academic (2016), search of *Major World Newspapers for tag OCCUPY WALL STREET, all outlets included, N = 134 front page articles in total. (11) LexisNexis Academic (2016), search of *Web Publications Combined for tag OCCUPY WALL STREET. Selected online publications were WashingtonPost.com, The Atlantic Online, Politico.com, and CNN.com, N = 103, 114, 112, and 112 articles, respectively.

Note: ‡: Variable imputed to carry over last known value. S&P500 value carried over from last market close; Google trends (weekly-measured variables) value applied to all days that week. Unemployment rate for month applied to every day of the month. Polls reflect the latest known data until a new wave of data is released.

For example, markets were assumed to be at the Friday closing price over the weekend, unemployment for the month reflects the latest monthly estimate by the Bureau of Labor Statistics, and polling data reflects the latest poll until new results are collected. Imputation did not carry forward indefinitely, however, and I therefore limit the analysis date to November 15, 2015, after which point not all data exists. While this form of imputation is ideally avoided, avoidance leads to alternate suboptimal results, namely ignoring speeches for a large swath of the presidency or dropping covariates from the model. In addition to these justifications, the imputation using the last known value is theoretically expedient. If the president or congress is expected to alter speeches in response to any of the covariates, that action is best predicated by using the last known value.

Lastly, I transformed the speech keyword data in two primary ways: (1) aggregating the theoretically related keywords into discrete categories through row addition and (2) using principal components analysis (PCA) on the keywords for each topic, chiefly the first principal component (highest ranking eigenvector) was used to analyze each category. By using dimensionality reduction, PCA has the added benefit of capturing potential latencies reflected across keywords. In sum, I analyzed the following speech categories: *Inequality, Fair Share, Wall Street,* and *Corporate Greed.* Beyond mirroring Occupy's objectives, as an open source analysis, my approach is modifiable and replicable. Summary statistics for the data are described in Table 2. Next, I turn to the formal analysis.

Formal Analysis

To analyze the data relative to my hypotheses, I conduct statistical analyses, beginning with descriptive statistics and F-tests to establish whether *Hypothesis 1* is upheld with respect to the speech categories. For speech categories passing this litmus test, I further explore bivariate analyses and multivariate modeling using time series regression, specifically the ARFIMA model, or autoregressive fractionally integrated moving average model, which accounts for the long-run autoregressive qualities prevalent in political and protest events.

Modeling Speech with "Long-Memory" Fractional Integration Models

In time series analysis, fractional integration reflects a broader class of "long-memory" time series models that hold particular promise for modeling political phenomena (Box-Steffensmeier and Tomlinson 2000). The ARFIMA model improves upon a deficiency of the more-prevalent ARIMA model, which allows the differencing parameter, d, to only take the value 0 or 1 (Box-Steffensmeier and Tomlinson 2000)¹⁰. Instead, d represents any real number in ARFIMA, where a value of $d \in (0, 0.5)$ is said to have finite variance and demonstrate long-memory, or more precisely, a "long-range positive dependence" (Baum and Wiggins 2000; Granger 1980). As a result of allowing fractional integration, the ARFIMA model presents a comparatively conservative modeling strategy that is more robust to misspecification than the errors that can occur from incorrectly using the restrictive differencing assumptions found in ARIMA (Lebo and Grant 2016). ARFIMA (p, d, q) models take the form:

$$\Phi(L)(1-L)^d y_t = \Theta(L)\epsilon_t \tag{1}$$

⁹ The first principal components had eigenvalues and (proportions of explanation) as follows: (a) Inequality - President: 5.02 (0.11); (b) Inequality - Congress: 10.95 (0.22); (c) Fair Share - President: 2.82 (0.47); (d) Fair share - Congress: 1.96 (0.32).

 $^{^{10}}$ In the ARIMA model, the parameters are p, d, and q. The parameter d may take the value 0 or 1, such that a value of 1 is said to be integrated and a value of 0 is said not to be integrated, and this case is alternatively referred to as an ARMA model (Box-Steffensmeier and Tomlinson 2000). For further discussion of the benefits of fractional integration and its application to social science research, see Lebo and Grant (2016) and Lanier and Dietz (2012).

where the errors (ϵ_t) are distributed approximately normal ($0, \sigma_\epsilon^2$); $\Phi(L)$ and $\Theta(L)$ reflect the autoregressive and moving average terms, respectively; (L) indicates the lag or backward-shift operator; and $(1-L)^d$ represents the fractional differencing operator (Box-Steffensmeier and Tomlinson 2000; Box-Steffensmeier and Smith 1998; Contreras-Reyes and Palma 2013). The autoregressive (2), moving average (3), and fractional differencing operator (4) terms can be expanded as follows (Baum and Wiggins 2000; Baum 2013):

$$\Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p \tag{2}$$

$$\Theta(L) = 1 + \vartheta_1 L + \dots + \vartheta_q L^q \tag{3}$$

$$(1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)}$$
(4)

In my analysis, I calculate the ARFIMA models with specifications of AR1, AR2, and MA1 terms, leaving a final ARFIMA (2, *d*, 1), where the differencing parameter, *d*, is optimized. For robustness, I calculated the ARFIMA models of both (1) the keyword count and (2) the first principal component (PCA) of the count data. In this way, I can evaluate not only the direct keywords but also the latent quality reflected across multiple keyword categories. Although some scholars utilize Poisson models (*c.f.* McAdam and Su 2002), the Poisson is inappropriate in this case because the presidential and congressional data are over-dispersed. Negative binomial models offer an alternative but fail to adequately address long-range persistence, although it should be noted that testing these models yielded similar results to the ARFIMA models.¹¹ To draw on the rationale of Box-Steffensmeier and Tomlinson (2000) and Zaller (1992), individuals with high "political sophistication" have the capacity to draw upon information both current and distant. Because senators, congressmen, and the president epitomize political sophistication, the exogenous shock of an Occupy event has the potential to manifest after the event subsides. Theoretically, the activity of the Occupy Wall Street movement could have a long-term lingering effect visible beyond the events of the day or even after the movement largely fades, an intuition echoing Tilly's (1999) suggestion of unforeseen movement effects.

RESULTS

I first examine the rhetoric of President Obama and Congress by time period. Was there a significant increase in the discussion of Occupy's objectives during the first year of Occupy Wall Street compared to either before its existence or after its peak? I address this question both graphically and through one-way analysis of variance (ANOVA) for each of the keyword categories for both President Obama and Congress. Here, I am interested not only in a difference between the groups (a significant F-test), but also whether there is a significant *increase* in the Occupy period followed by a significant *decrease* in the post-Occupy period. To illustrate greater detail, I subdivide the first year of Occupy into two six-month periods. Consider the average discussion of these speech categories by time period (Figure 2). From these plots, something curious should be apparent. For both President Obama and Congress, we witness an acute parallel increase in their discussion of "fair share" rhetoric. Recall that this category reflects sentiments that both Wall Street corporations and the wealthy should pay their fair share of taxes, a concept that the president frequently invokes by advocating his vision for an "America where everybody gets a fair shake and everybody does their fair share" (White House 2011a). During the height of Occupy,

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¹¹ General negative binomial models were estimated using heteroskedasticity and autocorrelation-consistent (HAC), Newey-West standard errors. Results from these models were substantively similar to the ARFIMA models.

we undoubtedly see an increase in the frequency of this rhetoric. F-tests not only confirm a significant difference across all periods for both the President (F=92.40, p<0.0001) and Congress (F=13.35, p<0.0001),

