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Occupy the government: Analyzing presidential and congressional discursive response to movement repression

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ABSTRACT

I examine the role of Occupy Wall Street in shifting presidential and congressional discourse on economic fairness and inequality. Using data from 4646 presidential speeches and 1256 congressional records from 2009 to 2015, I test different mechanisms, including repression, media coverage, public opinion, and presidential agenda-setting by applying a novel combination of web scraping, natural language processing, and time series models. I suggest that movement success can be measured in its ability to shape discursive opportunity structures, and I argue that the role of the president should be at the forefront of social movements research. Ultimately, I demonstrate (1) that the repression of Occupy protesters not only predicts media coverage but also increases discursive opportunities through President Obama and Congress, (2) that media coverage of Occupy predicts presidential discourse, (3) that the president's rhetorical shift increases congressional response, and (4) that this change persists after the movement faltered.

1. Introduction

Pounding the airwaves with a rhapsodic promise of change, the 2008 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 (Gitlin, 2012; Gould-Wartofsky, 2015). Occupy Wall Street mobilized this discontent and questioned 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 marches, but also heckled the president at his events (Memmott, 2011)[1]. The president listened. Since the emergence of Occupy, President Obama amplified his call to equality, arguing that every American deserves a fair shot and that *all* should pay their fair share, a phenomenon widely noted by political commentators (Berman, 2011; Henninger, 2011; Silver, 2012). Congress, to a lesser extent, joined the fray. Given these observations, I ask (1) *what measurable role did Occupy have in shifting political discourse by President Obama and Congress,* (2) *what was the duration of this shift,* and (3) *how can we best measure the mechanisms predicting this transformation?*

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[1] 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.

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0049-089X/

In this paper, I challenge the notion that movements only matter in how they achieve legislative victories or policy gains. Instead, I argue that a movement's ability to elevate its ideas into the discussion of a nation's highest officials reflects a victory that has the potential to elevate the national salience of the movement's cause and generate new political opportunities. Second, my analysis brings the role of the presidency to the forefront, and I suggest that research on congressional action must also consider presidential agenda-setting. Third, rather than examine discrete movement tactics, I argue that arrests can serve as a singular measure of movement *repression* and be used to predict subsequent discursive gains. Lastly, I demonstrate these results by leveraging a novel combination of computational and statistical methods to help lay the groundwork for movements research in the era of big data.

2. Situating Occupy Wall Street in social movements research

In September 2011, the Occupy Wall Street movement swept across the United States and around the globe, notably with its entrenched encampments in the heart of Wall Street's Zuccotti Park. The protests received extensive media coverage, particularly for their disruptive, non-institutional tactics, violent confrontations between protesters and police, and mass arrests (Calhoun, 2013; DeLuca et al., 2012; Xu, 2013).[2] A movement's ability to be flexible, spontaneous, and collaborative is integral to success (McCammon, 2012; Snow and Moss, 2014; Wang and Soule, 2012), and researchers who study Occupy's tactics, note that Occupy's use of social media helped facilitate the collective action that engendered widespread arrests across the country (DeLuca et al., 2012; Gaby and Caren, 2012; Gamson and Sifry, 2013; Snow and Moss, 2014). Some analysts argue that Occupy had effectively no influence on public opinion even if the plurality favor the "progressive taxation" proposed by President Obama (Bartels, 2012). Other commentators credit the movement with transforming awareness and understanding of economic inequality (Berman, 2011; Gaby and Caren, 2016; Klein, 2011; Krugman, 2011b). If Occupy shifted awareness of inequality, how was this change achieved, and how can we understand its success as a social protest movement?

2.1. Toward a discursive approach to movement success

Although policy gains establish movement success (Gamson, 1990), we should also consider long-term benefits, which are often only perceptible after the movement fades (Amenta, 2006:32; Soule and King, 2006; Tilly, 1999:268-9). In particular, I argue that we can define movement success by its ability to shape existing opportunity structures (Bloom, 2015; Ferree, 2003; Vasi et al., 2015), particularly shifts in (1) public and (2) political discourse. Following Koopmans and Olzak (2004), I link political and discursive opportunity structures (Bloom, 2015; Ferree, 2003; Vasi et al., 2015), where discursive opportunity reflects the "*political acceptability … of ideas*" or legitimacy, resonance, and visibility of topics in "political culture," which may appear in spoken or written discourse (Ferree, 2003:309; Koopmans, 2005; Koopmans and Olzak, 2004; Vasi et al., 2015:935). The political legitimacy of ideas—reflected in public opinion or political agenda—ground important dimensions of the political opportunity structure or *political context* facing movements (Bloom, 2015; Koopmans and Olzak, 2004). Discursive shifts that shape public opinion or establish political agenda therefore alter existing discursive and political opportunity.

(1) *Shifts in Public Discourse.* The "unintended social or cultural consequences" of movements (Amenta, 2006; McAdam, 1999:117-8; Tilly, 1999) include durable impacts on language and public discourse (Ferree, 2003; Ferree et al., 2002; Goodwin and Jasper, 1999). For example, both protesters and allied activists can create discursive opportunities in social and mass media that energize mobilization and shape public awareness (Koopmans and Olzak, 2004; Vasi et al., 2015). Thus, 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 (Burstein, 1999; Giugni, 1999; Goodwin and Jasper, 2003; Vasi et al., 2015). Indeed, some reports already indicate that Occupy has permeated our cultural lexicon (Alim, 2013; Gitlin, 2013; Stelter, 2011) and increased media discourse on inequality (Gaby and Caren, 2016). I suggest that Occupy's ability to shape presidential discourse facilitated these transformations. By advocating an issue to the American public, the president elevates its salience to the public and media (Behr and Iyengar, 1985; 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—serve as a tangible and prominent mechanism by which Occupy's ideas may gain acceptability and take on a lasting legacy in American culture (Behr and Iyengar, 1985).

(2) *Shifts in Political Discourse.* Beyond directly altering Americans' perception, the president influences Congressional debate (Canes-Wrone, 2006; Edwards and Wood, 1999). By many accounts, legislation begins with getting an issue on the agenda (Amenta et al., 2010:291; King et al., 2007; Olzak and Soule, 2009; Soule and King, 2006). Even where legislation does not immediately follow, congressional activity improves the likelihood of future legislation (Burstein et al., 2005; Soule and King, 2006). Further, congressional discourse approximates the legislative agenda and thereby deserves attention (Maltzman and Sigelman, 1996; Quinn et al., 2010). Given these points, I posit that *congressional attention is a movement goal* achievable through the office of the president. The degree to which a movement redirects presidential rhetoric through the existing opportunity structure—or uses the president to alter the opportunity

[2] Occupy's tactics were "disruptive" or "non-institutional" as opposed to "assimilative" or "institutional" (Amenta,2013).

structure facing future mobilization (Bloom 2015)—therefore offers an alternative sociological framework for assessing movement influence.[3]

2.2. Using arrests as a measure of movement repression

To examine discursive gains, I utilize Occupy arrests as an observable measure of movement *repression*, specifically, the physical detention of a protester by a law enforcement agent. In social movements literature, repression takes many forms, but generally includes action by state agents against movement challengers including surveillance, arrests, force, or violence, among other government tactics that amplify the risks of protest participation (Davenport, 2007; Earl, 2003, 2011; Tilly, 1978). Arrests reflect an aggressive form of repression, what Earl (2003) terms “observable coercion” by “state agents loosely connected with national political elites” (48-9; Earl, 2005).[4] Since repression may either deter or energize protest (Earl, 2011; Opp and Roehl, 1990; Rasler, 1996), we should understand its impact, particularly for *highly observable* acts of repression. Because arrests invite continuing media coverage, and news amplifies movement attention and shapes its perception (*c.f.* Amenta et al., 2009; Earl et al., 2003; Koopmans, 2005; Lipsky, 1968; Wouters and Walgrave, 2017),[5] arrests may yield discursive opportunities.

Beyond discursive opportunity, I also suggest movement scholars should differentiate between acts of disruption and acts of repression (Fig. 1). Repression scholars use movement *attributes* (such as protest size or radical goals) and movement *tactics* (such as property damage, sit-ins, or combativeness) to indicate threat and predict the likelihood of repression, including

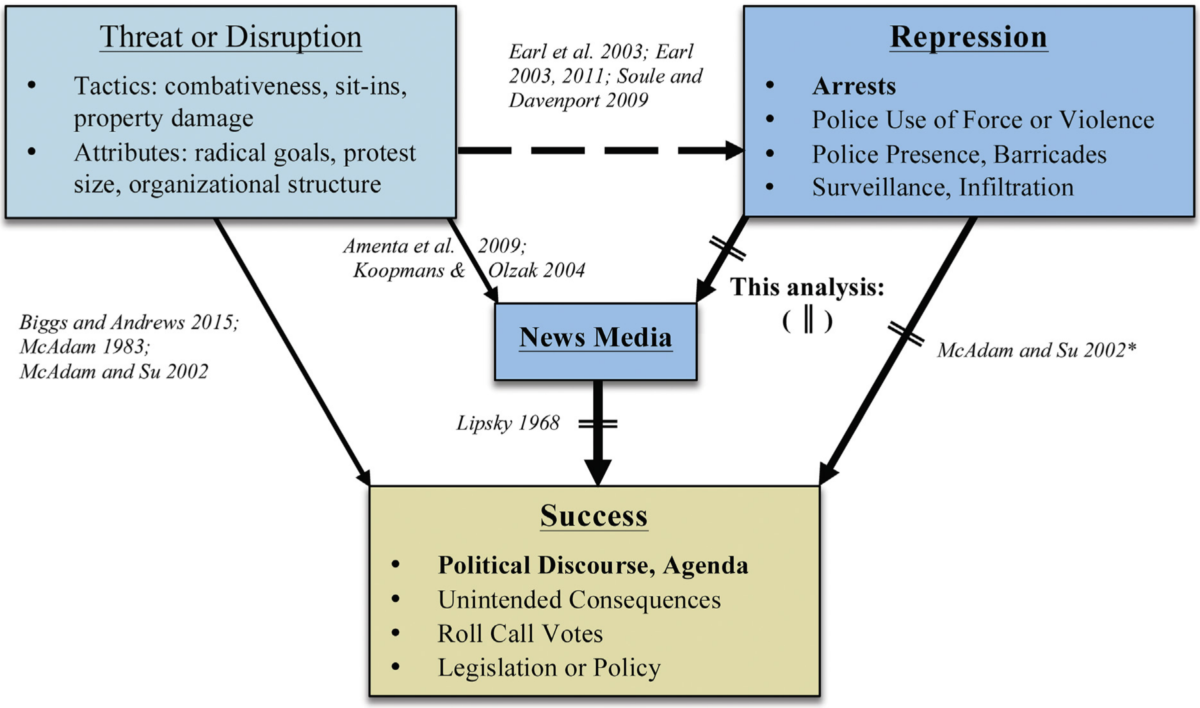

Fig. 1. Examining the role of repression in media coverage and movement success.
Note: Bolded text, that is, repression (arrests), news media, and success (political discourse, agenda) represent measures I analyze. Given citations are illustrative not exhaustive. Movement tactics and attributes can represent the level of threat or disruption (or lack thereof), and be used to predict the likelihood of repression or movement success (c.f. Earl et al., 2003; McAdam and Su, 2002; Soule and Davenport, 2009). If movement tactics or attributes do not constitute enough threat or disruption, repression is less likely (as represented by the dashed lined). *McAdam and Su (2002) use one metric of repression (violence by police) to predict success, but frame this act as disruption *not* repression.

