How Social Media Reduces Mass Political Polarization. Evidence from Germany, Spain, and the U.S.

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Abstract

A growing proportion of citizens rely on social media to gather political information and to engage in political discussions within their personal networks. Existing studies argue that social media create "echo-chambers," where individuals are primarily exposed to like-minded views. However, this literature has ignored that social media platforms facilitate exposure to messages from those with whom individuals have weak ties, which are more likely to provide novel information to which individuals would not be exposed otherwise through offline interactions. Because weak ties tend to be with people who are more politically heterogeneous than citizens' immediate personal networks, this exposure reduces political extremism. To test this hypothesis, I develop a new method to estimate dynamic ideal points for social media users. I apply this method to measure the ideological positions of millions of individuals in Germany, Spain, and the United States over time, as well as the ideological composition of their personal networks. Results from this panel design show that most social media users are embedded in ideologically diverse networks, and that exposure to political diversity has a positive effect on political moderation. This result is robust to the inclusion of covariates measuring offline political behavior, obtained by matching Twitter user profiles with publicly available voter files in several U.S. states. I also provide evidence from survey data in these three countries that bolsters these findings. Contrary to conventional wisdom, my analysis provides evidence that social media usage reduces mass political polarization.

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Mass political polarization is a signature phenomenon of our time. As such, it has received considerable scholarly and journalistic attention in recent years (see e.g. Abramowitz and Saunders, 2008 and Fiorina and Abrams, 2008). A growing body of work argues that the introduction of the Internet as a relevant communication tool is contributing to this trend (Farrell, 2012). Empirical evidence of persistent ideological sorting in online communication networks (Adamic and Glance, 2005; Conover et al., 2012; Colleoni, Rozza and Arvidsson, 2014) has been taken to suggest that Internet use may exacerbate mass political polarization. As Sunstein (2001) or Hindman (2008) argue, the Internet appears to create communities of like-minded individuals where cross-ideological interactions and exposure to political diversity are rare. This argument builds upon a long tradition of research that shows that political discussion in homogenous communication networks reinforces individuals' existing attitudes (Berelson, Lazarsfeld and McPhee, 1954; Huckfeldt, 1995; Mutz, 2006)

In this paper I challenge this conventional wisdom. I contend that social media usage – one of the most frequent online activities – reduces political polarization, and I provide empirical evidence to support this claim. My argument is two-fold. First, social media platforms like Facebook or Twitter increase incidental exposure to political messages shared by peers. Second, these sites facilitate exposure to messages from those with whom individuals have weak social ties (Granovetter, 1973), which are more likely to provide novel information. Consequently, despite the homophilic nature of personal networks (McPherson, Smith-Lovin and Cook, 2001), social media leads to exposure to a wider range of political opinions than one would normally encounter offline. This induces political moderation at the individual level and, counter intuitively, helps to decrease mass political polarization.

To test this hypothesis, I develop a new method to measure the ideological positions of Twitter users at any point in time, and apply it to estimate the ideal points of millions of citizens in three countries with different levels of mass political polarization (Germany, Spain, and the United States). This measure allows me to observe not only how their political preferences evolve, but also the ideological composition of their communication networks. My approach represents a crucial improvement over survey studies of political networks, which often ask only about close discussion partners and in practice exclude weak ties, limiting researchers' ability to study their influence.

In addition, I rely on name identification techniques to match Twitter users with publicly available voter files in the states of Arkansas, California, Florida, Ohio, and Pennsylvania. This allows me to demonstrate that my results are not confounded by covariates measuring offline political behavior. I also provide evidence from survey data in these three countries that bolsters these findings.

Contrary to previous results in the literature on social media and political polarization (see e.g. Conover et al., 2012), I find that social media does not increase political extremism. My analysis provides evidence that individuals who are embedded in heterogenous personal networks and who are exposed to diverse content become more moderate over time.

My findings have important implications for the study of political communication, social behavior, and democratic theory. First, this paper contributes to a growing literature on the importance of online personal networks in citizens' behavior (Bond et al., 2012; Tufekci and Wilson, 2012; Vaccari et al., 2013), by documenting how exposure to political messages on social media sites affects political preferences. My results underscore the consequential role that political diversity plays in citizens' political beliefs and, in doing so, they speak to a broad literature on the effects of cross-cutting exposure (Allport, 1954; Green and Wong, 2009; Mutz, 2006) and the role of political information exchanged in interpersonal networks (Klofstad, 2009; Leighley, 1990; McClurg, 2006). In addition, this paper highlights the rich potential of social media sites to transform the political process, and illustrate the value of social media data when it comes to examining questions about human behavior in new and exciting ways (Lazer et al., 2009).

1 Social media and mass political polarization

Citizens depend on their personal networks to gather political information, construct their political identities, and make their voting decisions (Berelson, Lazarsfeld and McPhee, 1954; Fowler, 2005; Huckfeldt and Sprague, 1991; Nickerson, 2008; Settle, Bond and Levitt, 2011; Sinclair, 2012). By dramatically reducing the costs of interpersonal communication, social media platforms like Twitter or Facebook have the potential to amplify the importance of peer effects in political behavior. In particular, social media introduces two key changes to how individuals communicate: first, it increases the volume of information to which individuals are exposed; and second, it affects the size and diversity of their personal communication networks. In isolation, the former is unlikely to exert large changes in voters' political behavior. More frequent contact with family and close friends – the peers traditionally thought to have a greater social influence – does not necessarily imply that citizens' exposure to political messages increases, since such information already flows through offline communication channels.

In this paper I claim that the most significant change associated with the increased usage of social media sites is the frequency of communication exchanges beyond the most immediate personal networks. Citizens are now exposed not only to their close friends' opinions, but also to political content shared by their co-workers, childhood friends, distant relatives, and other people with whom they form weak ties. In this section, I discuss the potential consequences of such inadvertent exposure (Brundidge, 2010) on citizens' political behavior and, in particular, in their ideological preferences.

1.1 Social Media Increases Exposure to Diverse Political Information

One in every ten people in the world logged onto Facebook yesterday.[1] Every week, Twitter users post over 3.5 billion 140-character messages.[2] An important part of this massive amount of content has to do with politics. For example, 97% of the current members in the 113th U.S. Congress, the governments of 77% of all U.N. member countries,[3] and virtually all political parties and candidates, media outlets and political journalists, interest groups and NGOs in most developed democracies have active social media accounts.

The increasing availability and heterogeneity of political information through the Internet and social media is radically transforming citizens' news consumption habits. By 2012, 41% of adult Americans saw news on social networking sites on a daily basis. When compared to other sources of information, social media is already more popular than newspapers (29%). Even though TV is still the predominant outlet to which citizens turn in order to keep up with current events (55%), that is not the case anymore among young adults (18-30 years old), who turn to social networking sites for news more often than TV (47% vs 34%).[4]

Early research on the political consequences of new information and communication technologies argued that the Internet would democratize the public debate, foster civic engagement and social capital, and increase dramatically the quality of political representation (Barber, 2003; Corrado and Firestone, 1996; Dahlgren, 2005). Theoretical models of opinion dynamics and social influence predict that such a context – where individuals are increasingly exposed to a diversity of opinions – should lead to social consensus (DeGroot, 1974), higher

[1] Source: Facebook Report First Quarter 2013 Results.
[2] Source: Twitter Official Blog, August 2013.
[3] According to a study by Twiplomacy.
[4] Source: Pew Research Center Poll on Biennial Media Consumption, June 2012, weighted estimates.

political tolerance (Mutz, 2002), and more efficient decision-making processes (Hong and Page, 2004). However, the empirical evidence up to this point challenges this theory. Studies of online behavior find persistent ideological sorting in online communication networks (Adamic and Glance, 2005; Conover et al., 2012; Colleoni, Rozza and Arvidsson, 2014), suggesting that the Internet functions as an "echo-chamber," where citizens are primarily exposed to like-minded political views.

One limitation of these empirical studies is their focus on self-selected exposure to explicitly political content (blogs, use of political hashtags, etc). However, these online activities represent only a small proportion of the time citizens spend online, which is now increasingly devoted to visiting social media sites such as Twitter or Facebook, particularly among young adults. One important characteristic of these platforms is that they generate *social consumption* of political information (Kaplan and Haenlein, 2010). Unlike news portals, blogs or online forums, the political information to which citizens are exposed through platforms like Facebook or Twitter is what their friends, family, co-workers, and acquaintances decide to produce or share. Even if news organizations and journalists are also present on social media sites, most users report receiving political messages from other individuals in their personal networks. According to a survey conducted by the Pew Research Center in 2013, half of Facebook and Twitter users get news on those sites, and for 78% of them this exposure to political information is incidental, through news posted by their "friends" and not news organizations or journalists.

The social consumption of news represents a consequential change in how citizens keep up with current political events. Since individuals are now *inadvertently* exposed to the news their friends and acquaintances decide to share (Brundidge, 2010), selective exposure to ideologically congenial information decreases (Lazarsfeld, Berelson and Gaudet, 1944; Sears and Freedman, 1967). As Messing and Westwood (2012) show, friends' recommendations are powerful social cues that reduce the role of partisan affiliation in news consumption. Their findings illustrate how individuals are likely to click through and read news stories shared by their friends and acquaintances even if they potentially disagree with the message of that story.

Of course, traditional media outlets and political actors are also present on social media, and therefore individuals self-select into networks that are at least in part endogenous to their political preferences.[5] However, there is ample evidence that online personal networks

[5]Another mechanism explaining self-selection in online communication networks is the fact that users can easily break online ties. According to the Pew Research Center, up to two thirds of social media users report to

overlap to a great extent with offline networks (Burke and Kraut, 2014), and that the strength of interpersonal relationships can be inferred from the frequency of online interactions on social media sites (Gilbert and Karahalios, 2009; Jones et al., 2013). The crucial difference is that social media facilitates the formation and strengthening of "weak ties" (Granovetter, 1973), which are more likely to provide novel information to which individuals would not be exposed otherwise through offline interactions (Bakshy et al., 2012; Mutz, 2006).

1.2 Political Diversity and Ideological Moderation

Previous studies of political discussion on social media have found that interactions take place predominantly among individuals with similar ideological positions, and that most political information shared through social media is generated by partisan individuals with extreme ideological positions (Barberá and Rivero, 2014; Colleoni, Rozza and Arvidsson, 2014; Conover et al., 2012; Smith et al., 2014). These patterns are often thought to suggest that social media platforms create "echo chambers" where individuals are primarily exposed to like-minded political views, which should exacerbate political polarization.

However, I claim that the effects of increased exposure to political information through social media vary in response to the degree of heterogeneity in citizens' personal networks. For citizens in ideologically diverse networks, higher exposure to political content will imply greater exposure to different viewpoints; i.e. "hearing the other side" (Mutz, 2006). In other words, partisan production and sharing of political information is perfectly compatible with diverse *consumption* of information. In fact, since weak social ties tend to be more ideologically heterogeneous than strong social ties (see e.g. Mutz, 2006, p.27), and most content individuals see on social media is generated by weak ties (Bakshy et al., 2012), my expectation is that social media will increase exposure to political diversity for most individuals.