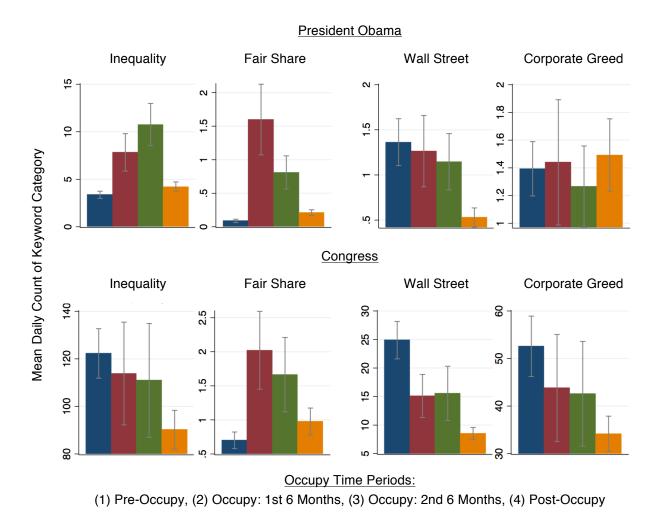


Figure 2. President Obama and Congress's Speech by Category and Time Period *Note:* Each bar in the bar graphs reflects a discrete time period as follows: (1) Pre-Occupy period, (2) Occupy: 1-6 months, (3) Occupy: 2-6 months, (4) Post-Occupy. Dates range from January 1, 2009 to November 15, 2015. Pre-Occupy period: 01-Jan-2009-16-Sep-2011. Occupy 1-6 Months: 17-Sep-2011-17-Mar-2011 Occupy 2-6 Months: 18-Mar-2011-17-Sep-2012. Post-Occupy period 18-Sep-2012-15-Nov-2015. Confidence interval bars are for 95%. F-tests with Bonferroni pairwise comparisons also conducted, reported in paper body.

but we also notice that there is a statistically significant *increase* in fair share discussion during the Occupy-period followed by a statically significant *decrease* after Occupy's decline (p<0.001 for both the President and Congress).

While there is a spike in "fair share" discussion for both President Obama and Congress during Occupy, the other keyword groups exemplify less consistent results. In the case of inequality, President Obama bolsters his discussion during Occupy and in fact speaks at greater length about inequality during the latter rather than the former six months of Occupy. Not only is there a significant difference by period (F = 43.57, p < 0.0001), but also Bonferroni pairwise comparisons illustrate there is a significant increase during Occupy followed by a significant decrease after Occupy's first year (p < 0.001). Conversely, this pattern does not likewise hold for congressional discussion of inequality. Both *Wall Street* and *Corporate Greed* categories show either little increase or actually appear higher before Occupy's rise. This may

reflect a heightened concern with the 2008 financial crisis and the role of Wall Street corporations in leading America into the Great Recession. As the economy began its slow recovery, President Obama and Congress discussed inequity with flagging frequency. Considering these affirmative results for inequality and fair share, I elect to focus on these categories for the remaining analysis.

Exploring the Bivariate Effect of Occupy Arrest Activity

Given the aggregate change by period, how does arrest activity factor into the equation? Consider the overarching pattern of Occupy arrests to the discussion of inequality and paying the fair share (Figure 3).

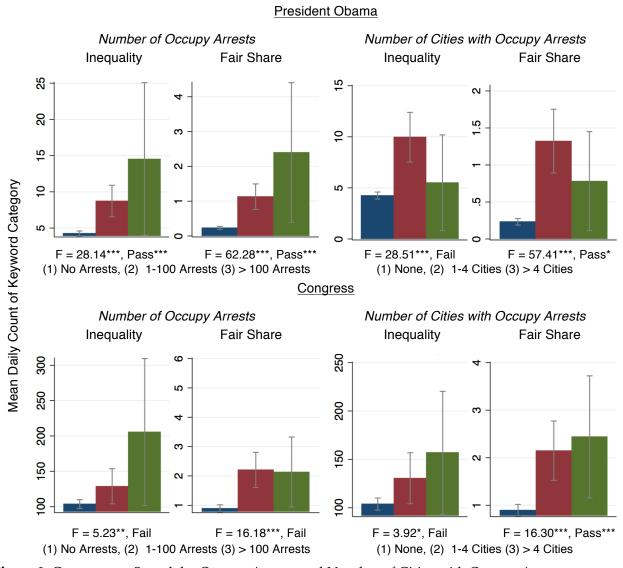


Figure 3. Government Speech by Occupy Arrests and Number of Cities with Occupy Arrests *Note*: Significance levels as follows: *p<.05, **p<.01, ***p<.001. All Y-axes represent the mean daily keyword count. Confidence interval bars are for 95%. F-tests with Bonferroni pairwise comparisons noted with full results in Appendix A, Table A1. 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" of the Bonferroni tests. 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.

Examining the figure, we see that on days without arrests, President Obama discussed inequality an average of 4.25 times compared to 8.73 times on dates with 1-100 arrests and 14.53 times on dates with more than a hundred arrests.

For Congress, we observe a similar pattern. Inequality discussion climbs from a baseline of 104 mentions to 129 and 206 uses as arrests increased. In fact, this pattern of concurrent increases in arrests and rhetoric prevails in most cases. For President Obama, increases exist at each stage for both inequality and fair share rhetoric. Congress likewise exhibits similar behavior with the only exception being fair share rhetoric versus *arrests*, which remains steady when comparing 1-100 arrests to greater than a hundred arrests.

By contrast, the patterns manifested for *arrest cities* differ for the president versus Congress. For example, although there are universal increases in the discussion of inequality and fair share rhetoric by the president on days with 1-4 or greater than four arrest cities compared to no arrest cities, we do not necessarily see increased discussion when there are more than four arrest cities compared to one to four arrest cities. In most contexts, discussion peaks in the 1-4 arrest city group. Graphically, the contrast between the presidential and congressional speech patterns is even starker. Whereas there is some vacillation for President Obama, congressional discussion consistently increases when comparing *no arrest* cities to 1-4 arrest cities and greater than four arrest cities.

The difference between *arrests* and *arrest cities* in the context of President Obama versus Congress has an important implication. Examining the F-tests, particularly the Bonferroni pairwise comparisons, we notice that *arrests* pass each test for President Obama but fail in both congressional instances. Conversely, *arrest cities* pass Bonferroni tests only for *fair share* speech, a result echoing the aggregate period differences for fair share discussion by Congress. Based on these findings, I test differentiated time series models, utilizing Occupy *arrests* to predict President Obama's speech but alternatively use the number of *cities with Occupy arrests* to predict congressional discussion. Before turning to the time series analysis, consider the contextual periodization of government response.

The Periodization of Presidential and Congressional Response

With the onset of Occupy Wall Street, a unique pattern unfolds in relation to the discussion of inequality and paying the fair share. Namely, inequality and fair share rhetoric spikes in the wake of Occupy arrests, particularly for President Obama. Consider, for example, the third day of protest, September 19, 2011—the first day President Obama spoke after the movement began. As he hammered the American tax system, which advantages the "wealthiest taxpayers and biggest corporations" who know best how to "game the system," Americans may very well have marveled at President Obama's condemnation of inequality, special interests, and multinational corporations (White House 2011b). Although this was not the first time the president had critiqued the tax codes' malleability for elites and corporate lobbyists, his particularly caustic rebuke of the status quo just days after Occupy Wall Street began exemplifies the fact that President Obama critiqued inequality most fiercely in the hours and days following mass arrests in the Occupy movement (Figure 4).

Although imperfect, the overarching pattern suggests more than mere coincidence. Consider for example the incident of police brutality shortly after the movement evolved. By mid-September, the volume of Obama's rhetoric on inequality and paying the fair share had diminished. On September 24, 2011, NYPD officers used excessive force on a group of peaceful albeit boisterous protesters as they marched from the financial district toward Union Square (Nir 2011). As police commanders peppersprayed a group of women and hurled a videographer headlong into a Volvo, more than 80 Occupy protesters were placed under arrest (Nir 2011; O'Donnell 2011).

