Using Twitter to Study Public Discourse in the Wake of Judicial Decisions: Public Reactions to the Supreme Court's Same-Sex Marriage Cases*

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Abstract

At the intersection of behavioral and institutional studies of policy-making lie a series of questions about how elite choices affect mass public opinion. Scholars have considered how judicial decisions—especially US Supreme Court decisions—affect individuals' support for specific policy positions. These studies yield a series of competing findings. Whereas past research uses opinion surveys to assess how individuals' opinions are shaped, we believe that modern techniques for analyzing social media provides analytic leverage traditional approaches do not offer. We present a framework for employing Twitter data to study mass opinion discourse. We find the Supreme Court's decisions relating to same-sex marriage in 2013 had significant effects on how the public discussed same-sex marriage and had a polarizing effect on mass opinion. We conclude by connecting these findings and our analyses to larger problems and debates in the area of democratic deliberation and big data analysis.

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1 Introduction

Twenty-first century political discourse commonly takes place on social media. Candidates at all levels use Facebook, Twitter and other microblogs in order to engage in more extensive, targeted campaigns than were previously possible (e.g., Conway, Kenski and Wang 2013). Elected officials now routinely use social media to bypass the traditional news media. Rainie et al. (2012) find that nearly 66% of social media users, roughly 40% of all adults in the United States, use the tool to engage in a variety of civic and political activities, including the expression of a political position. The events and topics on which people comment vary from the most pressing national issues of the day to issues that are only salient in very particular locations. Even judicial decisions, believed to be little noted and poorly understood among the mass public (e.g., Hoekstra 2000), often feature prominently in social media discourse.[1]

This paper reflects a collaboration between computer scientists and political scientists. Our primary goal is to demonstrate the utility of social media data for answering questions of interest to social scientists. Paired with appropriate techniques for analyzing and interpreting text, political speech in social media raises the possibility of new research on the development and change of public opinion. Naturally, computer scientists have already devoted considerable attention to the topic, especially on Twitter. Studies have investigated the effect of political and newsworthy events on the content of Tweets (Small 2011), the ability to forecast political elections with Twitter (Tumasjan et al. 2010), the structure of opinion networks (Bruns and Highfield 2013), engagement (Park 2013), polarization (Conover, Ratkiewicz, Francisco, Gonçalves, Flammini and Menczer 2011), and the dissemination of political news (Kwak et al. 2010). The vast amount of real-time data on political expression enables fine-grained measurement of opinion change, measurement of opinions about issues not traditionally captured by opinion polls or only rarely measured, examination of the consequences of unanticipated political events, and the evaluation of micro-level causal mechanisms by tracking individuals over a long period. It also presents an opportunity to capture revealed opinions as they manifest "naturally" in the world, reflecting similar rationales for techniques like focus groups or participant observation, where repeated exposure to forms of expression can reveal

[1] For reactions to the Supreme Court's 2012 decision on the constitutionality of the Affordable Care Act, see `https://storify.com/GNAdv/healthcare-storify-roundup`. For reactions to the Court's 2014 Hobby Lobby decision, see `https://storify.com/garytmills/reaction-to-supreme-court-decision-in-hobby-lobby`.

understandings that were unclear or misunderstood at first and where individuals are simply more free to express themselves as they would like.

Crucial to realizing these opportunities, however, is the development of clear conceptual interpretations of the information contained in political discourse on microblogs as well as the incorporation of techniques for converting microblog text data into interpretable quantities into the social sciences. Fortunately, though, the variety of information contained in natural language in political discourse is much greater than what we can glean from public opinion surveys that are limited to the battery of items that survey items are designed to test. Thus, we can use social media data to study not just policy positions among individuals but a variety of features of political discourse, such as opinion intensity and emotions such as anger or happiness.

To illustrate the potential utility of social media text in the social sciences, we report on a study of the impact of Supreme Court decisions on revealed public opinion. Our study also introduces a web tool for tracking opinions, which is freely available for use as a teaching or research tool. We focus on this topic first because of the normative importance of understanding links between the federal judiciary of the United States and public opinion. In light of the selection mechanism and tenure for Article III judges, the policy-making role of the federal judiciary poses a deep normative tension for democratic theory (e.g., Bickel 1962); and, in part because of this tension, scholars have devoted considerable attention to the role that courts might play in the formation and/or change of public opinion, as well as the courts' broader role in democratic deliberation (Dahl 1957, Franklin and Kosaki 1989, Gibson 1989, Ura 2014). The Supreme Court itself is also a common subject of discourse in social media. This is ultimately not all that surprising given the judiciary's role in the American policy making process. From the permissibility of abortion to the constitutionality of a national health care regulation, American judges are often involved in high-stakes political debates. Finally, we choose this subject because the social science theory of the Supreme Court's potential effects on public opinion is fairly clear. By choosing a subject area with clear empirical implications and an established record of high quality scholarship, we can more easily focus on how the analysis of social media text might complement existing research programs.

Although many applications are possible, we focus here on a particular study, set in the context of the Supreme Court's 2013 same sex marriage decisions in *United States v. Windsor* and *Hollingsworth v. Perry*. We consider whether the Supreme Court's decisions in these cases influenced revealed political opinions of microbloggers measured on a daily basis on Twitter. We compare the findings in which we restrict attention to a panel of frequent microbloggers to a very large daily random sample of microbloggers. Consistent with Franklin and Kosaki (1989) and Johnson and Martin (1998), and with microlevel implications of the argument developed in Ura (2014), we find that the Court's opinion was polarizing. We also find considerable evidence suggesting that the decision influenced *how* people expressed their policy opinions. We uncover a pronounced emotional effect concerning both the intensity and anger of expressed opinions in ways consistent with a polarizing effect on opinion. That Supreme Court decisions in salient cases impact the emotionality of policy discourse is not surprising in light of research on emotional responses to major political and economic events (e.g. Bollen, Mao and Pepe 2011) but it has yet to be incorporated in research on the role of the Supreme Court in American policy making. The finding has important implications for a wide variety of subjects, ranging from work on how political entrepreneurs might use emotion to advance their policy goals (Lupia and Menning 2009) to more particular concerns regarding how peak courts judges are incentivized to manage their images (Baum 2007, Davis 1994, Staton 2010).

In the next section, we lay out a series of theoretical expectations that derive from past work on the effect of Supreme Court decisions on public opinion. In Section 3, we describe the way in which social media data, especially Twitter, can be used to evaluate those predictions. Section 4 lays out a series of challenges to extracting theoretically-relevant quantities from Twitter data as well as our approaches to each challenge. Section 5 uses our data to evaluate our theoretical expectations about public discourse on Twitter around the same-sex marriage decisions, and the final section offers concluding remarks.

2 Theoretical Motivation

American democracy involves great tensions between distinct visions of democratic governance. Despite its majoritarian electoral system, the constitutional system fragments decisional processes across governing institutions in search of checks on authority, encouraging multiple governing pluralities and demanding cooperation. Likewise, its liberal constitution implies limits on the power of the American state, limits beyond which no governing coalition should be able to go. All of these features promote a somewhat more consensus-oriented vision.

Research on mass opinion and the Supreme Court addresses core normative concerns about the role of constitutional review in American governance, which emerge in a political system possessing democratic institutions at cross-purposes. Notably, scholars have asked whether it is valid in a democracy to allow unelected judges the ability to constrain the will of a majority through constitutional review (Bickel 1962). This concern is heightened by the general finding that the decisions of U.S. Supreme Court justices are powerfully related to the judges' personal, ideological policy preferences (e.g., Segal and Spaeth 2002). Yet, studies have also found that the Court's decisions, especially over the long-run, reflect well mass preferences over policy outcomes (e.g. Ura 2014, Mishler and Sheehan 1996), and if that is true, the so-called counter-majoritarian difficulty loses much of its bite. Explanations for this empirical pattern highlight the political appointment process (e.g. Dahl 1957), as well as the varying external incentives for judges to get in line with public desires (Carrubba and Zorn 2010, Martin 2006, Clark 2011).

A third rationale for the long-run link between Supreme Court decisions and mass preferences, is that the Supreme Court itself influences policy preferences through their decisions, their persuasive written opinions or both. We focus on this idea. The literature on the Supreme Court's impact on public opinion contains a few clear theoretical mechanisms, which imply quite different empirical implications. Thought is divided between arguments that anticipate a legitimizing effect of decisions and those that expect decisions to structure discourse and opinion but not necessarily legitimate a particular view.

The Supreme Court as a Legitimator The first line of thought, beginning with Dahl's (1957) essay on the majoritarian function of judicial review, suggests that the Supreme Court has the unique capacity among major institutions of American government to confer legitimacy upon policies, causing minority views to lose appeal in the face of those promoted by dominant governing coalitions (see Gibson and Caldeira 2009, Caldeira and Gibson 1992, Gibson 1989, Mondak 1994). Although Dahl was silent on the origins of this special authority, subsequent scholarship has offered a mechanism. Americans perceive the Court to engage in a decision-making process that is both principled and largely disconnected from routine political compromise and bargaining commonplace in the political branches (Hibbing and Theiss-Morse 1995). This belief about judging, what Scheb and Lyons (2000) call the "myth of legality," is a core element of the Court's legitimacy. Critically, it must be learned. It is believed to be developed through repeated exposure to judicial behavior, where legitimating symbols (e.g., robes, formal legal language, courtrooms) create a positive frame through which people judge the Supreme Court's proper role in the state and ultimately create a sense of loyalty to the institution (Gibson, Caldeira and Spence 2003, Gibson and Caldeira 2009). In light of its legitimacy, the Supreme Court is capable of two possible types of effects on public opinion. On one account, the Court is capable of changing support for particular policies. On another, although the Court may not persuade individuals to change their opposition to a policy, it can induce them to accept such a policy (e.g. Gibson 1989).