[3] Bloom (2015), illustrates that past movements, such as the Progressive Challenge, altered the political opportunity structure facing Black Anti-colonialists, who leveraged the opportunity structure to affect President Truman's agenda. In the same way, Occupy's ability to navigate the existing opportunity structure to redirect presidential and congressional agenda, alters the opportunity structure facing future mobilization.

[4] Scholars disagree on the severity of arrests. McPhail and McCarthy (2005) and Rasler (1996) mark arrests as a less severe form of repression. Earl (2005, 2011) instead argues that arrests are aggressive, co-occur with violence, and have long-term effects for those arrested.

[5] Amenta et al. (2009) include protest intensity and police as factors increasing newsworthiness. Disruptive protest increases daily news coverage. I elaborate on reasons arrests are newsworthy in discussing my hypotheses and show this in the analysis.

surveillance, use of force, or arrests (Earl et al., 2003; Soule and Davenport, 2009). This approach reveals a potential disparity.[6] For example, McAdam and Su (2002), simultaneously use action *by protesters* (violence or property damage) and action *by law enforcement* (violence toward protesters) as two discrete indicators of disruptive protest. Whereas action by protesters reflects movement *tactics*, the latter reaction by law enforcement is a method of *repression* predicted by the former (Earl et al., 2003; Soule and Davenport, 2009).

Given (a) the possible conflation of disruption and repression, (b) discrete studies using threat and disruption to predict either success or repression, and (c) the empirical reality that observable repression is newsworthy and can thereby attract subsequent political attention, I suggest that where *observable* repression exists, it may also directly predict media and political discourse. In the case of Occupy, what effect does observable repression, namely *arrests,* have on media coverage and the diffusion of movement ideas in political discourse?

2.3. Understanding Occupy's motivating issues

To answer this question, we must first know, *what were Occupy's motivating issues?* 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, 2011). Ostensibly, Occupy's mission statement exemplifies themes of (1) animus toward Wall Street and the financial collapse, (2) corporate greed and coercion over politics, (3) economic inequality between the top 1% and everyday citizens, and (4) 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 issues (DeTar, 2012; DeLuca et al., 2012; Gould-Wartofsky, 2015; Milkman et al., 2013a, b).

If politicians respond by coopting or strategically reframing a movement's issues, politicians will likely use the best information available, to which point, the movement's mission statement and reports conveying these claims reflect a viable resource. I examine political rhetoric for the discussion of these same topics, which I hereafter refer to as (1) Wall Street, (2) Corporate Greed, (3) Inequality, and (4) Fair Share rhetoric. When referring to these topics, I use the terms *ideas* or *issues* interchangeably with the realization that politicians' discussion of these topics may be reframed or differ from the movement's intended objectives (Ferree, 2003). Collectively, Occupy's radical goals challenge the economic and political interests of elites,[7] and by consequence, reify the protest's threat, predict increased police repression, and suggest diminished chances of movement success (Amenta et al., 1992; Amenta et al., 2010; Earl et al., 2003; Giugni, 2007; Kriesi et al., 1995).

3. Mechanisms of political response

To explain how repression may achieve discursive success, I draw upon *political opportunity structures*, which I argue can be embedded in a *political mediation* framework.

3.1. Political opportunity structures

In the basic formulation, *political opportunity* argues that political contexts determine historical fluctuations in protest activity and strength (McAdam, 1982). Limitations include failure to account for protest attributes or action (Amenta et al., 2010; Bloom, 2015; McAdam et al., 2001). A theoretical adaptation, known as "political opportunity structures" incorporates movement practices (Kitschelt 1986; Koopmans and Olzak 2004)—an idea Bloom (2015) refines by suggesting movements may harness political opportunities to garner influence. As shown by Bloom (2015), movements can (a) create credible threat and (b) take advantage of the opportunities left by past mobilizations to shift presidential agenda. That is, by creating *threat,* the movement's action under unique political contexts incurred the political *reaction* of discourse aligned with movement issues. As I elaborate below, such an opportunity framework can be embedded in the action-reaction approach to political mediation theory.

3.2. Political mediation models

Many scholars use political mediation theory (Amenta et al., 1992; Amenta, 2006; Andrews, 2004; Cress and Snow, 2000; Piven and Cloward, 1977), which contends that "specific movement strategies, activities, and forms in combination with specific political contexts" politically mediate movement success (Amenta, 2006, 2013:1; Amenta et al., 1992, 2010). A variant of political mediation, known as action-reaction models (Andrews, 2004; Piven and Cloward, 1977), views mobilization, particularly the *action* of "large-scale dramatic events," as a spark invoking a *reaction* by politicians or local authorities (Andrews, 2004; *c.f.* Lohmann, 1993). These models rely on an insight from political mediation. Chiefly, response to collective action depends on politicians' perception of how beneficial or detrimental concessions would be to political and business

[6] The disparity is only occasional. Some disruption scholars do recognize arrests as a valid measure of repression despite its infrequency in predicting discursive wins. See Andrews and Biggs 2006 (760, note 12).

[7] Occupy's main objectives reasonably reflect the idea of an economic ruling elite, a topic discussed across social science (*c.f.* Bartels, 2008; Domhoff, 2010; Gilens, 2005; Hacker and Pierson, 2010; Peters, 2013; Piketty and Saez, 2007).

interests (Amenta, 2006:24; Amenta, 2013; Amenta et al., 2010:298; Giugni, 1999). Herein lies the bridge to political opportunity structures (*c.f.* Bloom, 2015). I suggest action-reaction models can explain a movement's ability to navigate and shape political opportunity structures—that is, the specific *political contexts* that lead to future long-term success.[8]

Andrews (2004) elaborates on the action-reaction approach, outlining two response models for non-institutional movements: the *threat* and *persuasion* models.[9] The *threat* model suggests that elite political response to disruptive protest stems from political self-interest and seeks to enervate movements through repression, concession, or combination thereof (Andrews, 2004; Piven and Cloward, 1977; Tarrow, 1993). When politicians find little advantage or are opposed to the underlying issues, they may introduce new proposals and rhetoric to pacify the movement until the protest inevitably falters (Andrews, 2004; Piven and Cloward, 1977; *c.f.* Amenta, 2006:26). In such cases, movements must adopt more assertive action (disruptive or assimilative) to secure success (Amenta, 2013; Amenta et al., 1992; Cress and Snow, 2000).

The alternative *persuasion* model suggests that movements can mobilize sympathetic third parties, or *allies*, to champion movement claims, mobilize cultural artifacts, create discursive opportunity, and incorporate movement ideas in the political agenda (Andrews, 2004; *c.f.* Cress and Snow, 2000; Giugni, 2007; Vasi et al., 2015). Taken together, both the *threat* and *persuasion* models suggest that to the extent protest gains political attention, the response—including discourse or rhetorical framing—will increase after the movement's onset (Andrews, 2004; Giugni, 2007; Piven and Cloward, 1977). This prompts two related hypotheses:

Hypothesis 1a. There will be an increase in the discussion of Occupy’s issues by President Obama and Congress after the movement began.

In addition to a collective rhetorical shift, differences also exist at the daily timescale, where Occupy’s daily arrest activity prompts reaction in political discourse:

Hypothesis 1b. There will be a positive association between Occupy arrest activity and subsequent discussion of Occupy's issues by President Obama and Congress.

I expand on several points. First, protest catalyzes a “reactive relationship vis-à-vis the movement,” or “dialogue” between protesters and politicians (McAdam, 1983:746; Meyer et al., 2005:302). Termed “tactical innovation,” a dynamic arms war of escalating protest emerges to provoke recurring political response—as during the Civil Rights, Vietnam War, and Women’s Suffrage movements (McAdam, 1983:746; McAdam and Su, 2002; McCammon, 2003; Wang and Soule, 2016). I similarly expect heighted response to arrests as the result of disruption, especially if Occupy’s observed repression yields media coverage.

Second, increased government response follows precedent. While violent, threatening, or disruptive mobilizations have limited success in direct legislative gains (Amenta et al., 2010; McAdam and Su, 2002; Steedly and Foley, 1979), and are more successful when disruption affects economic rather than political interests (Biggs and Andrews, 2015), politicians do respond to movement threat using a combination of sympathetic rhetoric and concessionary symbolic acts (Amenta, 2006; Piven and Cloward, 1977; Tarrow, 1993). Congressional voting reflects one such symbolic gesture predicted by police violence against protesters (McAdam and Su, 2002).

Third, considering the result in McAdam and Su (2002), the effects of disruptive protest may actually be those of repression, in their case, police violence. Although McAdam and Su's (2002) study pertains to congressional voting rather than discourse, we can infer that given a higher likelihood of voting, increased discourse will also precede those votes (Soule and King, 2006; Quinn et al., 2010), and this expectation is consistent with action-reaction models. Because threatening or disruptive protest elicits repression (Earl et al., 2003; Soule and Davenport, 2009), I argue that political elites—physically removed from the locus of uprising—do not directly respond to on the ground disruption but instead respond to its reported and perceived aftermath (Wouters and Walgrave, 2017), namely movement repression.

3.3. The role of news media

Beyond directly affecting political response, movement repression may also predict media coverage, which in turn, influences politicians (Behr and Iyengar, 1985; Canes-Wrone, 2006). Consequently, I underscore a key insight from political mediation theory: “For a movement to be influential, state actors need to see it as potentially facilitating or disrupting their own goals” (Amenta et al., 2010:298). In other words, movement influence relies on politicians' *perception* of a movement, which is informed by their knowledge thereof (Wouters and Walgrave, 2017), and therefore, media is paramount (Andrews and Biggs, 2006; Andrews and Caren, 2010; Lipsky, 1968). In brief, media delimits protest salience and diffusion across cities, such that if media dismisses the movement, the protest will falter and go unheard (Andrews and Biggs, 2006; Lipsky, 1968:1151). Although the media shows less favorable treatment to disruptive or violent movements (Andrews and Caren,

[8] This argument is consistent with Amenta (2006), who states political mediation theory “builds on … political contexts” (23). Amenta (2006) argues “like Herbert Kitschelt” (30), that state political context—or as Bloom (2015) would say, political opportunity structure—matters. Amenta (2006) writes that political context neither secures nor “dooms challengers to ineffectiveness” (30). Instead, challengers must “match mobilization and strategy to specific political contexts” (Amenta 2006:14)—that is, match their actions to navigate existing opportunity structures.

[9] McAdam and Su (2002) also discuss the *threat* and *persuasion* approaches.

2010), disruptive protest more easily attracts the media spotlight and receives daily press (Amenta et al., 2009). Since disruptive tactics predict arrests (Earl et al., 2003; Soule and Davenport, 2009), by proxy, we can presume that as arrest activity increases, so too will media coverage. This leads to the following Hypothesis:

Hypothesis 2. There will be a positive association between Occupy arrest activity and subsequent front-page and online media coverage of Occupy Wall Street.

Since media coverage delimits movement success, issue salience, and political responsiveness (Amenta et al., 2009; Andrews and Caren, 2010; Behr and Iyengar, 1985; Canes-Wrone, 2006), I submit a corollary Hypothesis:

Hypothesis 3. There will be a positive association between Occupy news and the subsequent discussion of Occupy's issues by President Obama and Congress.