A long tradition of research has examined the relevance of political diversity in communication networks. Political deliberation among individuals of different opinions is a core component of most normative theories of democracy (Fishkin, 1991; Habermas, 1989; Lipset,

have ever ended an online connection ("unfriended" or "unfollowed"). These decisions are endogenous to factors like embeddedness (number of common friends) and homophily (similarity in personal characteristics), in the same way as offline tie dissolution (Kwak, Moon and Lee, 2012; Quercia, Bodaghi and Crowcroft, 2012). At the same time, however, this type of behavior is rare from an aggregate perspective when we consider that the median social media user has between 100 and 200 friends (Gonçalves, Perra and Vespignani, 2011), which implies that in practice social media users cannot control their exposure to political messages. (See also Appendix A for additional discussion.)

1959; Manin, Stein and Mansbridge, 1987; Mill, 1859). Computational models of opinion dynamics and social influence have shown that populations in diverse networks tend to become homogenous over time (Abelson, 1964; Axelrod, 1997; DeGroot, 1974). There is also broad empirical evidence that cross-cutting exposure is a powerful driving force for political tolerance (Allport, 1954; Mutz, 2002).

Building upon this body of work, my central hypothesis is that *exposure to politically diverse information on social media will induce political moderation*. Since social media increases exposure to heterogeneous communication networks, I thus expect social media to reduce political extremism for most individuals.

Two possible mechanisms explain this relationship. On one hand, cross-cutting interactions convey new information and lead to "greater awareness of rationales for oppositional views" (Mutz, 2002, p.114). If we conceptualize political identities as the result of a learning process of political socialization (Sears, 1983; Stoker and Jennings, 2008), individuals embedded in a political environment in which they receive conflicting information may tend to have weaker identities. As Berelson, Lazarsfeld and McPhee (1954, p.98) discuss, "a sense of security about one's judgment seems to be a function of the congeniality of the personal environment (...) Without their full support [of the people around him] it is not easy to hold strong political attitudes, and relatively few people do." A similar argument is put forth by Ortoleva and Snowberg (2013) by arguing that exposure to diverse information is likely to reduce overconfidence in political beliefs stemming from systematic exposure to biased sources, and should thus induce political moderation.

An alternative mechanism would have an affective component. Individuals on one extreme of the ideological distribution may now discover that other members of their personal network have completely different opinions, and therefore realize that holding such opinions is socially acceptable. This explanation would be consistent with views of partisan identification that underscore the role of interpersonal relations and social identities (Iyengar, Sood and Lelkes, 2012).

2 Research Design

2.1 The Promises and Pitfalls of Social Media Data

Previous studies on the effects of cross-cutting exposure rely primarily on surveys to measure political behavior and to characterize communication networks (Huckfeldt and Sprague, 1987; Leighley and Matsubayashi, 2009; Mutz, 2006). These surveys ask respondents to name their discussion partners and their ideological leanings, as well as the frequency of their interactions. This source of information has greatly advanced the study of social and political behavior, but it also has well-known problems that are common to most network studies and cast doubt on the validity of previous findings (Sinclair, 2011). Individuals often fail to list relevant ties or report false ties, and the accuracy rate in the measurement of communication networks is often less than 50% (Marsden, 1990). In addition, since these surveys often ask only about five or six discussion partners, weak ties are likely to be excluded, limiting in practice our ability to study their influence.[6]

As Sinclair (2011, p.444) argues, the ideal research design to study the role of communication networks would be a panel study that allows scholars to measure the political preference of each individual in the sample, as well as the political preferences of all members of her discussion network, at different points in time.[7] In this paper I demonstrate that social media data, in combination with the new methods I introduce, allows researchers to realize this ideal research design. My contribution in using this new source of information is therefore not only substantive – since I hypothesize that the use of social networking sites represents a significant change in the way citizens consume information – but also methodological. In particular, I claim that social media data presents advantages that will help researchers make great progress in the study of political behavior.

Analyses of political behavior require systematic information on the placement of voters and political actors on the relevant policy dimensions. Self-reported ideology estimates from

[6]Different solutions have been proposed to overcome these limitations, such as conducting snowball surveys on political discussion partners to examine concordance (Huckfeldt, Sprague and Levine, 2000), combining different sources of information to construct the network (Christakis and Fowler, 2007) or asking respondents to indicate their level of interaction with *all* potential network ties. However, these approaches become expensive or impractical as we increase the scale of our analysis.

[7]In particular, she claims that "a panel study would enable researchers to estimate a difference-in-differences estimator where the *treatment* –the politics of the social network ascertained at the first point in time– could be seen to have an effect by comparing the difference between individuals who either agreed with their network or disagreed with their network during the first survey, for example, with the second panel." (p.445)

surveys present problems such as social desirability bias and measurement equivalence (Bauer et al., 2014), and rarely allow research to place voters and political actors on a common scale (Jessee, 2009). As I have shown in previous work (Barberá, 2014), ideology estimates computed by modeling the structure of social media networks overcome these challenges (see also Bond and Messing, 2014). The large number of active users on these sites can be exploited to infer precise ideological positions by examining which political actors each user is following, under the assumption that users prefer to follow actors whose position on a latent ideological dimension is similar to theirs (see Section 2.3). In addition, the structure of this network is far from static, which facilitates the estimation of highly granular dynamic ideal points in real time, thus allowing researchers to examine longitudinal change in political preferences.

A second advantage of social media data is precisely its *social* component. Individuals are encouraged to "friend" and "follow" their friends, co-workers, and relatives. As a result, online personal networks are accurate replicas of citizens' offline networks, the more so as social media usage increases and reaches all age groups. In contrast with survey studies of political networks, social media data provides researchers with access to communication networks, which are observed unobtrusively and at any point in time without the need to field expensive surveys about discussion partners. In combination with the method I develop in this paper, this new source of data can provide information about the ideological position of most individuals in these networks, and a measure of how the ideological distribution of communication networks changes over time.

This series of advantages comes at the expense of one important limitation: social media users are not a representative sample of the voting age population. They tend to be younger, more likely to be educated, and more politically interested. However, given that political interest is often thought to be positively correlated with strength of ideological positions, my estimates of the effects of social media usage are likely to be conservative. In other words, if the entire population of the countries I analyze were active social media users, I would expect the effects I find in this paper to be larger in magnitude. However, without a precise estimate of these differences, and the availability of individual-level variables that allow to weight the sample to recover its representativeness, any inferences to be made about the entire population will be biased.

I address this potential concern in two ways. First, in my analysis I restrict my inferences to the population of active social media users in each country. This of course limits the generalizability of my findings, but not its substantive relevance (Nagler et al., 2014), since social media users represent a growing percentage of the population. Second, in Section 3.3 I replicate my main results using panel surveys with nationally representative samples of citizens in the same set of countries, arriving to similar conclusions. Combining the strengths of both sources of data increases the confidence in my results.

2.2 Case Selection

To test my hypothesis, I examine data collected from one of the most popular social media platforms, Twitter. This micro-blogging site enables individuals to post messages of up to 140 characters, called *tweets*. Each user can choose to *follow* other users, which will make their tweets appear on that individual's *timeline*. Two popular features of Twitter are *hashtags* (words or phrases prefixed with the # symbol that are used to group tweets by topic) and *retweets* (re-posting another user's content with an indication of its original author).

In comparison to other social media sites, Twitter presents four important advantages from a research perspective. First, citizens on Twitter get more news through this platform than from any other social media site;[8] and political actors are more active on Twitter.[9] This makes Twitter a more interesting source of information about how citizens receive political messages.[10] Second, most tweets are public.[11] This allows scholars to easily capture data related to the online activities of Twitter users and unobtrusively observe their behavior. Third, it is possible to link Twitter profiles to publicly available voter files through name identification in order to enrich our datasets with a variety of measures of offline behavior. In addition, a combination of geocoding techniques can be employed to identify the exact geographic location of each user. Finally, Twitter meets one of the crucial requirements to test my hypothesis: it is possible to infer how Twitter networks change over time (see Appendix A). In all, these four advantages demonstrate that Twitter data is an ideal source of information to examine how

[8] 50% of Twitter users get news from this site; vs 46% of Facebook and 19% of Youtube. Source: Pew Research Center.

[9] For example, 97% of Members of the U.S. Congress have a Twitter account, whereas 91% of them have a public Facebook account. In addition, actors with accounts on both platforms, such as Barack Obama, tend to have larger audiences on Twitter.

[10] In addition, note that Twitter timelines are always in chronologically inverse order. The equivalent feature on Facebook (News Feed) uses a proprietary algorithm to select what stories shared by friends each user sees when they log on, and in what order. This potentially reduces exposure to political information shared by weak ties, given that stories shared by close friends are prioritized. However, given that the specific rules used of this algorithm have not been made public, researchers can only speculate about whether this is the case or not.

[11] Twitter users can choose to protect their account and allow only their followers to read their tweets, but only a small minority – around 10% in the case of the U.S. sample of users discussed in Section 2.4 – chooses to do so.

exposure to diversity affects political beliefs.

The new methods I introduce in this paper can be used to test my hypotheses in any country where a high number of citizens are active on Twitter. For substantive and methodological reasons, I focus on three countries: Germany, Spain, and the United States. One potential concern in the study of mass political polarization is the existence of ceiling and floor effects: when polarization is at high levels, the estimated coefficients for variables that increase polarization will be biased downwards, and vice versa. The choice of these three countries alleviates this concern because of the variation in their levels of polarization. In Germany, public opinion has been found to be depolarized (Munzert and Bauer, 2013). In contrast, there is ample evidence of ideological and partisan sorting in the United States (see e.g. Bafumi and Shapiro, 2009; Bartels, 2000; Hetherington, 2009; Layman, Carsey and Horowitz, 2006). Spain represents an intermediate case – traditionally considered to have low levels of political polarization (Maravall, 1981), although increasing in the past few years (Montero, Lago et al., 2010).

Three additional reasons that justify my case selection are related to data availability. First, Twitter is a popular social media platform in Spain and the United States (Zeitzoff and Barberá, 2014), which increases the likelihood that online networks replicate offline networks. Twitter is less successful in Germany, in part due to a general trend of lower usage of social media networks in this country, but it is still popular from a comparative perspective (it's the 23th country in the world by total number of Twitter users). Second, panel surveys for the most recent national-level election are available for all three countries. These studies asked a nationally representative sample of respondents a battery of questions about their political behavior – including their self-reported ideology before *and* after the election – as well as their social media usage. To my knowledge, these are the only three election studies that included both types of questions and had a panel design. The availability of these surveys allows me to replicate my analysis of changes in political extremism as a result of social media usage using a different source of data. Finally, the availability of voter file records in the U.S. that can be easily matched with Twitter profiles allows me to enrich my dataset with additional covariates about offline behavior. Given the cost and difficulty of collecting and merging voter files from all 50 states, here I restrict my analysis to only five states that represent the ideological diversity of the United States: Arkansas (a "deep red" state, which gave 60.5% of the vote to Romney in 2012), California (a "deep blue" state, which gave 59.3% of the vote to Obama in 2012), Pennsylvania, Ohio, and Florida (three battleground states which gave 52.0%, 50.1%, and 50.0% of the vote respectively to Obama in 2012).

