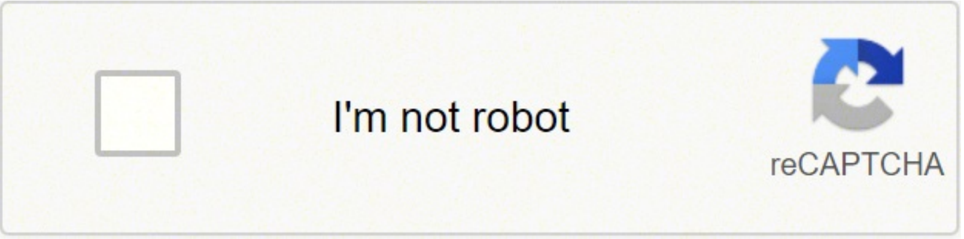
Fragmentation with example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Fragmentation with example

Define fragmentation with example. Internal fragmentation with example. Explain horizontal fragmentation with example. Internal and external fragmentation with example. Explain packet fragmentation with example. External fragmentation with example. Horizontal fragmentation with example. Packet fragmentation with example.

This article is a systematic and broad-scale study of the reasons behind the political fragmentation on social media. Using a comparative set of data from the discussion activities on twitter of 115 political groups from 26 countries, the report shows that ideologically farther groups interact less and that the groups at the ends of the ideological scale are more likely to have lower interaction patterns. In fact, the exchanges between centrists sitting on two different fronts of the right-wing division are more likely than the links between centrists and extremists belonging to the same ideological wing. in light of the results, the theory of exposure to different ideological views online is strengthened. a key thread of contemporary research on online political communication concerns what we could define the thesis of "fragmentation": the idea that online conversations on politics are typically divided into different groups, and that this division takes place according to ideological lines, with people who speak only with ideologically related people. pple primi 1 these models have affected many theorists of democracy, who have argued that exposure to different points of view is fundamental to develop well-informed citizens (gentzkow & shapiro, 2010, 2) who are also tolerant of others' ideas (nunn, crockett, & williams, 1978).their together (and on their fragmentation) have so far been amply descriptive descriptive analytical research exists at an individual level, which is treated more fully below). The main reason is that most studies that have examined the network level have been single ones (for example, for example, for individual country studies see Aragón et al., 2013; Colleoni et al., 2014; Conover et al., 2011; Garcia et al., 2015; Gruzd & Roy, 2014; Himelboim et al., 2013). This provides little space to study the change as each single country network typically contains only a handful of individual groups. Therefore, the field as a whole has not yet dealt with the question of which factors could lead more or less fragmentation in the discussion networks. The purpose of this study is to take a first step towards the remedy to this deficit, trying to explain the variation of political fragmentation levels through a large-scale multi-country study of online political discussion on Twitter. The article is structured as follows. Section One provides a clearer definition and conceptualization of political fragmentation, and builds theories and assumptions on the factors that might explain its appearance, focusing in particular on ideological variations between the different groups of the network in question. Section two outlines the method employed, explaining the collection of data from Twitter about political discussions in different EU countries during the 2014 European Parliament elections, and describing how key concepts are operational. Section three illustrates the results, with the evidence that ideology seems to lead the change in the intensity of fragmentation, with the role of ecremism considered particularly important. The results are then discussed in the light of their potential consequences for the circulation of ideas online. Explain political fragmentation in online discussion networks For the purposes of this article, online discussion networks are spaces such as forums, blogs and social media sites where people can engage in discussion and exchange of messages. In conceptual terms, political fragmentation occurs in such a network when, during discussions on politics, network participants begin to converse more with others who are ideologically similar to those who do with others who are ideologically different (Garcia et al. 2015, 47). Since exchange patterns between similar ideological groups fall (relatives to communication patterns within these groups) fragmentation becomes more serious, and conversations begin to resemble what were called "echo cameras", so people simply listen to their repeated viewpoint (Sunstein, 2002). Political fragmentation could therefore be defined as a feature of a discussion network as a whole: is more or less fragmented depending on the amount ofinside it. However, a discussion network may contain a number of different ideological groups, each of which communicates to varying varying degrees. Other groups: some pairs of groups can have quite lively exchanges, while others can hardly dialogue. Theoretical explanations of political fragmentation on social media have so far focused on behavioural characteristics at the individual level (see for example the review of research presented by Colleoni et al., 2014, pp. 318Ã¢320). While the aim of this article is to focus on macrostructure rather than individual behavior, it is still worth exploring these individual factors, since the macrostructure of social media discussions is the result of the behavior patterns of individual social media users. who are somewhat similar to themselves (McPherson, Smith-Lovin, MacPherson, Smith-Lovin, & Cook, 2001). This trend means that political fragmentation will naturally emerge in online discussions as people connect with others with similar views. Closely related