The repression of Occupy can create a discursive opportunity in news media that facilitates protest diffusion and public awareness (Andrews and Biggs, 2006; Ferree, 2003; Vasi et al., 2015), fueling further disruption, arrests, and media coverage (Koopmans, 2005; Koopmans and Olzak, 2004), which may in turn increase discussion of Occupy's issues by political elites.

3.4. *Differential mechanisms of presidential and congressional response*

Given their unique political contexts, I anticipate subtly different patterns of presidential and congressional response. Although we expect observable repression to predict government response, Occupy manifested different threats and navigated discrete opportunity structures for President Obama and Congress. In contrast to the relationship between Occupy Wall Street and the president, the case of Congress differs in propinquity to Occupy. Whereas Occupy Wall Street directly disparaged or heckled the president on several occasions and potentially threatened the president's solvency in the 2012 election (Berman, 2011; Memmott, 2011; Oxford Analytica, 2011), any one member of Congress did not equally face the same exposure. The burden of response disproportionately befell the president. Moreover, because the president reacts to world events and media attention (Behr and Iyengar, 1985; Canes-Wrone, 2006; Edwards and Wood, 1999; *c.f.* Chozick, 2012), an increase in Occupy news should more directly affect President Obama than Congress. Given the president's ability to set congressional agenda and prompt congressional debate (Edwards and Wood, 1999; Canes-Wrone, 2006), the president's rhetorical response serves 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. I therefore expect legislators to discursively respond to the president, formally:

Hypothesis 4. There will be a positive association between the discussion of Occupy's issues by President Obama and subsequent discussion by Congress.

I suggest an additional caveat. While Occupy arrests may motivate presidential rhetoric, we might instead expect increased congressional discourse given an increase in the dispersion of arrest activity, namely that arrests occur in more cities across the country. For example, business desegregation spread to cities surrounding Civil Rights sit-ins even if those cities were not directly targeted by protest (Biggs and Andrews, 2015). Since members of congress particularly care about businesses and wealthy constituents in their state or congressional district (Burstein, 1999; Gilens, 2005, 2012; Page et al., 2013), when Occupy arrests spread across multiple cities, an increasing number of congressional interests—and those in nearby localities—may be threatened, suggesting heightened congressional response. I therefore use the number of cities with Occupy arrests (arrest cities) versus the number of protesters arrested (arrests) to predict congressional versus presidential discourse, respectively.

My discussion thus far presumes Occupy was a threat. But what if the president acts as a sympathetic albeit qualified ally, and in responding to Occupy's repression, the president coopts movement frames to capitalize on a political opportunity? If we consider the high-profile news coverage of Occupy, we can see how progressive rhetoric garners greater traction when deployed in the immediate aftermath of the day's event (c.f. Behr and Iyengar, 1985; Giugni, 2007). 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 to write his place 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 goals, adjured the president to adopt a progressive model of attack against Republicans in the spirit of Theodore Roosevelt (Kantor, 2012).[10] If historians correctly chronicle the president's historic aspirations, President Obama would best amplify his discussion at moments of heightened public salience in the wake of Occupy Wall Street (Canes-Wrone, 2006).

To robustly establish the role of Occupy, I must also consider alterative explanations. The 2012 presidential election, public opinion, and the economy could each affect political discourse (Bonikowski and Gidron, 2016; Brooks and Manza, 2013; Canes-Wrone, 2006; Canes-Wrone and Kelly, 2013). While I control for these factors, the question remains whether Occupy catalyzed a causal shift in rhetoric. I will submit that Occupy played a causal role if the shift in discourse (a) follows the onset of Occupy, (b) lingers after its decline, and (c) the effect is best explained by arrests versus controls. Here, I draw a salient

[10] President Obama invokes Theodore Roosevelt in the Osawatomie speech, (Berman, 2011; Henninger, 2011), which I quote in the discussion.

point. If the president and Congress simply wish to quell the movement by ephemerally appropriating its rhetoric, debate should also cease with the movement. If however, the president sympathizes with the movement and wishes to curate his legacy, those ideas should persist even if somewhat abetted for the duration of the presidency.

Collectively, this study contributes to social movement research by examining repression's effect on the discourse of political elites. I argue that a movement's ability to navigate and shape existing opportunity structures—particularly the discourse of political elites—denotes an alternative framework for measuring movement success. Enlisting presidential support holds particular promise, given the president's unparalleled potential to elevate the national visibility and legitimacy of an issue. I hypothesize that Occupy arrest activity predicts subsequent discussion of Occupy's issues, both directly as well as indirectly through the news media and presidential agenda-setting. A presidential rhetorical shift will not only exemplify a dynamic response to repression but also Occupy's ability to redirect congressional attention and recast both the current and future historical dialogue on economic inequality.

4. Data and methods

I evaluate these claims using several data sources including text data from presidential speeches and congressional records as well as data on Occupy arrests and news coverage of Occupy. Below, I specify my measures and data collection.

4.1. Dependent variable data collection – presidential and congressional text

I collected President Obama's speeches and remarks from the White House, Office of the Press Secretary's public website. 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 also include weekly addresses (2016b); statements, op-eds, letters (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 presidential speeches and remarks, I developed a web-scraping application written in *Python* and *Shell* (Mausolf, 2016a).[11] With respect to President Obama, this yields 4, 646 speeches between January 21, 2009 and November 15, 2015. This script has multiple quality control measures to ensure proper content. For example, when trying to parse each speech URL, the code 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 and reevaluate the data. Where errors cannot be automatically resolved, the errant URLs are added to a separate file, which I collected manually. Although the president often presides as the sole speaker, 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 speeches by hand—removing lines and paragraphs not spoken by the president—resulting in a high quality corpus of speech data for the entire Obama presidency.

The Congressional Record documents the speeches and proceedings of Congress (both House and Senate) on days Congress is in session (United States, Government Printing Office 2016). For each day of the Congressional Record, a single PDF of the entire record exists, inclusive of the daily digest, extension of remarks, and proceedings of the House and Senate. I developed a second web-scraping script to download and convert these online PDF's to raw text (Mausolf, 2016b). In contrast to alternate efforts to collect the Congressional Record or press releases (Grimmer, 2013; Judd 2016), my code captures the entire daily record of all congressmen and senators in aggregate and does not further extract or subset individual politicians' remarks.[12] Given my preference for the entire record, the original PDF offers an already curated corpus and thereby minimizes errors in data collection and compilation.

4.2. Keyword extraction

Subsequently, I implemented code to analyze each presidential and congressional text for specific keywords and phrases related to Occupy's motivating issues (Mausolf, 2016c). This code builds a dataset of speech metrics consisting of a speech ID, date, summary statistics, and numerous keyword counts for pre-specified, theoretically-driven words and phrases expected to change in response to Occupy Wall Street (see Section 2.3 and Appendix B). Descriptive statistics of the resulting dataset can be found in Table 1.

[11] My web-scraping code automatically opens a web-browser, navigates the White House domains (2016a, d), saves every speech URL in a CSV (N $\approx$ 15, 900 URLs); sorts these URLs based on speaker; and then parses that speech, saving it with a unique filename in designated folders.

[12] Differentiating speeches by individual legislators can be useful in congressional analysis, especially if considering spatial metrics or other predictors by congressional district. I do neither, and instead contrast congressional and presidential response to Occupy arrest activity in time series. Additionally, legislators' positions may precede, start after, and end during the president's tenure. Combined with legislator absenteeism, analyzing individual legislators would introduce unnecessary model complexity and missingness to the data.

Table 1
Descriptive statistics of text data, 2009–2015.

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

Note: Total Days represents the number of days with presidential or congressional content. All days without speeches have keyword (and other text metric) counts of zero. Total Text Files reflects the number of text files in total. Whereas there was a maximum of one congressional record per day, the president might have several speeches at different states or venues on a single day. Total Words is the sum of all alphabetical words (including stop words) but excluding numbers and symbols.
Sources: Speech terms taken from the U.S. Congressional Record and the White House records (United States, Government Printing Office, 2016; White House, 2016a-d). Data was downloaded and counted using Python and Bash scripts (Mausolf, 2016a-c).

4.3. Measuring occupy Wall Street arrests

Data on Occupy Wall Street arrests came from an online database (Occupy Arrests, 2014). The dataset measures the number, date, and city of arrests, with a description and linked source. In total, 7775 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.[13] 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, which I verified with 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. These errors reflect disparities between when the news reports were published versus when the arrests transpired. Beyond 91% accuracy, the data subsample and my independent results are highly correlated ($r = 0.994$, $p < 0.001$), have high internal consistency (Cronbach's Alpha, $\alpha = 0.997$), and high inter-coder reliability (Cohen's Kappa, $\kappa = 0.881$, $p < 0.0001$). In sum, these metrics illustrate the excellent quality of the arrest data.

4.4. 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 can 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).[14] Although news media is a common resource in social movements research (Amenta et al., 2009; Earl et al., 2004; Kim and McCarthy 2016), I discretize front-page news considering the prominence of lead articles (Behr and Iyengar, 1985; Koopmans and Olzak, 2004). To facilitate a daily time series, I converted covariate data not already on a daily scale using the last known value. 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 were collected. Imputation did not carry forward indefinitely, however, and I therefore limit the analysis to November 15, 2015, after which, not all covariate data exists.

While 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 alters speeches in response to any of the covariates, they would reasonably predicate their response on the last known value.

Lastly, I transformed the speech keyword data by (1) aggregating the keywords into discrete categories through row addition and (2) using principal components analysis (PCA) on the keywords for each topic. For PCA, I used the first principal component (highest ranking eigenvector) to represent each speech category.[15] By using dimensionality reduction, PCA captures potential latencies reflected across keywords that might not otherwise be represented through simple aggregation.

[13] 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.

[14] LexisNexis was used to collect media coverage (see Table 2). *Major World News Occupy coverage prominently features front-page stories by the New York Times and Washington Post, followed by other major U.S., Canadian, and U.K. papers such as the Guardian. There is extremely sparse if any coverage by other major international newspaper sources. The alternative choice of *U.S. Newspapers and Wires would be dominated by wire services and obscure U.S. local papers. I chose *Major world news, to preference prominent front-page articles versus equally weighting front-page coverage from the New York Times and small local papers.

[15] 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).

Table 2
Descriptive statistics of model variables, 2009–2015.