The Supreme Court as a Divider Whereas there is considerable evidence in support of Dahl's claim that the Supreme Court enjoys a unique supply of legitimacy, the literature is considerably mixed with respect to the Court's ability to legitimate particular views of public policy (see Ura 2014). A second line of thought sees the Supreme Court not as a source of persuasion in matters of public policy but as an important generator of policy outcomes. As Franklin and Kosaki (1989, 763) write, "When the Court rules on politically controversial cases, it may establish the law of the land, but it does not put an end to debate." The Court nevertheless impacts public views of policy. On Franklin and Kosaki's structural response model, the impact of judicial decisions lies in the way that decisions structure deliberation. Specifically, Supreme Court decisions provide salient topics for discussion groups, where prior beliefs are challenged at times and yet frequently reinforced through repeated interaction with likeminded people. When groups are divided on an issue, far from legitimating policy outcomes, the Supreme Court will polarize. Ura (2014) suggests a similar prediction, relying on the model of thermostatic response applied to the Supreme Court. Like Franklin and Kosaki, Ura views Supreme Court decisions as policy outputs, which can cause the same kinds of public reactions that follow the final decisions of other major policymaking institutions. Under the thermostatic response model (Wlezien 1995), the public is able to encourage its representatives to seek preferred policies, because individual reactions to policies, once aggregated, signal desires to continue moving policy in a particular direction or to pull it back. Simply, a policy that is viewed as more liberal (conservative) than ideal is met with demands for a more conservative (liberal) policy. For all but the most liberal or conservative policies implied by Supreme Court opinions, this argument would anticipate polarized discourse. Individuals whose preferences lie to the left of the policy implied by the Court will demand a more liberal policy response; individuals whose preferences lie to the right will demand a more conservative policy response.

2.1 Empirical Implications

We estimate a number of features of revealed policy opinions in the context of Twitter, focusing here on the issue of same sex marriage: support/opposition to policies that promote same sex marriage, as well as the intensity and anger with which these opinions are expressed. As we discuss, expectations about changes in support for the policy are clear, in light of existing models. There has been less work on the emotional effects of court decisions. However, research more generally on emotional features of political interactions with elites has direct implications for the non-policy features of public discourse in the wake of judicial decisions. Banks and Valentino (2012), for example, show that individuals are more likely to experience anger when they are in situations they dislike and for which they can find a responsible party to blame. Political messaging, such as campaign ads, can trigger significant emotional responses among the public (e.g., Brader 2005). Modern media, especially electronic media, has contributed to more emotional reactions among the public to policies debates (e.g., Hibbing and Theiss-Morse 1998). We believe that emotional responses should largely follow along the lines of the existing models of opinion change, as we discuss below.

What should we expect to observe in the wake of the Supreme Court's *Windsor* and *Perry* decisions? Theoretical expectations are quite clear given a set of assumptions about the decisions and the context in which they were made. The first issue concerns the kind of policy implied by the decisions. It is important that we can articulate the policy's ideological nature so that we know what changes in opinion to expect. By defining marriage as only a union between a man and a woman *Windsor* found that Section 3 of the federal Defense of Marriage Act violated due process and equal protection principles applicable to the Federal Government under the Fifth Amendment. *Perry* found that supporters of California's ballot initiative banning same sex marriage lacked standing to appeal an adverse ruling in federal court, the consequence being that California's Proposition 8 was found to be unconstitutional under the 14th amendment. Taken together, the decisions reflect a liberal policy; however, it is important to recognize that the Court could have gone further. By failing to reach the equal protection issue in Perry, the Supreme Court left untouched state laws limiting marriage equality.[2] In *Windsor*, the Court's federalism analysis highlighted the States' traditional role in defining marriage, and by so doing raised questions about whether a state could validly restrict marriage to one man and one woman. The critical point is that the decisions resulted in a liberal policy outcome, though not an extremely liberal one.[3]

The second issue concerns the context in which the debate was taking place. At the time of the decision, opinion on the matter was fairly divided, with 50% of the general public supporting same sex marriage, roughly 42% opposing it, and 8% unsure. Support among liberals was estimated to be about 79% and only 30% among conservatives.[4] The decisions were handed down in a charged and divided policy area.

Given these assumptions, we know what to expect under the theoretical accounts reviewed above. Under a legitimation model, we should observe opinion moving in the direction of greater support for same sex marriage. Under both the structural and thermostatic response models, we should observe polarization. Of course, the natural question concerns polarization among which groups. We consider two, largely because we can identify members of these groups in our sample. The first are ideological groups. We will consider opinion change among conservatives and liberals, who were generally divided on this issue as reported by nationally representative polls. Second, we consider opinion groups – specifically groups of individuals who differed with respect to the same sex marriage issue prior to the decision. Focusing on this second grouping ensures that we have low within group variance in opinion compared to between group variance – the group is constructed to ensure that this is true. If the Court had a primarily polarizing effect on opinion, we should observe that liberals became more supportive of same sex marriage and that conservatives became more opposed. This should be particularly likely for liberals on the far left and conservatives on

[2]This issue, of course, was reached in Obergefell v. Hodges, 576 U.S. (2015), where the Court found that the prohibition of marriage between two members of the same sex violated both the due process and equal protection clauses of the 14th amendment.

[3]See discussion in Eric Restuccia and Aaron Windstorm's "Federalism and the authority of the states to define marriage." SCOTUSblog, June 27, 2013. Also, see conservative blog reaction to Melissa Harris-Perry's interpretation of the same sex marriage decisions, e.g., Noah Rothman's "Gay Marriage Rulings Make MSNBC's Harris-Perry Sad Because They Gut 'Power of Federal Government.' June 26, 2013. MEDIAite.

[4]See `http://www.pewforum.org/2015/07/29/graphics-slideshow-changing-attitudes-on-gay-marriage/`.

the far right. Similarly, we ought to observe that supporters prior to the decision expressed more support afterward, and that those in opposition expressed stronger opposition.

Now, consider the implications for the anger and intensity with which opinions were expressed. Under Franklin and Kosaki's structural response model, we ought to observe that liberals and those in support of same sex marriage should have reacted with less angry Tweets after the decision, whereas conservatives and those in opposition to the policy should have expressed more anger after the decision. Under the thermostatic response model, both liberals and conservatives should have responded with greater anger, whereas moderates should not have reacted. This "anger at the extremes" prediction is particularly likely on the far left and far right, precisely where people would have been most frustrated under the thermostatic response model. Finally, under the legitimation model, all Tweeters should have responded with less anger.

Intensity presents an interesting scenario. It is possible that intensity would have changed in ways identical to anger, under each model. That is to say, it is plausible that each model suggests the same implications for intensity and anger. Other reactions are plausible, though. For example, it is possible that liberals (and supporters) became more supportive and yet intense simultaneously in the wake of the decision.

3 Studying Politics with Twitter

There are two challenges social scientists confront when studying politics with Twitter. First, how do the quantities measured and analyzed in computational science map onto the theoretical constructs that underlie well-developed social scientific theories? Second, the logistical and mechanical challenges for wrangling and handling microblog data need to be made manageable for the myriad applications to which social scientists would put them.

3.1 What is a tweet? Conceptualizing microblog data

Scholars have devoted extensive effort to understanding the nature of public opinion, especially what it means for a person to express an opinion (see, e.g., Zaller 1992). Interpreting the meaning of responses to public opinion polls, statements in focus groups, claims about voting in exit polls, and the like have all been carefully studied (e.g., Traugott and Price 1992, Huckfeldt 1995). As a result, scholars have developed sophisticated understandings of the effects of issue salience, information and media exposure, framing and priming, and myriad other factors that can affect how individuals translate their thoughts on a political topic into revealed statements of opinion (e.g., Achen 1975, Iyengar and Kinder 1987). One finding that cannot be escaped, though, is that there is considerable differentiation in how much people know and think about politics.

At the same time, there has been little research on how political statements on microblogs relate to well-conceptualized notions of public opinion (cf. Marwick and Boyd 2011). In examining consumer confidence, O'Connor et al. (2010), for example, show a correspondence between aggregate sentiment on Twitter and public opinion polls, especially with respect to trends. However, a correspondence between aggregate trends is not the same as a direct connection between individual utterances on microblogs and theoretically-relevant quantities in theories of public opinion. Nevertheless, our knowledge about the content of microblogs is growing quickly, and this is promising for understanding the role of social media like Twitter in disseminating information and playing the role of traditional media outlets. Indeed, the mass media has a large presence on Twitter, and scholars have demonstrated the importance of the media for shaping and informing public opinion (e.g., Iyengar and Kinder 1987, Prior 2007).