to homophilia is the concept of "selective exposure" (Knobloch-Westerwick & Meng, 2009), a phenomenon whereby people select information or sources they already agree with while filtering others (Garrett, 2009a). If we look at online discussions as a source of information, then the mechanism of selective exposure will produce results similar to those of homophilia, in that people choose to participate in online discussions that they already agree with. Another mechanism identified is the tendency of individuals to moderate their opinions in line with what they perceive as the group norm (Garcia et al., 2015), or at least to remain silent if they feel they are outside this norm (Scheufele, 2000). These microlevel mechanisms are generally well known and widely tested (see, for example, the review of research presented in Knobloch-Westerwick, 2015). However, by themselves, they offer little reason to expect observed levels of fragmentation to vary at higher levels of observation, such as between pairs of groups, which is the main focus of this paper. This variation could only be caused by factors that also vary between pairs of groups, thus contributing to the improvement or moderation of these microlevel mechanisms.The most obvious factor that varies between pairs of groups is their respective ideological position. Ideology could have different effects on the microlevel mechanisms identified above, and thus on the extent to which pairs of groups interact. First, and more clearly, it is theoretically plausible that the ideological distance Groups are increasing, so is the fragmentation between them. As groups drift further into an ideological space, members of each group perceive those from the other group as ideologically less similar, and thus less likely to make connections with them (following the omopily mechanism). They are also likely to disagree with their arguments more, and thus more likely to selectively ignore their communication (following the selective exposure mechanism). This line of theory leads to the first hypothesis tested in this article: H1: As the ideological distance between groups increases, will interact midsecondy, it is also possible that the type of ideology has an impact on the group's tendency to fragment. Groups on the left and right of the political spectrum attract support from different socio-demographic strata; And it is possible that socio-demographic factors have an influence on the predisposition to homopilic and selective exposure (Garrett, 2009b). There are also qualitative differences between the two sides of the spectrum on the left" which could further accentuate these mechanisms: individuals from groups sitting on both sides of the divide (although not far apart in terms of scale of the Axis itself) However, they are probably likely to perceive themselves as dissimilar, and thus may have a tendency to talk less about them than groups that are a similar distance apart but on the same side of the scale (some evidence for this idea is provided in Feller et al. 2011). These ideas are supported by descriptive works on political fragmentation which have repeatedly shown that groups on different sides of the left political divide seem to have different internal models of communication, although no consensus has emerged on the direction of the relationship: some studies have found the right end of the spectrum to be more densely connected (Conover et al. 2011; Hargittai et al., 2008; Warner, 2010), while others found the opposite (BarberÃÂ¡, 2014); One study even found evidence for both conclusions using different measures (Colleoni et al., 2014). These works then test the second hypothesis to be tested: H2: when groups come from different sides of the left right, they will interact in a lexical way, the â¨¬ Âextremismâ¨ of a group's ideology can also play a role. As Stroud (2010), individuals with attitudes at extremes of the ideological scale show more pronounced tendencies toward selective exposure than those in the middle, a result attributed to the greater certainty that individuals typically have in their beliefs (see also Johnson , Bichard, & Zhang, 2009; Sunstein, 2009; Wojcieszak, 2009). Elements of this line of thought can also be seen in "Media Media" theory, where people with strong pre-existing opinions are more perceive alternative viewpoints as part of Bias, and then ignore or filter them (K. Kim, 2011; Y. Kim, 2011). 2011). Dynamic could also be self-reinforcing, since the discussion with mentality individuals similar to how, it can also lead to the polarization of attitudes to ideological extremes, which in turn stimulates a further fragmentation (Huckfeldt, Morehouse Mendez, & Osborn , 2004; Myers & Lamm, 1975). This branch of theory leads to the final hypothesis tested in this article: H3: How the ideology of a group becomes more extreme, interacting less with other grupposwhiles this article places an important focal length on ideology as a driver for political fragmentation, there are Even a variety of other factors that are worth considering as control variables. First, the overall size of a political group could make a difference: the larger political groups may have less likely to communicate with the smaller ones as they could be perceived as less worthy of consideration. This idea is supported by AragÃ³n et al. Those who have found communication models divergent between small and large political groups (AragÃ³n et al. 2013). Furthermore, even the state of different political groups in the largest political system differs: some will be related to political parties that are impending in the government