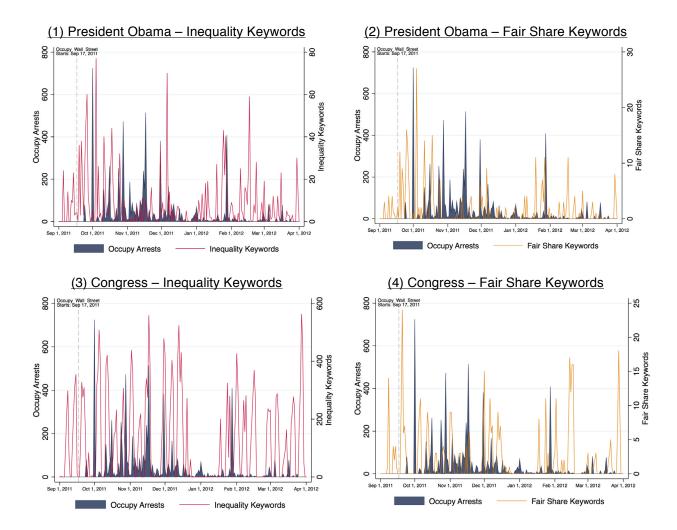


Figure 4. Timing of President Obama and Congress's Speech versus Occupy Arrests *Note:* Occupy Wall Street begins on September 17, 2011. Data displayed on a daily timescale. Timescale truncated to September 1, 2011 to April 1, 2012 to illustrate sufficient detail. Cumulative results for the entire time period displayed in Figure 6.

By 8:30 P.M. that evening, and for the next few days thereafter, President Obama's references to inequality and the "fair share" skyrocketed as leftwing pundits condemned the unwarranted police brutality. Consider the president's remarks that evening:

We've got to ask the folks who have benefited most—the wealthiest Americans, the biggest, most profitable corporations—to pay their fair share....Republicans are already dusting off their old talking points. That's class warfare, they say...When you start saying, at a time when the top one-tenth of 1 percent has seen their incomes go up four or five times over the last 20 years, and folks at the bottom have seen their incomes decline—and your response is that you want poor folks to pay more? Give me a break. If asking a billionaire to pay the same tax rate as a janitor makes me a warrior for the working class, I wear that with a badge of honor. (White House 2011c)

Just days after the unrest on September 24, 2011 hundreds of protesters took over the Brooklyn Bridge on October 1, 2011, an act that not only clogged a New York traffic artery but also resulted in the arrest of

700 protesters (Associated Press 2011). Donning his self-ascribed badge of honor as a "warrior for the middle class," President Obama, revamped his remarks, weaving together anti-Wall Street charisma, dissatisfaction with inequality, and the need for all to pay their fair share. Consider his words on October 4, 2011 just three days after the Brooklyn Bridge incident:

Over the last decade...the deck kept being stacked up against middle-class Americans...When we wanted to pass Wall Street reform...lobbyists and special interests spent millions to make sure we didn't succeed....[We've] got to ask the wealthiest Americans, the biggest corporations to pay their fair share. (White House 2011a)

The President was not alone in this line of argument. Both congressmen and senators adopted a similar rhetoric against inequality, emphasizing again the need for those at the top to pay their fair share. Consider the words of Senator Reid (D., NV) and Representative Hastings (D., FL) the following day, October 5, 2011 (United States 2011):

The American people believe it is time for millionaires and billionaires to pay their fair share to help this country thrive. Americans from every corner of the country and every walk of life agree...Wealthy Americans agree. Two-thirds of the people making more than \$1 million a year said they would gladly contribute more. – Sen. REID (D).

During these difficult economic times, the wealthiest of Americans should be paying their fair share in taxes...Why are we giving tax breaks to Wall Street CEOs and Big Oil Executives, instead of helping the millions of Americans who are struggling. Thanks to loopholes in the tax code, M. Speaker, the rich keep getting richer. The top one percent of earners are responsible for 20 percent of the nation's annual income...The wealthiest Americans have rigged the tax system in their favor to the detriment of the middle class. They've changed the rules to their own financial advantage. - Rep. HASTINGS (D).

Although these reflect but a few examples, these quotations help illuminate and contextualize the pattern of rhetoric illustrated in Figure 4. Spikes in arrests are followed by an increase in critical rhetoric by the President and a subsequent echo of support (or dissention) by members of Congress. Although these observations provide rich empirical detail, such analyses cannot account for the confounding explanations such as the presence of the news media, public interest, or phenomenon such as autoregressive or moving average trends. To robustly establish the role of Occupy in such a complex political system, I utilize time series models with multiple parameters, which I unpack in the following section, beginning with the models for presidential rhetoric.

Unpacking the Parameters for the President's Speech

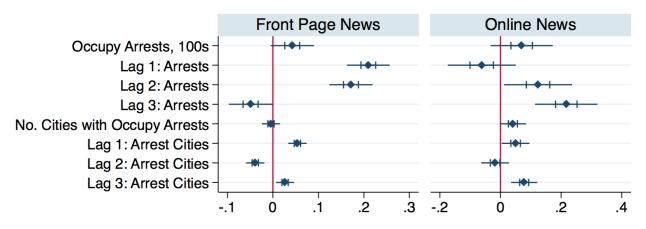
I expand the preceding analysis by using a multivariate time series approach. Theoretically, I expect the number of arrests on a given day to be associated with increasing discussion of inequality and the fair share. While changes may occur the same day, because speeches often take longer to rewrite in response to protest events, we might reasonably expect speech rhetoric to peak in the days following Occupy unrest. We might also anticipate daily political speech to be serially autocorrelated with the speeches in previous days. For these reasons, I include not only the current day's arrests but also lags for Occupy protesters arrested one, two, and three days past. ¹² In testing, the directionality, magnitude, and

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¹² I tested the results using only arrests. I ran the model with lag 1 only...lag 19 only, and then a model with lags 1-19. The effects when estimated in isolation or all at once are all but indistinguishable. See Appendix A, Table A6.

significance is consistently unaffected by the number of lags included (Appendix A, Table A6). As indicated in the literature review, a critical factor to consider is media coverage, especially prominent media such as front page news (Andrews and Caren 2010; Edwards and Wood 1999). Not surprisingly news coverage of Occupy increases, particularly after police brutality, mass disruption, and mass arrests. Notably, the number of protesters arrested predicts both front page and online news of Occupy (Table 3).

Table 3. ARFIMA Models of Today's Front Page and Online Occupy News, 2009-2015



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.

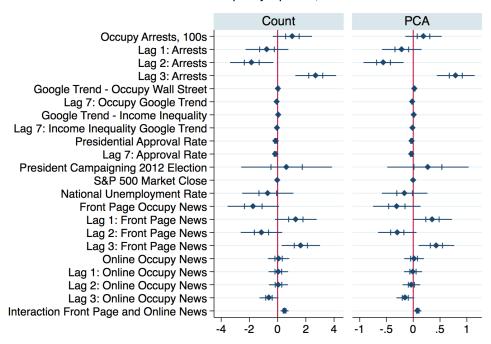
In particular, the number of arrests one and two days ago predict current *front-page* news. The number of cities with arrests yesterday is also predictive. To a lesser extent, arrests two and three days past and the number of current-day arrest cities predict today's *online news*. To incorporate the news cycle, I thus include not only same-day news, but also the lagged news cycles, going back three days. Since past arrests predict future news coverage, the extent that the news coverage of Occupy predicts the discussion of inequality and fair share rhetoric can be thought of as a subsequent ramification of Occupy arrests. Thus, while I include the news media and lags, news coverage necessarily follows Occupy. Beyond the news, I also include lags for public perception via Google Trends. Because Google trend data is a weekly constant, I lag these values by one week. Likewise, I utilize the same one-week lag for the presidential approval polls available from Rasmussen. The campaign dummy variable, unemployment rate, and S&P 500 index are modeled continuously without lags or leads. In terms of model results, I display coefficient plots with traditional regression tables reserved for Appendix A.

