

**How Twitter divides the Dutch parliament:
Social and Political Segregation in the following, @-
mentions and retweets networks**

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How Twitter divides the Dutch parliament: Social and Political Segregation in the following, @- mentions and retweets networks

For Peer Review Only

Abstract

Communication on Twitter by MPs with other MPs may facilitate the formation of cross-party solidarity networks, as well as provide public micro deliberation, making differences between parties visible. At the same time, divisions of Twitter networks along party lines, or other social dimensions, may lead to online interaction that strengthens information bubbles and political polarization. Despite the prospering field of social media studies, important knowledge gaps remain, particularly on the complex of Twitter's *multilayered network developments*. In this contribution, we scrutinize the extent to which and why Twitter networks among MPs, formed by following, @-mentioning and retweeting relations, are segregated along party membership lines and sex, age and ethnicity. Our unique dynamic perspective allows us to rigorously study network segregation dynamics by disentangling the impact of social inbreeding homophily, structural network effects, characteristics of MPs, and feedback mechanisms between the three Twitter layers. Theoretically, we integrate the online-network literature with that on the political consequences of the digital architecture of social media platforms and their political use. Combining descriptive network statistics with *SIENA* analyses of network dynamics for Dutch MPs at three points in time after the 2017 elections, we find that *political* segregation patterns are strongest within the retweet-layer and weakest in the @-mention layer. While social inbreeding homophily is prominent in the offline world, we found no consistent indication of the MP Twitter networks to be *socially* segregated. The interrelations between the three Twitter network layers aggravate party-based segregation.

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2
3 **1. Introduction**
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5 Twitter is a popular communication tool among politicians. Twitter is easy to use and it allows
6 politicians to directly communicate with colleagues, journalists, pundits and voters (e.g. Spierings,
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8 Jacobs, and Linders 2019; Tromble 2018). When looking at with whom MPs actively connect and
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10 interact on Twitter, particularly other politicians are strongly overrepresented (van Vliet et al., 2020).
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12 Communication and engagement among MPs via Twitter may facilitate the formation of cross-party
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14 solidarity network as well as provide public micro deliberation that allow citizens to get a better
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16 understanding of policy considerations and differences between parties. However, these Twitter
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18 networks might develop strongly across party lines or other important social dimensions such as sex,
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20 age and ethnicity, strengthening information bubbles and political polarization.
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26 Despite its relevance, research into the Twitter networks among MPs is relatively rare in the
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28 prospering field of social media studies in political communication. What do we know about MPs
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30 intraparlimentary networks? Hsu and Park (2012) showed that members of the 18th Korean National
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32 Assembly were more likely to have links to fellow party members than to non-members, and Del Valle
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34 and Bravo (2018) demonstrated that the Twitter networks among Catalan parliamentarians are
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36 segregated along party and ideological lines. Adding to such country studies, more recently, a
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38 sophisticated cross-country comparison of parliamentary Twitter networks demonstrated that party-
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40 based segregation is common, although differing between layers, and partly grounded in institutional
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42 and political contextual differences (Praet et al., 2021). While highly insightful, these studies do not
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44 study the role of social network structures, demographic segregation, Twitter layers’ interrelatedness,
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46 and network development.
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51 Despite the increasing scholarly attention to the topic, important knowledge gaps remain.
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53 First, most previous studies did not move beyond valuable descriptive analyses. An important
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55 exception is the study of Valle and colleagues (2022) in which exponential random graph models are
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57 used to explain the state of the @mention network. However, these authors relied on just one
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59 snapshot of that Twitter network. To make more substantiated causal claims, longitudinal network
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data and methods to model network dynamics are called for. Second, some studies include the different network layers Twitter offers (follows, @mentions, retweets) and compare the results for them, but how the formation of these networks is *interrelated* is largely neglected.