at a given time, while others could be in opposition. Previous research has shown that looming political forces often make less use of democratic occupational opportunities (Herrnson, Stokes-Brown, & Hindman, 2007): it could be that online groups related to looming political forces are therefore even less connected to the rest of the Discussion network as a whole. Method This article aims to collect a sufficiently wide sample of pairs of groups within discussion networks in a variety of countries in such that the hypotheses identified above the political fragmentation can be tested on a large scale and that general conclusions can Be drawn. This large-scale data collection has several new methodological challenges, since most studies have therefore examined the networks of individual country and have used techniques that do not easily adapt to more countries. In this section, the methods used will be described, starting with a description of the data collection approach, then passing to introduce a fragmentation measure between pairs of groups in a discussion network, before finally describing the independent variables used in the study . The data collection data for the study are taken from Twitter, a social media platform that allows users to distribute short messages (known as Ã ¢ â,¬ Å "tweetsÃ ¢ â,¬) to groups of people who have chosen to receive them (known as followers) and to engage in question with other users. Twitter is the only important social media network that is frequently used for discussion in a variety of countries and that makes its data generally available for research purposes, and was therefore widely used in the previous research on the structure of online discussion networks. The structure of the conversation on Twitter is made visible throughwhich represent the inclusion of the â¨¬ ÅUsername" of another Twitter user in a tweet. When one user mentions another in the tweets they create, it indicates a direct connection between them (but, of course, the mentioned user may not reciprocate the connection). This practice of mentioning occurs in a variety of situations. A user can write an original message about another user and then include their name in it. A user can also reply to a message from another user, in which case that other user is automatically mentioned in the reply. Finally, a user can "retweet" a post produced by another user (which involves rebroadcasting this post to all their followers): Again, this retweet will include a mention of the user who originally created the post (as well as any other referrer in the original post). Collecting a sample of tweets from Twitter and looking at the mention patterns found within them, allows you to observe the structure of the discussion networks that appear on the platform. The "nodes" in these networks are Twitter users, and direct â¨¬ Âedges" are created between users every time they mention another. An illustrative example of this type of discussion network can be found in Table 1. The short The set of tweets described in the table is real, although the Twitter usernames have been changed and the text is slightly modified to preserve the privacy of the participants. The first Tweet is an original tweet from the user â¨¬ Â¨ @ Bluepartyâ¨¬ (Twitter usernames are prefixed with the @ symbol). This Tweet mentions another user (@stephanie), so a border is created in the network from @blueparty to @stephanie. This tweet attracts a response from @john, who then mentions @blueparty (and @stephanie) in their response, creating two more borders. Another user (@Paul) then replies to @ JohnÄ¨Â's Tweet, mentioning all the people who had been mentioned previously, and thus creating three more borders. Table 1Example of on-board training in a political discussion network on Twitter user on Twitter. @ BluepartyÂ¢. @Stephanie This are delivered a petition calling for prison reform @ Johnâ¢ @ BlueParty @ Stephanie Didnâ¢ â¨ T we have a vote on this? Less than six years ago? And the answer was no? @john @john @blueparty @ john @ stephanie @ Paul @john @blueparty @stephanie no. We had a vote specifically on the reduction of sentences not in reform in general @Paul Ã¢ â ´@John @Paul Ã¢ â ´ @Blueparty @Paul Ã¢ â ´@StephanieÃ¢ When studying Twitter networks in this way, a key initial question is How to select tweets to include in the analysis: clearly, a different subset of the t Tweet may involve a different chat structure. The most commonly deployed strategy literature on political fragmentation on social media (applied, e.g., AragÃ³n et al. 2013; Conover et al. 2011; Feller et al. 2011; Garcia, Mendez, SerdÃÂ¼lt, & Schweitzer, 2012; HIMELBOIM ET. ET. 2013) is a collection of tweets containing "hashtags" of political relevance (a word preceded by the "####" symbol that is used to indicate that a tweet is connected to a specific topic), often around the time of a key moment of national politics, as an election. This data collection allows you to observe the communication activity within those defined as "ad hoc publics" (Bruns & Burgess, 2015) that are formed through the discussion activities of people using these hashtags when you exchange comments. The political importance of hashtags is designed to ensure that the conversations observed relate to politics. In this article, the 2014 European Parliament elections were chosen as a key event for observation. The European Parliament elections are useful as they allow us to observe political discussion networks in a wide range of countries (there are 28 EU Member States) focusing on the same fundamental event. However, it has decided not to follow a