	N	Mean	SD	Min	Max
Dependent Variables[1]					
President Obama					
Inequality Terms Count	2510	4.62	9.23	0	92
Fair Share Terms Count	2510	0.31	1.28	0	27
Inequality Terms PCA	2510	0.00	2.24	−1.31	28.38
Fair Share Terms PCA	2510	0.00	1.68	−0.30	49.62
Congress					
Inequality Terms Count	2510	106.09	154.84	0	1112
Fair Share Terms Count	2510	0.99	3.02	0	39
Inequality Terms PCA	2510	0.00	3.31	−2.17	23.27
Fair Share Terms PCA	2510	0.00	1.40	−0.46	16.89
Independent Variables[2]					
Occupy Wall Street Protesters Arrested	2510	3.10	27.14	0	724
Occupy Wall Street Protesters Arrested (100s')	2510	0.03	0.27	0	7.24
Number of Cities with Occupy Protester Arrests	2510	0.18	0.88	0	14
Public Perception Controls					
U.S. Google Trend: "Occupy Wall Street"[3]	359	2.25	10.48	0	100
U.S. Google Trend: "Occupy Wall Street", Imputed ‡	2507	2.26	10.48	0	100
U.S. Google Trend: "Income Inequality"[4]	359	26.95	19.39	0	100
U.S. Google Trend: "Income Inequality", Imputed‡	2507	26.86	19.29	0	100
Political Controls					
President Obama's Approval Rate (Percent)[5]	2357	48.36	3.84	41	69
President Obama's Approval Rate (Percent), Imputed ‡	2507	48.29	3.80	41	69
President Obama Campaigning in 2012 Election	2510	0.09	0.28	0	1
Economic Conditions Controls					
S&P 500 Market Close	1725	1469.28	384.81	676.53	2130.82
S&P 500 Market Close, Imputed ‡[7]	2509	1471.00	385.68	676.53	2130.82
National Unemployment Rate	83	7.85	1.54	5	10
National Unemployment Rate, Imputed ‡[9]	2510	7.87	1.52	5	10
Media Coverage of Occupy Wall Street					
Major World Newspapers, Front-Page Coverage[10]	2510	0.05	0.32	0	6
Prominent Online News Coverage[11]	2510	0.17	1.05	0	17
Exposure					
Words (Daily) – President Obama	2510	2637.32	3156.97	0	21,971
Total Words (millions) – President Obama	2510				6.62 M
Words (Daily) – Congress	2510	74,780.16	106,965.70	0	663,001
Total Words (millions) - Congress	2510				187.70 M
Dates				1-Jan-2009	15-Nov-2015

Sources: (1) Speech terms taken from the U.S. Congressional Record 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 Python and Bash scripts (Mausolf, 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.

In sum, I analyzed the aforementioned speech categories: *Wall Street, Corporate Greed, Inequality,* and *Fair Share*. I detail summary statistics in Table 2 and describe the formal analysis below.

4.5. Formal analysis

I begin the analysis by conducting F-tests on each speech category. For topics passing this litmus test, I run bivariate analyses and multivariate time series models, 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.

4.6. 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 (*c.f.* Olzak and Ryo, 2007), which allows the differencing parameter, d, to only take the value 0 or 1 (Box-Steffensmeier and Tomlinson, 2000).[16] 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:

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

where the errors (ε_t) are distributed approximately normal $(0, \sigma_\varepsilon^2)$; $\Phi(L)$ 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):

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

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

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

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 or negative binomial models (*c.f.* McAdam and Su, 2002; Olzak and Ryo, 2007; Olzak and Soule, 2009), the Poisson is inappropriate because my data are over-dispersed. Negative binomial models fail to adequately address long-range persistence, although it should be noted that testing these models yielded similar results to the ARFIMA models.[17] For robustness, alternative ARFIMA specifications were tested without effect (Appendix A).[18]

To draw on the rationale of Box-Steffensmeier and Tomlinson (2000) and Zaller (1992), individuals with high "political sophistication" have the capacity to recall 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 repression of Occupy Wall Street 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.

5. 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 ideas 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 with F-tests for each keyword category. Here, I am interested not only in a difference between the groups but also whether there is a significant *increase* in the Occupy period followed by a significant *decrease* in the post-Occupy period. To show greater detail, I subdivide the first year of Occupy into two six-month periods. I display the results in Fig. 2.

From these plots, a rhetorical shift is apparent. For both President Obama and Congress, we witness an acute, parallel increase in their fair share discourse. Recall that this category reflects sentiments that 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

[16] 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). See Lebo and Grant (2016) and Lanier and Dietz (2012) for further discussion.

[17] 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.

[18] For robustness, I find similar results in presidential and congressional models that include Occupy arrests and arrest cities as well as an exposure control using a log transformation of the total number of words in the dependent variable text records (Appendix A, Tables A4 and A6). I used the raw count of arrests and arrest cities versus a log transformation. Insofar as politicians respond to movement repression, they will react to the raw number of protesters arrested or cities with arrests rather than compute the natural log of repression in evaluating response. Beyond the theoretic justification, log transforming the count data distorts the data integrity, particularly since it must be manipulated to avoid dropping values of zero. If arrests are to be logged, so too would the counts of other count covariates such as the news. Model interpretability would greatly suffer. Using log arrests does not substantively alter the results or interpretation (and raw arrests are more informative in terms of AIC and BIC).

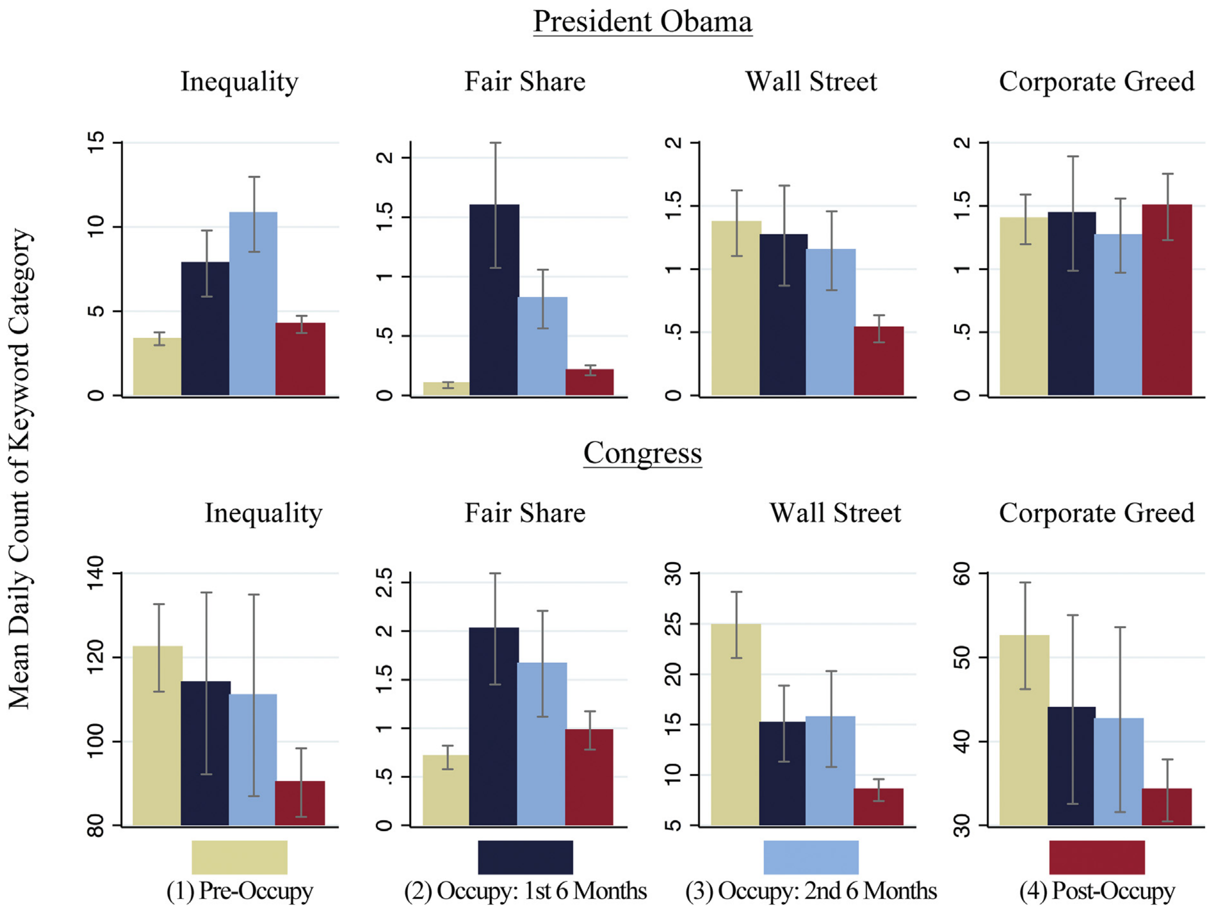

Fig. 2. President Obama and Congress's speech by Category and time period.
Note: Each bar in the bar graphs reflects a discrete time period as follows: (1) Pre-Occupy period, (2) Occupy: 1st 6 months, (3) Occupy: 2nd 6 months, (4) Post-Occupy. Dates range from January 1, 2009 to November 15, 2015. Pre-Occupy period: 01-Jan-2009-16-Sep-2011. Occupy 1st 6 Months: 17-Sep-2011-17-Mar-2011 Occupy 2nd 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 as reported in the paper.

“America where everybody gets a fair shake and everybody does their fair share” (White House, 2011a). During the height of Occupy, we undoubtedly see an increase in 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 ($F = 13.35$, $p < 0.0001$), 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), thereby substantiating *Hypothesis 1a*.

While there is a spike in fair share discussion during Occupy for both President Obama and Congress, the pattern of other keyword groups differs. In the case of inequality, President Obama amplifies his inequality discourse during Occupy and in fact speaks at greater length about inequality during the second rather than the first 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 prior to the rise of Occupy. As the economy began its slow recovery, President Obama and Congress discussed these topics with flagging frequency. From the perspective that response is strategically framed (Ferree, 2003), the diminished discussion of Wall Street and corporate greed may reflect a strategic rhetorical choice to redirect discussion to inequality or paying the fair share rather than directly disparage the vested corporate interests that bankroll political campaigns (Domhoff, 2010:166; Hacker and Pierson, 2010; Kuttner, 2010:15). Given the positive findings for inequality and fair share rhetoric, I limit remaining analysis to these categories.

5.1. *Exploring the bivariate effect of Occupy Arrest activity*

In light of these rhetorical shifts, does daily arrest activity also alter discourse? Consider the relationship of Occupy arrests to inequality and fair share discourse that same day (Fig. 3).[19] 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. Significant increases exist for both inequality and fair share rhetoric by the president. For Congress, we observe a similar albeit insignificant pattern. Inequality discussion climbs from a baseline of 104 mentions to 129 and 206 uses as arrests increased. Congressional fair share rhetoric likewise increases with some versus no arrests.