Recent studies of content on Twitter have revealed that 85% of Twitter content is related to spreading and commenting on headline news (Kwak et al. 2010). Table 1, for example, shows a sample of Tweets relating to same-sex marriage posted around the date of the US Supreme Court's June 2013 decisions on the constitutionality of DOMA and Proposition 8. These Tweets represent the range of uses to which Twitter was put in this case. The first few Tweets express factual information, mostly "re-Tweeting" from the mass media. The next few express strong personal sentiment on the issue, from both directions. The last few represent conjecture about national opinion and the on-going policy debate. In brief, what we see here is that political information and policy opinion is the dominant theme in Tweets about same-sex marriage. Together, the extant studies and our illustrative example imply that Twitter has became a portal for the public to express opinions. In the context of politics, Twitter content, together with Twitter users' information, such as users' profiles and social networks, have shown reasonable power of detecting users' political leanings (Conover, Gonçalves, Ratkiewicz, Flammini and Menczer 2011) and predicting elections (Tumasjan et al. 2010). Although promising, the effectiveness of using Twitter content

Date	Tweet
June 26, 2013	#NOH8 BREAKING: #SCOTUS strikes down #DOMA, granting legally married same-sex couples more than 1,000 federal rights and benefits.
June 26, 2013	DOMA is unconstitutional
June 25, 2013	The expected #SCOTUS rulings in #DOMA and #Prop8 will be announced 10 years, to the day, of the decision in Lawrence v. Texas.
June 26, 2013	BREAKING NEWS: #DOMA is unconstitutional, #SCOTUS rules in a 5-4 decision. SPECIAL REPORT: http://t.co/DZjtPBN6Ej
June 26, 2013	Congratulations LGBT community!! Congratulations America!! Congratulations World!! This is a victory for humanity!! #DOMA
June 26, 2013	If you don't support gay marriage just keep your mouth shut. If two people are in love their IN LOVE it doesn't matter what gender they are.
June 24, 2013	One more reason I disapprove gay marriage. Im not saying if you are gay i will hate you, its your life. But its my opinion. (1 Corn. 6:9)
June 24, 2013	By declaring opposition to gay marriage a hate crime, the Left is demanding State persecution of Christians. The war is now open, violent.
June 26, 2013	My take on #SCOTUS #DOMA : Decision Has Implications for Immigration Debate http://t.co/GuoXjZIVYl
June 26, 2013	#DOMA: What Happens Next? See the full image and read more: http://t.co/FxGe2sy6nZ http://t.co/XkMlJjO0id
June 28, 2013	New Jersey: The next battleground on gay marriage. http://t.co/7Nlna0SKLu

Table 1: *Examples of three dominant types of Tweets relating to same-sex marriage.* Tweets posted between June 25 and June 27, 2013. The first set of Tweets consists of factual, news-type Tweets; the second set consists of strong personal sentiment; the third set consists of reflections and speculation about broader national sentiment.

to measure public political opinions remains unclear. Several studies show a limited correlation between sentiment on Twitter and political polls in elections (O'Connor et al. 2010).

Connecting these observations to social scientific work on opinion formation, we believe that individuals' statements on Twitter are in many ways conceptually analogous to the model of opinion formation underlying Zaller's (1992) theory of public opinion. Tweets are utterances that reflect the thoughts in one's mind, especially as shaped or primed by the Twitter network in which one interacts. To the extent a Tweet contains political information, the Tweet reflects one's ideological and policy views, particularly opinions recently activated by one's Twitter network. In much the same way as opinion and media choices and ideology all interact simultaneously (e.g., Prior 2007), Twitter's environment is one in which individuals' Tweets are at least in part statements about their policy opinions. As such, we consider Twitter an important example of social expression of opinion.

3.2 Who is a tweeter? Relating our samples to the American public

Certainly, the people who participate in political discourse on Twitter do not constitute a random cross-section of the public, and scholars have set out to assess the demographic correspondence between the "Twitter-verse" and the American public. For example, we know that individuals who Tweet tend to be more male and urban than the general public, but also that there is increasing gender diversity and racial diversity on Twitter over time (Mislove et al. 2011). At the same time, studies in a variety of contexts have found that the volume and content of political discourse is predictive of mass opinion and that research findings conducted on more clearly-defined populations are replicable in the Twittersphere (e.g., Tumasjan et al. 2010, Conover, Gonçalves, Ratkiewicz, Flammini and Menczer 2011, Bermingham and Smeaton 2011, Barberá and Rivero 2014), in many ways similar to how experimental results are often replicable using convenience samples, such as Mechanical Turk (e.g., Berinsky, Huber and Lenz 2012). Nevertheless, because we do not have a better measure of the representativeness of our sample, our analysis will focus on the presence (or absence) of empirical patterns among the Tweets of those people participating in political discourse on Twitter. While we anticipate that current research aimed as estimating the demographic and geographic features of Tweeters will help future studies build from these findings to further generalize, as we discuss below there are distinct strengths to using these data to study the effects of sudden events, like Supreme Court decisions, on political discourse.

3.3 How do we use microblogs? Obtaining and working with Twitter data

A second challenge to using microblogs to study politics is that, as contrasted with standard tools of the discipline like public opinion polls or legislative voting records, obtaining and working with microblog data presents a new set of technical and logistical challenges. We describe our approach to working with and handling Twitter data. Twitter provides a streaming API to deliver Tweets in real-time. An API, or application programming interface, is simply a set of protocols for how software interacts with other software—e.g., your own computer software and Twitter's software. Twitter's API provides a mechanism for accessing and retrieving Twitter data by specifying "filters" to identify which Tweets one wants to record. There are several types of filters can be applied to the API. A *Language filter* selects only Tweets written in that particular language will be delivered. The language of a Tweet is determined by Twitter's language classifier. A *Keyword / phrase filter* can represent topics and help select on-topic Tweets. If specified, Tweets containing at least one of the keywords or phrases will be delivered. A *User filter* be used to track groups of interest. If specified, all Tweets authored or retweeted by the particular users will be delivered. If none of the filters is specified, Twitter streaming API will continuously produce 1% random samples of all Tweets. When the filters are applied, the API will send all the Tweets that match the filtering parameters as long as the volume is lower than 1% of all Tweets. Once the percentage of matched Tweets is higher than 1%, the API will only return a random sample up to the 1% cap.[5]

We outline the architecture of our data collection and analysis in Figure 1. First, the Twitter stream is *filtered* by using topically relevant keywords, language filters, and desired author char-

[5] Additionally, one might try to automatically identify misleading keywords (e.g., ambiguous terms), and words that are highly predictive of relevance but are not included in our set of keywords. For this, we would use well established computer science techniques for topic detection and tracking (e.g., Allan 2002, Cataldi, Di Caro and Schifanella 2010). Note that these techniques can also be applied for *cross-language* topic tracking, i.e., to also identify relevant Tweets on the same topic in other languages, notably Spanish (Nastase and Strapparava 2013, Larkey et al. 2004). To evaluate the performance of these discovered keywords, one could use ongoing manual labeling efforts to evaluate whether those terms should be included in the set of keywords for each topic. We are aware of the potential issue of Twitter manipulation through bots, crowdsourcing, organizations, or colluding individuals. This is an active area of research in computer science, with existing techniques that would allow us to at least detect manipulation retroactively (e.g., Lee, Tamilarasan and Caverlee 2013) (and remove such Tweets from our data), and potentially extend this to near-real time detection of rumours and mis-information (e.g., Qazvinian et al. 2011), to reduce the effect on the resulting opinion estimates.

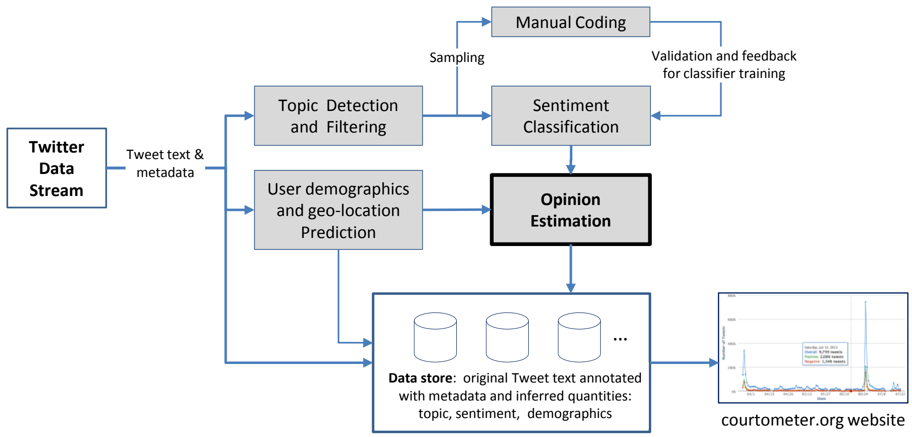

Figure 1: Architecture of the Twitter-based opinion estimation system

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acteristics. The resulting set of relevant Tweets are automatically annotated with a pipeline of topic-specific *classifiers*, annotating each tweet with estimated author demographic information, topic salience, support, emotional intensity, and other quantities of interest, which are then used for *opinion estimation*. The Tweet text, as well as the original and inferred metadata, are stored in a database. (We describe our coding and classification procedures in greater detail below.) Finally, all the summary and estimated statistics, as well as tools for developing new topics of interest, are made available through a web server, on which we publicly release our data. We describe next the collection of Tweets and the construction of relevant measures from those data. In the conclusion, we describe our online methods for data dissemination. While we focus our analysis in this paper on our particular case study—same-sex marriage—the framework, architecture, and analytic methods are general. Upon publication, we will deposit all code to replicate our analyses or apply our techniques and tools to any substantive context.

3.4 Our study: same-sex marriage and the Supreme Court

As the discussion above suggests, developing a set of keywords to search is more of an art than a science. We began with several keywords that were particularly prominent ("DOMA" and "Prop 8"). We developed keywords and requested a sample of Tweets that matched the keywords. The keywords used are "ssm", "same sex marriage", "DOMA", "Prop8", and "gay marriage". We also specified the language of sampled Tweet to be English only. Our procedure produced over

2,500,000 Tweets between March 26, 2013 and August 10, 2013, with 87,575 daily Tweets on average. On June 26, 2013, the day the Supreme Court decided its two gay marriage cases, we collected 335,399 Tweets on the gay marriage topic. The precision (i.e., fraction of retrieved Tweets manually verified to be on-topic) was 92.3%. This provides strong support for the accuracy of our topic filtering techniques based on designing a set of precise keywords for each topic.