In this contribution, we will therefore investigate segregation *dynamics* in the three *interrelated* Twitter networks in more detail, both theoretically and empirically. To provide a theoretical understanding of these dynamics, we bring together the conceptual notion of digital architectures, or affordances, from the political communication literature (Bossetta 2018; Jacobs & Spierings, 2016) and the literature on segregation dynamics in online social networks (Boutyline & Willer, 2017; Hofstra et al., 2017; Lin & Lundquist, 2013; Wimmer & Lewis, 2010). We particularly provide a more thorough understanding of MPs digital social networks with respect to four issues of political segregation: (a) to what extent are the Twitter networks among MPs segregated and does that remain when accounting for network mechanisms?; (b) to what extent are the observed segregation patterns along party membership lines on Twitter a by-product of social homophily (i.e., the preferences to form ties with socio-demographic similar others)?; (c) to what extent do the segregation patterns within the three network layers formed by following, @-mentioning and retweeting relations reinforce or mitigate each other?; and (d) how do these segregation patterns and dynamics develop?

Our empirical focus will be on how relations within the three layers of the Twitter network among the 150 Dutch MPs have evolved after the national elections of 2017. After these elections, 13 parties were presented in Parliament by 150. In parliament, parties need to collaborate, not only to form and support a government, but also to find majorities for specific proposals and to become an effective party in either coalition or opposition. In such a setting, we might expect less clear party and ideological division lines running across MPs' Twitter networks (cf. Praet et al., 2021), whereas MPs from different parties might form networks around for instance gender or minority status. In other words, if ideological and party divides are still found in the Netherlands among members of the Lower house, this is a strong confirmation of the prior findings by del Valle and Bravo (2018).

Methodologically, we take advantage of unique longitudinal complete network data on Twitter relations among Dutch MPs collected in April, June and September 2017. We will first visually inspect these networks before giving a formal description of the observed degree of segregation. We will complement this descriptive part with a Stochastic Actor-Orientated Modelling approach as implemented in the R package *RSiena* (Ripley et al., 2021; Snijders et al., 2010). This method is well-suited to disentangle the impact of structural network effects, characteristics of MPs, and the Twitter digital architecture on segregation dynamics.

2. Theoretical background

Multi-dimensionality: Segregation in Twitter along political and social dimensions.

It has been a well-established finding that social interactions are more likely between people who are similar (McPherson et al., 2001). In part, this is the result of the opportunity structure, i.e., the availability of contact partners within and outside one’s group. Initial levels of segregation in networks may be amplified by common structural network processes such as reciprocity (i.e., “If you scratch my back, I will scratch yours.”) and transitivity (i.e., “Friends of friends become friends.”). Over and above such structurally-induced segregation, people commonly have preferences to interact with similar others. The latter are called inbreeding homophily preferences, which surface in the choices that individuals make regarding whom to form ties with. In the representation literature this is reflected in the concept of homosocial capital: a network with similar people leads to shared norms, values and perceptions, leading to predictability and trustworthiness being ascribed to similar politicians (Bjarnegård & Kenny, 2015).

Network segregation is observed across a wide array of social dimensions and for different type of social relations, but studies on segregation in extended online networks have remained rare. One may intuitively expect that the degree of segregation would be less pronounced in online than offline networks and in extended versus core networks, because online there are fewer structural constraints and because the (emotional) risk involved in forming ‘wrong’ relations in extended

networks of weak ties is lower than in core networks formed by strong ties. That being said, corroborative empirical evidence for this idea has been meagre at best (Hofstra et al., 2017). Regarding our focus, the online Twitter networks of MPs cannot be considered a core network, but MPs will be exposed to each other in parliament regularly nevertheless. It can thus be expected that real-life social cleavages matter, but it remains an open question whether those cleavages based on sex, age and ethnicity are indeed mitigated by Twitter or whether Twitter reifies these social divides in parliament.

As in other countries, Dutch political parties differ in their socio-demographic composition (Supplementary Material A). For instance, after the 2017 elections, women were underrepresented in parliament (54 MPs, 36%) and in most factions, women hold a numerical minority position. The mean age of MPs in parliament does slightly deviate downwards from the mean age in the general Dutch electorate (45 versus 50), but there are striking differences across parties. The MPs of the Senior Interest Party 50Plus, have a mean age of 65 year. The mean age of MPs of the radical left Socialist Party ('SP') is just over 38. Lastly, in The Netherlands, the share of MPs with a visible ethnic-minority background reflects the share of ethnic-minority citizenships of the electorate fairly well (Van der Zwan et al., 2019). But once again, we observe marked differences across parties.