2.3 Dynamic Ideal Point Estimation Using Social Media Data

In this paper I examine whether citizens in more diverse discussion networks tend to become more moderate over time. An empirical analysis of this relationship requires systematic information about the placement of each individual – and those in her communication network – on a single latent dimension characterized as *ideology*. In the growing literature on the measurement of individual attributes from social media profiles (Back et al., 2010; Kosinski, Stillwell and Graepel, 2013), different studies have demonstrated that Facebook and Twitter networks can be scaled to compute highly precise ideology estimates that replicate conventional measures of ideology (Barberá, 2014; Bond and Messing, 2014). However, these methods generate estimates that are essentially static in the short run, and therefore cannot be used to test my hypotheses, which focus on longitudinal changes in political ideology. Building upon these models, here I introduce a new method that allows me to compute dynamic ideology estimates for all Twitter users at any point in time.

My method relies on the assumption that Twitter users prefer to follow political actors (politicians, think tanks, news outlets, and others) whose position on the latent ideological dimension is similar to theirs. This assumption is similar in nature to that of spatial voting models (see e.g. Enelow and Hinich, 1984). The decision to follow is considered a costly signal that provides information about Twitter users' perceptions of both their ideological location and that of political accounts. Such cost can take two forms. If the content of the messages that users read as a result of their following decisions challenges their political views, it can create cognitive dissonance. Second, given the fast-paced nature of Twitter, it also creates opportunity costs, since it reduces the likelihood of being exposed to other messages, assuming the amount of time a user spends on Twitter is constant. In other words, these decisions provide information about how social media users decide to allocate a scarce resource – their attention.[12]

The statistical model I employ was developed in an article published in *Political Analysis* (Barberá, 2014). This model is similar in nature to latent space models applied to social networks (Hoff, Raftery and Handcock, 2002), item-response theory models (see e.g. Linden and Hamlbleton, 1997), and other methods that scale roll-call votes or campaign contributions into latent political dimensions (Bonica, 2014; Clinton, Jackman and Rivers, 2004; Poole and Rosenthal, 2007). I consider ideology as a position (ideal point) on a latent dimension, and

[12] While obviously less costly than campaign contributions or votes in a legislature, the assumption behind this model is similar in nature to that justifying how donations and roll-call votes can be scaled onto a latent ideological dimension (Bonica, 2014; Poole and Rosenthal, 2007).

infer these positions based on observed following decisions under the assumption that, all things being equal, users will decide to follow those political actors that are located close to their own position on this latent space. As the distance between the user and a given political actor increases, the probability of following decreases.

More specifically, suppose that each Twitter user $i \in \{1, \ldots, n\}$ is presented with a choice between following or not following a political account $j \in \{1, \ldots, m\}$ in period $t \in \{1, \ldots, T\}$, where j is a political actor who has a Twitter account. Let $y_{ij} = 1$ if user i decides to follow user j, and $y_{ij} = 0$ otherwise. For the reasons explained above, I expect this decision to be a function of the squared Euclidean distance in the latent ideological dimension between user i and j in period t: $\gamma||\theta_{it} - \phi_j||^2$, where $\theta_{it} \in \mathbb{R}$ is the ideal point of Twitter user i in period t, $\phi_j \in \mathbb{R}$ is the ideal point of Twitter user j, and γ is a normalizing constant. The subscript t indicates that users' ideology can vary over time.

The probability that user i follows a political account j in period t is then formulated as a logit model:

$$P(y_{ijt} = 1|\alpha_j, \beta_i, \gamma, \theta_{it}, \phi_j) = \text{logit}^{-1}\left(\alpha_j + \beta_i - \gamma||\theta_{it} - \phi_j||^2\right) \quad , \tag{1}$$

where α_i and β_j are random effects that account for the differences in the baseline probability of following and being followed; and are equivalent to measures of political interest for user i and of popularity for political account j.

I estimate this model using MCMC methods, dividing the computation in two stages. First, I estimate the parameters indexed by j by running the model with a sample of "informed" users – those who follow 10 or more political accounts using the Stan programming language (Stan Development Team, 2012). Then, after identifying the posterior distribution of the j parameters, I rely on the independence assumption to compute the user-level parameters, indexed by i, individually using a parallelized Metropolis-Hastings algorithm (Metropolis et al., 1953). In order to identify the model, I assume $\theta_{it=T} \sim N(0, 1)$, where T is the last period.[13]

[13]Note that I also assume that users' ideology parameters are independent over time for each individual. This is of course a strong assumption, since individuals tend to have stable political preferences. It is possible to model these longitudinal dependencies by using a random walk prior on this set of parameters: $\theta_{it} \sim N(\theta_{it-1}, \Delta_{\theta_{it}})$, where $\Delta_{\theta_{it}}$ is an evolution variance parameter that is fixed a priori and parameterizes how much smoothing takes place from one time period to the next (Martin and Quinn, 2002). However, this more complex model yields estimates that are highly correlated with the simpler approach I take in this paper, since the data I use to estimate ideology in each period remains constant in most cases. Unlike the study by Martin and Quinn (2002), where Supreme Court justices vote on a different set of cases each year, here I observe whether individuals are following or not a fixed set of political accounts at any point in time.

(See Barberá, 2014 for additional details about identification of the model and estimation.)

As I explain in the following section, I apply this method to estimate the ideological positions of millions of individuals in Germany, Spain, and the United States in 2013 and 2014. Appendix B provides evidence that the resulting estimates replicate conventional measures of ideology.

2.4 Data

The first step in my analysis is to identify the sample of active Twitter users in each country. I do so by compiling a list of users who follow *at least one political account* in a set of popular profiles on Twitter that includes 1) all leading political figures, 2) all political parties with accounts on Twitter; and 3) all national-level media outlets and political journalists with more than 5,000 followers.[14] This represents a total of m=379 in Germany, m=480 in Spain, and m=620 political accounts in the United States.[15]

Next, I obtained the entire list of followers (as of July 2014) for all political accounts in each country, and aggregated them into a single list by country in order to identify the total population of users that follow at least one political account, resulting in a total of n=1,156,751 users in Germany, n=5,915,698 users in Spain, and n=30,799,261 in the United States.[16] [17]

The final step of my data collection process was to construct the communication networks

[14]In order to construct this dataset, I relied heavily on the lists compiled by the politics aggregator electionista.

[15]In the case of the United States, this list includes, among others, the Twitter accounts of all Members of Congress with more than 5,000 followers, the President (`@BarackObama`) and Vice-President (`@JoeBiden`), the Democratic and Republican parties (`@TheDemocrats`, `@GOP`), candidates in the 2012 Republican primary election (`@THEHermanCain`, `@GovernorPerry`, `@MittRomney`, `@newtgingrich`, `@timpawlenty`, `@RonPaul`), relevant political figures not in Congress (`@algore`, `@HillaryClinton`, `@SarahPalinUSA`, `@KarlRove`, `@GeorgeHWBush`), think tanks and civil society group (`@Heritage`, `@HRC`, `@OccupyWallSt`, `@BrookingsInst`), and journalists and media outlets that are frequently classified as liberal (`@nytimes`, `@msnbc`, `@NPR`, `@KeithOlbermann`, `@maddow`, `@MotherJones`) or conservative (`@limbaugh`, `@glennbeck`, `@FoxNews`, `@drudge_report`).

[16]I do not include the nearly 30 millions users who only follow Barack Obama, but not any of the other political accounts, since they are likely to be located outside of the United States.

[17]Note that this sample only includes individuals who follow at least one political actor. However, given that the list of actors includes the most popular Twitter media outlets in each country (for example, the New York Times, El País, and Der Spiegel), this is a relatively low threshold. Although Twitter does not release information about the number of users in each country, the existing survey data in each of these three countries suggests that the sample size in my study is close to the total number of Twitter users in each country: 19% of online adults in the United States (34 million users), 28.1% of online adults in Spain (8.2 million users), and 6% of online adults in Germany (3 million users).

for the users in the sample; this is, who they are following on Twitter. This is a time-consuming process, since it requires multiple queries to the Twitter API for each user; and the restrictive rate limits Twitter imposes on access to this dataset. For this reason, I limit my analysis to a random sample of 50,000 active users in Germany and 50,000 users in Spain and to the sample of 94,441 users matched with voter files in the United States (see Section 2.5 below).[18] I collected the list of other accounts each of these users follows on Twitter in order to observe the size and composition of their communication networks, and then matched this new dataset with the entire set of ideology estimates, which allows me to measure the ideological composition of their networks.

2.5 Matching Twitter profiles with voter records

In order to identify the location from which each user is tweeting, I collected a massive dataset of geolocated tweets from August 2013 to June 2014 using the R package "streamR" (Barberá, 2013). This dataset includes a total of 1.2 billion tweets, of which 3.3 million were sent from inside Germany, 24 million from Spain, and 200 million from the United States. After aggregating this dataset at the user level, I was able to obtain the exact geographic location of 175,000 users in Germany, 825,000 users in Spain, and 4.4 million users in the United States. While users who add location information to their tweets are not a random sample of all Twitter users, this source of information will prove crucial in validating the ideology estimates (see Appendix B) and in matching Twitter profiles with voter registration records.

Using this dataset of geolocated tweets, I identified a list of Twitter users located in each of the five states I consider in my analysis.[19] This list includes a total of 45,496 users in Arkansas, 697,031 users in California, 339,878 users in Florida, 193,933 users in Pennsylvania, and 193,111 users in Ohio. Each of these users was then mapped to a county and city using the shape files indicating the boundaries of the administrative regions in each state. Finally, exploiting the fact that most Twitter users report their real name on their profiles, I matched

[18] I define as *active* Twitter users those who have sent at least one tweet in the past year, follow 100 or more other accounts, and have 25 or more followers. This simple filter allows me to exclude from the sample spam bots and inactive users (see Barberá, 2014, p.6 for further discussion).

[19] Since this list would exclude users who never attached location information to their tweets, I expanded it by collecting two additional samples of 70 million tweets filtering by keywords related to the 2012 Presidential election, the 2014 SuperBowl, and the 2014 Academy Awards, and parsed the "location" field of each user's profile using regular expressions to find additional users who report being located in each state (e.g. "ohio", "OH", "cleveland", "columbus", etc.). Finally, I converted this location into geographic coordinates using the Data Science Toolkit geocoder.

as many of these accounts as possible with records of voter registration in each state, publicly available through the Secretary of State. I matched a profile with a voter whenever there was a unique match of first and last name within a county. When there were multiple voters or accounts with the same name in a county, then they were matched only if their city of residence was identical. A total of 3,468 users (7%) were matched in Arkansas, 54,146 (8%) in California, 8,557 (3%) in Florida, 13,213 (7%) in Pennsylvania, and 15,027 (8%) in Ohio.[20] Although the available information for each voter varies across states, for all these users I was able to identify their gender, party affiliation, and turnout in the 2012 primary and presidential elections.

3 Results

In this section I provide evidence from social media data and surveys in support of the hypothesis that exposure to diverse political messages induces political moderation. First, I show that, contrary to the conventional wisdom, most Twitter users in Germany, Spain, and the United States are exposed to a high degree of political diversity in their personal networks. Then, I employ a panel design to demonstrate that individuals who receive politically diverse messages become less extreme over time. Finally, I analyze survey data from these three countries using a similar panel design, finding that social media usage has a positive effect on political moderation.