hashtag-based data collection strategy, as it is not something that can be easily extended to multiple countries: hashtags are inevitably specific to language and often specific to country (referring to particular events of national political life) and therefore the choice of equivalent hashtags in many different national contexts would be difficult. Instead, the article makes use of a complete list of all official usernames available on Twitter of the main political parties and leaders of the 28 EU Member States (collected by the Euandi project) see Garzia, Trechsel, De Sio, & De Angelis, 2015). The data collection involved the collection of all tweets written by these users or mentioned one of them (only one username per political party was used, with the preference given to the party leader username; Otherwise, the party account username itself).3 Table 1 also gives the impression of a typical conversation captured by this method: A central party account creates a tweet, of course, if this approach is effective in eliminating potential country-specific prejudices, on the other hand, we need to recognize the limits of the strategy compared to the hashtag-based approach. The data collected represent only a partial account of all the political discussion that took place on Twitter at the time of the elections: the tweets relating to the elections will not be collected but that do not mention the party's account. The data collection window was opened from 11 May to 10 June, during which tweets were collected by the API (Streaming Application Programming Interface), a web service that allows structured data collection from the Twitter platform. This isIt was chosen because it provided a sample of data both before and after the elections took place, which makes it possible to test the sensitivity of the results in the elections themselves (the precise day of the elections varied between the countries, and in fact some elections took place in several days: however all were held between May 22 and 25). In total, 1.426.620 tweets were observed in the time window that were created or referred to at least one of the party's user names in the list. The focus of this article explains the variation of the level of fragmentation between different groups within a general discussion network. So each observation in the data set is a couple of discussion groups that formed around two party-specific Twitter usernames (the calculation of the extent of fragmentation between the couple is described below). Discussion groups were coupled within countries (explaining basic communication patterns would be interesting but it is outside the scope of this article), with how many possible couples formed in each country (for example, if a country had three party-specific Twitter usernames, X, Y and Z, then three pairs were formed: {X,Y}, {X,Z} and {Y,Z}). However, the extent to which the specific user names of the individual party were mentioned on Twitter varied considerably and not all parties who participated in the elections had enough data to be included in the final analysis. As the goal was to generate as many observations as possible, the rules for inclusion were made as permissive as possible: the parties were included if they had an official account that was mentioned at least once in the viewing window; if they had an available ideological score (as described below) and if they were competitors in a country that had at least one other part that also met these criteria (such as a couple of parties could be formed). In total 115 parts have had enough data to form part of the analysis, from 26 different countries (on 28 EU Member States, only Croatia and Latvia have no representation in the dataset). These 115 parts were formed in 237 different pairs which are the observations in the dataset. Measurement of fragmentation between discussion networks couples As described in the theoretical section, this article tries to measure (and explain) the extension of fragmentation between these discussion groups. The measurement of fragmentation was another area that presented a challenge of methods. The primary approach in literature is to label individuals who participate in conversation networks as belonging to an ideology or another through a sort of manual or automatic analysis of content. Then, various network metrics can be calculated which determineThe real structure of the observed conversation is linked to the way users are labeled. However, this is another technique that does not scale well at the context of a large number of observations in a vast selection of This problem is faced through the development of a metric fragmentation, F, which can be calculated for a couple of discussion groups without the need for a prefixed allocation of individuals as belonging to a group or another. The measure is inspired by the work of War, Meira, Cardie and Kleinberg (2013), which developed a measure of polarization of the network, P, based on the comparison between the activity of the "confinite" knots (i.e. nodes that communicate with members of both groups within the network) and the activity of the "internal" nodes that communicate only within a group; the measure also has remarkable similarities with the E-I index of Krackahrdt and Sternsâ¦ (Krackhardt & Stern, 1988), a measure that tries to measure up to what point a certain group is located more or less externally in its communication models, and which has previously been used in the studies on online political fragmentation (Hargittai et al., 2008). follow. To begin with, for each of the 237 pairs of political parties, a direct network