Modeling Presidential Speech

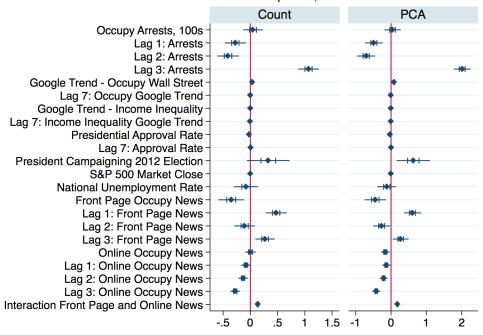
I display the ARFIMA models of presidential speech in Table 4. A brief examination of these models reveals that Occupy Wall Street arrests three days ago predict President Obama's present-day speech on both inequality and paying the fair share. Note that the coefficients for the current-day arrests, arrests yesterday, and arrests two days past either demonstrate a lack of statistical significance or present significance in the opposite direction. This is not to say that current day arrests do not matter only that the effect is not significant in contrast to arrests three days past when controlling for other explanations, autocorrelation, and moving average effects. For example, negative binomial models illustrate a significant effect for both current day arrests and arrests three days past (Appendix A, Table A7).

Table 4. ARFIMA Models of President Obama's Speech, 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 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 Appendix A, Table A2.

Because these models lack control for autocorrelation (which is highly significant in the ARFIMA model), there is specification error in the negative binomial models, even though they offer similar substantive interpretations. The effects here are also unaffected by the total number of included lags (Appendix A, Table A6).¹³ Instead, what we see in Table 4, is that the interaction term of today's front page news and today's online news about Occupy Wall Street drives the president's conversation on inequality and paying the fair share for that day. In both the inequality and fair share models, the effect is positive and highly significant. For the fair share models, front page Occupy news yesterday and three days past predicts a significant increase in the discussion of paying the fair share. Likewise, front-page news three days past predicts an increase in presidential discussion of inequality. Controlling for news coverage of Occupy, we still see that the number of protesters arrested predicts increased discussion of inequality and paying the fair share, all else equal.

When we take a step back to think about these results, they intuitively follow our expectation. In the hustle and bustle of daily presidential events, breaking news and intelligence on Occupy presents a viable outlet through which advisors counsel the president about daily protest developments. While the number of protesters arrested yesterday drives today's front-page media ($\beta = 0.21, p < 0.001$), it is the media coverage of the protest that spawns immediate response. Once the dust has settled, the president and his staff have time to rewrite speeches to argue against inequality and urge that the wealthy pay their fair share. After three days, the president and staff have had time to grasp the situation, and while media coverage three days ago is still an important factor in each model, even more, the president weighs the number of protesters arrested when calculating the language and tenor of his response.

Modeling Congressional Speech

Turning to congressional discussion of inequality and paying the fair share, we notice a subtly different pattern. As previously indicated, I employ the number of cities with Occupy arrests as a predictor. As discussed in the introduction, I posit that the degree of discussion by the president influences congressional debate. To the extent that Occupy is influential on the president raises the possibility that Occupy's influence in turn transcends the chambers of Congress. By incorporating the president's speech as a predictor, I further tease these complex relationships apart. Consider the models of congressional speech displayed in Table 5. Examining the congressional models, we witness that the number of present day cities with Occupy arrests has a positive and significant effect on the frequency of inequality and fair share discussion by Congress. Furthermore, the number of cities with Occupy arrests yesterday also predicts an increase in congressional discussion of fair share rhetoric today.

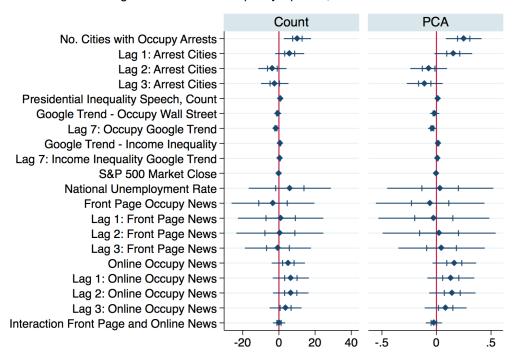
In contrast to the presidential models, the news manifests a lesser role. In only one model (fair share PCA) was the news significant. Thus, although the news has robust predictive power in the presidential models, it is far less predictive of congressional speech. In part, this result illustrates a substantive disparity between *arrests* and *arrest cities*. While we might witness several hundred arrests in a single city, those events directly affect the constituents of only a few legislators whereas orchestrated protest events that result in arrests across the country potentially impact a larger portion of Congress. Yet, for the president, mass arrests in any city likely warrants response. It is through *the agenda-setting abilities of the president that Occupy Wall Street exercises the most sway on Congress*.

¹³ Ibid.

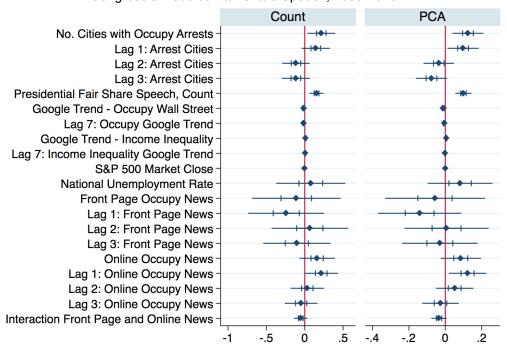
¹⁴ For robustness, I also include additional models that include both Occupy arrests and a control for the exposure to include a log transformation of the total number of words in the Congressional record. The results are similar (Appendix A, Tables A3 and A5).

Table 5. ARFIMA Models of Congress's Speech, 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 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 Appendix A, Table A4.

Indeed, we can see that of all the predictors, the effect of presidential speech is among the most influential (Table 5). For example, President Obama's discussion of inequality predicts a significant increase in congressional discussion of inequality ($\beta=0.81, p<0.001$) and ($\beta=0.01, p<0.05$), for both the count and PCA models, respectively. Although the size of the coefficient is small relative to arrests, this difference reflects the scale of the predictors. Whereas an additional city with Occupy arrests predicts an increase of 10 congressional keywords, an additional mention of inequality by the president predicts approximately one additional congressional citation of inequality. Regarding fairness, one additional presidential mention of paying the fair share predicts a highly significant increase in congressional fair share discussion ($\beta=0.15, p<0.001$). This finding underscores Occupy's indirect influence. By shaping presidential discussion, Occupy's efficacy has a ripple effect in Congress.

Examining the Dynamic Impact of Occupy between the President and Congress

Examining the results, what do these models convey in terms of Occupy's impact?

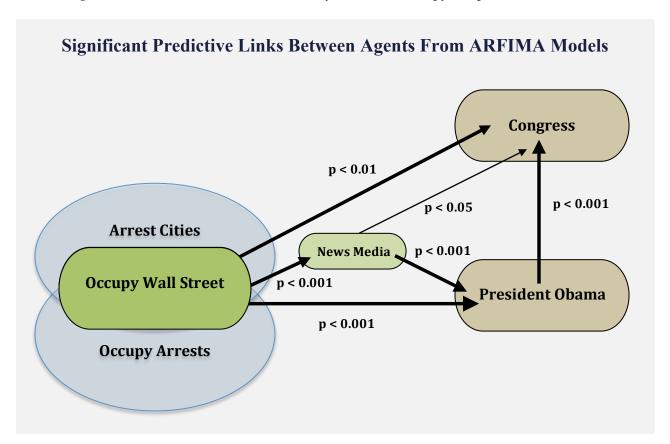


Figure 5. Significant Predictive Links Between Agents from ARFIMA Models *Note:* Solid lines indicate statistically significant coefficients in one or more models. Edge thickness weighted by statistical significance of the most significant factor in any model. Significance levels using z-test. p<.05, p<.01, p<.001. Indicated probabilities denote that one or more ARFIMA models has a coefficient predicting the directed edge at the specified probability threshold.

As synthesized in Figure 5, Occupy Wall Street's use of disruptive protest predicts a statistically significant increase in news media coverage, presidential discussion, and congressional debate. Namely, Occupy arrests and cities with arrests yesterday predict *front-page news*. Occupy arrests two and three days past also predict *online news*. Collectively, the recent arrest activity of Occupy Wall Street yields media coverage of Occupy, which as we saw in Table 4, promotes increased presidential discussion about

Occupy's interests in economic fairness and equality. Among the most salient effects, the number of protesters arrested three days ago strongly predicts an increase in the president's discussion of inequality and paying the fair share.