Considering these differences in social composition across parties, political segregation in Twitter networks could be the result of selective interaction along party lines, as well as of social inbreeding homophily, selecting Twitter partners based on attributes other than party membership. In this contribution, we will assess exactly that: the extent of political segregation, the degree of sex, age and ethnicity-based network segregation in Twitter networks, and the extent to which political segregation in Twitter networks along party-membership among Dutch MPs is a by-product of social inbreeding homophily (cf. Kalmijn 1998).

Multiplexity: segregation in different layers of the Twitter network

Networks come in many different types and sizes. Even when we focus on a single social media platform, different layers of social networks are created due to different types of interaction being

part of the platform's affordances or digital architecture (Bossetta 2018). Three of the most prominent layers of interaction on Twitter include follow relations, retweets and @-mentions. Discussing the nature of these forms of interaction provides our next theoretical building block.

On Twitter, one can follow another account in a non-reciprocal way. Once a connection is made, the tweets of the followee will appear in the timeline of the follower. Following an account could thus indicate that a follower finds the content posted by the followee interesting, regardless of whether one agrees or disagrees with the content of that followee. Forming following relations can also be used strategically to boost the prominence of an account, because it will increase the likelihood that one's own tweets are shown in the timelines of others with whom no following relation is formed.

Next, Twitter allows users to copy a post of another user and push it to their own followers via the retweet function. Retweeting a message indicates that the original tweet is deemed an interesting enough intervention in the public debate to pass it on to one's own followers. Although politicians tend to explicitly claim that a retweet is not necessarily an endorsement (Klinger and Svensson 2015; Metaxas et al. 2015), particularly among politicians, retweeting a message of another politician one disagrees with is relatively unlikely, because the retweet function is mainly a passing on of content (Praet et al., 2021). Retweets are of the three relationship types the one most likely to signal positive affect.

In contrast, of the three, the @-mention functionality of Twitter is most likely to be used by politicians for debating with opponents and to signal negative affect, next to forging cross-party alliances (Del Valle et al., 2022). There are two ways in which one could @-mention others. First, a user can write a post and invite others to be aware of, or respond to that post by including the person in the message using the @-mention. If one does so, the @-mentioned account gets a notification, strongly increasing the likelihood that the tweet is noticed by the @-mentioned person. Second, below each tweet, Twitter puts a small speech bubble icon via which users can directly, but publicly, reply to a message. Overall, the @-mention is thus used for 'calling upon a person', holding conversations, and debating (Del Valle et al., 2022; Spierings & Jacobs, 2019).

Given their different functions, and the presumed different emotional valence attached to the different type of ties, MPs may hold different structural positions in each network-layer (Del Valle & Bravo, 2018; Praet et al., 2021). So far, while some scholars compared the different networks, it has remained unclear how the different Twitter network types co-evolve. Does debating with opponents makes following relations with opponents more likely, or are MPs more likely to ignore their opponents and prefer to engage in debates with MPs they already follow? In the present contribution we take this so-called multiplexity into account. We will assess the extent to which the degree of segregation differs across layers, and how segregation in one layer of the Twitter network impacts segregation in another layer.

Multiple time points: development of segregation in Twitter over time.

Additionally, we expand on previous work by investigating the over-time development of the three Twitter networks. We will investigate how the Twitter networks among Dutch MPs have evolved over a period of 6 months, in between the 2017 elections and the formal instalment of the new government.

Politicians of the same party who have been elected as MP are likely to have worked together before or during the campaigns leading up to the election. Their shared social contexts will undoubtedly have led to homogeneity in their offline relations, and could have translated into their online Twitter relations. Following this line of reasoning and the lead of previous research demonstrating the ubiquitous presence of network segregation (Colleoni, Rozza, and Arvidsson 2014; Del Valle and Bravo 2018), we thus expect to see at least some degree of segregation in the Twitter networks based on party-membership shortly after the time when parliament is established.

The degree of segregation is, however, unlikely to be stable. Common structural network dynamics like reciprocity and transitive closure may act as catalyzer and may contribute to the further over-representation of intra-party relations (cf. Del Valle et al., 2022). On the other hand, the presumed initial segregation may be overcome merely because offline contact and exposure to dissimilar MPs in the actual parliament increases. Our unique time window enables us to assess the

development of segregation over time and, for the first time, to rigorously scrutinize the role played by network mechanisms in the evolution of the Twitter networks.