was created. This network at the level of couple is composed of all individuals who have mentioned at least one of the two specific user names of the party belonging to that couple of political parties (also includes the same party users). These individuals are network nodes, and direct edges between nodes were created when an individual mentions another one during the data collection period in the form described in the previous Table 1 (if individuals mention multiple times, multiple edges are created). Figure 1 provides a simplified example of this network. Two side knots, labeled X and Y, sit at the center of the network, with six other knots (labeled from 1 to 6) around them. The direction of the arrows indicates a knot that mentions another one during the observation window. For example, node 2 mentions the X node, so they are connected by an arrow. Open in a new tabDownload F folder on a toy network. Two group of party nodes, Nx and Ny, which represent users who have mentioned each group (the group also includes the group itself). In the example of Figure 1, Nx = {X,1,2,3} and Ny = {Y,3,4,5,6}. Note that nodes can be members of both sets if they mentioned both parties These two party nodes groups allow to define a set of border nodes, Nb, which includes any Nx node that mentions a knot in Ny and vice versa. In this case: Nb = {3.4}. This in turn allows to define a final set of purely internal knots, Ni, which represents all the knots that are not part of Nb. In this case: Ni = {X,Y,1,2.5,6}. This classification of the nodes allows to classify the edges of the network according to their point of origin: the edges starting from internal knots (in Ni) are included in the set of inner edges, Ei, andstarting from border nodes (Nb) are included in the whole borders. borders.Eb. In this case: Ei = [[1 † 'x], [2 †' x], [2 † '1], [5 †' y], [6 † 'y]} while EB = {[3 †' X], [3 † 'y], [4 †' 1], [4 † 'y]. As pointed out above, in the real networks used in the study, the same board can appear several times if a user mentioned other multiple times during the viewing window (this allows to weight F for the volume of communication between the nodes). The exact metric used to measure the fragmentation between a pair of groups, F, is then given by the following formula: where | EI | eb | Represent the cardinality (or size) of the EI and EB sets. Potential values range from â'1 to 1, with higher numbers indicating greater degree of fragmentation. In the example of figure 1, | ei | = 5 and | eb | = 4, then it is valued at (5 â € "4) / (5 + 4), that is 1/9. This low positive number indicates a slight degree of fragmentation (i.e., a slightly higher amount of internal discussion than between the group discussion). When using f use suits well at hand, it is worth reflecting on the likely consequences of its Limiting key: that has no independent means to assign users to groups, and is therefore based solely on the structure of communications (most than on their content). This is likely to measure more fragmentation than it actually exists: a discussion group that does not contain any connection to another group would seem highly insulated using this method, however, such group could actually contain bright internal patterns disagreement by individuals of competing ideologies (which simply did not mention other political parties during the viewing window). While this is a limitation, it is also one that is, probably, defendable in this case. First, while the structure of communication models does not reveal the whole story, it shows something: If, for example, the user names of two parts are connected by a strong set of limit nodes, the conclusion that the fragmentation is low should be correct, regardless of the content of the messages flowing between them. Secondly, any prejudices present in the measure is the same for all party pairs, and since the main objective is to explain the variation between party pairs (almost offering an estimate of the point of fragmentation levels), any bias that applies evenly is not too harmful .Figure 2 provides an illustrative view of how F refers to the overall network structures in real data collected during the viewing window. Four different party pairs were selected for the image in a range of different F levels. The figure shows how the F score increases as the amount of edges (the eb set) decreases compared to the quantityUncovered edges (set EI). At lower levels of F the border starts to dominate the general graph and in fact the double group structure becomes more difficult to see. Metric, in other words, seems to capture the basic intuition behind fragmentation. However, the figure also suggests that F F Be sensitive to the relationship between the dimensions of the two groups (for example, the high high score in the figure refers to a couple comprising a relatively large and relatively small group). The sensitivity of the models to this factor is therefore tested below. Open in new TabDownload SlideParty Pairs at different levels of independent variables of F. The operating variables of the independent variables will now be described. The main independent variable in the study is the ideology of political groups. In order to operate ideology, the parties in the dataset were classified on the left scale (see E.G., Castelli & Mair, 1984). The left parties tend to promote policies related to economic redistribution and equality; While right-handed parties promote policies related to individual freedom and free market. The parties on the extremes of both scales favor more radical and far-reaching visions of these policies. These scales are