In addition to the daily sample of Tweets, in early May 2013 we identified 673 frequent Tweeters regarding the "same-sex marriage" topic.[6] This panel of Tweeters is important to rule out a plausible source of sample selection bias that might emerge by only focusing on the daily random sample of tweets. For example, it could be that support for same sex marriage (or opinion intensity) is constant over time but that after the Supreme Court's same sex marriage decisions, only those Tweeters with extreme views chose to tweet. To be sure, in this scenario the Supreme Court's decision would have influenced the process by which political views are expressed publicly, which is interesting in its own right; however, such a process would not be consistent with the notion that the Supreme Court can change opinion in any of the ways the theories we evaluate suggest. By focusing on a panel of individuals who tweet often and who tweeted both before and after the decisions, we are able to observe potential changes in support/intensity/anger among the same set of people. To construct the panel, we tracked every Tweet of the most frequent Tweeters over a 3-month period. Critically, the individuals in our panel do not know they are in a panel; we are simply collecting all of their public utterances on Twitter. We refer to the daily sample of Tweets as our "random sample" of Tweets, recognizing, though, they do not represent a national probability sample, or anything approaching one. We refer to the set of Tweets from our panel as our "panel sample."

4 Extracting Theoretically Useful Information from Tweets

Our data on Tweets about same-sex marriage provide an opportunity to illustrate the potential for microblog data to speak to our motivating normative and theoretical questions as well as

[6] Our sampling procedure required that we identify the most frequent 1,000 tweeters in our initial daily samples of Supreme Court tweeting as generated by our keyword search. Of the 1,000 most frequent tweeters, we identified individuals who were suitable for our study. To be included, a frequent tweeter had to have been in our sample both before and after the Supreme Court's decisions in the same sex marriage cases. This allowed us to observe potential changes in tweeting behavior. This restriction resulted in an analyzable sample of frequent tweeters of 673.

some of the conceptual and measurement challenges this approach presents. However, measuring the nature of opinion as revealed by Twitter presents two important measurement tasks. First, we must infer opinion content from natural language. Fortunately, there exist many tools for extracting sentiment from textual sources, like Tweets, and there is an active area of research in computer science concerned with customizing those tools for the unique features of microblogs and for extracting more complex quantities than generic "sentiment." Second, many of the theories of opinion formation make predictions that are differential across different types of individuals. Most important, many of these theories predict that one's political ideology should influence how one reacts to political information. As we show below, though, there are reliable and valid ways to estimate Tweeter ideology from information publicly available about individuals on Twitter.

4.1 Measurement task 1: extracting information from natural language

As noted, there exists a suite of tools for quantifying features of natural language, and which is the best approach is context-dependent. We illustrate a general approach that is nevertheless customized to our particular setting—Tweets about same-sex marriage and the Supreme Court's decisions in June 2013. To measure the content of the Tweets we collected, we adopted classification algorithms specifically designed to detect three features of Tweet content we expect to be present and variable in Tweets about same-sex marriage: supportiveness, intensity, and anger.[7]. Each of the measures is handled by one classifier. For example, to estimate supportiveness of Tweets, we classify every Tweet to one of the following classes: supportive, neutral, and opposing. For intensity, the classes are intense vs. non-intense. And for anger, the classes are angry, neutral, and happy. As noted above, all code and data will be publicly released upon publication, and future researchers can train our classification algorithms on alternative data.

We begin by manually labeling a set of "training" Tweets. We developed detailed labeling instructions, hired Political Science graduate students as labelers and trained them in-person. To train the classifier, we labeled 1,400 Tweets, sampled at the rate of 100 per day, over the period of

[7]A measure of public opinion regarding support for same sex marriage is obviously required for the study. We also believed that it would be helpful to measure opinion intensity and anger for theoretical reasons – believing that these concepts are naturally linked to the polarizing or legitimating role that the Supreme Court might play in U.S. politics. However, we also sought to measure intensity and anger because these concepts are commonly the subject of public opinion research (e.g. Lodge and Tursky 1979, Sears and Valentino 1997, Weeks 2015, Huddy, Mason and Aarøe 2015). We believe it important to demonstrate that these concepts can be validly measured in Twitter text.

two weeks, immediately prior and subsequent to the DOMA and Prop 8 decisions. Coding rules for the research assistant tasks can be found in the appendix. Inter-coder reliability, as measured by the Fleiss κ statistic, is highest on the "relevance" (95%) and "support" (99%) items and lower on "anger" (93%) and intensity (88%). With the human-labeled Tweets in hand, we developed our classification algorithms to automatically label Tweets.

Our classification algorithm measures the presence of "features" in each Tweet and estimates the relative predictive weight of each feature, given the distribution of those features in our manually-labeled Tweets. To classify Tweets, we developed several groups of features to represent them in feature space:

- Popularity: Number of times the message has been posted or favored by users. As for a Tweet, this feature means number of Retweets and favorites.
- Capitalization and Punctuation: It has been shown that capitalization and punctuation carry valuable signals of emotional intensity in sentiment analysis.
- The text: Unigram, bigram, and trigram of the Tweet text.
- Character N-gram in text: Trigram and four-gram of the characters in the Tweet text.
- Sentiment score: The score is computed via a comprehensive sentiment dictionary, SentiWordNet[8], as well as stylistic features described in Barbosa and Feng (2010).

We experimented with a variety of automated classification algorithms, and for this experiment report the performance of the Naive Bayes algorithm, which is simple, fast, and shown to be surprisingly robust to classification tasks with sparse and noisy training data (Zhang 2004). The classification performance, using 10-fold cross validation, for supportiveness, intensity, and anger of the tweet text is reported in Table 2. Even with the small amount of training data, the classifier is able to accurately identify supportive and neutral Tweets, with precision of 73% and 76% respectively, but not the more rare occurrences of opposing Tweets. Classifier performance is also acceptable for distinguishing emotionally intense from dispassionate (factual) Tweets, of which there was a 69% majority in our sample.

[8]http://sentiwordnet.isti.cnr.it/

Quantity	Value	Precision (%)	Coverage (%)	Accuracy(%)
Support	Supportive (48%)	73	74	68
	Neutral (45%)	76	67	
	Opposed (7%)	17	30	
Emotional Intensity	Intense (31%)	56	60	73
	Dispassionate (69%)	81	79	
Sentiment Polarity	Pleased (10%)	48	31	69
	Neutral (79%)	84	78	
	Angry (11%)	24	45	

Table 2: *Preliminary sentiment classifier performance for Tweets on "Gay Marriage" topic, 10-fold CV, 1,400 tweets.*

Indeed, we find that our classifier reliably recovers the levels of support, intensity, and anger among Tweets on a daily basis. Figure 2 shows a comparison of the classifier's estimates of each of these features and the "ground truth"—the labels our research assistants assigned. As this figure demonstrates, we recover both the levels and the trends in sentiment. This evidence demonstrates that the features we select and classification algorithm we adopt reliably and validly predicts sentiment, at least as captured by our human-labeled Tweets. Importantly, these results demonstrate that we can validly and reliably train a simple classification algorithm to recover sentiment in highly contextual political texts—here, Tweets about same-sex marriage. For scholars seeking to use Twitter or similar microblog textual data to study public opinion, our evidence reveals that converting those data into meaningful quantities we can study with the discipline's standard tools is simply a matter of manually labeling a small number of documents not dissimilar from common practices and the application of standard classification algorithms to automatically label millions of additional documents.

Turning from the manually-labeled Tweets to our full samples—both the random sample and the panel sample—Figure 3 reports the results of our classification. The top row reports the results from our random sample of Tweets, and the bottom row reports the results from the relevant Tweets among our panelists. The three columns show the daily average value for each of the dimensions we label (the points are scaled the the number of collected Tweets each day), along with a smoothed trend (the line shows a loess smoother with a 95% confidence band).[9]

[9] Recall we trained our classifier and evaluated its performance on data from a two-week period around the Court's decision. One might be concerned that our estimates from points in time further away from that date might be less valid, if one believes that the relationship between sentiment and language was substantially different during the weeks surrounding the decision than it was months before or after. We have evaluated the performance of our

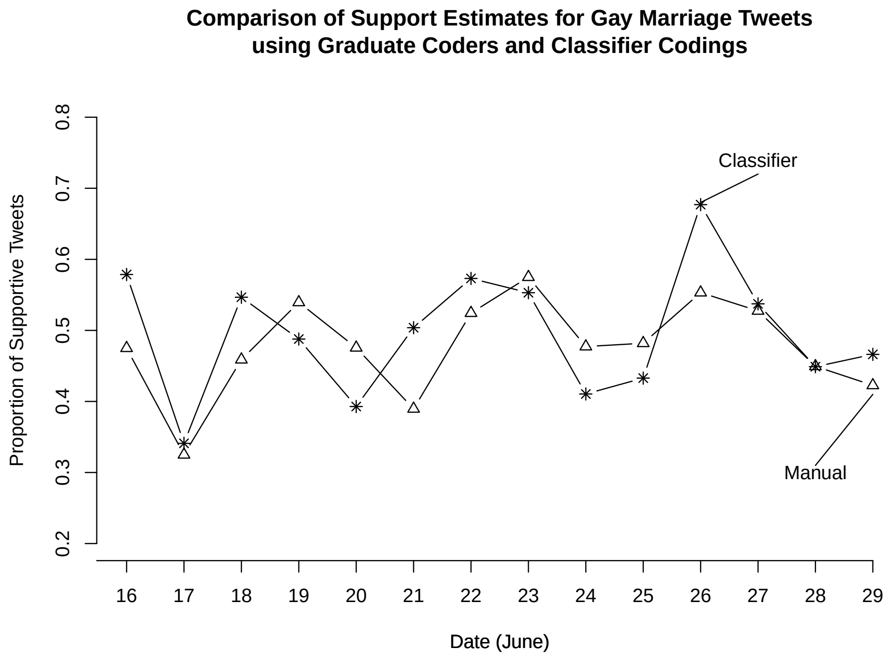

Figure 2: *Comparison of human-assigned labels and classification algorithm-assigned labels.* The open points show daily averages of human-labeled Tweets. The solid points show daily averages of classification algorithm-labeled Tweets.