For Congress, although the number of cities with Occupy arrests predicts an increase in congressional debate, even more powerful is the indirect flow of Occupy's influence over presidential discussion that in turn predicts congressional conversation on inequality and paying the fair share. By systematically working through the models in this fashion, we can best demonstrate the role of Occupy in catalyzing a shift in presidential and congressional rhetoric.

DISCUSSION

Reflecting on these results, where do the initial hypotheses stand? Regarding the first hypothesis, we saw a statistically significant increase in the discussion of both inequality and paying the fair share by President Obama and a statically significant increase in Congress's discussion of the fair share during the Occupy period compared to either before or after the movement. Thus, the results exemplify the first hypothesis. Most substantively, we have also seen consistently across all presidential models that the number of protesters arrested is highly predictive of an increase in presidential rhetoric about the movement's cause. In particular, arrests three days past are the most predictive of presidential speech. Similarly, the number of cities with Occupy arrests predicts an increase in Congress's discussion of inequality and paying the fair share. Recalling the second hypothesis:

Hypothesis 2: There will be a positive chronological association between Occupy arrest activity and discussion of Occupy's objectives by President Obama and Congress in the hours and days following the event.

As we have seen throughout the analysis, Occupy's disruptive and highly mobilized tactics, heralded favorable results. The incidence of Occupy arrests was not only predictive of a growing national conversation in response to news coverage of Occupy, but also in catalyzing an increase in presidential rhetoric. Likewise, the number of cities with Occupy arrests predicts an increase in discussion of inequality and paying the fair share by legislators. So too, does Occupy's influence upon the president yield increases in congressional debate. For all presidential and congressional models, the data reflects a long-term dependency. In particular, the ARFIMA models show both AR-1 and MA-1 trends to be widely significant, indicating a high degree of dependence in the time series. Similarly, the coefficients for each model all have statistically significant values of the differencing term $d \in (0, 0.5)$, which indicates both finite variance and exemplifies long-memory, or more precisely, a "long-range positive dependence" (Baum and Wiggins 2000; Granger 1980). These results suggest that even after the decline of Occupy's disruption and arrests, the ramifications of heightened economic rhetoric persisted in the long-run time series. Recall the third hypothesis:

Hypothesis 3: If Hypotheses 1-2 are true, the increase in President Obama and Congress's rhetoric will be causal to the Occupy Wall Street movement, namely:

*H*3_{*A*}: The rhetorical shift followed the onset of Occupy Wall Street.

 $H3_B$: The rhetorical shift lingered after the decline of Occupy Wall Street.

*H*3_{*c*}: The rhetorical shift is best explained by the onset of Occupy Wall Street versus the controls.

Regarding the first sub-hypothesis $H3_A$, we have seen that there is first and foremost a difference in the observed rhetoric prior to Occupy versus after Occupy began, particularly for fair share discussion. As seen in the ANOVA, this was a highly significant increase followed by a significant decrease. Graphically, the cumulative results are even more stunning (Figure 6):

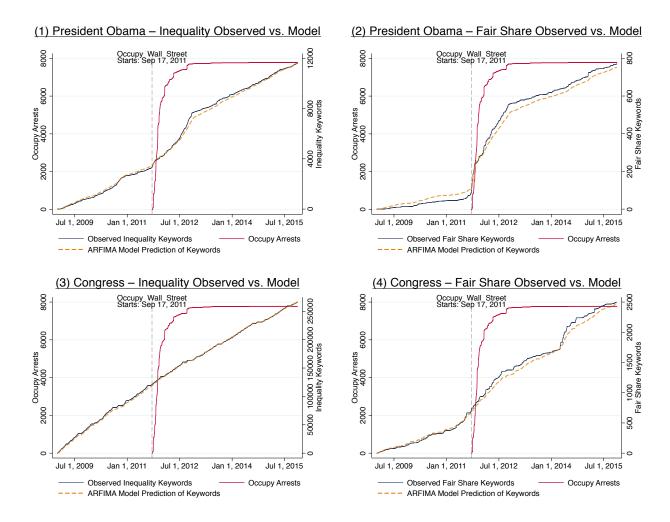


Figure 6. Government Cumulative Observed and Modeled Speech versus Occupy Arrests *Note*: Observed Values of ARFIMA Model Predictions from Tables 4 and 5 (Count Models) for Inequality and Fair Share rhetoric by President Obama (Table 4) and Congress (Table 5). Occupy arrests are displayed in each graph (acutely increasing solid line). The two closely correlated lines are observed speech (solid line) versus predicted speech (dashed line). Vertical dashed line marks the beginning of Occupy Wall Street, September 17, 2011.

Prior to Occupy Wall Street, the discussion of inequality and paying the fair share certainly existed, but not to the same extent as after Occupy began. The increase in the wake of Occupy is most observable in the first months and first year of the social movement, particularly for fair share discussion by the president (Figure 6.2), and yet the shift appears to have lingered well beyond the protest's peak and at a rate greater than before the movement ever emerged. Substantiating this graphical pattern, the ARFIMA models establish the statistical veracity of a long-term dependency, namely that the effects on the president's rhetoric carry forward, even after the predictive factor of Occupy arrests declined. This result, demonstrates hypothesis $H3_B$.

Lastly, as was evident across all the models, the activity of Occupy Wall Street was a durable and robust effect, appearing across every presidential model. As illustrated, the president's words point to

increased congressional discussion of inequality and paying the fair share. The complex flow of Occupy's influence, as visualized in Figure 6, also suggests a causal interpretation of Occupy's impact. Recall that these models included controls for the economic state of the nation (the financial markets and unemployment rate), the president's political approval, the public's awareness of Occupy Wall Street's ideas, and media coverage of Occupy events. Yet, by and large, the best explanation of all such factors, was in fact the arrest activity of Occupy Wall Street, and this fact substantiates $H3_{\mathcal{C}}$.

Given these results, there is an understanding temptation to label these results as a causal effect. Certainly from the evidence presented, Occupy is the best explanation and causally predictive, *ceteris paribus*. Yet, many facets are unobserved or unknowable in this analysis, and these omitted variables could affect the results. If there is an unforeseen flaw in the models or data collection, the results could also be suspect. Even forestalling such routine caveats, we can only confidently say that the rhetorical response reflects a manifested *public* shift in political dialogue, which may be divorced from the president's private beliefs.

Behind the scenes of the White House, a team of advisers, communications directors, speechwriters and other staff consult with the president and carefully debate the content of projected public speech. Influential members of this team, rather than the president could have guided the observed rhetorical shift. So too, could internal White House polling and intelligence. Moreover, backroom agendas from the Democratic National Committee and the Republican National Committee could have actively coordinated to argue in favor or against both the impulse of Occupy and the president's efforts of agenda setting.

As previously theorized, both President Obama and Congress face a myriad of competing interests. On one hand are the Occupy protesters. At other fronts rest the American public and interested business parties who fund presidential and congressional election campaigns, in addition to said unforeseen influences of advisers and the president's personal motivations to craft his legacy. Although causality remains a contested attribution, the pointed fact demonstrably clear from this analysis, is that the arrest activity of Occupy Wall Street protesters is a positive and statistically significant predictor of both presidential and congressional discussion about inequality and who should pay the fair share.

Collectively, while the attribution of ultimate causality may never be known, it appears likely that given the current robustness of the results, Occupy played a pivotal role in modifying the rhetoric of President Obama and Congress to enhance the focus on economic inequality. From one perspective, these results reaffirm the power of a flexible, multi-issue mobilization to tactically innovate using social media to organize the mass assemblies, encampments, and disruption necessary to garner arrests and media attraction (McCammon 2012; Snow and Moss 2014; Wang and Soule 2016). Following past movements research, we again see the efficacy of mass organized disruption, building off McAdam and Su's (2002) results that violent and unruly protests are more efficacious for legislative gains. For other reasons, my results also call to question an additional factor not explored by McAdam and Su (2002), namely the role of the president. In the case of Occupy and President Obama, we have witnessed that Occupy arrests influence the president's rhetoric both directly and indirectly, which in turn predicts the degree of discussion by Congress. This finding of presidential agenda setting echoes past political science research (Edward and Wood 1999) but casts doubt on the sociological study of movements such as McAdam and Su (2002) that consider a protest's effect on Congress without simultaneously considering the role of the president in effecting that change. In future work, movement scholars should pay deference to the role of the president when assessing the efficacy of social movements in obtaining legislative gains or other congressional action. Past movements work should be reevaluated to assess the role of the president in achieving legislative gains.