By contrast, the patterns manifested for *arrest cities* differ for the president and Congress. Although there are universal increases in the discussion of inequality and fair share rhetoric by the president on days with arrests in *some* cities, we do not

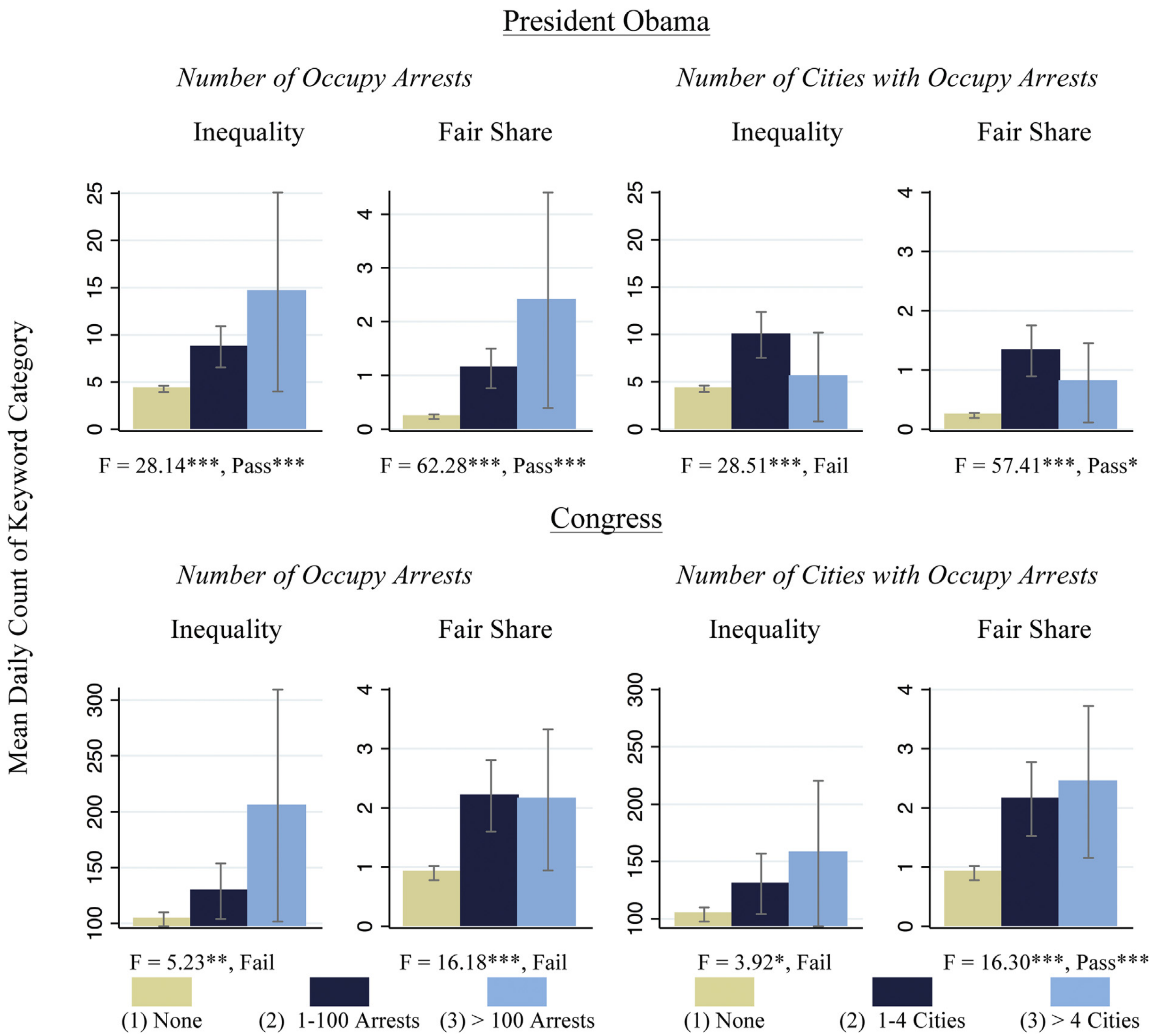

Fig. 3. Government speech by Occupy arrests and number of cities with Occupy arrests.
Note: Significance levels as follows: *p < 0.05, **p < 0.01, ***p < 0.001. Results in this table are for daily arrest activity (unlagged) versus daily speech (unlagged). All Y-axes represent the mean daily keyword count. Confidence interval bars are for 95%. F-tests with Bonferroni pairwise comparisons noted with full results (both lagged and unlagged) 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.

[19] Fig. 3 has un-lagged arrests versus keyword counts the same day. Lagged and un-lagged results are displayed in Appendix A, Table A1.

necessarily see increased discussion when there are more than four arrest cities compared to only one to four arrest cities. Graphically, the contrast between the presidential and congressional speech patterns is apparent. Whereas presidential response to arrest cities varies, congressional discussion consistently rises on days with arrests in some cities versus none and is significant for fair share discourse. Similar results are seen when arrests are lagged one day (Appendix A, Table A1).

The difference between *arrests* and *arrest cities* for President Obama versus Congress substantiates my theoretical expectation. Examining the F-tests, particularly the Bonferroni pairwise comparisons, we notice that *arrests* pass each test for President Obama but fail in both congressional cases. Conversely, *arrest cities* pass Bonferroni tests only for *fair share* speech. I therefore test differentiated time series models, using arrests to predict presidential speech and arrest cities to predict congressional debate. Before turning to the models, I contextualize the pattern of government response.

5.2. Contextualizing presidential and congressional response

With the onset of Occupy Wall Street, a dynamic pattern unfolds. Namely, inequality and fair share discourse spikes in the wake of Occupy arrests, particularly for President Obama. Consider 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 often critiqued inequality most fiercely in the hours and days following mass arrests in the Occupy movement (Fig. 4).

Although imperfect, the pattern suggests more than coincidence. By mid-September, presidential inequality and fair share discourse had diminished. On September 24, 2011, New York City police pepper-sprayed protesters and arrested more than 80 Occupy demonstrators as they marched from the financial district toward Union Square (Nir, 2011; O'Donnell, 2011). By 8:30

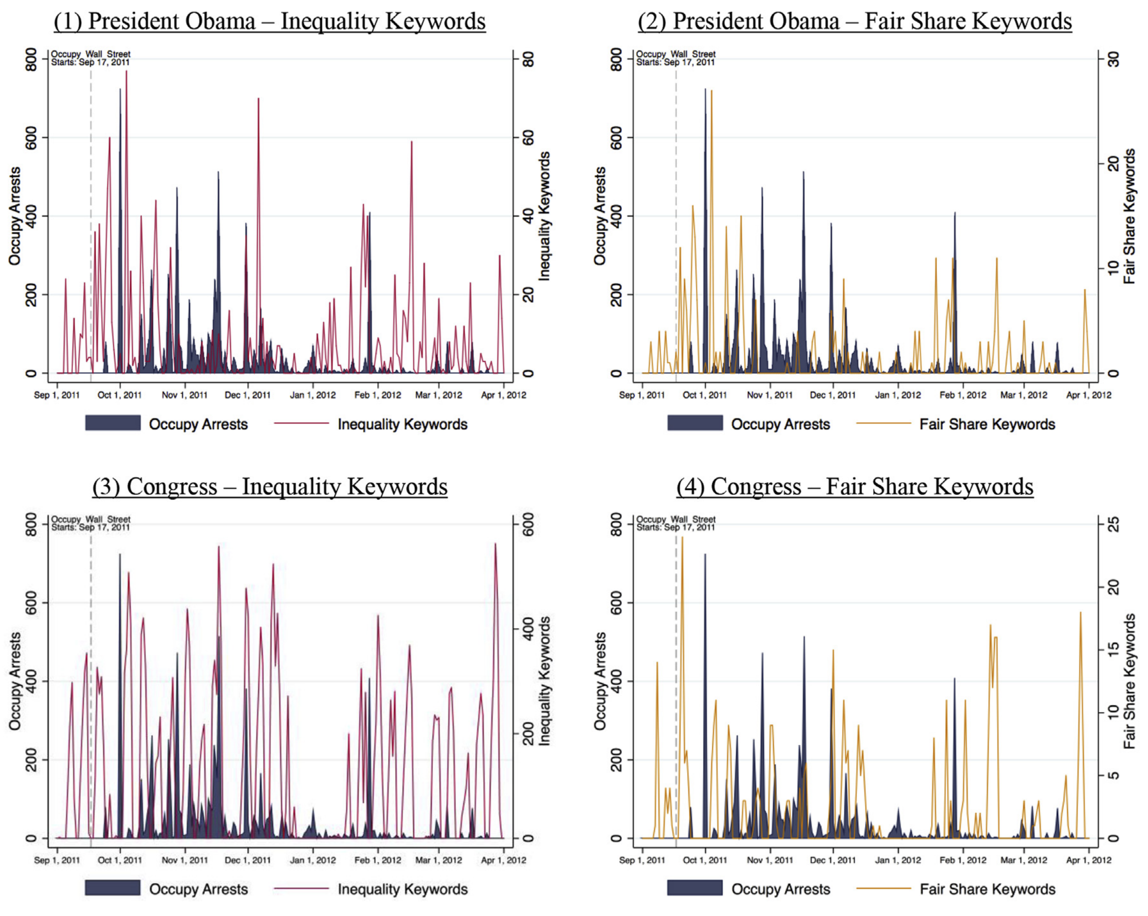

Fig. 4. Timing of president Obama and Congress's speech versus Occupy arrests.
Note: Occupy Wall Street begins on September 17, 2011. Data displayed on a daily timescale. Timescale truncated to September 1, 2011 to April 1, 2012 to illustrate sufficient detail. Cumulative results for the entire period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

p.m. that evening and for several days thereafter, President Obama's inequality and fair share rhetoric skyrocketed as leftwing pundits condemned police brutality (O'Donnell, 2011). Consider the president's remarks that evening, September 24, 2011:

> 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 … You start saying, at a time when the top one-tenth of 1 percent has seen their incomes go up … 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 later on October 1, 2011, hundreds of protesters blocked the Brooklyn Bridge, 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 working 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, 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. Democrats adopted a similar discourse, emphasizing the need for the wealthy 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, 2011b):

> 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. - Sen. REID (D)

> 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 … Thanks to loopholes … the rich keep getting richer. The top one percent … 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)

The majority of congressional response came from Democrats, who offered supportive rhetoric. At the same time, Republicans refuted the president, such as Senate Minority Whip Jon Kyl (R., AZ), who on September 21, 2011 stated, "This is supposedly so millionaires and billionaires pay their fair share.…According to Obama mythology, millionaires and billionaires pay lower tax rates than average Jacks" (United States, 2011a). Although these are but a few examples, the quotations help contextualize the pattern of discourse illustrated in Fig. 4. Spikes in arrests are followed by an increase in presidential rhetoric and a subsequent echo of support (or dissention) by members of Congress. Of course, such analyses cannot account for the presence of the news media, public interest, or autoregressive or moving average trends. To robustly establish Occupy's role, I utilize time series models, which I unpack in the following section.

5.3. Unpacking model parameters

I expand the preceding analysis by using ARFIMA models. Although I expect arrests to be associated with subsequent discourse, because speeches may take longer to rewrite in response to repression, we might reasonably expect discourse to peak several days following arrests. We might also anticipate daily political speech to be serially autocorrelated with past speeches. I include not only the current day's arrests but also lags for arrests one, two, and three days past. Since movements may go unheard without media, I also control for news coverage.

First, I consider the direct effect of repression on news (*Hypothesis 2*). As we can see in Table 3, arrests predict both front-page and online news of Occupy. In particular, the number of arrests one and two days ago and the number of arrest cities yesterday predict current *front-page* news. To a lesser extent, arrests two and three days past and the number of current arrest cities predict today's *online news*. To control for the news cycle, I therefore include not only same-day news, but also the lagged news cycles, going back three days in both presidential and congressional models. Since past arrests predict future news coverage (confirming *Hypothesis 2*), the extent that Occupy news predicts inequality and fair share rhetoric can be viewed as a secondary effect of Occupy arrests. Beyond the news, I also include lags for public perception via Google Trends. I lag Google trend data and Rasmussen polls by one week. The campaign dummy variable, unemployment rate, and S&P 500 index are modeled continuously without lags or leads.

5.4. Modeling presidential speech

I display presidential models in Table 4. A brief examination of these models reveals that Occupy Wall Street arrests three days ago predict President Obama's present-day inequality and fair share speech. 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

Table 3
ARFIMA time series models: Front-page and online occupy news, 2009–2015.