Expectations

Given the rationale outlined above and based on previous research on segregation in Twitter networks (Colleoni et al., 2014; Del Valle et al., 2022; Del Valle & Bravo, 2018; Hsu & Park, 2012; Praet et al., 2021), we expect to observe at least some degree of segregation along the party dimension in all three Twitter networks of Dutch MPs, and thus that MPs are more likely to interact on Twitter with same party MPs relative to MPs from different parties, even after we take into account other network mechanism (Hypothesis 1).

Since political parties have different social compositions and inbreeding homophily has been observed previously across a wide array of social dimensions (e.g., sex, age and ethnicity), for different type of offline and online networks, we expect to observe social divisions on twitter along these social dimensions as well (Hypothesis 2a), and that political segregation in Twittersphere will in part be a by-product of social inbreeding homophily in these social dimensions (Hypothesis 2b).

Moreover, we expect that segregation will be most pronounced in the retweet layer of the Twitter network, as this type of relation is of the three most likely to be formed between MPs who evaluate each other positively (Hypothesis 3a). In a similar vein, the @-mention relation will, in contrast, be formed relatively more between political foes as they debate each other on Twitter. Hence, of the three layers, we expect to observe the lowest degree of political segregation in the @-mention layer (Hypothesis 3b).

From previous research, we know that exposure to others is a very important determinant for tie formation and maintenance (Rivera et al., 2010). Hence, we expect that the digital proximity that results from a follow relation on Twitter will increase opportunities for both MPs to retweet each other's tweets or to react on tweets via @-mentions. Consequently, we expect follow relations to increase retweet and @-mention relations and thus that the degree of segregation in the retweet and

@-mention layer is in part the result of the degree of segregation in the follower layer (Hypothesis 4a and 4b). Similarly, when an MP retweets another MP's tweet or @-mentions this MP, this may be an incentive for the second MP to become closer to the first MP and to start following this MP. Thus, we expect that segregation in the friendship network will also be in part the result of segregation in the retweet and @-mention network (Hypothesis 4c and 4d).

Finally, we could expect that initial levels of segregation may deepen, because of inbreeding homophily and structural network dynamics, in line with the idea of the development of political echo chambers. On the other hand, networks may become more integrated over time because of the meeting opportunities with dissimilar MPs in the House. MPs may also form new strategic follower relations with dissimilar MPs, because they want to be informed on the Twitter content of these dissimilar MPs and forge alliances. Similarly, MPs may enter @-mention discussions with political opponents on Twitter, either steered by genuine political motives or to strategically increase Twitter visibility. From a theoretical perspective of network dynamics and digital architectures, both mechanisms are likely to occur and we cannot deduce an a priori expectation on whether deepening or easing segregation will dominate. Therefore, we only formulate a research question on this to explore the development of segregation in Twitter over time: To what extent do the different forms of segregation in the different layers of Twitter networks among MPs deepen or ease over time? (Research question 1)

3. Data and methods

The Netherlands is a Twitter frontrunner. Of the 150 politicians who entered parliament in 2017, we could find 147 twitter handles. Via the Twitter REST API follower and retweet relations were mapped and via the Twitter SEARCH API @-mention relations were mapped, at three time-points (April 2017, June 2017, September 2017).

The sex of MPs is taken as reported on the ballot. MPs' age was collected via the official website of the House of Parliament. We considered 16 MPs to having an *visible ethnic-minority*

background, using a common contextual definition and procedure in the literature on representation: name and photo recognition or being well-known as such (Bloemraad and Schönwälder 2013).

In our multivariate explanatory models, we take into account several control variables at the ego, alter and dyad-level: party-leadership, position on the election list, (difference in) incumbency status of MPs, whereby we defined incumbency as having been Member of Parliament before the 2017 election. Physical proximity within parliament is based on the seating positions of MPs in April 2017 as shown in the ‘Debat Direct’ app (<https://www.tweedekamer.nl/debat>). The 150 seats are allocated to the parties by the presidium based on party size and ideological position, with for instance the socialists (‘SP’) have seats on the left and the populist radical right (‘PVV’) on the right. We acknowledge that our physical proximity measure to some extent overlaps with ideological proximity between parties.