A number of interesting patterns emerge. Consider first "supportiveness". In the random sample, there is a relatively high level of support, though there is some fluctuation in supportiveness over time. Among the panelists, by contrast, there is a lower level of overall support, combined with a slight trend toward neutrality. Indeed, to the extent frequent Tweeters on a subject constitute "opinion elites" or at least politically interested citizens, we should expect somewhat more moderate overall opinion, because the mix is more likely to contain Tweeters from all political orientations than the random sample of Tweeters. Further, perhaps surprisingly, while there was an increase in overall supportiveness after the Supreme Court's same-sex marriage decisions, it was not *immediate*; rather, it was not until later in the summer that supportiveness spiked.

Consider next the intensity metric. Here, we find greater variability in the random sample before the decision than in the panel. However, we also see a clearer pattern in the panelists, with a steady decrease in intensity over the late spring, in the run-up to the Court's decision. However, by early June, well before the decision, intensity had more-or-less bottomed out and remained

classifier by manually labelling a set of 200 Tweets from earlier in the period. We find that the classifier's accuracy is comparable, though marginally higher, in the time period further away from the weeks around the decision date.

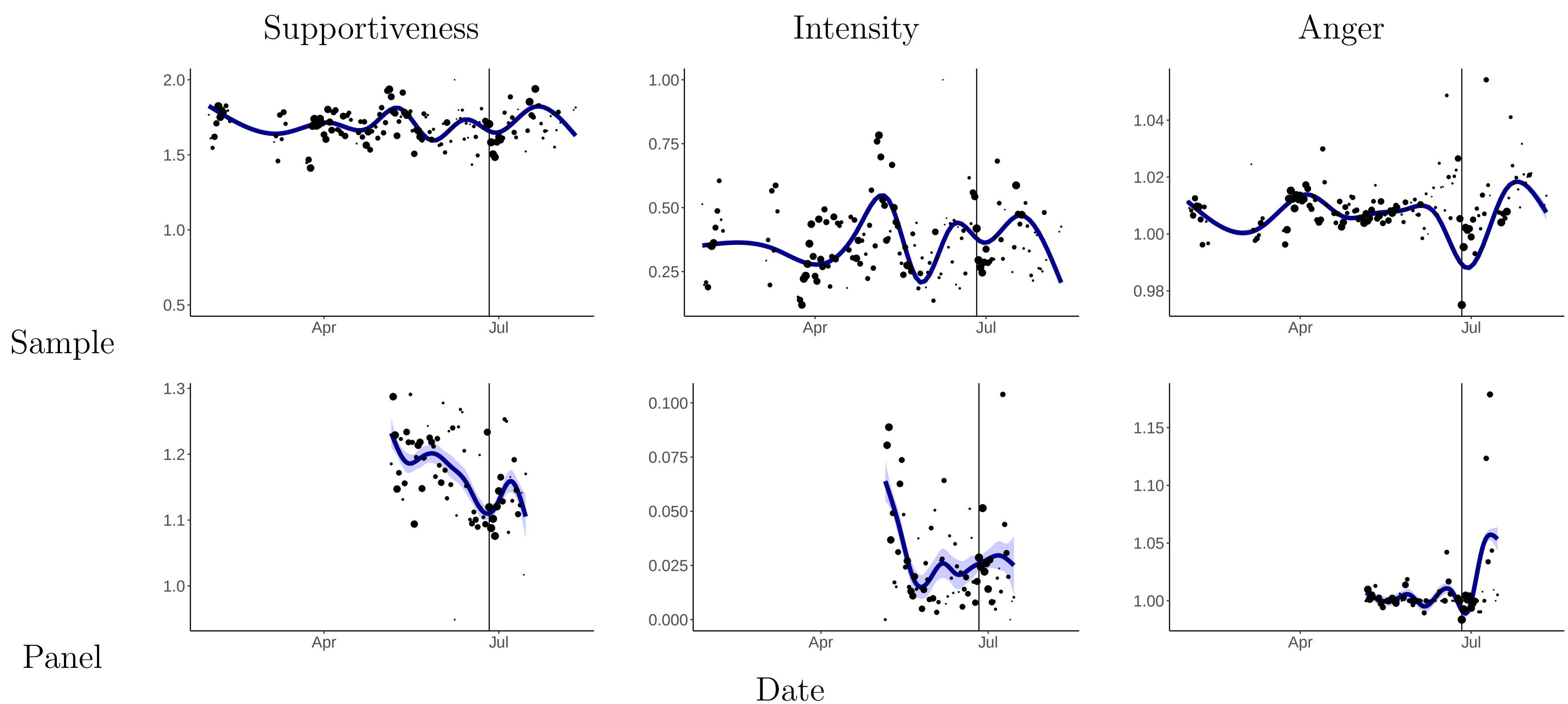

Figure 3: *Trends on three sentiment features among the random sample and panel Tweets.* The first column shows supportiveness for same-sex marriage; the second column shows Tweet intensity; and the third column shows Tweet anger. The top row shows the random sample, and the bottom row show the panelists' Tweets. The points show daily averages and are sized proportional to the number of Tweets collected that day. The lines are fit lines from a GAM smoother; shaded areas show 95% confidence bands.

low and flat through the Court's decision. Nevertheless, despite greater variability in the random sample, the Court's decision does not appear to be associated with any change in intensity. To the extent we might expect the Court's decision to excite liberals and infuriate conservatives, we might expect an increase in intensity after the Court rendered its decisions, but we see no such pattern.

Finally, consider anger. Notice there is virtually no variation in anger before the Court's decision. However, on the day of the decision there is a drop in anger, followed by a jump in anger during the days following the decision. We detect this in not only the random sample but among the panelists as well. And, critically, that increase in anger continues steadily throughout the summer until the end of our sample.

4.2 Measurement task 2: measuring features of individual Tweeters

The second measurement task we face concerns collecting information about not just what Tweeters say, but *who* they are. There exist several studies in computational science designed to estimate the distribution of demographic groups in social media and on Twitter, but we require information about individual Tweeters. There exists a wide range of tools that can be used to estimate a Tweeter's gender, location, or age group, but an important variable for most political science applications is Tweeter ideology. Large public opinion polls often use a 5- or 7-point self-placement scale. So, ideally, we would administer a survey to each Tweeter in our data to develop an index of conservatism/liberalism for each individual. This is not possible, for several reasons. Twitter's Terms of Service prohibit us from directly contacting the individuals whose Tweets we monitor and collect. However, some users voluntarily provide some indicators of their ideology through their public profiles. For example, some Tweeters self identify as "Republican" or as "conservative". Indeed, in our panel sample, 176 Tweeters indicate their political ideology in some form in their profile. Unfortunately, that percentage is still relatively low, and one might worry that relying on self-reported ideology in a public profile induces substantial selection bias in terms of which Tweeters for whom we have a measure of ideology.

To overcome these limitations, we develop a latent variable model to estimate latent ideology for the Tweeters. Our model rests on the assumption that who one "follows" on Twitter is a manifestation of latent ideology. Using the structure of Tweeters' social networks to infer their ideology is an idea that has recently been advanced and validated in a variety of Twitter settings

(Barberá 2015). The key insight is that once accounting for individuals' level of activity on Twitter and the extent to which some Tweeters are more or less popular, the propensity for any Tweeter to "follow" another is decreasing in their ideological dissimilarity. We model whether one follows another as a function of their distance in some latent space and evaluate whether that space can be interpreted as "ideology." Of course, we recognize that not all subjects on Twitter may not be equally discriminating across the latent dimension; some individuals may be followed by Tweeters across the latent dimension, whereas others may be followed only by people very close to them. Our model allows the effect of distance between a Tweeter and an individual to be followed to vary across "followed" individuals.

Consider a set of N Tweeters and J followed individuals. Let F be an $N \times J$ matrix, where $f_{ij} = 1$ if Tweeter in row i follows individual in column j and 0 otherwise. We assume each Tweeter and followed individual has a location θ in a latent 1-D space. Formally, our model is given by

$$\Pr(f_{ij} = 1 | \alpha, \beta_j, \theta_i, \theta_j) = \Phi\left(\alpha + \beta_j \cdot (\theta_i - \theta_j)^2\right) \qquad (1)$$

where Φ is the cumulative normal distribution. Of course, the model given by equation (1) is not identified without further restrictions. We identify the scale by assigning a prior distribution to the unobserved ideal points, such that $\theta \sim N(0, 1)$. Even with that constraint, the model is still only identified up to a polar rotation (Jackman 2001). As we show below, self-declared political ideology is well-correlated with the latent dimension we recover. We therefore select the polarity of the model that makes self-declared conservatives more likely to be at the right end of the dimension and self-declared liberals more likely to be at the left end of the dimension. Finally, we assign diffuse normal priors to the intercept and slope parameters. Specifically, we assume that the intercept has an improper uniform prior and that the slope parameter has a strictly negative uniform prior, enforcing the assumption that increasing distance decreases the propensity to follow someone else: $\alpha \sim U(-\infty, \infty)$ and $\beta_j \sim U(-\infty, 0)$ for $j = 1, \ldots J$. We program and estimate our model in `R` and `JAGS` (R Development Core Team 2009, Plummer 2003).