The Occupy case, however, additionally challenges the paradigm that *movements not moments* matter beyond legislative gains (*c.f.* Calhoun 2013; Gitlin 2013a). Disruptive social movements, as measured by the number of protesters arrested, can yield substantive rhetorical shifts. On one hand, my

results bolster political mediation theory, where the president channels sympathetic rhetoric to placate the movement and forestall policy changes until the movement fades from lack of sustainability (Amenta 2006; Piven and Cloward 1979). Although the dialogue between Occupy and the president may have dampened potential policy, so to did the nonhierarchical structure of the movement. Further, because President Obama persisted with his rhetorical shift long after Occupy ceased to be a threat to administrative or business interests, some other force appears to be at play.

One might think the president's rhetorical shift is simply an "electoral proximity" effect or a "populist critique of elite power" used to bolster his campaign (Bonikowski and Gidron 2016:1611; Canes-Wrone 2006:23), but such notions are unsupported because (a) the President's aggressive take toward inequality surpassed, rather than matched, attitude and policies supported by public opinion (Bartels 2012; Brooks and Manza 2013; Canes-Wrone and Kelly 2013), (b) the effects extended beyond the presidential election, and (c) whether President Obama was actually campaigning was inconsistently significant across the models. Alternatively, taking a theory of the president approach, we can, in viewing the president as a political actor, justify his response to Occupy as an opportunity to champion ideas he already held and to use the momentum of Occupy to lend greater credence to his affirmation thereof. Arguably, the arrests of Occupy protesters afforded the president a political opportunity to shape the dialogue and cast himself in the role of a transformative president, as suggested to him by White House historians (Kantor 2012). This theory also better fits within the populist framework of his first presidential campaign. The president's very embrace of populism as a second-term sitting president, after Occupy subsided, after the election, and all the while lacking strong public support makes this case a historical outlier and suggests that personal political aspirations are the driving response to the opportunity Occupy afforded (Bonikowski and Gidron 2016). Under this theoretical lens, championing favorable rhetoric in the wake of the Occupy protests, exemplifies an ideal strategic moment to respond to the movement, set congressional agenda, and maximize the visibility of the president's role in shaping the debate.

Whereas President Obama's speeches in the wake of Occupy Wall Street were significant because of the movement's currency and its relatively ambiguous nature in the eyes of the American public, his later speeches are more telling for the narrative of legacy craftsmanship. One such speech came on December 6, 2011 in Osawatomie Kansas. This speech is significant because it came after the movement had lost much of its popularity, garnered a reputation as a nuisance, and even among Democrats received only "muted support" because of the lingering ambiguity surrounding its goals (Saad 2011). In Kansas, Obama minced no words:

There are some who seem to be suffering from a kind of collective amnesia...they want to go back to the same policies that stacked the deck against middle-class Americans for way too many years...I am here to say they are wrong....These aren't 1 percent values or 99 percent values. They're American values.... In the last few decades, the average income of the top 1 percent has gone up by more than 250 percent to \$1.2 million per year....Inequality...gives an outsized voice to the few who can afford high-priced lobbyists and unlimited campaign contributions, and it runs the risk of selling out our democracy to the highest bidder....That is the height of unfairness. (White House 2011d)

Coming just days after a two-week slew of escalating violence and arrests—including the NYPD removal of protesters from Zuccotti Park, the infamous pepper-spraying of passive UC-Davis students, and the arrests of hundreds of protesters in major cities nationwide—Obama's speech certainly aligns itself with the protesters' chief complaints of economic frustration in the nexus of American capitalism. In his speech, President Obama directly references those "occupying the streets of New York" and the "1 percent and 99 percent" dichotomy that bolstered Occupy's acclaim, an impressive recognition considering it came from the Commander in Chief during a nationally televised address. Rather than a

singular policy of political mediation, Occupy Wall Street afforded the president a prodigious opportunity to adopt the message of Occupy and rebrand this impulse as an agenda-setting moment not only to help secure his second term as president but also to bolster his legacy as a transformative figure as suggested by White House historians (Kantor 2012).

Reflecting on this final thought and the analysis presented here, Occupy impacted both presidential and congressional speech, particularly shaping the discussion about inequality and the idea that everyone deserves a "fair shot" and that all must pay their "fair share". While rhetorical shifts do not traditionally fall in the wheelhouse of social protest efficacy, I posit that this represents a long-term win. By helping sway the voice of Congress and more importantly, the White House, Occupy Wall Street matters because it catalyzed a shift in the current societal and future historical dialogue about inequality. Through its use of *disruptive*, *innovative protest*, Occupy recast the discussion of politicians who have limited words and time, and in this victory, perhaps, both Occupy and the President can take pause and unite in pondering this progressive solidarity.

REFERENCES

- Alim, H. Samy. 2013. "What if We Occupied Language?" Pp. 211-220 in *Occupy the Future*, edited by David B. Grusky, Doug McAdam, Rob Reich, and Debra Satz. Cambridge, MA: MIT Press.
- Amenta, Edwin. 2006. When Movements Matter: The Townsend Plan and the Rise of Social Security. Princeton, NJ: Princeton University Press.
- Andrews, Kenneth T., and Neal Caren. 2010. "Making the News: Movement Organizations, Media Attention, and the Public Agenda." *American Sociological Review* 75(6):841-866.
- Associated Press. 2011. "700 Arrested on Brooklyn Bridge after Protest." *USA Today*, October 2. Retrieved January 25, 2012 (http://www.usatoday.com/news/nation/2011-10-01-Wall-Street-protest-Brooklyn-Bridge.htm).
- Bartels, Larry. 2008. Unequal Democracy: The Political Economy of the New Gilded Age. New York: Russell Sage.
- Bartels, Larry. 2012. "Occupy's Impact Beyond the Beltway." *Moyers & Company*, January 18. Retrieved April 19, 2012 (http://billmoyers.com/2012/01/18/has-the-occupy-movement-altered-public-opinion/).
- Baum, Christopher F. 2013. "The ARFIMA (Long Memory) Models." *Boston College*. Retrieved December 10, 2015 (http://fmwww.bc.edu/ec-c/s2013/327/EC327.S2013.nn5.slides.pdf).
- Baum, Christopher F., and Vince Wiggins. 2000. "Tests for long memory in a time series." *Stata Technical Bulletin* 57, sts16.
- Berman, Ari. 2011. "In Osawatomie, Obama Embraces New Populist Moment." *The Nation*, December 6. Retrieved June 5, 2016 (http://www.thenation.com/article/osawatomie-obama-embraces-new-populist-moment/).
- Bonikowski, Bart, and Noam Gidron. 2016. "The Populist Style in American Politics: Presidential Campaign Discourse, 1952-1996." Social Forces 94(4):1593-1621.
- Box-Steffensmeier, Janet M., and Renee M. Smith. 1998. "Investigating Political Dynamics Using Fractional Integration Methods." *American Journal of Political Science* 42(2):661-689.
- Box-Steffensmeier, Janet M., and Andrew R. Tomlinson. 2000. "Fractional integration methods in political science." *Electoral Studies* 19:63-76.
- Brooks, Clem, and Jeff Manza. 2013. "A Broken Public? Americans' Responses to the Great Recession." American Sociological Review 78(5):727-748.