Analytical strategy

We will start with a visual inspection of the directed ties present in the three network layers, and with formal statistics of the extent of segregation. There are many ways to measure segregation in social networks (Bojanowski & Corten, 2014). Staying close to our definition of segregation, we start with comparing intragroup and intergroup densities (i.e., ratio of observed to all possible ties). While easy to interpret, this does not account for relative groups sizes or differences in MPs activity and popularity, which are known to cause structurally induced differences in intra- and intergroup densities. Therefore, we also report Newsman’s Assortativity Coefficient, which is 1 when all dyads are formed within-groups and 0 when the probability to observe a within group dyad is solely the result of proportionate mixing.

Although the descriptive part will inform us about the actual segregation in the network layers, they do not provide explanations for the found segregation or the development therein. For that we focus on how Twitter relations are formed and broken, controlling for structural (or: endogenous) network effects and for ego, alter and dyad covariate effects (or: network-exogenous effects). The latter capture the extent to which ego, alter and dyad characteristics influence the likelihood that a

Twitter relation is present. For the statistical analysis of these network data we turn to the Stochastic Actor Oriented Model (SAOM) as implemented in SIENA (Simulation Investigation for Empirical Network Analysis), which we will estimate in R (R Core Team, 2021) with the package RSiena (Ripley et al., 2021).

With RSiena, tie changes are modelled as resulting from actions by actors. An important assumption of the implemented SAOM is that of the so-called *ministep*. Only one actor per time is allowed to make one tie change. The decision on tie change is based on how the actor evaluates the current and possible future network structures in its direct vicinity. How these networks are evaluated is determined by the so-called evaluation function: $f_i^{net}(x) = \sum_k \theta_k^{net} s_{ik}^{net}(x)$. θ_k^{net} refers to the estimated parameters of the model and these parameters of the evaluation function are what we are interested in. Each actor evaluates the attractiveness of its own local network environment. This is why s_i has a subscript i . Actor i is most likely to take the ministep that will result in the network with the highest attractiveness value. The interpretation of the parameters of the evaluation function resembles the interpretation of a logistic regression: $\exp(\theta_k^{net})$ is the ratio of the probabilities to observe network x_a versus x_b , under the ceteris paribus condition that the only difference between these networks is that $s_{ik}^{net}(x_a) - s_{ik}^{net}(x_b) = 1$.

Following the RSiena manual (Ripley et al., 2021), we started with a preliminary model for the three dependent network-variables in which we included (uniplex) structural network effects (for the mathematics see chapter 12 of the RSiena manual (Ripley et al., 2021)): (a) the *out-degree effect*: the likelihood to observe a tie; (b) the *reciprocity effect*: the extent to which forming a reciprocated tie is more likely than a non-reciprocated tie; (c) *in-degree popularity* and (d) *out-degree activity* because MPs who receive/send many ties at time T may also receive/send many ties at time $T + 1$; (e) the *out-degree popularity effect*: the covariance between indegrees and out-degrees; (f) the *transitive triplets effect* to test network closure (i.e. “friends of friends are my friends”), and (g) the *shared popularity effect*, capturing possible complex contagion processes, whereby MPs are more likely to form a new (follower, @-mention, retweet) relation to a specific MP when they observe that other MPs with

similar relations as oneself also have a relation to this specific MP (c.f., Harrigan, Achananuparp, and Lim 2012).

In Model 1, we subsequently included controls for MPs activity and MPs popularity: *political party, party-leadership, position on ballot, and incumbency status*. The dyadic control covariates were: *MPs similarity in incumbency status* and the *seating distance* between MPs. Moreover, this model also includes our main variable of interest, namely the dyadic *similarity in MPs' party membership* with which we intend to test Hypotheses 1. Positive values indicate that MPs are more likely to form ties with co-party members than with MPs from a different political party.

To assess the degree of segregation along sex, age, and ethnic lines and the extent to which segregation along party division lines is a by-product of online social inbreeding homophily (Hypotheses 2a and 2b), Model 2 includes *same sex, absolute age difference, same visible ethnic minority status*. To filter out ego and alter effect biases, Model 2 also included the corresponding covariates at the ego and alter level (*sex, age, visible ethnic minority*). With Model 2, we also compare the remaining degree of party segregation across the three dependent variables (Hypothesis 3).