We identify the universe of Tweeters that each individual Tweeter "follows." We refer to the Tweeters in our panel as "Followers" and the individuals they follow as "Followees." We subset the data and retain only those Followees in the top 1% of the distribution of the number of Followers one has. This results in 1551 Followees remaining in our data. Similarly, we subset the data and retain only those Followers in the top 80% of the distribution of the number of Followees for each Tweeter. This results in 522 Followers remaining in our data. (The distribution of Followees per Follower is extremely right skewed.) We then estimate the latent ideal points, θ, for the Followers in our data (as well as the Followees, of course). Of the 2073 individuals in the matrix, 21 appear as both Followers and Followees. This suggests that rather than collecting data on Tweets among an insular network of individuals talking to each other, we have data on Tweets by people who are part of broader Twitter networks.

The estimates we report below are based on a 10,000-iteration simulation (thinned by 10), after a discarded 10,000-iteration burn-in period. Standard diagnostic tests suggest the model converges and mixes within the burn-in period. Figure 4 reports the distribution of posterior mean estimates of θ_i for each of the 522 Twitter Followers in our data. We divide the data into three groups—those self-identifying as conservative, those self-identifying as liberal, and those who do not declare a political preference. Conservatives are individuals who self-identify as conservative or Republican in their profile; Liberals are individuals who self-identify as liberal or Democrat in their profile. This plot provides strong evidence of the validity of our measurement model. Self-identified liberals are distributed around a mode to one end of our scale, whereas self-identified conservatives are distributed around a model to the other end of our scale. The average ideal point for self-identified liberals is -0.14, whereas the average ideal point for self-identified conservatives is 0.22, and the t-statistic for the difference between these two groups is 12.3, (147 df).

Importantly, Tweeters who do not self-declare as either liberals or conservatives are distributed bimodally. There is a mode right around the self-identified liberals, and another mode right around the self-identified conservatives. This finding is consistent with the interpretation of our estimates a measure of ideology, in a world in which self-identification as liberal or conservative on Twitter is not necessarily associated with being an ideological extremist; rather whether one chooses to self-identify as liberal or conservative may be a function of features other than their ;agent ideological predispositions, such as interest in politics, profession, or general public profile.

Finally, it bears mentioning who some of the most liberal and conservative Tweeters in our sample are. We focus on the Followees, as they tend to be high-profile institutions (they have many followers, by definition), whereas the Followers (members of our panel) tend to be private

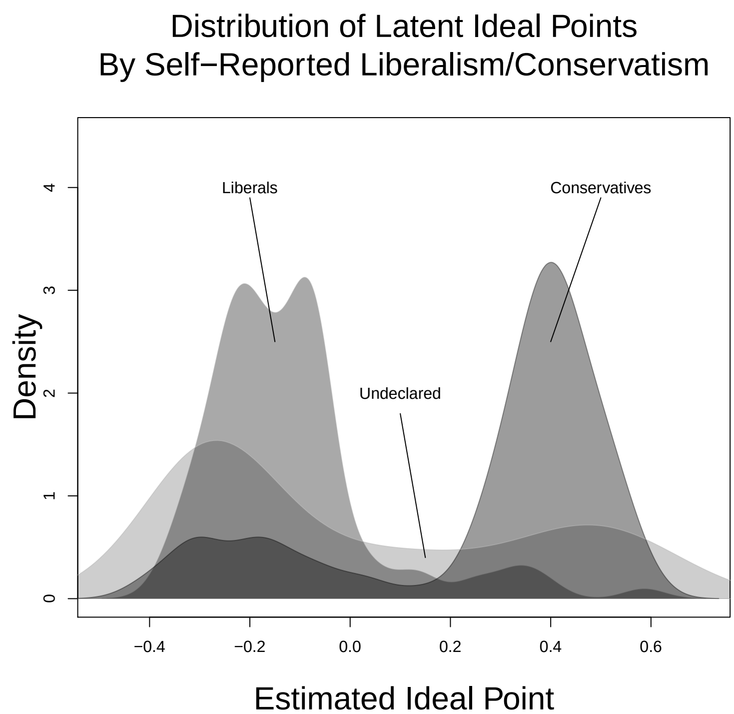

Figure 4: *Estimated ideal points of Tweeters in the panel study.* Figure shows posterior mean estimates of latent ideology for individuals in our Twitter panel. Those labeled Liberals are individuals who identify themselves as either liberals or Democrats in their Twitter profiles. Those labeled Conservatives are individual who identify themselves as either conservatives or Republicans in their Twitter profiles. Those labeled Undeclared did not indicate a political preference in their Twitter profiles. Estimates based on a 10,000-iteration simulation after a discarded 10,000-iteration burn-in period. Plot shows distribution of posterior means.

individuals. However, because all of these individuals are scaled in a common dimension, the Followees are useful for interpreting what it means to be at one end of the dimension. Also, recall that this panel is constructed of Tweeters who often Tweet about same-sex marriage. Among the individuals at the far-right end of the dimension—those we interpret as "most conservative"—are "Team Santorum KY", a Rick Santorum-led political group; "Roaring Republican", a conservative group whose profile says that "#Liberalism is a disease"; "Patriot Airborne", a self-described "Proud #NRA member"; and "Andrea Silver", a Tweeter whose profile says "Christian, Pro-Israel, Pro-constitution." Among the most liberal members of our group are "Big Gay News", a gay media account; "SEIU", the official Twitter account of the Service Employees International Union; "SenateDems", the Twitter account of the Senate Democratic Policy and Communications Committee; and "GOP Unplugged", a Twitter account that mocks Republican politicians. These examples are consistent with Barberá's (2015) validation of this type of model as a method for recovering latent ideology.

5 Evaluating the Effects of SCOTUS Decisions on Twitter Discourse

With the data and measurement issues addressed, we are now equipped to turn to our theoretical motivation—how do Supreme Court decisions affect the nature and content of public political discourse. We evaluate each of the two primary dimensions of discourse described above, in turn.

5.1 The effect of SCOTUS decisions on supportiveness

To evaluate our first set of predictions—that the SCOTUS decisions either increase supportiveness with respect to marriage equality policies or polarize opinion among ideological and opinion groups, we first direct attention to Figure 3. There, we saw little appreciable change in supportiveness associated with the Supreme Court's same-sex marriage decisions in June 2013. In fact, if anything, the supportiveness in Tweets about same-sex marriage after the decisions was *lower* than before. The average level of supportiveness in the random sample before the decision was 1.68 and 1.56 after, $t > 57.1$. The average level of supportiveness in the panel was 1.13 before the decision and 1.11 after, $t > 3.3$. However, while these differences are statistically meaningful simply because

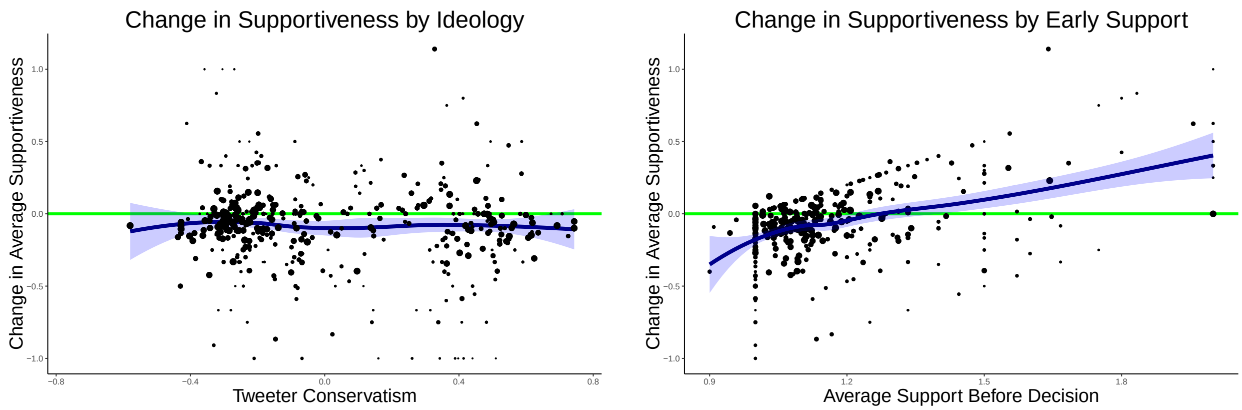

Figure 5: *Change in panelists' supportiveness after the Supreme Court's decisions, as a function of conservatism and early support.* Left-hand panel shows signed change in panelists' average supportiveness as a function of their estimated latent conservatism. Right-hand panel shows signed change in panelists' average supportiveness as a function of their average support before the Supreme Court decisions. All change measures exclude Tweets on the day of the Supreme Court's decisions. Lines are locally-weighted GAM regressions with 95% confidence intervals. Points are sized proportional to the number of Tweets collected from each panelist.

of the sheer magnitude of the data, those differences are extremely small in an absolute sense. In any event, they provide no support for the proposition that the Supreme Court's decisions shifted opinion in favor of same-sex marriage.