3.1 Measuring Exposure to Diversity on Social Media

Previous studies of diversity in communication networks operationalize exposure to dissonant views as the proportion of discussion partners that disagree with the respondent on a series of political items, usually political ideology, partisanship, and vote in presidential elections (Mutz, 2002; Huckfeldt, Johnson and Sprague, 2004). Here I adopt a similar approach by measuring *exposure to diversity* as the proportion of users in an individual's network who do not share her ideology. This operationalization captures whether citizens are "hearing the other side," this is, whether they are potentially exposed to political information that is

[20] Note that this is a conservative matching strategy. Since exact coordinates (from Twitter) and addresses (from voter files) are available, it would be possible to use a probabilistic model to match both datasets. However, in this paper I have chosen to focus only on perfect matches in order to ensure the results of the analysis are not driven by issues in the name matching procedure.

not congenial with their political beliefs. To do so, I divide the users in each country into two groups, liberals and conservatives, according to whether their ideology estimates (θ_i) are greater or lower than the average in each country (which is zero by construction). This measure of exposure to diversity is therefore equivalent to the proportion of each user's network that is located on the opposite side of zero. For example, if an individual is a liberal, this variable would consist on the proportion of users she follows who are conservatives.

To demonstrate that my results are robust to different operationalizations of this variable, I also consider an alternative version of this indicator, *exposure to high diversity*. This second variable considers only exposure to *strong* conservatives or liberals; those with an ideology estimate more than one standard deviation away from the center.[21] I operationalize it as the proportion of users in an individual's network who do not share her ideology, over all users in the network with a strong ideological position. Following the previous example, for a liberal, this variable would consist on the proportion of users she follows who have an ideology estimate greater than one, over the proportion of users in her network who have an ideology estimate greater than one (strong conservatives) or lower than minus one (strong liberals). This second measure also addresses one potential concern in the measurement of exposure to diversity, namely that individuals close to zero will tend to have higher levels of diversity in their networks by construction.

In order to ensure that the estimation of ideology and exposure to diversity are independent, I exclude from this second measure all political actors that were used to estimate ideology, as well as all "verified accounts." Verification is granted by Twitter to public figures, including journalists and media outlets, in order to certify that their profile corresponds to their real identity.[22] By not considering these individuals (around 100,000), I am able to focus on the political information that users are receiving from other ordinary users, which includes their friends, relatives, co-workers and other individuals with whom they are acquainted offline.

I apply these two measures to examine the ideological distribution of the personal networks for the sample of individuals I consider. The median user in my dataset follows 285 other accounts. On average, 38% of the users they follow are included in the full sample of users in each country. This implies that I am not able to estimate the ideology of many of the other individuals they follow, and therefore I exclude them from the analysis. However, this is not

[21] Note that the distribution of ideology in each country is normalized prior to the analysis so that it has mean zero and standard deviation one.

[22] This list is accessible through the twitter.com/verified user account.

consequential for my analysis since these users are unlikely to be sharing information about politics, given that they do not follow any political account.[23] As a result, their exclusion shouldn't affect my estimation of the diversity in the political information to which users in my sample are exposed to.

Table 1: Median of Network Diversity Estimates (2014), by Country

	Exposure to Diversity	Exposure to High Diversity
No homophily	$\simeq 0.50$	$\simeq 0.50$
No diversity	0.00	0.00
Germany	0.44	0.39
Spain	0.45	0.40
United States	0.33	0.22

Note: exposure to diversity indicates the average proportion of individuals in each user's network who do *not* share her ideological classification (for example, for a liberal, it would be the proportion of conservatives in her network). Exposure to high diversity is equivalent, but classifies as liberal or conservative individuals only users more than one standard deviation from the mean. Verified users are excluded from the estimation of both measures.

Table 1 presents descriptive statistics for the two measures of exposure to heterogeneity I consider. In both cases I find that the median individual is exposed to high levels of diversity in all three countries, even if personal networks are less ideologically heterogeneous that one would expect if they were randomly created, which is consistent with the existing literature on ideological homophily (McPherson, Smith-Lovin and Cook, 2001). Communication networks in Germany and Spain tend to be more heterogeneous than in the United States. In these two countries, the median user tends to have an almost balanced distribution of ideology in her network, with 44% and 45% of users not sharing her ideological classification, whereas this proportion is only 33% in the United States. Note that, in the absence of ideological homophily, this measure would be approximately 50%.[24] When we consider only individuals with strong ideological positions in users' networks, these proportions are lower, but still reflect a high

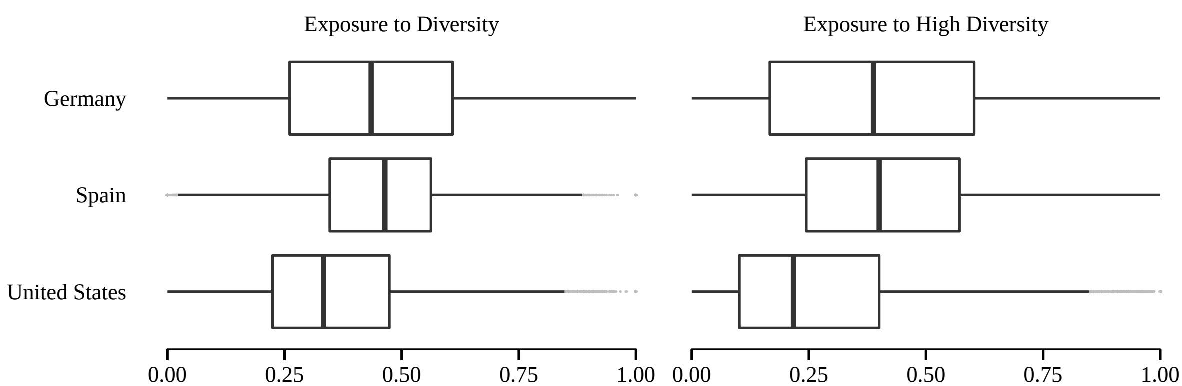
[23]To demonstrate that the number of political accounts each user follows is equivalent to a measure of political interest, I used crowdsourcing techniques (Benoit et al., 2014) to show that individuals who follow more political accounts send more tweets about politics. In order to do so, I took a random sample of 100 users in the United States, stratified by the number of political accounts, and downloaded their 100 most recent tweets. Then, I used Crowdflower to ask contributors to code each of the 10,000 tweets as being "about politics" or not. The intercoder reliability, computed using a random sample of 100 coded tweets, was 93.4%. After aggregating the tweets by user, I found that the correlation between the (logged) number of politicians they follow and the proportion of tweets about politics that each individual sent is $\rho = 0.40$.

[24]The exact proportion in each country depends on the underlying distribution of ideology, which is approximately normal and symmetric with mean zero and standard deviation one by construction.

degree of exposure to diverse opinions.

Figure 1 displays the full distribution of the two measures of exposure to heterogeneity for each country. I find that over 75% of users in each country are embedded in networks that include 25% or more individuals with whom they disagree, as indicated by the location of the first quartile of the distribution. Even if most of the mass of this distribution is to the left of the center, which indicates that most users are embedded in homophilic networks as expected, a non-negligible proportion of individuals are exposed to networks composed by a majority of individuals with whom they disagree.

Figure 1: Distribution of Network Diversity Estimates (2014), by Country

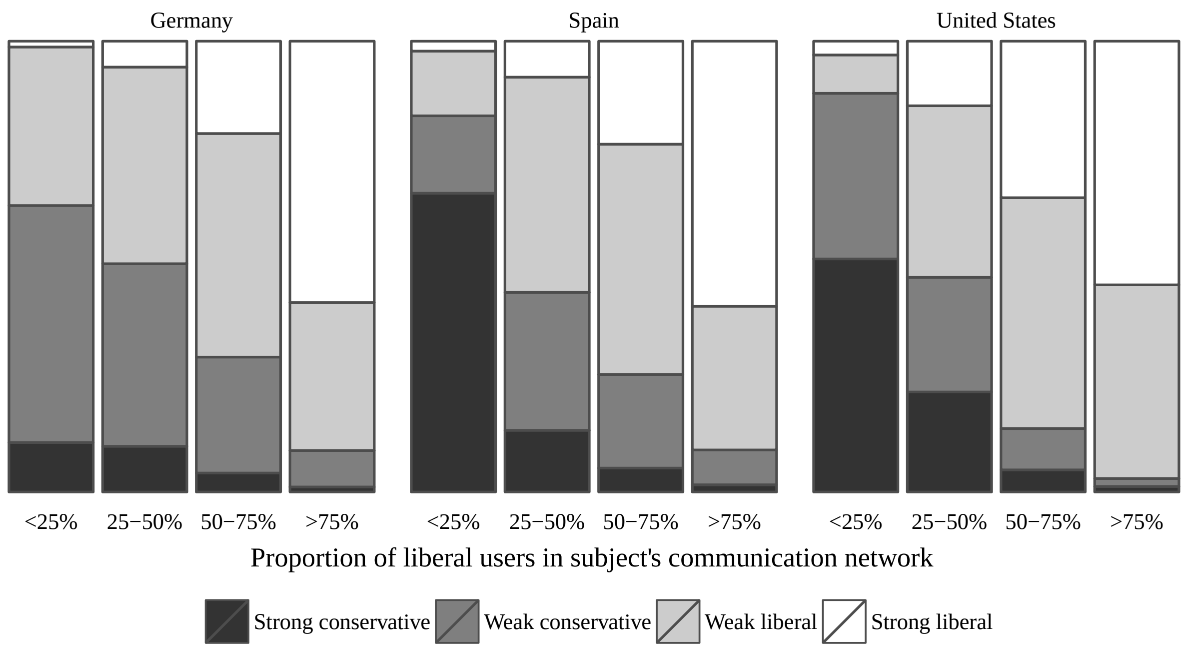


Note: exposure to diversity indicates the average proportion of individuals in each user's network who do *not* share her ideological classification (for example, for a liberal, it would be the proportion of conservatives in her network). Exposure to high diversity is equivalent, but classifies as liberal or conservative individuals only users more than one standard deviation from the mean. Verified users are excluded from the estimation of both measures.

3.2 Network Diversity and Ideological Moderation

I now turn to examine the relationship between exposure to diverse opinions on social media and political moderation. The most common approach in the existing literature is to examine how the strength of political positions varies as a function of the ideological distribution of each respondent's communication network, using a cross-sectional design. An analysis of the individuals in my sample yields similar results to those in previous studies. As I show in Figure 2, which replicates Chart XLIV (p.99) in Berelson, Lazarsfeld and McPhee (1954), most individuals exposed to political diversity hold moderate ideological positions. Here I divide all individuals in my sample into four groups, according to their ideology (conservative or liberal, depending on whether their ideological position is greater or lower than zero) and extremism (strong or weak, depending on whether their ideological position is more than one standard deviation away from zero or not). I find that individuals whose network is overwhelmingly conservative or liberal, on the left and right bars of each panel, tend to be primarily strong conservatives and liberals respectively. For example, the last bar on the right in the Germany panel shows that over 50% of individuals whose communication network contains more than 75% of liberals are strong liberals.