certainly simplifications of the complexity of political life. And yet they are also widely used both in a popular speech and in an academic research as a way to understand politics and represent the easiest way to classify a wide variety of groups. The particular classifications for each party were taken from the Parlgov dataset (DÃƒÂ¶ring, 2012), which uses a 10-point scale ranging from 0 (extreme left) to 10 (extreme right). The Ideological Scale Diplomatic Parties have allowed the calculation of an ideological scale the three main independent variables that refer to each of the three hypotheses. First, the ideological distance between the parties could be measured, which is the absolute value of the difference between their two ideological scores. Secondly, the parts were coded as belonging to the left or right of the political scale. Finally, Ã ¢ â,¬ Å "ExtremismÃ ¢ â,¬ of a party of a party could be measured, which is simply the absolute value of the distance of their ideological score from the central ground score of 5. This variable, Obviously, it takes a value between 0 and 5 at the level of the individual party; The total extremism inside a couple of parts can therefore be used from 0 to 10.Then control variables. The size of a political group was given by the number of votes won in the 2014 elections, measured as a percentage of total votes. This allows the specification of the difference in size between the groups, with an expectation that a greater difference in size would lead to more fragmentation. Even the political status of the party in question was recorded (ie if it were incumbent in the government or in opposition). This allows a specification of the relationship between the parties: if they are both incumbent in the government, both in opposition, and if it is a pair of opposition in-genus Finally, the relationship between Tweet observed for the pair of parties was measured, which is simply the number of tweets observed for the smallest party divided by the number observed for the larger party. This controls for potential effects on the score f caused by In size between the two groups in question, as described above. Analysis The initial descriptive statistics on the data collected are presented in Table 2. There is a wide variation in the degree of fragmentation (f) between different groups, with the observed data covering the entire range of possible values (even if the data They are SKEWED to the right.) There is also considerable variety in the absolute dimensions of couples in terms of number of participants (nodes,) with some less than 100 and some who have tens of thousands. The smaller groups have a concern because, when the number of contributions is small in absolute terms, the measure in which the observed level of fragmentation is influenced by single nodes and edges it has increased: so it can be potential for the Small groups of scores f be noisy. This point will be revisited in the analytical section. It is worth emphasizing that there are some correlations between independent variables: in particular as pairs of groups that are from different sides of the left right axis could be provided, or which consist of an incumbent party and an opposition party, are typically Even more distant in ideological terms. The measure of the ideological distance is also strongly related to the score of extremism. Descriptive table for pairs of numeric variable parts. Min. Max. MENA. SD. Left position torque 5 175,299 10,629 24,777 Observed edges 14 1,152,127 77,539 169,947 f Â'1.0 1.0 Â'.25 .56 ideological distance .00 8.30 2.98 1.86 Extremism .90 8.30 4.13 1.42 Differences of size .00 40.6 9.85 8.87 categorical variables 237 Analysis makes use of a series of multilevel models, so party torque observations are nested in the countries and country differences themselves are modeled as random effects.4 This type of model is appropriate in this Conditioning considering that the observations are taken from different countries and that the variation in the overall size of fragmentation could be provided between different political systems. A potential concern for this modeling strategy is naturally the fact that the same party can appear in more than more than a couple of observations, thus creating an addiction in some data points. In this regard, however, it is worth emphasizing that as nodes are not strictly assigned to a group or another, what is a node â € œInterinteroâ € when considering that a couple of parts can instead become a node Â € œBondanteâ € When considered a different couple of parts. Therefore, as the parties do not give a fixed contribution to or the internal or boundary nodes in every couple of which they are part, the problem of dependence between the observations is not too big. 5Model Fit was evaluated The use of marginal and conditional R2 values (Nakagawa & Schiolzeth, 2013). The Marginal R2 provides a measure of the quantity of variation explained by the individual level predictions while the conditional R2 gives the total number of variation explained by the complete model: comparing the two also reveals the quantity of variation explained by the country's level differences. The main results are presented in Table 3. This table contains two series of models, one that addresses the effect of the ideological distance between the parties (models from 1.1 to 1.3), and one facing the effect of extremism (models from 2.1 to 2.3). These variables are analyzed in separate models because, as highlighted above, they are highly related. Table 3 multi-layer models explaining fragmentation (F) for party pairs. The observations are grouped into national groups. . 