Turning to the polarization predictions, Figure 5 shows the change in average supportiveness among all members of our panel who Tweeted both before and after the Supreme Court's decisions, as a function of their estimated conservatism (left panel) and their supportiveness before the decision (right panel). In each panel, the points show individual panelists *change* in supportiveness, and the points are sized proportional to the number of Tweets we have from each panelist. The lines are loess smoothers with 95% confidence bands. As is clear, we do not observe opinion change consistent with the expectation that the decision polarized the views of liberals and conservative.

The right-hand panel of 5, which summarizes results for the same set of people studied in the left-hand panel,[10] suggests that opinion does seem to have polarized among competing opinion groups. If there was a polarization of opinion following the Supreme Court's decision, would should expect to see an upward slope. Such a slope would be consistent with an increase in support

[10] A natural concern in this analysis is that the individuals for whom we have an ideology score are the most connected/involved individuals in all of our data. As such, it is possible that we would not see change in opinion conditioned on ideology only because the individuals studied have relatively fixed opinions as a consequence of their considerable engagement with the topic. To ensure that we address this concern, the analysis of polarization by prior support includes only the individuals who have ideology scores.

for marriage equality among supporters and a corresponding decrease among opposers. This is precisely what we observe. Being more supportive of same-sex marriage before the decision is associated with an increase in supportiveness after the decision; being more opposed to same-sex marriage before the decision is associated with a decrease in supportiveness after the decision.

5.2 The effect of SCOTUS decisions on intensity and anger

To investigate how the Supreme Court's decisions affected intensity and anger in opinion, consider Figure 6. This figure reports conditional distributions of anger and intensity over time, for supportive and opposed Tweets using a loess smoother over time among both supportive and opposed Tweets. We interrupt the smoother at the date of the Supreme Court's same-sex marriage decisions in June 23 in order to avoid artificially smoothing away sharp jumps that might take place at the decision. (One could, alternatively, estimate a smoother across all of the observations, which we have done. The same basic findings emerge. However, because the effects we predict and detect are both sudden and temporary, they are easiest to see with separate fits to the two periods.) As above, the top row shows the random sample; the bottom row shows the panel.

Under the legitimation hypothesis, the Supreme Court's decisions ought to have decreased intensity and anger, especially among individuals who were opposed to marriage equality. Under the polarization hypothesis, anger should have increased among opposers and decreased among supporters. Intensity may have increased or decreased following the opinion. Consider first intensity. In the random sample (the top panels of Figure 6), among opposed Tweets we see a relatively low level of intensity that is constant up until the decision date. Among supportive Tweets, by contrast, we see a higher, and increasing, level of intensity over time, leading up to the decision. In the panel, however, whereas opposed Tweets are, just as in the random sample, less intense and relatively constant in the level of intensity before the decision, supportive Tweets are decreasingly intense over time. That is, intensity is going up among supportive Tweets in the random sample, but down in the panel. However, in both the random sample and the panel, we see spikes in intensity among both supportive and opposed Tweets, followed by a steady, and fast, decrease in intensity in the days following the decision. With respect to intensity, the evidence is clearly inconsistent with a legitimation effect. Of course, the evidence is also inconsistent with a polarizing effect, if what we were to anticipate was that supporters would grow less intense. Yet again, it is entirely

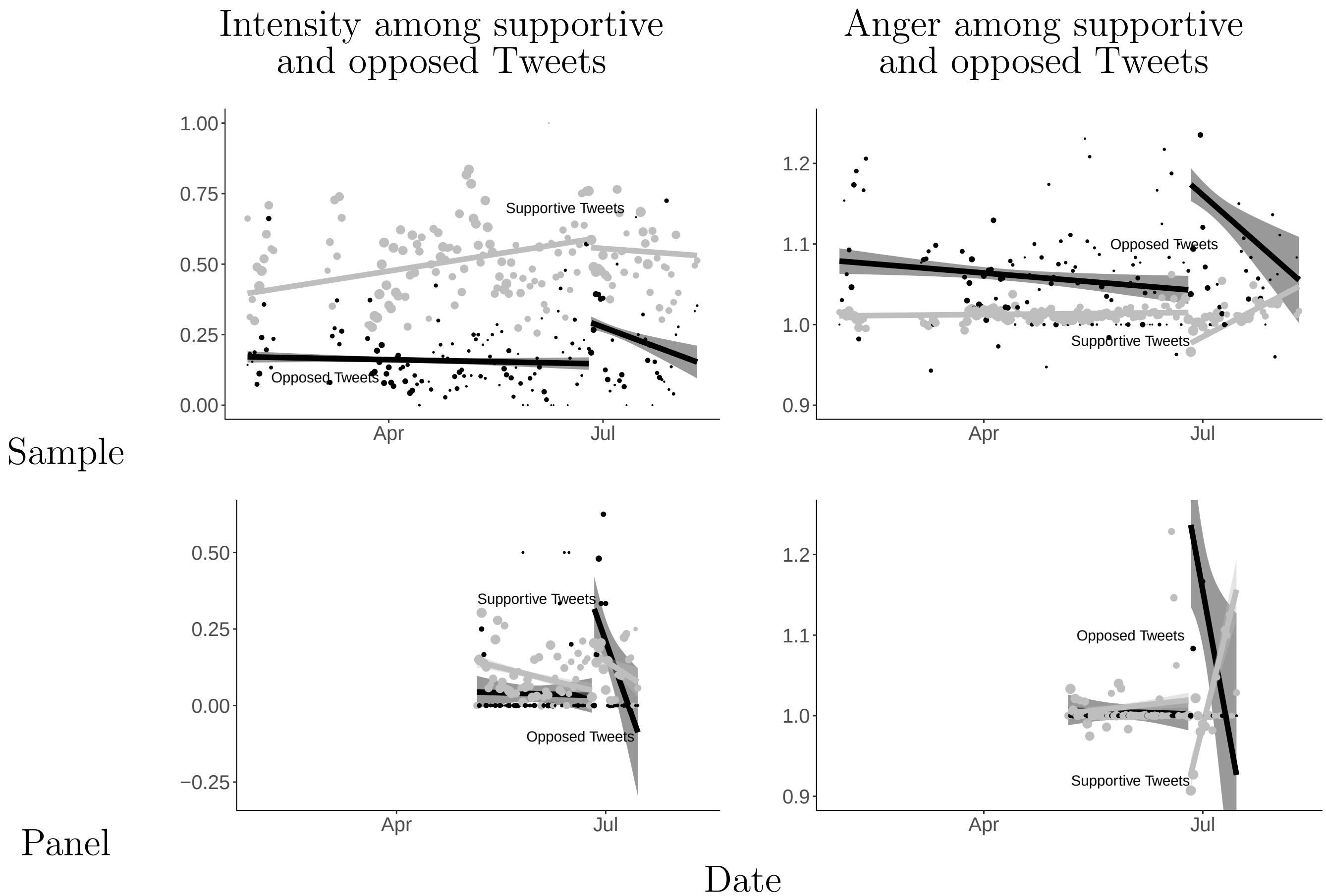

Figure 6: *Estimated intensity and anger among Tweets by estimated supportiveness over time, January 31, 2013-August 11, 2013.* Left column shows estimated intensity among Tweets by day, divided into Tweets estimated to be supportive and opposed to same-sex marriage, and those before and after the Supreme Court's decisions in same-sex marriage cases. Right column shows estimated anger among Tweets by day, divided into Tweets estimated to be supportive and opposed to same-sex marriage, and those before and after the Supreme Court's decisions in same-sex marriage cases. Top row shows the random sample of Tweets; the bottom row shows the panel of Tweeters.

possible that major Supreme Court decisions intensify both support and opposition. This is what we observe.

Consider next anger. In both samples, in the immediate days after the Court's decisions, we see a sharp drop in anger among supportive Tweets, and a sharp increase in anger among opposed Tweets. There is absolutely no evidence that individuals who were initially opposed to marriage equality, either those in our random sample of Tweeters or in our panel, exhibited considerably less anger in the way that they express their opposition following the Supreme Court's decision. The results are strongly consistent with the argument that the Court's decisions polarized opinion groups.

5.3 Discussion

We find considerably more evidence suggestive of a polarizing effect of the Supreme Court's decisions in *Windsor* and *Perry*. In fact, we find no evidence supporting a legitimizing effect. The Supreme Court may have been structuring discourse on same sex marriage, but it is very unlikely that it caused individuals to be more tolerant or changed their particular views on the subject. In this section, we consider two aspects of the patterns summarized above. Specifically, we highlight the dynamics of opinion change following the decision and the lack of a polarizing effect among ideologues. These patterns raise important questions about what kind of theoretical mechanism might explain the patterns of polarization we observe.

5.3.1 Dynamics

A cursory glance at Figure 6 suggests that although the Court may have significantly increased anger among those opposed to same sex marriage (and decreased anger among supporters), the effects were short-lived. Indeed, the pattern seems to ultimately reverse itself. This is, as it turns out, consistent with Franklin and Kosaki's (1989) account. As we note above, Franklin and Kosaki imagine that salient policy outcomes create topics for conversation among opinion groups. This is exactly what happens in social media, even in Twitter. And one generator of discussion on Twitter is the reaction of groups opposed to your opinion. We have documented a rise in anger among same-sex marriage opponents. The subsequent rise in anger among supporters may well reflect a reaction to the anger among opponents. Indeed, a casual read of a sample of Tweets from during that period corroborates such an interpretation. Among the most angry Tweets on the day of the same-sex marriage decisions are:

- RT @TalentsMomMLG: `#HOLLYWOOD` `#SanFran` `#SAMESEX` MARRIAGE IS legal tonight UR ATTACK AGAINST `#FAMILY` `#Prop8` MAY APPEAR Victory BUT `#GOD` WINS
- RT @arkansasafmilso: I want to know why we tolerate gay marriage and we tolerate abortion but we can't tolerate Paula Deen saying the N wor
- I have to be tolerate of abortion and gay marriage to be politically correct BUT I get called horrible names bc I don't support that? What?