- Brown, Wendy. 2011. "Occupy Wall Street: Return of a Repressed Res-Publica." Theory & Event 14(4).
- Calhoun, Craig. 2013. "Occupy Wall Street in Perspective." The British Journal of Sociology 64(1):26-38.
- Canes-Wrone, Brandice. 2006. Who Leads Whom? Presidents, Policy, and the Public. Chicago: University Of Chicago Press.
- Canes-Wrone, Brandice and Jason P Kelly 2013. "The Obama Presidency, Public Position Taking, and Mass Opinion." *Polity* 45(1):85-104.
- Cherkis, Jason. 2011. "UC Davis Police Pepper-Spray Seated Students In Occupy Dispute." *The Huffington Post*, November 20. Retrieved January 27, 2012 (http://www.huffingtonpost.com/2011/11/19/uc-davis-police-pepper-spray-students_n_1102728.html).
- Contreras-Reyes, Javier E., and Wilfredo Palma. 2013. "Statistical Analysis of Autoregressive Fractionally Integrated Moving Average Models in R." *Computational Statistics* 28(5):2309-2331.
- DeLuca, Kevin M., Sean Lawson, and Ye Sun. 2012. "Occupy Wall Street on the Public Screens of Social Media: The Many Framings of the Birth of a Protest Movement: OWS on the Public Screens of Social Media." Communication, Culture & Critique 5(4):483-509.
- DeTar, Charlie. 2012. Occupy Research General Survey: Facet Browser. OccupyResearch.Net. Retrieved March 11, 2015 (http://occupyresearch.net/orgs/).
- Domhoff, G. William. 2010. Who Rules America? Challenges to Corporate and Class Dominance. 6th ed. Boston: McGraw Hill Higher Education.
- Earl, Jennifer, Andrew Martin, John D. McCarthy, and Sarah A. Soule. 2004. "The Use of Newspaper Data in the Study of Collective Action," *Annual Review of Sociology* 30:65-80.
- Edwards, George C., and Dan B. Wood. 1999. "Who Influences Whom? The President, Congress, and the Media." *The American Political Science Review* 93(2):327-44.
- Fligstein, Neil, and Doug McAdam. 2011. "Toward a General Theory of Strategic Action Fields." *Sociological Theory* 29(1):1-26.
- Gaby, Sarah and Neil Caren. 2012. "Occupy Online: How Cute Old Men and Malcolm X Recruited 400,000 US Users to OWS on Facebook." *Social Movement Studies*, 11(3-4):367-74.
- Gamson, William A. 1990. The Strategy of Social Protest, 2nd ed. Belmont, CA: Wadsworth.
- Gamson, William A., and Micah L. Sifry. 2013. "The #Occupy Movement: An Introduction." *The Sociological Quarterly* 54(2):159-63.
- Gilens, Martin. 2005. "Inequality and Democratic Responsiveness." Public Opinion Quarterly 69(5):778-96.
- Gitlin, Todd. 2012. Occupy Nation: The Roots, the Spirit, and the Promise of Occupy Wall Street. New York: HarperCollins.
- Gitlin, Todd. 2013a. "Occupy's Predicament: The Moment and the Prospects for the Movement." *The British Journal of Sociology* 64(1):3-25.
- Gitlin, Todd. 2013b. "Postoccupied." Sociological Quarterly 54(2):226-28.
- Giugni, Marco. 1999. "How Social Movements Matter: Past Research, Present Problems, Future Developments." Pp. xiii-xxxiii in *How Social Movements Matter*, edited by Marco Giugni, Doug McAdam, and Charles Tilly. Minneapolis, MN: University of Minnesota Press.
- Goodwin, Jeff, and James M. Jasper. 2003. *The Social Movements Reader: Cases and Concepts*. Malden, MA: Blackwell.
- Google Trends. 2015a. "Occupy Wall Street," *Google*. Retrieved November 26. (https://www.google.com/trends/).
- Google Trends. 2015b. "Income Inequality," *Google*. Retrieved November 26. (https://www.google.com/trends/).
- Gould-Wartofsky, Michael A. 2015. *The Occupiers: The Making of the 99 Percent Movement*. New York: Oxford University Press.
- Granger, C.W.J. 1980. "Long Memory Relationships and the Aggregation of Dynamic Models." *Journal of Econometrics* 14:227-38.

- Hacker, Jacob S., and Paul Pierson. 2010. *Winner-Take-All Politics: How Washington Made the Rich Richer-and Turned Its Back on the Middle Class*. New York: Simon & Schuster.
- Heaney, Michael T., and Fabio Rojas. 2014. "Hybrid Activism: Social Movement Mobilization in a Multimovement Environment." *American Journal of Sociology* 119(4):1047-1103.
- Henninger, Daniel. 2011. "Obama's Godfather Speech: The president sounds more like a Corleone than a Roosevelt." Wall Street Journal, December 8. Retrieved July 28, 2012 (http://online.wsj.com/article/SB10001424052970203413304577084292119160060.html).
- Kantor, Jodi. 2012. "Now, a Chance to Catch Up to His Epochal Vision." *New York Times*, November 7. Retrieved November 7, 2012 (http://www.nytimes.com/2012/11/07/us/politics/now-a-chance-to-catch-up-to-his-epochal-vision.html).
- Kim, Hyun Woo, and John D. McCarthy. 2016. "Socially Organized Sentiments: Exploring the Link Between Religious Density and Protest Mobilization, 1960-1995." Social Science Research 60:199-211.
- Klein, Ezra. 2011. "Wonkbook: Occupy Wall Street occupies Obama's 2012 campaign." *The Washington Post*, December 7. Retrieved June 5, 2016 (https://www.washingtonpost.com/blogs/ezra-klein/post/wonkbook-occupy-wall-street-occupies-obamas-2012-campaign/2011/12/07/gIQAZVN0bO_blog.html).
- Krugman, Paul. 2011a. "Confronting the Malefactors." *New York Times*, October 6. Retrieved June 7, 2016 (http://www.nytimes.com/2011/10/07/opinion/krugman-confronting-the-malefactors.html).
- Krugman, Paul. 2011b. "Oligarchy, American Style." *New York Times*, November 3. Retrieved June 7, 2016 (http://www.nytimes.com/2011/11/04/opinion/oligarchy-american-style.html).
- Kuttner, Robert. 2010. A Presidency in Peril: The Inside Story of Obama's Promise, Wall Street's Power, and the Struggle to Control Our Economic Future. White River Junction, VT: Chelsea Green Publishing.
- Lanier, Drew N., and Tracy L. Dietz. 2012. "Time Dynamics of Elder Victimization: Evidence from the NCVS, 1992 to 2005." *Social Science Research* 41(2):444-63.
- Lebo, Matthew J., and Taylor Grant. 2016. "Equation Balance and Dynamic Political Modeling." *Political Analysis* 24(1):69-82.
- LexisNexis Academic. 2016. "LexisNexis Academic." Retrieved January 26, 2016 (https://www.lexisnexis.com/hottopics/lnacademic/).
- McAdam, Doug. 1983. "Tactical Innovation and the Pace of Insurgency." *American Sociological Review* 48:735-54.
- McAdam, Doug. 1999. "The Biographical Impact of Activism." Pp. 117-46 in *How Social Movements Matter*, edited by Marco Giugni, Doug McAdam, and Charles Tilly. Minneapolis, MN: University of Minnesota Press.
- McAdam, Doug and Yang Su. 2002. "The War at Home: Antiwar Protests and Congressional Voting, 1965 to 1973." *American Sociological Review* 67(5):696-721.
- McCammon, Holly J. 2003. "Out of the Parlors and Into the Streets: The Changing Tactical Repertoire of the U.S. Women's Suffrage Movements." Social Forces 81(3):787-818.
- McCammon, Holly J. 2012. *The U.S. Women's Jury Movements and Strategic Adaptation: A More Just Verdict.* New York: Cambridge University Press.
- Memmott, Mark. 2011. "Obama Gets Heckled, Occupy-Style." NPR, November 22. Retrieved May 11, 2015 (http://www.npr.org/sections/thetwo-way/2011/11/22/142663754/obama-gets-heckled-occupy-style).
- Meyer, David S., Valerie Jenness, and Helen Ingram. 2005. *Routing the Opposition: Social Movements, Public Policy, and Democracy*. Minneapolis, MN: University of Minnesota Press.
- Mills, C. Wright. 1959. The Sociological Imagination. New York: Oxford University Press.
- Milkman, Ruth, Stephanie Luce, and Penny Lewis. 2013a. *Changing the Subject: A Bottom-Up Account of Occupy Wall Street in New York City*. New York: The Murphy Institute.