	Front-Page News		Online News	
	Article Count Beta	SE	Article Count Beta	SE
Occupy Wall Street Protesters Arrested (100's)				
Base: Arrests Today	0.04	(0.02)	0.07	(0.05)
Lag 1: Arrests Yesterday	0.21***	(0.02)	−0.06	(0.06)
Lag 2: Arrests Two Days Past	0.17***	(0.02)	0.12*	(0.06)
Lag 3: Arrests Three Days Past	−0.05*	(0.02)	0.22***	(0.05)
Number of Cities with Occupy Arrests				
Base: Arrest Cities Today	−0.00	(0.01)	0.04	(0.02)
Lag 1: Arrest Cities Yesterday	0.05***	(0.01)	0.05*	(0.02)
Lag 2: Arrest Cities Two Days Past	−0.04***	(0.01)	−0.02	(0.02)
Lag 3: Arrests Cities Three Days Past	0.03**	(0.01)	0.08***	(0.02)
Constant	0.03	(0.08)	0.09	(3.04)
AR-1	0.13	(0.10)	−0.60***	(0.12)
AR-2	0.05	(0.04)	0.03	(0.02)
MA-1	−0.52***	(0.12)	0.56***	(0.11)
D	0.38***	(0.05)	0.49***	(0.01)
$Sigma^2$	0.07***	(0.00)	0.34***	(0.01)
Log Likelihood	−226.84		−2198.84	
AIC	481.68		4425.68	
BIC	563.25		4507.26	
N	2507		2507	

Note: Significance levels using z-test. *p < 0.05, **p < 0.01, ***p < 0.001. Models 1–2: ARFIMA (2, d, 1) models of article counts with OIM S.E. Front-page news articles found by LexisNexis Academic (2016), search of *Major World Newspapers for tag OCCUPY WALL STREET, all outlets included, N = 134 front-page articles in total. Online news articles found by 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. Coefficient plots displayed in Table A2.

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), but lack control for autocorrelation (highly significant in the ARFIMA models), thereby showing the importance of correctly modeling autoregressive and moving average trends. In testing, ARFIMA results are unaffected by the number of included lags.[20]

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 ARFIMA 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. In sum, the models support *Hypothesis 3*. Nevertheless, even controlling for news coverage of Occupy, we still see that the number of protesters arrested predicts increased presidential discussion of inequality and paying the fair share, all else equal.

When we reflect on the results, they intuitively follow our expectation. In the managed chaos 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 ($\beta = 0.21,\ p < 0.001$), media coverage of the protest prompts immediate response. Once the president and his staff have time to reflect on the number of protesters arrested, they can adjust or rewrite speeches to argue against inequality and urge that the wealthy pay their fair share. After three days, while media coverage 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, which as shown in the models, confirms *Hypothesis 1b* with respect to presidential speech.

5.5. Modeling congressional speech

Turning to congressional response, we notice a subtly different pattern. Consider the models of congressional speech displayed in Table 5. Examining the congressional models, we witness that the number of present day arrest cities has a positive and significant effect on the frequency of inequality and fair share discussion by Congress, also exemplifying support for *Hypothesis 1b*.

[20] In testing, the directionality, magnitude, and significance is consistently unaffected by the number of lags included. I tested the results using only arrests on a model with lag 1 only … lag 19 only, and then a model with lags 1–19. Results available upon request.

Table 4
ARFIMA time series models of president Obama's speech, 2009–2015.

	Inequality				Fair Share			
	(1) Count		(2) PCA		(3) Count		(4) PCA	
	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Occupy Wall Street Protesters Arrested (100's)								
Base: Arrests Today	1.05	(0.71)	0.19	(0.17)	0.05	(0.09)	0.04	(0.12)
Lag 1: Arrests Yesterday	−0.76	(0.77)	−0.21	(0.19)	−0.28**	(0.10)	−0.49***	(0.13)
Lag 2: Arrests Two Days Past	−1.84*	(0.78)	−0.56**	(0.19)	−0.41***	(0.10)	−0.70***	(0.13)
Lag 3: Arrests Three Days Past	2.70***	(0.74)	0.79***	(0.18)	1.07***	(0.10)	2.01***	(0.12)
Public Perception Controls								
U.S. Google Trend: "Occupy Wall Street"‡								
Base: Occupy Google Trend Current Date	0.04	(0.06)	0.02	(0.02)	0.04***	(0.01)	0.09***	(0.01)
Lag 7: Occupy Google Trend Last Week	−0.05	(0.05)	−0.02	(0.01)	0.00	(0.01)	−0.00	(0.01)
U.S. Google Trend: "Income Inequality"‡								
Base: Inequality Google Trend Current Date	0.06*	(0.02)	0.01*	(0.01)	0.00	(0.00)	−0.00	(0.00)
Lag 7: Inequality Google Trend Last Week	−0.04	(0.02)	−0.01	(0.01)	−0.01*	(0.00)	−0.01	(0.00)
Political Controls								
Presidential Approval Rate ‡								
Base: Presidential Approval Current Date	−0.14	(0.11)	−0.03	(0.03)	−0.02	(0.01)	−0.03	(0.02)
Lag 7: Presidential Approval Last Week	−0.17	(0.11)	−0.04	(0.03)	0.00	(0.01)	0.00	(0.02)
President Campaigning for 2012 Election	0.64	(1.64)	0.27	(0.39)	0.33	(0.20)	0.63**	(0.24)
Current Economic Conditions Controls								
S&P 500 Market Close ‡	−0.00	(0.00)	−0.00	(0.00)	−0.00	(0.00)	−0.00	(0.00)
National Unemployment Rate ‡	−0.70	(0.93)	−0.16	(0.22)	−0.08	(0.11)	−0.12	(0.14)
Media Coverage of Occupy Wall Street								
Major World Newspapers, Front-Page Coverage								
Base: Front-Page Occupy News Today	−1.73	(0.93)	−0.31	(0.23)	−0.35**	(0.12)	−0.45**	(0.15)
Lag 1: Front-Page Occupy News Yesterday	1.29	(0.75)	0.36	(0.18)	0.47***	(0.10)	0.61***	(0.12)
Lag 2: Front-Page Occupy Two Days Past	−1.15	(0.75)	−0.30	(0.18)	−0.10	(0.10)	−0.27*	(0.12)
Lag 3: Front-Page Occupy Three Days Past	1.65*	(0.69)	0.43*	(0.17)	0.27**	(0.09)	0.27*	(0.11)
Online News Coverage								
Base: Online News Today	0.07	(0.39)	0.02	(0.09)	0.00	(0.05)	−0.16*	(0.06)
Lag 1: Online News Yesterday	0.05	(0.35)	−0.01	(0.09)	−0.08	(0.05)	−0.13*	(0.06)
Lag 2: Online News Two Days Past	0.06	(0.34)	−0.03	(0.08)	−0.13**	(0.04)	−0.21***	(0.06)
Lag 3: Online News Three Days Past	−0.62	(0.34)	−0.15	(0.08)	−0.28***	(0.04)	−0.42***	(0.06)
Interaction Today's Front-Page X Online News	0.49***	(0.14)	0.08*	(0.04)	0.14***	(0.02)	0.18***	(0.02)
Constant	30.04	(15.60)	5.60	(3.74)	2.25	(1.97)	2.69	(2.37)
AR-1	0.56***	(0.05)	0.54***	(0.05)	0.48***	(0.06)	0.45***	(0.07)
AR-2	−0.08**	(0.03)	−0.10***	(0.03)	−0.04	(0.03)	−0.05	(0.03)
MA-1	−0.73***	(0.06)	−0.66***	(0.08)	−0.63***	(0.08)	−0.59***	(0.09)
D	0.37***	(0.06)	0.33***	(0.06)	0.30***	(0.06)	0.27***	(0.07)
$Sigma^2$	74.07***	(2.10)	4.42***	(0.12)	1.25***	(0.04)	2.00***	(0.06)
Log Likelihood	−8929.27		−5404.34		−3830.97		−4414.70	
AIC	17914.55		10864.67		7717.94		8885.41	
BIC	18077.62		11027.75		7881.01		9048.48	
N	2500		2500		2500		2500	

Note: Significance levels using z-test. *p < 0.05, **p < 0.01, ***p < 0.001. Terms, designated by ‡, imputed to carry over last value or convert to a daily scale. Models 1–4: ARFIMA (2, d, 1) models of count data and PCA of count data with OIM S.E. Coefficient plots displayed in Table A3.

Furthermore, the number of cities with Occupy arrests yesterday predicts an increase in congressional fair share rhetoric. In contrast to the presidential models, the news was significant in only one model (fair share PCA). Thus, although the news has robust predictive power in the presidential models, it is far less predictive of congressional speech.

Yet, of all the covariates, the effect of presidential speech is among the most influential, offering strong support to *Hypothesis 4*. For example, President Obama's inequality discourse predicts a significant increase in congressional discussion of inequality ($\beta = 0.96,\ p < 0.001$) and ($\beta = 0.02,\ p < 0.01$), for both the count and PCA models, respectively. Although the coefficient is small, this difference reflects the scale of the predictors. Whereas an additional city with Occupy arrests predicts 10 additional congressional keywords, another presidential mention of inequality predicts an approximately proportional increase in congressional response. Regarding fairness, presidential discussion of paying the fair share both today and yesterday predicts a highly significant increase in congressional fair share discourse ($\beta = 0.20,\ p < 0.001$) and ($\beta = 0.16,\ p < 0.001$), respectively. Even stronger results are found in the PCA model. Indeed, it is through *the agenda-setting abilities of the president that Occupy Wall Street exercises the most congressional influence.*

Table 5
ARFIMA time series models of Congress's speech, 2009–2015.