1.1. 1.2. 1.3. 2.1. 2.2. 2.3. Ideology .17 ** .10â € .29 *** Extremism .14 ** .10 * .22 *** Left-rectum pair Â'.26 * Â'.16 Â'.46 ** Â '.01 Â'.01 Â'.03 difference in size .01 .13 * .01 .14 * Iâ € "or pair .14 .20 .13 .16 orâ €" or pair .10 .21. 05.10 - 28. - 34. - 28. Â'.32 *** Observations 237 237 161 237 161 Margin R2 .01 .07 .21 .01 .07 .21 conditioned R2 .77 .81 .75 .78 .81 .76 Model 1.1 investigates the effect of two key variables of interest, ideological distance and left-right dismasked pairs, on the fragmentation index. The 1.2 model includes a series of theoretically relevant control variables, while model 1.3 limits observations to party pairs with at least 1,000 knots, to check if the small pairs affect the overall results. The results of the ideological distance in Model 1.1 go in the expected direction and are statistically significant: how the parties are further distinguished in ideological space, communication between them decreases. This result becomes only significant borderline in model 1.2, but it is still significant in model 1.3. Thus, overall, there is a reasonable support for the idea that the increase in the ideological distance between the parties causes an increase in fragmentation (hypothesis 1). The term for a wrong left-right torque is also significant in models 1.1 and 1.3. However, it is also unexpectedly positive, indicating that couples from different sides of the left-right divide more than those on the same side (directly contradicting the hypothesis 2). This suggests, for example, that (keeping the ideological distance constant) a given center-left party would communicate more with a center-right party that with an extreme-left party. A way to explain this counterintuitive result is that it supports the hypothesis 3, which states that as the ideology of a group becomes more extreme, interacting less with other groups. This idea is tested in models from 2.1 to 2.3, which look at the impact of extremism rather than the ideological distance. The extremism (which is the sum of both extremists) extremists) For both parts of the couple) is statistically significant in all models. This shows that as one or both sides in a pair of matches tend towards ideological extremes, communication patterns decrease and fragmentation increases. This provides strong support for hypothesis 3. The term for a left-handed failure is, meanwhile, statistically insignificant in these models. This means that overall there is a small support for hypothesis 2 (which has specified that the parties from different sides of the right to the left "divided to the left should interact less). It is worth commenting briefly on the control variables in models 1.1" 2.3. There are some evidence that a growing difference in size between parts leads to weaker communication models, although this result was found only in models limited to at least 1,000 knots (1.3 and 2.3). There was no evidence that the impending or opposition state made a difference in any pattern. Meanwhile, the term for the relationship between tweets between parts was significant in all models, confirming F's sensitivity to this factor. It is also worth highlighting R2 scores. Conditional R2 is quite high in all cases, while marginal R2 is quite low. This indicates a large amount of variation at the country level. Marginale R2 stands at its highest levels in models operating on the subset of party pairs with at least 1,000 knots. As suggested above, this may indicate that F scores for very small party couples are more unreliable. Although the above analysis shows that extremism is important, it does not reveal precisely what effect it has. In particular, it does not show whether extremist parties connect less or if the centrist parts are less willing to connect to their extremist counterparts. One way to deal with this is to look at how the borders are distributed within the boundary between pairs of centrist and extremist parts between the two sets of nodes parts (NX and NY). If a higher percentage of the edges started in NX compared to NY, then it seems reasonable to conclude that the Group around the Party X is making more external connections than part Y. The 237 observations in data sets, 99 represent a couple of parts Containing a centrist and an extremist (definition of centers as parties with extreme scores below or equal to 2,5, which is the center of the scale, and extremists as parts with scores greater than 2.5). This set of 99 parts was explained in over 198 in-pair party observations, and the proportional contribution of each at the border of their pair was measured. The level of contribution was found negatively related to the extremism score of a party (R = Â '20), providing evidence that are actually extremist parties that communicate less. This is what this is about.is statistically significant if estimated within a multi-level model with nested parts in countries and robust to include all control variables in table 2 above. However, there is obviously oneproblem in the data used to estimate this model (as each pair of parts generates two observations). Therefore, the statistical significance of the results should be considered suggestive rather than conclusive. It is interesting to note that the same exercise was conducted for the parties involved in left-right couples, and no statistically significant differences were found. This undermines the idea that the left and right parts have fundamentally different communication patterns. A potential objection to these results is that it is not clear how sensitive alternative means of sampling data from