- Milkman, Ruth, Penny Lewis, and Stephanie Luce. 2013b. "The Genie's Out of the Bottle: Insiders' Perspectives on Occupy Wall Street." *Sociological Quarterly* 54(2):194-98.
- New York Times. 2012. "Times Topics: Occupy Wall Street." New York Times, January 11. Retrieved January 26, 2012 (http://topics.nytimes.com/top/reference/timestopics/organizations/o/occupy_wall_street/index.html).
- Nir, Sarah Maslin. 2011. "Video Appears to Show Wall Street Protesters Being Pepper-Sprayed." *City Room*, September 25. Retrieved October 23, 2011 (http://cityroom.blogs.nytimes.com/2011/09/25/video-appears-to-show-protesters-being-pepper-sprayed/).
- Occupy Arrests. 2014. "OccupyArrests.com Sources. How Many Have Been Arrested during Occupy Protests." Retrieved March 14, 2015 (http://stpeteforpeace.org/occupyarrests.sources.html).
- Occupy Wall Street. 2011. "About." *OccupyWallSt.org*. Retrieved November 28, 2011 (http://occupywallst.org/about/).
- O'Donnell, Lawrence. 2011. "The Last Word with Lawrence O'Donnell," aired September 26, 2011. Transcript. Retrieved 23 October 2011 (http://www.msnbc.msn.com/id/44691102/ns/msnbc_tv/t/last-word-lawrence-odonnell-monday-september/#.TqSBiXLld8E).
- Oxford Analytica. 2011. "'Occupy Wall Street' threatens to undercut Obama." October 21. Retrieved January 28, 2012 (http://www.oxan.com/Analysis/DailyBrief/Samples/OccupyWallStreetThreatensObama.aspx).
- Panagopoulos, Costas. 2011. "Occupy Wall Street Survey Results October 2011" New York: Center for Electoral Politics and Democracy-Fordham University.
- Peters, David J. 2013. "American Income Inequality Across Economic and Geographic Space, 1970-2010." Social Science Research 42(6):1490-1504.
- Piketty, Thomas and Emmanuel Saez. 2007. "How Progressive Is the U.S. Federal Tax System? A Historical and International Perspective." *Journal of Economic Perspectives* 21(1):3-24.
- Piven, Frances Fox. 2006. Challenging Authority: How Ordinary People Change America. Lanham, MD: Rowman & Littlefield.
- Piven, Frances Fox, and Richard A. Cloward. 1979. Poor People's Movements: Why They Succeed, How They Fail. New York: Vintage Books.
- Rasmussen Reports. 2016. "Obama Approval Index History." Retrieved February 23, 2016 (http://www.rasmussenreports.com/public_content/politics/obama_administration/obama_approval_index_history).
- Saad, Lydia. 2011. "Support for 'Occupy' Unchanged, but More Criticize Approach." *Gallup*, November 21. Retrieved January 26, 2011 (http://www.gallup.com/poll/150896/Support-Occupy-Unchanged-Criticize-Approach.aspx).
- S&P Dow Jones Indices. 2015. "S&P 500 Report." *McGraw Hill Financial*, November 15. Retrieved November 15, 2015 (http://us.spindices.com/indices/equity/sp-500).
- Silver, Nate. 2012. "Why Obama Will Embrace the 99 Percent." New York Times, February 15. Retrieved February 16, 2012 (http://www.nytimes.com/2012/02/19/magazine/nate-silver-obama-reelection-chances.html).
- Snow, David A., and Dana M. Moss. 2014. "Protest on the Fly: Toward a Theory of Spontaneity in the Dynamics of Protest and Social Movements." *American Sociological Review* 79(6):1122-43.
- Steedly, Homer R., and John W. Foley. 1979. "The Success of Protest Groups: Multivariate Analyses." *Social Science Research* 8(1):1-15.
- Stelter, Brian. 2011. "Camps Are Cleared, but '99 Percent' Still Occupies the Lexicon." *New York Times*, November 30. Retrieved December 1, 2011 (http://www.nytimes.com/ 2011/12/01/us/we-are-the-99-percent-joins-the-cultural-and-political-lexicon.html?_r=1&ref=occupywallstreet).

- Tilly, Charles. 1999. "From Interactions to Outcomes in Social Movements." Pp. 253-69 in *How Social Movements Matter*, edited by Marco Giugni, Doug McAdam, and Charles Tilly. Minneapolis, MN: University of Minnesota Press.
- United States, Department of Labor: Employment & Training Administration. 2016. *Unemployment Insurance Weekly Claims Data*. Retrieved February 16, 2016 (http://www.oui.doleta.gov/unemploy/claims.asp).
- United States, Government Publishing Office. 2016. "Congressional Record." Retrieved February 14, 2016. (https://www.gpo.gov/fdsys/browse/collection.action?collectionCode=CREC).
- United States, Government Publishing Office. 2011. "Congressional Record," October 5. Retrieved February 14, 2016. (https://www.gpo.gov/fdsys/pkg/CREC-2011-10-05/pdf/CREC-2011-10-05.pdf).
- Wang, Dan J., and Sarah A. Soule. 2012. "Social Movement Organizational Collaboration: Networks of Learning and the Diffusion of Protest Tactics, 1960-1995." American Journal of Sociology 117(6):1674-1722.
- Wang, Dan J. and Sarah A. Soule. 2016. "Tactical Innovation in Social Movements: The Effects of Peripheral and Multi-Issue Protest." *American Sociological Review* 81(3):517-48.
- White House, Office of the Press Secretary. 2011a. "Remarks by the President at a DNC Event," October 4. Retrieved December 17, 2011 (http://www.whitehouse.gov/the-press-office/2011/10/04/remarks-president-dnc-event).
- White House, Office of the Press Secretary. 2011b. "Remarks by the President on Economic Growth and Deficit Reduction." September 19. Retrieved December 17, 2011 (http://www.whitehouse.gov/the-press-office/2011/09/19/remarks-president-economic-growth-and-deficit-reduction).
- White House, Office of the Press Secretary. 2011c. "Remarks by the President at Congressional Black Caucus Foundation Annual Phoenix Awards Dinner." September 24. Retrieved December 17, 2011 (http://www.whitehouse.gov/the-press-office/2011/09/24/remarks-president-congressional-black-caucus-foundation-annual-phoenix-a).
- White House, Office of the Press Secretary. 2011d. "Remarks by the President on the Economy in Osawatomie, Kansas." December 6. Retrieved December 17, 2011 (http://www.whitehouse.gov/the-press-office/2011/12/06/remarks-presidenteconomy-osawatomie-kansas).
- White House, Office of the Press Secretary. 2016a. "Speeches and Remarks." Retrieved January 16, 2016 (https://www.whitehouse.gov/briefing-room/speeches-and-remarks).
- White House, Office of the Press Secretary. 2016b. "Your Weekly Address." Retrieved January 16, 2016 (https://www.whitehouse.gov/briefing-room/weekly-address).
- White House, Office of the Press Secretary. 2016c. "Statements and Releases." Retrieved January 16, 2016 (https://www.whitehouse.gov/briefing-room/statements-and-releases).
- White House, Office of the Press Secretary. 2016d. "Press Briefings." Retrieved January 16, 2016 (https://www.whitehouse.gov/briefing-room/press-briefings).
- Xu, Kaibin. 2013. "Framing Occupy Wall Street: A Content Analysis of *The New York Times* and *USA Today*." International Journal of Communication 7:2412-2432.
- Zaller, John R. 1992. The Nature and Origins of Mass Opinion. Cambridge, UK: Cambridge University Press.

APPENDICES

For brevity, the appendices have been omitted from the print version of the current paper. They are available online at http://jmausolf.github.io/rsf_sicss/documents/appendix.pdf for review.