Figure 2: Political Moderation is Related to Heterogeneity in Communication Networks



Note: each bar displays the probability distribution of the four ideological categories for individuals embedded in networks with that level of exposure to other liberal accounts. For example, the first bar indicates that less than 1% of individuals whose network includes less than 25% of liberal users is a strong liberal.

As I show in Table 2, this negative relationship between exposure to diversity and political extremism holds after controlling for potential confounders, such as network size.[25] Here, I report the results of multivariate linear regressions of political extremism – the absolute distance between each individual and the political center, that is, the absolute value of her ideology estimate – as a function of exposure to diversity, controlling for covariates such as the number of users followed by each individual in the sample, her number of followers, the total

[25]Individuals with larger networks tend to have moderate ideological positions, since in general network size increases exposure to diversity (see e.g., Huckfeldt, Johnson and Sprague, 2004, p.211)

of tweets she has sent, and her level of political interest (measured as the logged number of political accounts she follows; see footnote 23).[26] (See Tables 6 and 7 for descriptive statistics of all variables in the regressions.)

Table 2: OLS Regressions of Political Extremism on Exposure to Diversity

	Germany		Spain		United States		
Exposure to Diversity	-1.20*	-1.13*	-1.77*	-1.72*	-0.66*	-0.66*	-0.66*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Total users followed (log)		-0.03*		-0.04*		-0.06*	-0.06*
		(0.00)		(0.00)		(0.00)	(0.00)
Total followers (log)		0.04*		0.07*		-0.00	-0.00
		(0.00)		(0.00)		(0.00)	(0.00)
Total tweets sent (log)		0.01*		-0.01*		0.01*	0.01*
		(0.00)		(0.00)		(0.00)	(0.00)
Political Interest		0.08*		0.02*		-0.06*	-0.06*
		(0.00)		(0.00)		(0.00)	(0.00)
Registered Dem.							0.01*
							(0.00)
Registered Rep.							0.05*
							(0.00)
Voted in 2012 Election							0.03*
							(0.00)
Intercept	1.19*	1.00*	1.56*	1.41*	1.16*	1.50*	1.47*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
N	50000	50000	50000	50000	93078	93078	93078
R^2	0.12	0.14	0.17	0.18	0.07	0.11	0.11
Resid. sd	0.68	0.67	0.58	0.58	0.39	0.38	0.38

Note: * significant at $p < 0.05$. Standard errors in parentheses. Dependent variable: political extremism (absolute value of political ideology for each user). Exposure to diversity is the percentage of users in each individual's network of the opposite ideological category (excluding verified users). Political interest is measured as the (logged) number of political accounts that each user follows. All models in the United States include state-fixed effects, with Ohio as reference category.

Of course, a crucial limitation in this cross-sectional analysis is that assignment of discussion partners is not exogenous to ideological distance, since individuals may select the members of their personal network based on perceived agreement. In this particular case, citizens with strong political positions may decide to create ties on social media only with other individuals who share their political positions. If this is the case, then the results in my previous section overestimate the importance of network diversity.

Finding an exogenous source of variation in exposure to political diversity through social

[26]This table also yields other interesting results about the correlates of political extremism. As expected, individuals who follow a larger number of users (and thus have larger networks) tend to be more moderate. In the United States, registered Republicans have positions farther from the center on average than registered Democrats and non-registered voters; and turnout is positively correlated with political extremism as well.

media is a hard problem. One option would be an online field experiment in which social media users are randomly assigned to be exposed to more or less politically extreme messages shared by their friends (see Bakshy et al., 2012 for a similar experiment conducted on Facebook). However, without introducing deceptive messages, this design restricts the magnitude of the treatment to the total number of diverse messages that are shared in each user's network. As a result, without raising ethical concerns, it is challenging to design an experiment that properly captures the effect I hypothesize in this paper.

In the absence of an experimental design that randomizes exposure to political diversity, the second best approach is a panel design that examines whether individuals in diverse personal networks become moderate over time. As Sinclair (2011) discusses, this type of panel analysis helps to relax the assumptions necessary regarding selection. It doesn't completely address all potential concerns about endogeneity, but it would need to be the case that individuals who *will become* moderate self-select into diverse networks for my estimated effect to be biased, which is more unlikely, specially after conditioning on other covariates.

As described in Section 2.1, the analysis of Twitter data, in combination with the new methods I introduce here, allows us to realize this ideal research design. In order to do so, I estimated the ideological position of all individuals in my sample as of July 2014 and January 2013.[27] As earlier, I measure political extremism as the absolute value of each individual's ideology estimate.[28] Consistently with previous findings in the literature on partisanship and ideology (Converse, 1969; Stoker and Jennings, 2008), I found that this variable is highly stable over time: for 79% of individuals in my sample, it didn't change more than 0.05 (5% of a standard deviation). The other 20% are divided evenly between users who become more extreme and users who become more moderate, with the average user becoming 0.01 standard deviations more moderate between these two time periods. In addition, I also measured the level of political diversity to which each individual is exposed to by examining the ideological distribution of the users in her personal Twitter network as of January 2013.[29]

To examine whether individuals in diverse networks become moderate over time, I estimated multivariate linear regressions of political extremism (in 2014) as a function of expo-

[27] To infer changes in Twitter networks, I exploit the fact that friends and follower lists are returned in chronologically inverse order, and that the creation dates for each user account can be estimated from its numeric ID number. Combining these two features, I am able to infer the list of other accounts each user followed as of January 2013: it will include all accounts in the list after the first account that was created in 2013. See Appendix A for additional details on this method.

[28] Note that the final sample size I consider here is lower since users who created their account after January 1st, 2013 are not included in the analysis.

[29] For more details about how to infer change in Twitter networks, see Appendix A.

sure to political diversity on social media (in 2013), conditioning on the previous levels of political extremism for each individual.[30] As in the earlier regression models, I also control for the effect of other potential confounders related to social media activity and offline behavior.

Table 3: OLS Regressions of Political Extremism in 2014 on Exposure to Diversity in 2013, Conditional on Previous Levels of Political Extremism

	Germany	Spain	United States	
Exposure to Diversity (2013)	-0.18*	-0.19*	-0.20*	-0.20*
	(0.01)	(0.01)	(0.00)	(0.00)
Political Extremism (2013)	0.88*	0.86*	0.83*	0.83*
	(0.00)	(0.00)	(0.00)	(0.00)
Total users followed (2013, log)	-0.00	-0.01*	0.01*	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
Total followers (log)	0.01*	0.00*	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
Total tweets sent (log)	-0.01*	0.01*	-0.01*	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
Political Interest (2013)	-0.01*	-0.00	-0.03*	-0.03*
	(0.00)	(0.00)	(0.00)	(0.00)
Registered Dem.				0.01*
				(0.00)
Registered Rep.				-0.02*
				(0.00)
Voted in 2012 Election				0.01*
				(0.00)
Intercept	0.17*	0.22*	0.21*	0.20*
	(0.01)	(0.01)	(0.01)	(0.01)
N	23893	32919	74515	74515
R^2	0.84	0.80	0.69	0.69
Resid. sd	0.30	0.28	0.23	0.23

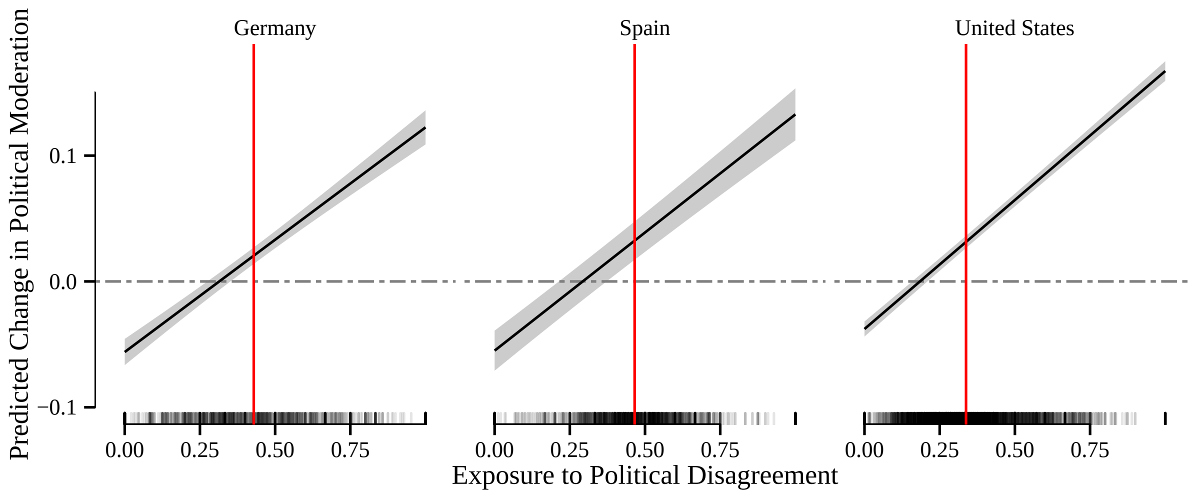
Note: * significant at $p<0.05$. Standard errors in parentheses. Dependent variable: political extremism in 2014 (absolute value of political ideology for each user). Exposure to diversity is the percentage of users in each individual's network of the opposite ideological category (excluding verified users). Political interest is measured as the number of political accounts that each user follows. All models in the United States include state-fixed effects, with Ohio as reference category.

My results, reported on Table 3, show that individuals in diverse networks become more moderate over time, even after controlling for their previous level of political extremism. To facilitate the interpretation of the effect I estimate here, in Figure 3 I display the predicted change in political extremism for the average individual, at different values of network diversity.

The results here highlight the important role that exposure to diverse political information

[30] Note that this model is mathematically similar to regressing change in political extremism from 2013 to 2014 on exposure to political diversity.

Figure 3: Individuals in Diverse Networks Become Less Extreme Over Time

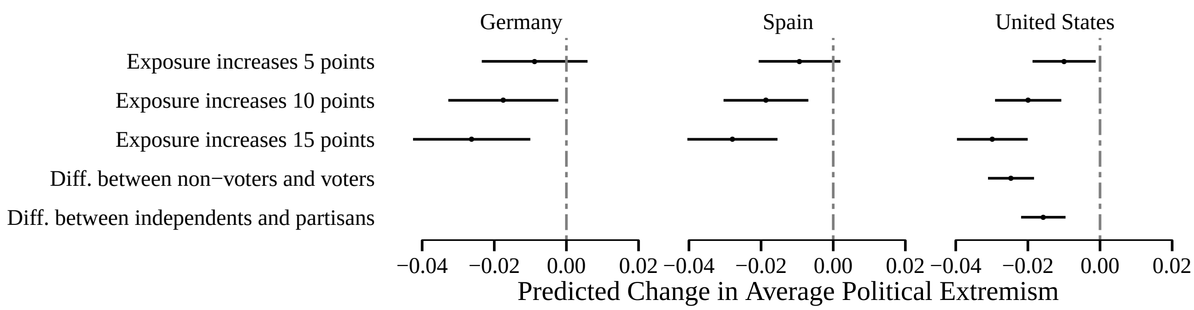


Note: each panel displays the predicted change in political extremism from 2013 to 2014 for the average individual (with a 95% confidence interval; estimated using the coefficients in Table 3 at different values of exposure to diversity, for each country, holding other covariates at their means.

plays in shaping political beliefs. Individuals who receive information from primarily one side of the ideological spectrum tend to become even more extreme over time. In the extreme case in which their network is fully homogenous, the expected effect has a size of around 10% of the standard deviation in the dependent variable. However, as diversity in the levels of political information increases, the expected change becomes negative in all three countries. The exact level at which it becomes negative varies across countries, in ways that are consistent with the existence of floor and ceiling effects: in the United States, only a relatively small amount of diversity (over 20%) is necessary for individuals to become moderate; whereas in Germany and Spain it needs to be closer to 40–45%. At the same time, however, as illustrated with the rug plots on the bottom of this figure and the box plots in Figure 1, a majority of individuals in all three countries have values of network diversity at which we would expect them to become moderate over time.