	Inequality				Fair Share			
	(1) Count Beta	SE	(2) PCA Beta	SE	(3) Count Beta	SE	(4) PCA Beta	SE
Number of Cities with Occupy Arrests								
Base: Arrest Cities Today	10.24**	(3.84)	0.25**	(0.08)	0.25**	(0.09)	0.14***	(0.04)
Lag 1: Arrest Cities Yesterday	5.77	(4.08)	0.15	(0.09)	0.16	(0.09)	0.11**	(0.04)
Lag 2: Arrest Cities Two Days Past	−3.79	(3.98)	−0.08	(0.09)	−0.12	(0.09)	−0.04	(0.04)
Lag 3: Arrests Cities Three Days Past	−2.20	(3.87)	−0.10	(0.08)	−0.11	(0.09)	−0.07	(0.04)
President Obama's Inequality Speech (Count)								
Base: Inequality Speech Today	0.96***	(0.27)	0.02**	(0.01)				
Lag 1: Inequality Speech Yesterday	0.25	(0.30)	0.01	(0.01)				
Lag 2: Inequality Speech Two Days Past	−0.22	(0.30)	−0.00	(0.01)				
Lag 3: Inequality Speech Three Days Past	−0.26	(0.27)	−0.01	(0.01)				
President Obama's Fair Share Speech (Count)								
Base: Fair Share Speech Today					0.20***	(0.05)	0.12***	(0.02)
Lag 1: Fair Share Speech Yesterday					0.16***	(0.05)	0.10***	(0.02)
Lag 2: Fair Share Speech Two Days Past					0.01	(0.05)	0.03	(0.02)
Lag 3: Fair Share Speech Three Days Past					−0.10*	(0.05)	−0.05*	(0.02)
Public Perception Controls								
U.S. Google Trend: "Occupy Wall Street"‡								
Base: Occupy Google Trend Current Date	−0.67	(1.00)	−0.02	(0.02)	−0.02	(0.02)	−0.01	(0.01)
Lag 7: Occupy Google Trend Last Week	−1.70	(0.92)	−0.04	(0.02)	−0.02	(0.02)	−0.01	(0.01)
U.S. Google Trend: "Income Inequality"‡								
Base: Inequality Google Trend Current Date	0.70	(0.41)	0.02	(0.01)	0.01	(0.01)	0.01	(0.00)
Lag 7: Inequality Google Trend Last Week	0.46	(0.41)	0.01	(0.01)	0.01	(0.01)	0.00	(0.00)
Current Economic Conditions Controls								
S&P 500 Market Close ‡	−0.05	(0.05)	−0.00	(0.00)	−0.00	(0.00)	0.00	(0.00)
National Unemployment Rate ‡	5.99	(11.58)	0.03	(0.25)	0.08	(0.23)	0.08	(0.09)
Media Coverage of Occupy Wall Street								
Major World Newspapers, Front-Page Coverage								
Base: Front-Page Occupy News Today	−3.43	(11.69)	−0.06	(0.25)	−0.16	(0.29)	−0.08	(0.14)
Lag 1: Front-Page Occupy News Yesterday	0.96	(12.03)	−0.03	(0.26)	−0.32	(0.25)	−0.18	(0.12)
Lag 2: Front-Page Occupy Two Days Past	0.42	(12.27)	0.02	(0.26)	−0.07	(0.26)	−0.07	(0.12)
Lag 3: Front-Page Occupy Three Days Past	−0.08	(9.33)	0.06	(0.20)	−0.14	(0.22)	−0.06	(0.11)
Online News Coverage								
Base: Online News Today	5.31	(4.70)	0.17	(0.10)	0.18	(0.12)	0.09	(0.06)
Lag 1: Online News Yesterday	6.56	(5.08)	0.13	(0.11)	0.20	(0.11)	0.11*	(0.05)
Lag 2: Online News Two Days Past	6.57	(5.02)	0.15	(0.11)	0.06	(0.11)	0.06	(0.05)
Lag 3: Online News Three Days Past	3.75	(4.51)	0.09	(0.10)	0.02	(0.11)	0.01	(0.05)
Interaction Today's Front-Page X Online News	0.11	(1.74)	−0.02	(0.04)	−0.05	(0.05)	−0.03	(0.02)
Constant	93.21	(151.18)	1.31	(3.25)	−0.24	(2.97)	−0.91	(1.13)
AR-1	1.02***	(0.03)	1.00***	(0.03)	0.78***	(0.06)	0.84***	(0.08)
AR-2	−0.49***	(0.02)	−0.47***	(0.02)	−0.21***	(0.02)	−0.18***	(0.02)
MA-1	−0.49***	(0.05)	−0.49***	(0.05)	−0.61***	(0.07)	−0.67***	(0.10)
D	0.21***	(0.04)	0.21***	(0.04)	0.21***	(0.05)	0.14*	(0.06)
Sigma^2	13511.12***	(382.15)	6.32***	(0.18)	7.51***	(0.21)	1.67***	(0.05)
Log Likelihood	−15436.92		−5852.39		−6068.52		−4187.18	
AIC	30931.84		11762.79		12195.03		8432.36	
BIC	31100.74		11931.69		12363.93		8601.26	
N	2500		2500		2500		2500	

Note: Significance levels using z-test. *p < 0.05, **p < 0.01, ***p < 0.001. Terms, designated by ‡, imputed to carry over last value or convert to a daily scale. Models 1–4: ARFIMA (2, d, 1) models of count data and PCA of count data with OIM S.E. Coefficient plots displayed in Table A5.

5.6. *Occupy's dynamic impact and the question of causality*

In retrospect, what was Occupy's impact? As previously demonstrated, there was a statistically significant increase in congressional fair share discourse and presidential inequality and fair share rhetoric after Occupy emerged (*Hypothesis 1a*).

As synthesized in Fig. 5, the repression of Occupy Wall Street predicts a statistically significant and subsequent increase in news media coverage (*Hypothesis 2*), as well as presidential and congressional debate of Occupy's issues. (*Hypothesis 1b*). These results pass through multifaceted channels. Whereas we see the direct effect of Occupy arrest activity on President Obama and Congress, observable repression also yields media coverage, which increased discussion of Occupy's issues, particularly by the president (*Hypothesis 3*). The president's inequality and fair share discourse in turn predicts significant increases in subsequent congressional debate (*Hypothesis 4*). By capturing congressional attention, Occupy won discursive

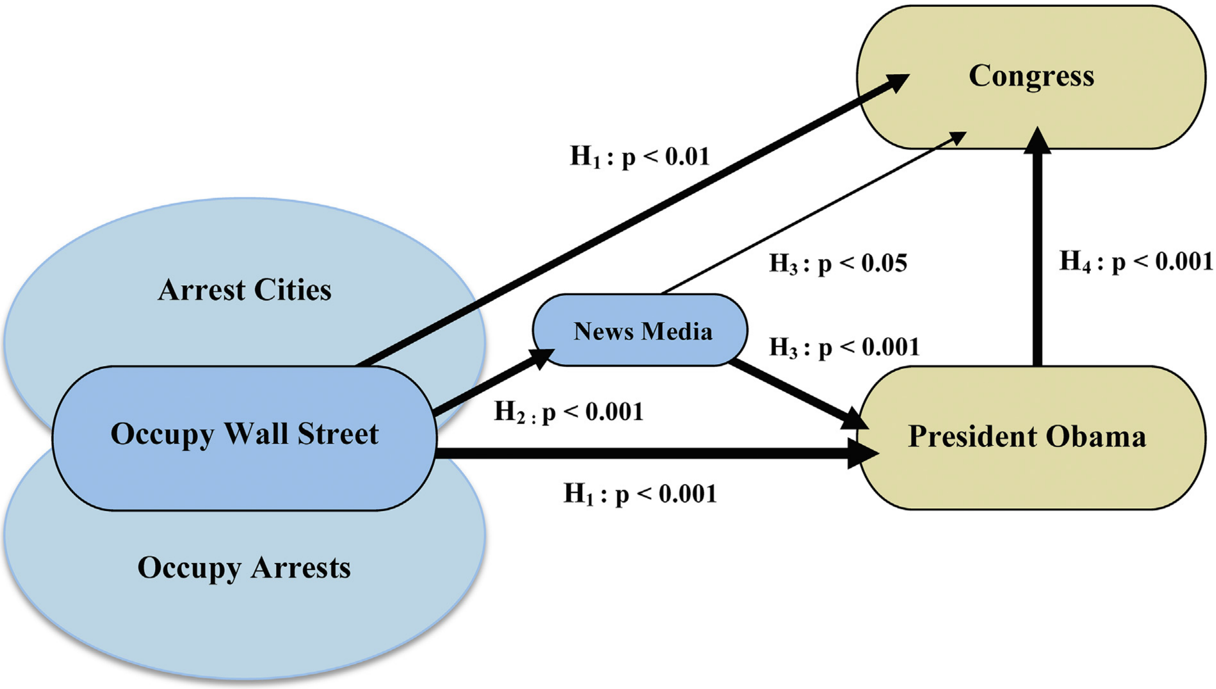

Fig. 5. Significant dynamic relationships shown in ARFIMA models.
Note: Solid lines indicate statistically significant coefficients in one or more models. Edge thickness weighted by statistical significance of the most significant factor in any model, reported next to the indicated Hypothesis. Significance levels using z-test. Indicated probabilities denote that one or more ARFIMA models has a coefficient predicting the directed edge at the specified probability threshold.

victories, increasing the visibility and legitimacy of its motivating issues. Given repression's dynamic role in occupying government rhetoric, what can be said about Occupy's causality?

First, we know that the increase in fair share and inequality discourse followed the onset of Occupy Wall Street. F-tests exemplify a highly significant increase followed by a significant decrease. We can also appreciate the cumulative results graphically (Fig. 6). Although discussion of these topics existed before Occupy, President Obama dramatically increased his fair share discourse during the first year of protest (Fig. 6.2). Yet, the discursive shift lingered well beyond the Occupy's peak and at a rate greater than before the movement emerged.

Second, each presidential and congressional model substantiates the graphical interpretation and exemplifies that the discursive shift lingered, even as arrests declined. 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. Moreover, each model has statistically significant differencing terms, $d \in (0, 0.5)$, indicating both finite variance and long-memory, or more precisely, a "long-range positive dependence" (Baum and Wiggins, 2000; Granger, 1980). Even after the Occupy's decline, heightened rhetoric on economic inequality persisted.

The significant pattern of Occupy's influence across the models suggests a causal interpretation. Recall that these models included controls for the economic state of the nation (financial markets and unemployment rate), the president's political approval, the public's awareness of inequality and Occupy Wall Street, and media coverage of Occupy events. Yet, by and large, the best and most consistent explanation was in fact the direct and indirect effects of Occupy arrest activity.

There is an understanding temptation to claim causality for Occupy's role in shifting government rhetoric. From the evidence presented, Occupy is the best explanation and causally predictive, *ceteris paribus*. Yet, many facets are unobserved or unknowable, and these omitted variables could affect the causal narrative. Omitted variables or unforeseen flaws in the models or data collection could bias the results. Even forestalling such routine caveats, I can only confidently say that the response reflects a manifested *public* shift in political dialogue, which may be divorced from politicians' *private* beliefs or motivations.

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. Although causality remains a contested claim, the pointed fact demonstrably clear from this analysis, is that Occupy's repression predicts a positive and statistically significant increase in presidential and congressional discourse about the movement's key issues.

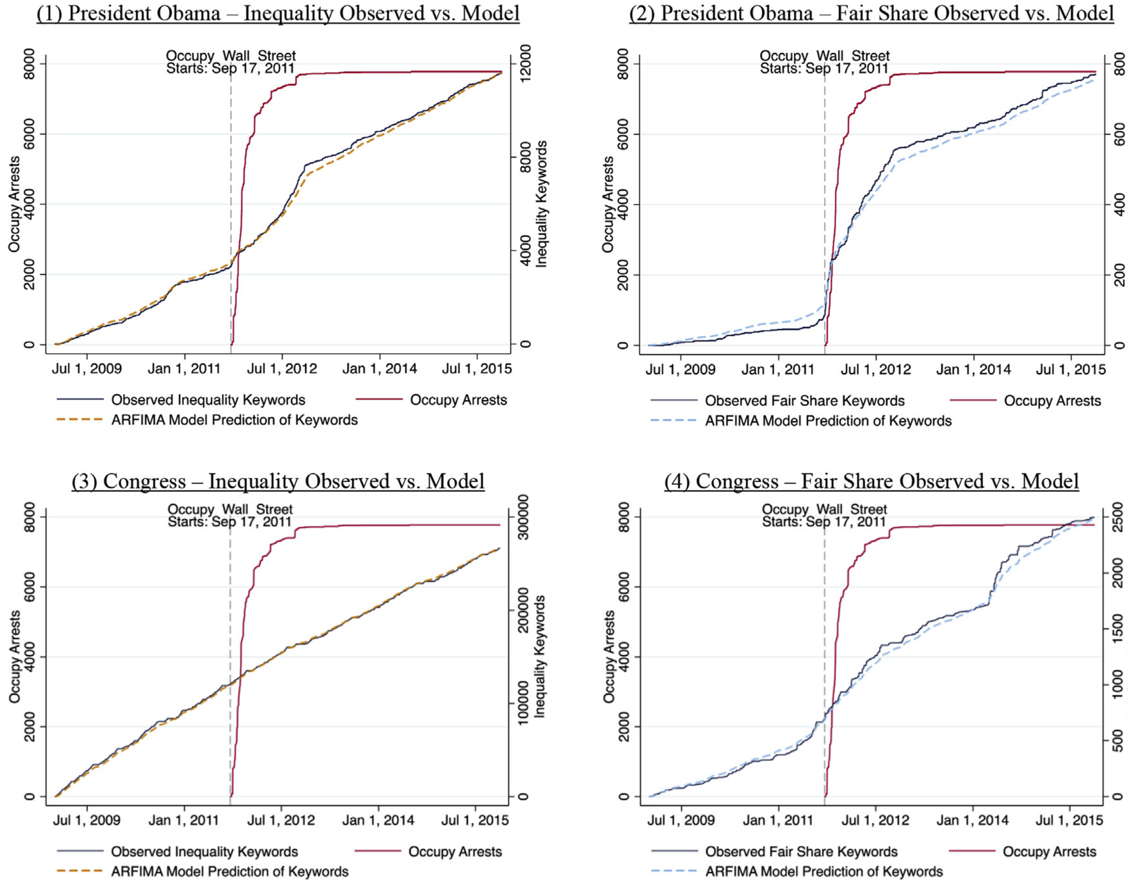

Fig. 6. Government cumulative observed and modeled speech versus Occupy arrests.
Note: Observed Values of ARFIMA Model Predictions from Tables 4 and 5 (Count Models) for Inequality and Fair Share rhetoric by President Obama (Table 4) and Congress (Table 5). Occupy arrests are displayed in each graph (acutely increasing solid line). The two closely correlated lines are observed speech (solid line) versus predicted speech (dashed line). The vertical dashed line marks the beginning of Occupy Wall Street, September 17, 2011. An interactive plot of the observed data is available online.