In these examples we see evidence of strong emotional reactions driven by discontent with the decision (Banks and Valentino 2012). They also raise precisely the type of arguments that deeply anger supporters of same sex marriage, e.g., that God opposes homosexuality; that opposition to marriage equality is often linked with other types of intolerance, including racial intolerance; and, that families are somehow harmed by marriage equality.

These trends reveal an important consequence of the Supreme Court's decisions. The content of Tweets about same-sex marriage exhibited notable emotional shifts in the days following the Supreme Court's decisions. However, it appears those shifts were short-lived. Nevertheless, because of the importance of emotional reactions for political choice and opinion, these potentially short-lived bursts in anger and intensity have direct implications for the efficacy and validity of political reaction to Court decisions. Indeed, in the modern political environment in which events take place at such a rapid pace and the mass public (via social media) are more directly engaged with real-life political events, short-lived emotional reactions may have more long-term consequences than in the past when the institutions of representation were better equipped to temper momentary passions. In any event, that we detect such strong emotional bursts in the wake of the Court's decision illustrates the effect of the Supreme Court decisions beyond simply moving individual opinion. The comparable effects in both our panel and in the random sample of Tweets reveals the emotional reactions were limited to neither occasional Tweeters nor opinion leaders; rather sharp changes in intensity and anger seem to be general phenomena in social media discourse after the cases were decided. These findings suggest, then, that national political discourse may take on a very different character depending on how much policy debates can be separated from the events triggering the deliberation itself.

5.3.2 The Lack of a Polarized Response among Ideologues

The second notable finding is the lack of a polarizing effect among liberals and conservatives. The decisions seem to have produced no noticeable change of any kind associated with particular ideological positions. We believe that this finding, interesting in its own right, may speak to the mechanism underlying political discourse in Twitter. To consider how, we refer back to the two mechanisms that suggest a polarizing effect. The thermostatic response account suggests that individuals react to policy stimuli by revealing relative preferences for policy change in the direction of their ideal policy. As long as conservatives and liberals have divergent preferences in the context of same sex marriage, we ought to observe polarization. The structural response account suggests that individuals react to policy stimuli by discussing events among members group members. Importantly, it does not predict polarization in all cases. Polarization depends on patterns of within-group and between-group variation. When distinct groups have relatively low within-group variation on an issue and yet between-group variation is high, we expect polarized responses, as repeated discussion among group members only reinforces prior beliefs. However, if between-group variation is relatively low (and especially so if within-group variation is high), then we would not expect polarization.

Despite aggregate changes in opinion with respect to same sex marriage, pronounced differences among ideological groups remain. In 2013, whereas the percentage of self-described liberals for favored same-sex marriage was 73%, it was only 30% among conservatives. In general, most conservatives oppose same sex marriage whereas most liberals support it. Thus, on both accounts we might expect to observe polarization, which of course we do not. Yet consider Table 3,[11] which summarizes marginals from an aggregation of polls conducted by the Pew Research Center. Although it is generally true that conservatives and liberals (here proxied with measures of partisanship) differ greatly on marriage equality, among the young the differences are far less pronounced. Indeed, a majority of young conservatives (54%) actually support the policy. In so far as our Twitter sample likely over-represents the younger parts of the American population, it is perhaps not surprising that we failed to find that the Supreme Court polarized ideological groups. Although the thermostatic response account does not seem to account for it, the structural response account, which highlights a deliberative response to public policy outcomes, suggests a possible explanation.

6 Conclusion

Our analysis gives rise to three related points concerning the connection between classical normative and positive questions that define political science and modern computational social scientific techniques data data. While only a single step forward in terms of analytic results, we believe the findings reported here can help lay the groundwork for such burgeoning interdisciplinary work.

[11] The source for the data presented is the Pew Research Center. The study is described at `http://pewrsr.ch/1eeoegc`.

	In favor (%)	Oppose (%)	Don't know (%)	N
General public	50	43	8	3005
Republicans	33	61	6	1223
Ages 18-29	54	42	4	165
30-49	35	58	6	301
50-64	27	68	6	396
65 +	18	72	9	342
Democrats	62	31	7	1433
Ages 18-29	76	22	2	258
30-49	63	30	8	394
50-64	57	35	8	392
65 +	50	40	10	378

Table 3: *Support for same-sex marriage by party and age, Spring 2013. Partisans include those who self-describe as affiliated in addition to "leaners." Data is aggregated from polls taken between March and May of 2013. Source. Pew Research Center.*

First, our findings speak to the way we can use modern social media and "big data" to study fundamental problems concerning the nature of democratic deliberation, the implications of modern social media for democratic discourse, and the empirical implications of normative democratic theory. Second, our findings speak to the growing interest among political scientists in using social media to evaluate theories of politics. Third, our study illustrates the potential for realizing compound returns to investing in interdisciplinary work, especially between social and computer scientists.

Normative democratic theory and big data. While we believe microblog data can be used to great effect to study a variety of theoretical problems in political science, we are motivated most directly by theoretical questions about the nature of political discourse and deliberation. One of the key issues in this area of study is the role of engagement with diverse opinions for healthy democratic deliberation. Normative theories of democracy often suggest that effective deliberation and consensus building is associated with exposure to diverse viewpoints (e.g., Barber 1984). One line of research suggests that mass media can foster democratic deliberation, because the mass media generally exposes one to a greater variety of viewpoints than do interpersonal discussions (e.g., Mutz and Martin 2001). However, in the context of the modern media environment, especially that of cable news and social media, concerns arise that it has become increasingly easy to self-select into a political echo chamber (see, for example, Prior 2007). Such a trend may raise particularly troubling normative implications in the context of modern social media (Sunstein 2008). Much research on social media, and Twitter, in particular, though, suggests that social media does not function as an echo chamber and that individuals are actually exposed to a great variety of political viewpoints on microblogs (e.g., Yardi and Boyd 2010).

What might be the consequences of social media *qua* political echo chamber for political deliberation? Several areas of research suggest possible consequences. For example, research on momentum in politics argues that cognitive responses to hearing consensus opinion can motivate individuals to search for arguments that justify joining the consensus viewpoint (see Mutz 1997, for a discussion). If Twitter is a political echo chamber, one might infer that encountering little variation in opinions on social media indicates a consensus viewpoint and therefore adapt her opinions accordingly. However, such cognitive responses are not necessarily unidirectional. Encountering opinions that are counter to one's prior beliefs may cause one to update their opinions about the source of the information and convince oneself the source of information is wrong (e.g., Huckfeldt and Sprague 1995). Our data show that important dynamics in political discourse take place in the context of Twitter. We see evidence of the Supreme Court having an effect on public opinion similar to what has been documented elsewhere—it moves some "opinion moderates" in support of the policy it endorses but has a polarizing effect on the most opinionated among the public. In addition, we see emotional dynamics following a Supreme Court decision not dissimilar to what we might expect in other arenas. Thus, while we do not demonstrate whether Twitter is an echo chamber, we do show trace evidence of meaningful political discourse and deliberation on social media. We believe these are positive findings for scholars seeking to leverage the potential for social media to provide empirical leverage on important questions of normative significance—questions previously not amenable to empirical study.

Using social media data to study politics. As we noted at the outset, modern computational techniques have been brought to bear on social media to study political phenomena. There is much promise in this work, in part because of the facility with which scholars can acquire massive amounts of data about political opinions and behavior. Moreover, not only are those data easy and cheap to access, but they provide metrics of potentially more intimate political behavior and beliefs than could be captured in a traditional public opinion survey. Our study has focused on Twitter, largely because it is the social medium that most closely meets our research interest needs. However, scholars have relied on, and continue to make use of, many forms of social media data to study politics. For example, studies use Facebook, YouTube, and similar platforms to study political organization and mobilization, political awareness, and political participation, among other political actions (e.g., King, Pan and Roberts 2013, Bond et al. 2012). However, further development of analytic techniques is still needed. For example, a pressing question concerns what kinds of general conclusions about politics can one draw from social media data. What is the selection process that underlies participation on social media, and how representative are data on social media of the larger polity? Especially if one wants to make use of media such as Twitter to study public opinion, scholars will have to confront these challenges.

The role of theory in the big data revolution. Further, we believe the analysis here demonstrates the potential for bringing together "big data" with theoretical models of politics. As we noted at the beginning of this paper, the computational revolution in the study of politics has already begun. However, much of the cutting edge work is computational in nature, not political. As our example from the introduction about forecasting elections with Twitter mentions illustrates, big-data empirical political science is in need of techniques to more concretely tie the metrics we develop to theoretical concepts. For example, a recent symposium in *PS: Political Science and Politics* was concerned with the relationship among formal theory, causal inference, and big data, with particular attention being paid to how one uses theoretical models to direct measurement strategy. The considerable analytic potential presented by social media makes the role of theory in modern empirical scholarship even more central, as theoretical interpretation is particularly important in an empirical setting in which there is sufficient power to detect statistically meaningful relationships among virtually any data one may use. We anticipate future research can, and will, continue to address these deep questions about the use of theory in a world of abundant data.

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