To understand the substantive magnitude of this effect, I simulated how the levels of mass political polarization in the sample of Twitter users in each country would change in response to changes in their exposure to diversity. While there are many different definitions of mass political polarization in the literature (Fiorina and Abrams, 2008; Bramson et al., 2013), here I focus on polarization as *dispersion* in the distribution of policy preferences in the public. Thus I operationalize it as the average absolute distance between each user's ideal point and the ideological center, zero by construction. I then estimated how each user's level of political extremism would change if her exposure to diversity would increase by 5, 10, and 15 points, and aggregated these changes to estimate the aggregate effect in the distribution of political extremism. These three quantities correspond to increases of approximately one third, two thirds, and one full standard deviation in this variable, and represent realistic scenarios (e.g. a 5-point increase would imply that one in every twenty individuals in a user's communication network changes her ideology so that it is now dissonant with the user's political views).

Figure 4: Simulated Effect of Changes in Exposure to Diversity on Mass Political Polarization



Note: each panel displays the predicted change in mass political polarization, measured as the average absolute ideological position of users in the sample, in response to changes in levels of exposure to diversity. To facilitate the comparison, I also provide confidence intervals for the difference in political extremism between voters and non-voters; and between individuals who are affiliated with a party and those who are not.

Figure 4 displays the results of these simulations. As expected, increasing exposure to diverse opinions on social media has a negative effect on mass political polarization. To facilitate the interpretation of this result, this figure also displays 95% confidence intervals for the difference between voters and non-voters in their levels of political polarization, as well as the difference between users affiliated with a party in the voter files and those who are not affiliated. I find that a 10-point increase in exposure to diversity for the entire sample would have a negative effect on mass political polarization approximately equal to the difference by party affiliation; whereas a 15-point increase would have a predicted impact similar in magnitude to the difference by turnout.

3.3 Evidence from Survey Data

The results in the previous sections have provided evidence that exposure to diverse opinions on social media has a negative effect on political extremism, and that this effect is large in magnitude. Since most Twitter users are embedded in ideologically heterogenous networks, this set of results suggests that social media has a moderating effect overall. In order to further explore this potential effect on the entire population, now I turn to the analysis of panel surveys conducted with a nationally representative sample of citizens. The use of survey data allows me to compare citizens with and without social media accounts, which is necessary in order to estimate how social media usage affects political extremism, at the individual level, and mass political polarization, at the aggregate level.

In particular, the surveys I employ are the 2012 ANES Time Series study, the 2011 Spanish pre- and post-election study conducted by the Centro de Investigaciones Sociológicas and the 2013 German Longitudinal Election Study. These three studies interviewed a large sample of citizens right before and right after the election.[31] While the questionnaire varies greatly across countries, the key covariates necessary for my analysis were included in all three studies, with similar questions, which allows the comparability of my results across countries.[32]

In order to be as consistent as possible with the previous analysis, I estimate OLS regressions with *political extremism* in the post-election wave as outcome variable. Political extremism is measured as the absolute distance between the left-right self-placement of each individual (in a 10-point scale in Spain and Germany, 7-point scale in the U.S.) and the position of the country's average respondent.

The main independent variable is a dummy indicating whether the respondent reported having an active social media account. The proportion of respondents who use social media in each survey are: 61% in Spain, 27% in the United States, and 22% in Germany.[33] Finally, as in the regression model in the previous sector, I condition on the level of ideological extremism in the first wave by introducing it as a covariate in the regression model, in addition to other potential confounders: gender, age, education level, ideological self-placement, vote in previous election, and exposure to political information on newspapers and TV. (Tables 8 and 9 provide summary statistics for all the variables in the model.)

[31]The German GLES conducted a total of seven waves, but here I use only the first and last waves.

[32]Note that the German study was conducted online, as well as most of the U.S. study, but the Spanish survey was conducted face-to-face. As a result, all my analyses are restricted to users who report having Internet access.

[33]In Spain, this was the exact wording of the question, but in the American and German studies subjects were only asked about whether they received political information through social media sites during the campaign. As a result, it is not possible to distinguish whether respondents who said "no" to these questions do not have an account or did not receive political information. In my analysis, I assume that most social media users were at least exposed to some political information and therefore operationalize this variable as a dummy, with value zero for subjects who answered "no" to this questions, and value one if the user reported receiving *any* information through social media sites.

Note that, unlike the analysis in the previous section, the use of survey data does not allow me to observe the extent to which social media users are exposed to politically diverse content. As a result, my model only estimates the *average* effect of social media usage. As I have shown in the previous section, most individuals are embedded in ideologically heterogeneous network, which leads me to hypothesize that social media usage should have a moderating effect on individuals' ideological positions, holding all else constant.

Table 4 presents the results of my analysis. I find that individuals who reported using social media in Spain and the United States became more politically moderate after the campaign, holding all else constant. This coefficient is statistically significant at conventional levels. Considering that political ideology is a highly stable political trait, the size of the the effect is relatively large (around 6% of the standard deviation of the dependent variable in Spain; 4% in the U.S.), and approximately equivalent to the difference between men and women in this variable.

However, the estimated coefficient for the social media use variable in Germany is not significantly different from zero. One possible explanation for this result could be the different wording for this question in this country (see footnote 33). When respondents are asked to report whether they received information about the election on social media, it could be that only politically interested users remember receiving it – even if most social media users likely were exposed to at least some information about the campaign. If this underreporting is occurring, we would expect the coefficients to be biased towards zero, because individuals interested in politics tend to be located away from the ideological center, and to self-select into less diverse networks. In other words, if this variable is capturing *political* social media usage, this result would be consistent with what I found in the previous section: social media usage induces political moderation only when individuals are exposed to diverse networks.

With this caveat, the results in this section provide additional evidence from a completely different source of data in support of my findings. It also illustrates the shortcomings associated with survey studies: since we cannot observe whether and how respondents use social media platforms, or their personal networks, it is difficult to make inferences about the mechanism that may explain this result.

Table 4: OLS Regressions of Political Extremism (Last Wave) on Social Media Usage

	Germany	Spain	U.S.
Social Media Use	-0.01	-0.07*	-0.04†
	(0.06)	(0.03)	(0.02)
Political Extremism (first wave)	0.63*	0.49*	0.66*
	(0.02)	(0.02)	(0.02)
Interest in Politics	0.05*	0.02	0.05*
	(0.03)	(0.02)	(0.01)
Intercept	-0.08	1.32*	0.23*
	(0.19)	(0.17)	(0.11)
Demographic controls	✓	✓	✓
Political controls	✓	✓	✓
Media controls	✓	✓	✓
District fixed effects	✓	✓	✓
N	2,886	2,607	4,486
R^2	0.42	0.31	0.52
Resid. sd	1.07	1.03	0.63

Note: Robust standard errors, clustered by land (Germany), province (Spain) or state (U.S.), in parentheses. * significant at $p < 0.05$, † significant at $p < 0.10$. Dependent variable: absolute distance between ideological self-placement and political center in post-election wave (positive values correspond to more ideologically extreme individuals becoming more ideologically extreme). Observations are weighted using survey weights. Demographic controls: gender, age, age squared, education. Political controls: ideological self-placement, vote for liberal or conservative candidate or party in previous election. Media controls: reads politics on newspapers, watches politics on TV.

4 Conclusions

Social media is transforming the way in which citizens consume political information. Individuals now have access to a wider span of viewpoints about news events, and most of this information is not coming through the traditional channels, but either directly from political actors or through their friends and relatives. Furthermore, the interactive nature of social media creates opportunities for individuals to discuss political events with their peers, including those with whom they have weak social ties. In this paper, I have examined how this two-fold change affects mass political polarization.

Contrary to a growing body of work that suggests that the Internet functions as an "echo chamber," where citizens are primarily exposed to like-minded political views, my findings demonstrate that most social media users receive information from a diversity of viewpoints. By developing a new method that allows me to estimate dynamic ideological positions of social media users and those in their communication networks, I have provided empirical evidence from a panel design showing that exposure to political diversity on social media has a positive effect on political moderation, and that it reduces mass political polarization.

These findings contribute to the existing literature on political behavior in three different ways. First, they underscore the "strength of weak social ties" in users' communication networks (Granovetter, 1973). Up to now, most studies of political networks relied on surveys about discussion partners, which in practice excluded weak ties. The use of social media data allows me to unobtrusively observe individuals' full personal networks. In doing so, I find levels of exposure to diverse opinions that are much greater than what was previously thought. In addition, as social media usage grows, the aggregate level of heterogeneity in political networks for the entire population is likely to increase. This also raises relevant questions about its overall impact on society. Increasing exposure to diverse opinions is often considered positive for democratic stability from a normative point of view. As Lipset (1959, p.97) argues, "the chances for stable democracy are enhanced to the extent that social strata, groups and individuals have a number of cross-cutting politically relevant affiliations." However, it could be the case that its impact on other political outcomes is not as desirable. For example, Mutz (2002) and Huckfeldt, Johnson and Sprague (2004) find that cross-cutting exposure discourage political involvement. In future research, I plan to address whether exposure to political diversity through social media sites also has this counterintuitive effect.

Second, my results provide new evidence of varying levels of mass political polarization across countries. Most of the theories explaining this phenomenon are in essence comparative, since they refer to contextual variables such as party strategies (Fiorina, Abrams and Pope, 2005), income inequality (McCarty, Poole and Rosenthal, 2006), characteristics of the media environment (Prior, 2007) or the context in which individuals develop their political identities (Stoker and Jennings, 2008). However, there is surprisingly little work on the causes of this phenomenon from a comparative perspective. In this paper I focused only on three countries due in part to data availability constraints, but note that the main analysis here could be replicated in any country with a large number of Twitter users. Although the ideology estimates are not comparable across different countries without additional "bridging" assumptions, it is the case that political actors and citizens are located on a common ideological space within each country. It would be interesting to examine, for example, how the relative ideological positions of political parties affects voters' positions, using existing indicators of party system dispersion (Alvarez and Nagler, 2004), or the relationship between media system pluralism (Hallin and Mancini, 2004) and mass political polarization, exploiting the method presented here to estimate the ideological positions of media outlets (Barbera and Sood, 2014).