6. Discussion

This paper contributes to the broader literature empirically, methodologically, and theoretically. To summarize the empirical results, I demonstrate that Occupy played a pivotal role in shifting the national political conversation of President Obama and Congress to enhance the focus on economic fairness and inequality. These patterns present in complex ways. Occupy's arrest activity predicts subsequent increases in Occupy news coverage, which in turn predicts increased presidential—and to a lesser extent—congressional discourse. Controlling for media, Occupy's repression has a direct effect on increasing subsequent presidential and congressional conversation. The president's discussion of Occupy's objectives is particularly salient, and has significant agenda-setting power over congressional debate on Occupy's issues.

Augmenting the empirical analysis, this paper yields several methodological implications. First, the majority of social movements research does not apply time series models to understand the timing of government response (Amenta et al., 2010). The complex dynamics between movements and political elites can have autoregressive or moving average properties and long-term dependencies as shown in this analysis and by other scholars (Box-Steffensmeier and Tomlinson, 2000; Olzak and Ryo, 2007). Because ARFIMA models are more conservative than ARIMA models and better able to capture long-term dependencies (Box-Steffensmeier and Tomlinson, 2000; Lebo and Grant, 2016), ARFIMA models offer improvements over existing applications of ARIMA, negative binomial, or Poisson time series models (*c.f.* Giugni, 2007; McAdam and Su, 2002; Olzak and Ryo, 2007; Olzak and Soule, 2009).[21] Second, my research illustrates the utility of combining

[21] Analyses relying on rare events can alternatively be approached with rare-events logistic regression models (Andrews and Biggs, 2006; King and Zeng, 2001), though such models cannot adequately control for autoregressive or moving average trends like ARFIMA models. Possible tradeoffs in the ARFIMA (or ARIMA) models include distributional assumptions of the time series compared to Poisson or Negative Binomial models, which lack the same ability to capture autoregressive, moving average trends and long-term dependencies.

computational approaches to collect and analyze text archives, which can be applied to social movements research. Although a number of scholars have used computational methods to collect or analyze text data (Bail, 2012; Grimmer, 2013; Judd, 2016), my work illustrates new directions that text data can be used and combined with a regression design to understand movement success.

Although these methods offer a way to advance movements research in the era of big data, understanding the *timing* of protest response also informs existing literature. Response to Occupy's repression begins with media coverage. Arrest activity of Occupy predicts increased front-page news the next day and online coverage in the next several days. Given Occupy's disruptive tactics and radical goals (DeLuca et al., 2012), which suggested heightened police repression (Earl et al., 2003; Soule and Davenport, 2009); my results are consistent with past findings of media responsiveness to disruptive protest (Amenta et al., 2009).

Rather than disruption *per se*, however, my analysis illustrates that movement *repression* directly and powerfully predicts news media. I suggest that repression is not only more easily measured from secondary sources, but also avoids two limitations in existing research. First, using repression avoids omitting a potential intermediary factor. Although disruptive tactics and movement threat predict repression, because repression ensues threatening mobilizations and predicts the media coverage that politicians respond to, I caution against testing the efficacy of disruptive protest without also examining highly observable repression, such as arrests. This caveat raises a question for future research. Does disruptive protest that co-occurs with repression have an effect independent of repression? For example, McAdam and Su (2002) illustrate congressional response to police violence against protesters but reveal mixed results to measures of disruptive protest. A second limitation, therefore, is the possible conflation of disruption and repression. Violence against protesters by police is a clear measure of *repression* (Davenport, 2007; Earl, 2003, 2011; Tilly, 1978), but without incorporating a theory of repression (Earl, 2003), scholars risk mistaking the consequence of disruption as a proxy thereof. Future analyses should model disruption in time series with repression to examine media and political response. By demonstrating the *salience of repression* to predict discursive opportunities, I pave the way to integrating two largely discrete approaches in social movements research.

While the results do not capture media sentiment toward protest disruption, repression, or issues (Andrews and Caren, 2010; Gaby and Caren, 2016), my analysis supports past findings that media is integral to movement success (Andrews and Biggs, 2006; Ferree, 2003; Lipsky, 1968), particularly in gaining the attention of politicians (Behr and Iyengar, 1985; Canes-Wrone, 2006). Yesterday's front-page media coverage of Occupy and current day interaction of front-page and online news predict heightened response from the president, whose discussion of these matters predicts increased debate in congress that same day and the day thereafter.

The finding of presidential agenda-setting further echoes past political science research (Edwards and Wood, 1999) and suggests movement scholars should not consider a protest's congressional impact without simultaneously considering the president's agenda-setting *role* in effecting that change (*c.f.* Bloom, 2015; McAdam and Su, 2002; Soule and King, 2006). My work reveals how *repression* can mobilize elite political allies (Wouters and Walgrave, 2017) and supports Bloom's (2015) finding that movements can alter presidential agenda. Whereas Bloom (2015) argues past insurgency altered the opportunity structure leveraged by Black Anti-colonialists to redirect President Truman's civil rights agenda, I suggest Occupy's redirection of presidential and congressional agenda bolsters the legitimacy of its ideas and therefore alters the opportunity structure facing future mobilization. Among other differences, I distinguish my analysis from Bloom (2015) by looking at the dynamic, daily effects of repression in time-series.

Future work should continue to consider the president when examining movement effects on legislative gains, agenda-setting, other congressional activity. For example, past analyses of congressional action, agenda-setting, or response to movements (King et al., 2007; McAdam and Su, 2002; Soule and King, 2006) could be expanded. I would especially encourage research that reexamines movements' ability to mobilize presidential agenda-setting in past cases of legislative success. Insofar as a mobilization's ideas are appropriated or otherwise adapted by the president shapes the political context mediating movement success (Amenta, 2006, 2013; Amenta et al., 1992, 2010; Bloom, 2015). Because congressional debate raises the possibility of eventual policy change (Burstein et al., 2005; Soule and King, 2006), examining a movement's capacity to coopt presidential support and influence congressional debate is an understudied factor warranting further exploration.

An additional pathway for future research will be to computationally expand on partisan differences in reactive discourse, such as the proportion of time spent by political allies versus opponents in responding to the president as well as the sentiment and linguistic complexity attached to this speech. As indicated by my exploration, the majority of the congressional debate was affirmative rhetoric by the president's party, in this case Democrats, in addition to critical response from Republicans. Such phenomena suggest my argument would primarily hold under conditions of political alignment between movement and president, such that the repression of left-wing but not right-wing movements would garner discursive victories under Democratic presidencies, with the opposite expectation under Republican administrations.

Besides repression's indirect effects on media and presidential agenda-setting, the direct effect of Occupy's repression has important implications for both the *threat* and *persuasion* models (Andrews, 2004; Piven and Cloward, 1977). Both models suggest that when disruptive protest emerges, politicians may respond by appropriating movement objectives (Andrews, 2004; Ferree, 2003; Giugni, 2007; Piven and Cloward, 1977). I extend these analyses by demonstrating that rather than respond to disruptive protest, politicians appropriate movement rhetorical frames in response to movement *repression*. By their tactics and radical goals, Occupy was a threat (Soule and Davenport, 2009), and the increased discourse of Occupy ideas is consistent with the threat response model (Andrews, 2004; Giugni, 2007). The persuasion model alternatively suggests that movements can coopt the discourse of sympathetic third parties—in Occupy's case, President Obama (Andrews, 2004; Cress and Snow, 2000; Giugni, 2007; Vasi et al., 2015).

One might think the president's rhetorical shift is simply an "electoral proximity" effect or a "populist critique" to buttress his campaign (Bonikowski and Gidron, 2016:1611; Canes-Wrone, 2006:23), but such notions are unsupported because (a) the president's speech 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 campaigning was inconsistently significant.

Instead, I demonstrate that Occupy successfully navigated the political opportunity structure to achieve discursive victories (Bloom, 2015; Ferree, 2003; Koopmans and Olzak, 2004). As a multi-issue movement (Milkman et al., 2013a), Occupy mobilized support for economic fairness, particularly through the president and his influence on Congress. I posit these topics aligned with the president's political interests and his aspirations to cast himself in the role of a transformative president, as suggested to him by White House historians (Kantor, 2012). 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 (Bonikowski and Gidron, 2016), suggesting that President Obama acted as an elite *ally* and that his response was consistent with the persuasion model (Andrews, 2004; *c.f.* Ferree, 2003). If Occupy motivates the agency of a presidential ally—I posit that echoing movement issues in the wake of Occupy's repression exemplifies an ideal strategic moment for the president to respond to the movement, set congressional agenda, invigorate public discourse, and thereby maximize Occupy's discursive gains and 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 (Saad, 2011), his later speeches point to Occupy's lasting influence. 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, President Obama spoke with conviction:

> 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 spate of escalating violence and arrests—including the police's removal of protesters from Zuccotti Park, the infamous pepper-spraying of passive UC-Davis students, and nationwide arrests of protesters in major cities (Kennicott, 2011; Stelter, 2011)[22]—President Obama's speech aligns itself with Occupy's concern of economic inequality in the nexus of American capitalism (*c.f.* Berman, 2011; Henninger, 2011). 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.

Reflecting on this final thought, Occupy altered both presidential and congressional speech, shaping the discourse about inequality and the idea that everyone deserves a "fair shot" and that all must pay their "fair share." While discursive shifts do not always constitute protest efficacy, I propose that Occupy's creation of discursive opportunity raises the possibility of long-term legislative success. 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 discursive and future historical dialogue about inequality. The *repression* of Occupy recast the discussion of politicians who have limited words and time, and in this victory, perhaps, both Occupy and President Obama can take pause and unite in pondering their progressive solidarity.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.ssresearch.2017.07.001.

[22] These events are well documented. See also Occupy Arrests (2014) and its sources.

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