Twitter are. The networks used use both normal tweets and retweets of conversation: However, retweets have shown to exhibit several network structures in the previous research (Conover et al., 2011). In addition, the data collection window includes both the period before and after the election, but the conversation models were shown several before and after this type of critical joint (Garcia et al., 2015). Finally, making use of "weight" networks creates the potential for small numbers of very active users, which can send a lot of messages and then create very strong connections, to have a disproportionate influence on the results. To test the robustness of the results to these alternative means of sampling data, duplicates of the 1.1-2.3 models were estimated with five different sampling methods: do not use recovery data; using only recovery data; using only the data before the election; using only the data from after the election; and using an unweighted network. The key results of ideological distance and extremism have been robust to all these different specifications, except for recovery data, where the terms still indicated in the same direction but have not been more statistically significant. This supports the idea that tweets and retweets conversation can produce very different network structures (although it is also worth noting that retweets have constituted only 27% of the complete data set: the fact that the data was more limited could also explain the discrepancy found here). Overall, however, these additional models offer good support for the idea that the results are robust to different sampling data media. Discussion and conclusion This article tried to provide a first large-scale analytical treatment of the reasons behind the emergence of political fragmentation on social media, defined as the widely observed phenomenon of online networks self-organizing in groups along ideological lines. Based on a new dataset from Twitter, and working at party-pair level, it has shown that fragmentation varies within networks, with some groups that communicate more than others. He found good evidence to support the idea thatideological among groups plays a role in explaining this variation, with particular evidence that the extremist parts communicate less. In fact, the centrist parts (even differentThe left-right division) was more likely to communicate that a centrist party and extremist from the same side of the left-right division. Furthermore, when the dynamics of the individual parties have been taken into consideration in the second step of the analysis, it was not detected that the left and right parts have different communication models, contradicting a series of previous search pieces. These results have been robust for a variety of alternative model specifications. These results have implications for the theory of online political fragmentation and in fact the most general online discussion. You can do different points. One of the main concerns advanced by the theorists of political fragmentation concerned the exposure to alternative views, with concerns that the development of "Eco rooms" online will lead to people who listen to their repeated opinions and again. The evidence presented here, on the contrary, show that many communications occur between different ideologies, especially through the left-right division but within the Center-Earth. In fact, the true area of separation seems to occur with people who hold extreme ideologies, which separate both from people from other points of view and even people who hold moderate more versions of their point of view. This can indicate that the most important factor is, as Stroud suggested (2010), the certainty with which people hold beliefs, rather than ideological differences between individuals. Another factor concerns some of the other decisive fragmentation factors. There were some evidence that the position of a political party within the political system changes the way they interact with technology: larger games seemed generally to communicate less with other groups. It is intriguing to find that the parties that have more successfully offline are generally more disconnected online, and it is meaningful because it shows that online fragmentation is not just a result of decisions taken from individuals online; The offline context has an impact. However, the tests also minano the idea that the left and right parts have fundamentally different communication models, at least on Twitter, and therefore that the qualitative differences between these two types of ideology generate more or less fragmentation. In the future, any study of individual countries that realize these differences should be aware of the fact that they cannot reflect a general trend. It is worth concluding by highlighting issues that could not be addressed in this study, indicating so potential indications for further research. Two points are distinguished. First, the measures used were â € œnaÃ¯veâ € as they did not pay any attention to the content of the messages (or even the type of person who sent the message). Secondly, The data in the article is a snapshot, it is not able to deal with thunderstorm dynamics, which research has suggested could play a role in fragmentation. Since the search continues in these sectors, we will continue to understand more more what drives the emergence of political fragmentation in online discussion groups. Acknowledgment The work was funded by the VOX-Pol Network, which is funded by the 7th EU Framework Program (submission number 312827). 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