Finally, this paper contributes to a growing literature on the importance of online personal networks in citizens' behavior (Bond et al., 2012; Tufekci and Wilson, 2012; Vaccari et al., 2013). As individuals spend an increasing part of their time online, the importance of the information they receive through online platforms such as social media sites is likely to increase. In addition to its substantive interest, this represents a unique opportunity for researchers. Social media platforms allows researchers to observe behavior unobtrusively, to estimate latent traits that may suffer from social desirability bias, to quantify exposure to political information, and to measure network structures at a very low cost. This paper illustrates the promise of social media data to address standing questions about social and political behavior, such the effect of exposure to diverse opinions on political beliefs.

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A Inferring Change in Twitter Networks

Most social networking sites do not provide researchers access to historical graph data (e.g. lists of followers at any given time) through their APIs. However, one important advantage of Twitter is that when one of these lists is obtained directly from the API, it returns the list of ties in chronologically inverse order to when they were created: the most recent tie appears first on the list, and the oldest tie appears last. (When downloading a list of followers, for example, the first 100 user IDs included in the list would correspond to the 100 users who most recently followed this account.) In addition, user IDs are assigned in chronological order, which makes it possible to identify the date in which each account was created even without querying the API. The combination of these two features allows research to infer how Twitter networks have evolved over time.

Table 5 illustrates how this could be achieved with a fictional user who has ten followers (all listed here). This list allows us to infer that the list of followers for this account as of January 2013 included 5 users (users 6 to 10). The reason is that user number 5 created her account in January 1st, 2013. As a result, all other users in this list must necessarily have been following the account *before* that date, because otherwise they would be placed above it in the list. As the size of the lists of followers and friends increases, the accuracy of the inferences about the size and composition of the network at different times becomes more granular. In the case of popular political accounts, it is even possible to examine change day-by-day.

Table 5: List of Followers of a Hypothetical Twitter User

Order	User ID	Creation Date
1	2216887652	2013-11-27
2	2202829855	2013-11-19
3	946232461	2012-11-13
4	216329491	2010-11-16
5	1055821436	2013-01-02
6	879758070	2012-10-14
7	299251861	2011-05-15
8	121222011	2010-03-08
9	52827727	2009-07-01
10	71770673	2009-09-05

One important limitation of this approach is that it doesn't allow researchers to observe users who decide to "unfollow." In this example, it may be possible that someone was following this user (and therefore was included in the list) for a long period of time, but decided to break this connection before I captured the list. As a result, we cannot fully observe the network as it was in the past. However, I claim that this does not affect the validity of my analysis for two reasons.

First, "unfollowing" behavior is relatively rare, and for the most part due to accounts that are deleted or flagged as spam. As an example, I compared the list of followers of Michele Bachmann in November 2012, collected directly from the API then, with the list for the same account as of April 2014. Of the 158,457 followers she had in November 2012, 137,025 (86.5%) still follow her almost two years later. Of the 21,432 users who "unfollowed" her, only 15,728 still have active accounts, which results in a total "unfollowing" rate below 10%. In contrast, she gained 57,380 new followers over the same time period (36% more).

Even if this type of behavior is rare, it could induce some bias in the analysis if it is driven by ideological distance. If users decide to unfollow other users who they perceive as ideologically extreme before we can actually observe their network, we could be underestimating their past degree of exposure to political diversity. The model I develop to estimate ideology assumes that the decisions to follow political actors are guided by ideological distance, and there is empirical evidence showing that the same logic applies to decisions to "unfollow."[34] But that's not the case for ordinary users. In a comparison of a random sample of 300 users in the Ohio sample in the paper, whose friends lists I collected at two different points in time (April 2014 and August 2014), I find that ideological distance is not a statistically significant predictor of decisions to unfollow: the predicted probability of "unfollowing" for two users with ideological distance equal to zero is 2.1%; whereas for two users with distance equal to one is 2.2%.

[34] I estimated a logistic regression where the outcome variable is the decision to unfollow Michelle Bachman and the independent variable is the ideological distance with respect to each user, with the number of political actors each user follows as a control variable. The probability that the average follower decides to "unfollow" her is 2.7% if their distance is zero, but increases to 5.7% if their distance is one. This difference is statistically significant.

B Validation: Twitter-Based Ideal Points Replicate Conventional Measures of Ideology

In this section I provide a summary of the ideology estimates for the three countries included in my study. To validate the method, I will use different sources of external information to assess whether this procedure is able to correctly classify and scale Twitter users on the left or right side of the ideological dimension.

My analysis is divided in four parts, with each of them providing a different type of evidence to the validation. First, I show that Twitter-based ideal points replicate existing measures of ideology for elites (legislators and political parties) in the three countries I examine. Then, I validate mass ideology at the aggregate level by examining groups of Twitter users by state and city in the United States, where highly precise ideology estimates are available. I also validate mass ideology at the individual level using information about voters' party registration history. Finally, I demonstrate that longitudinal changes in estimated ideology are valid by analyzing voters who changed their party affiliation during the period I analyze.

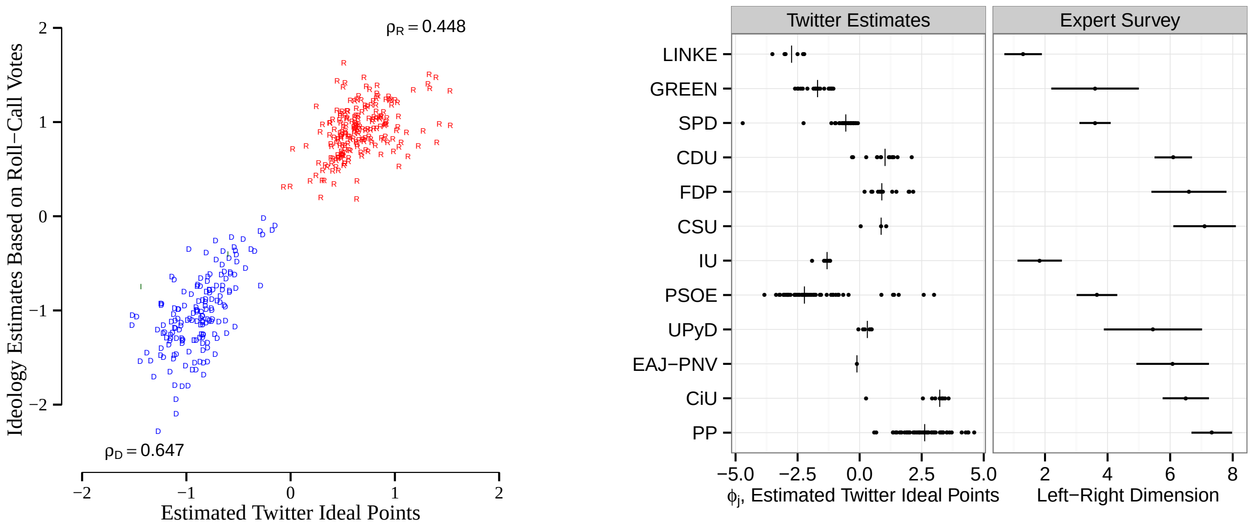
The first set of results I focus on are those from the United States. Panel (a) of Figure 5 compares ϕ_j, my Twitter-based estimates for 381 members of the 113th U.S. Congress with more than 5,000 followers with their ideal points based on their roll-call votes in Congress (Jackman, 2014). I find that the estimated ideal points are clustered in two different groups, that align well with party membership. The correlation between Twitter- and roll-call-based ideal points is $\rho = .95$. Furthermore, if we examine the most extreme legislators, we find that their Twitter-based estimates also position them among those with the highest and lowest values on the ideological scale. Within-party correlations are also relatively high: $\rho = .45$ for republicans, $\rho = .65$ for democrats.

Turning to the results in the two European countries I consider, panel (b) of Figure 5 shows that Twitter based estimates of the locations of political elites are congruent with other measures based on surveys of experts. Here, each dot represents the position of an individual that belongs to each party: a public official (the president or a member of the cabinet, for example), a candidate or the main Twitter account of the party. I focus on the six parties with the highest vote share in each country in the last national-level election. Thee vertical lines indicate the location of the median user within each party. To facilitate the comparison, the right panel shows estimates for the same parties according to the 2010 Chapel Hill Expert Survey (Bakker et al., 2012).

Figure 5: Validation of Ideology Estimates for Political Actors

(a) Members of the 113th U.S. Congress

(b) Party Elites in Spain and Germany



Note: Panel (a) compares θ_j, the ideal point estimates based on Twitter follower networks of 381 members of the 113th U.S. Congress (x axis) with their ideology scores estimated from roll-call votes (Clinton, Jackman and Rivers, 2004) on the y axis. The correlation between these two variables is $\rho = .949$. Within-party correlations are shown in the figure. Panel (b) displays the ideal point estimates of members of political parties in Spain and Germany with the ideological location of each party on a left-right scale ranging from 0 (left) to 10 (right), as estimated on the basis of expert surveys (Bakker et al., 2012).

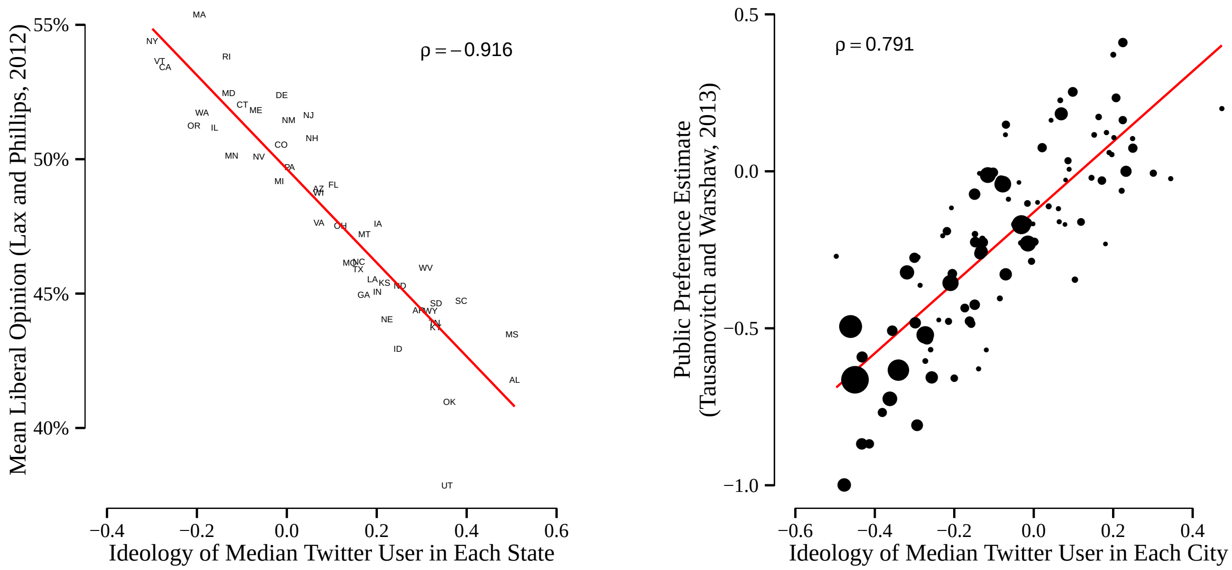
As in case of the United States, this set of results shows that my estimation method is able to classify accounts according to the party to which they belong. With few exceptions, all Twitter accounts from the same party are clustered together, and parties with similar ideologies are located in similar positions on the latent ideological dimension. Furthermore, the order of the parties seems to be similar to that reported by different studies based on expert surveys for the left-right dimension in these two countries.

Now I assess whether the estimated ideal points for ordinary citizens are also valid. Figure 6 provide evidence that validates Twitter-based ideology estimates at the aggregate level. Panel (a) shows that the estimated estimated ideal points for the median Twitter user in each state are highly correlated (ρ = -.916) with the proportion of citizens in each state that hold liberal opinions across different issues, as estimated by Lax and Phillips (2012) combining surveys and demographic indicators using multilevel regression and post-stratification methods. Panel (b) replicates this comparison, but focusing on the top 100 most populated cities in the United States, and using the estimates computed by Tausanovitch and Warshaw (2013) using

Figure 6: Validation of Ideology Estimates for Citizens

(a) Statewide Averages of Ideology

(b) City-level Averages of Ideology

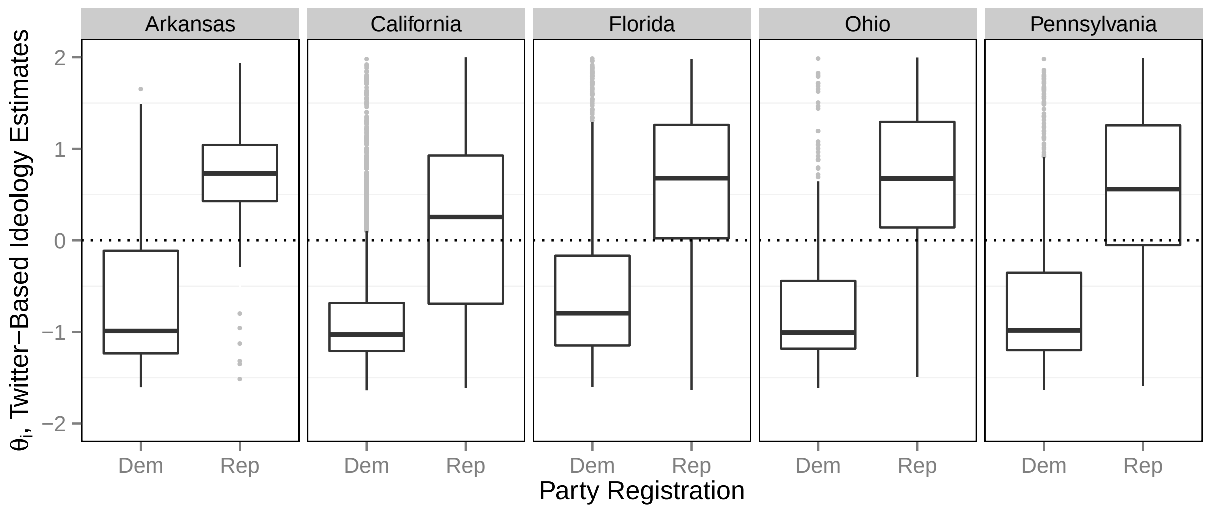


Note: Panel (a) compares the estimated ideological location of the average Twitter user by state (x axis) with the proportion of citizens holding liberal opinions across different issues, estimated using a combination of survey and sociodemographic data Lax and Phillips (2012) (right). The correlation between these two variables is $\rho = -0.916$. Panel (b) compares the estimated ideological location of the average Twitter user by city, for the top 100 most populated cities in the U.S., with estimates of political preferences computed using a similar technique (Tausanovitch and Warshaw, 2013). The size of each point corresponds to the population size of each city, on a log scale. The correlation between these two variables is $\rho = 0.785$.

a similar method that relies on the aggregation of survey data. The correlation here is ρ=.785. In both cases, the correlations of the Twitter-based ideology estimates at each level of analysis with the proportion of the vote-share for Obama in 2012 remain high but their magnitude is slightly smaller (ρ=-.872 and ρ=-.732), which suggests that the meaning of the emerging dimension in my estimation is closer to ideology than to partisanship

Finally, in order to further examine the validity of the ideal points at the individual level, I compare these estimates with partisan registration records for the sample of Twitter users matched to the publicly available voter files in Arkansas, California, Florida, Ohio, and Pennsylvania. Figure 7 displays the distribution of ideology estimates for Twitter users registered as Democrats and Republicans in each state (n=66,128). As expected, the mean ideal point for registered Republicans is higher (more conservative) than the mean estimated ideal point for registered Democrats. In addition, most registered Republicans have estimated ideal points to the right of the estimated ideal points of most registered Democrats. In fact, a threshold of $\theta_i = 0$ predicts party affiliation with 83% accuracy, therefore achieving a performance on the upper end of machine learning classifiers in previous studies (Cohen and Ruths, 2013).

Figure 7: Ideal Point Estimates and Party Registration



Note: each panel displays the distribution of ideology estimates by party affiliation for a sample of Twitter users who were matched with the publicly available voter file in five different states. A threshold of $\theta_i = 0$ predicts party affiliation with 83% accuracy.

C Additional Tables and Figures

Table 6: Descriptive Statistics, Social Media Data (Germany and Spain)

Germany

Variable	min	mean	sd	max	N
Political Extremism (2013)	0	0.82	0.77	4.59	24,138
Political Extremism (2014)	0	0.67	0.72	4.96	50,000
Exposure to Diversity (2013)	0	0.42	0.21	1	23,893
Exposure to Diversity (2014)	0	0.44	0.21	1	50000
Count of users followed (2013)	1	870.9	4,666.1	200,382	24,138
Count of users followed (2014)	101	1,205.9	7,326.2	578,976	50,000
Count of followers (2014)	26	1,922.2	35,997.3	6,554,994	50,000
Tweets sent	1	3,621.3	13,508.7	895,675	50,000
Political Interest (2013)	1	5.58	13.13	233	24,138
Political interest (2014)	1	5.15	13.53	280	50,000

Spain

Variable	min	mean	sd	max	N
Political Extremism (2013)	0	0.72	0.62	4.61	33,003
Political Extremism (2014)	0	0.76	0.64	4.64	50,000
Exposure to Diversity (2013)	0	0.45	0.17	1	32,919
Exposure to Diversity (2014)	0	0.45	0.15	1	50,000
Count of users followed (2013)	1	428.8	3,176.9	383,386	33,003
Count of users followed (2014)	101	789.2	4,272.5	400,638	50,000
Count of followers (2014)	26	1,084.9	23,090.7	3,018,682	50,000
Tweets sent	1	2,939.7	9,148.5	521,803	50,000
Political Interest (2013)	1	3.05	6.2	252	33,003
Political interest (2014)	1	3.43	7.04	253	50,000

Note: Variables that change over time were measured as of January 2013 and July 2014. Political interest is the number of political accounts each user follow. The missing values in the network heterogeneity measure correspond to users who only follow one political account.

Table 7: Descriptive Statistics, Social Media Data (United States)

Variable	min	mean	sd	max	N
Political Extremism (2013)	0	0.92	0.39	2.2	74,739
Political Extremism (2014)	0	0.91	0.41	2.2	93,078
Exposure to Diversity (2013)	0	0.35	0.18	1	74,515
Exposure to Diversity (2014)	0	0.36	0.16	1	93,078
Count of users followed (2013)	1	411.2	1,440.3	109,586	74,739
Count of users followed (2014)	102	666.8	2,636.6	247,500	93,078
Count of followers (2014)	26	2,342.3	77,749.8	12,765,264	93,078
Tweets sent	1	3,459.2	8,087.5	494,082	93,078
Political Interest (2013)	1	4.66	7.79	216	74,739
Political interest (2014)	1	6.09	11.03	520	93,078
Turnout	0	0.68	0.47	1	93,078
Registed Democrat	0	0.44	0.5	1	93,078
Registered Republican	0	0.2	0.4	1	93,078
Age	16	40.33	15.88	100	92,807

Note: Variables that change over time were measured as of January 2013 and July 2014. Political interest is the number of political accounts each user follow. The missing values in the network heterogeneity measure correspond to users who only follow one political account.

Table 8: Descriptive Statistics, Survey Data (United States)

Variable	min	mean	sd	max	N
Political extremism (pre-election wave)	0.17	1.18	0.9	3.17	4,486
Political extremism (post-election wave)	0.17	1.17	0.9	3.17	4,486
Social Media Usage (dummy)	0	0.27	0.44	1	4,486
Interest in Politics	0	2.47	1.09	4	4,486
Frequency of political discussion	0	1.77	2.06	7	4,486
Female	0	0.50	0.50	1	4,486
Age	17	50.18	16.4	90	4,486
Education	1	3.12	1.14	5	4,486
Voted for Obama	0	0.41	0.49	1	4,486
Voted for Romney	0	0.32	0.47	1	4,486
Voted for other candidates	0	0.02	0.15	1	4,486
Reads politics on newspapers	0	0.54	0.5	1	4,486
Watches politics on TV	0	0.79	0.41	1	4,486
Ideology (pre-election wave)	1	4.17	1.47	7	4,486

Table 9: Descriptive Statistics, Survey Data (Germany and Spain)

Germany

Variable	min	mean	sd	max	N
Political extremism (pre-election wave)	0.43	1.96	1.35	5.57	2,886
Political extremism (post-election wave)	0.43	1.85	1.32	5.57	2,886
Social Media Usage (dummy)	0	0.22	0.41	1	2,886
Interest in Politics	1	3.58	0.93	5	2,886
Frequency of political discussion	0	1.46	1.55	7	2,886
Female	0	0.45	0.50	1	2,886
Age	18	48.06	14.52	83	2,886
Education	1	2.80	0.96	4	2,886
Voted for CDU/CSU	0	0.25	0.43	1	2,886
Voted for SPD	0	0.22	0.41	1	2,886
Voted for other parties	0	0.24	0.43	1	2,886
Reads politics on newspapers	0	0.35	0.48	1	2,886
Watches politics on TV	0	0.83	0.38	1	2,886
Ideology (pre-election wave)	1	5.43	2.27	11	2,886

Spain

Variable	min	mean	sd	max	N
Political extremism (pre-election wave)	0.33	1.61	1.19	5.33	2,607
Political extremism (post-election wave)	0.33	1.57	1.21	5.33	2,607
Social Media Usage (dummy)	0	0.61	0.49	1	2,607
Interest in Politics	1	2.39	0.90	4	2,607
Frequency of political discussion	1	2.89	0.97	4	2,607
Female	0	0.46	0.50	1	2,607
Age	18	38.44	12.6	84	2,607
Education	1	3.75	1.46	6	2,607
Voted for PP	0	0.37	0.48	1	2,607
Voted for PSOE	0	0.24	0.43	1	2,607
Voted for other parties	0	0.19	0.39	1	2,607
Reads politics on newspapers	0	0.29	0.45	1	2,607
Watches politics on TV	0	0.56	0.5	1	2,607
Ideology (pre-election wave)	1	4.67	1.98	10	2,607