In Model 3, we model Twitter's digital architecture consequences by adding structural multiplex effects, between on the one hand the follow layer and on the other hand the retweet and @-mention layer: *crprod* and *crprodRecip*. With the *crprod* effect we assess the likelihood for an MP who has a follow relation with another MP at time T will also 'send' a retweet or @-mention relation to this other MP at time T + 1. The *crprodRecip* effect captures the effect that if an MP has a specific relation with another MP (e.g., follow relation) at time T, this MP will 'receive' a different relation from this other MP (e.g., retweet or @-mention) at time T + 1. This model allows us to investigate whether segregation in one layer of Twittersphere causes segregation in another layer (Hypothesis 4).

Finally, to answer Research question 1 on the development of networks and to assess whether similarity in party memberships between MPs becomes more or less important in explaining changes in the Twitter layers over time, we included an interaction between *period* (with the value '1' for period

2 (June to September) and '0' for period 1 (April to June)) and our dyadic variable *same party* in Model 4.

The dataset, all our code and results are accessible via our replication website hosted at github (**).

4. Results

Observed segregation

The networks that existed in April 2017 are summarized in Figure 1. The node positions reflect the seating positions within parliament. It becomes apparent immediately that the density is much higher in the follower network than in the @-mention or retweet layer. This means that MPs are more likely to be connected as follower-followee than that they regularly retweet or @-mention each other, which is logical given the architecture of the platform, with the following connections being permanent (unless actively broken) in addition to focusing on a period outside election campaigns, in which activity is much higher.

The node size in Figure 1 is based on outdegree. In each layer of the Twitter network, we observe quite some variation across MPs in outdegree. However, the figure also shows that it are not necessarily the same MPs who have a relative high outdegree in each network layer. That MPs hold different network positions in each layer is also evidenced by the modest Spearman's rank order correlation between follower outdegree and @-mention outdegree (.39) and between the @-mention outdegree and retweet outdegree (.53). These observations underscore the importance to investigate the degree of segregation and underlying mechanism in the three network layers separately but interdependently.

While Figure 1 provides insight in the layers of the Twitter network, they do not (easily) show whether twitter division lines run across the different political parties in the House of Parliament, although it seems that, as expected, especially @-mention relations go across party boundaries, while

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retweet relations predominantly exist between MPs of the same party. The picture becomes sharper would we look at reciprocated ties only (Supplementary Material B).

<<<Figure 1>>>

Segregation indices

We observe that Twitter relations with MPs of the same political party are more common than with MPs of other parties (e.g., 0.71 over 0.19 for follower networks at T1; Table 1). This holds true for all network layers within Twitter and all three time points. Also based on Newman’s Assortativity Coefficient, we conclude there is segregation along party lines: all respective values are positive (Table 2: row ‘party’). While in line with our expectations and most of the international literature on party-based segregation, they do not replicate the results of Praet et al. (2021) for the Netherlands. Most likely because in the latter study the members of both the Lower and Upper house are included and analyzed as one network.

Turning to the different socio-demographic axis of segregation, Twitter relations with same-sex MPs are not substantially more common than different-sex relations. MPs who have a similar age (i.e., less than a 6-year difference) are more likely to have twitter ties than MPs with a dissimilar age, and follower relations on Twitter between MPs with the same ethnic background are more common than follower relations between MPs with a different ethnic background. But, all in all, for these social dimensions differences in within-group and between-group densities are relatively small, as is confirmed by the Newman’s Assortativity Coefficients (Table 2).

Based on to Newman’s Assortativity Coefficient, our conclusion is that party division lines are most pronounced within the retweet network. This is in line with the architectural reasoning that retweets are generally endorsements of the original tweet (cf. Praet et al., 2021). In contrast to our expectation, party segregation is weakest within the follower layer.

Over time relatively more different-party ties were forged in both the following (ratio same party to different party at T1: $0.71/0.19=3.74$ and at T3: $0.74/0.22=3.36$; Table 1) and retweet (from 34 in T1 to 25 in T3, Table 1) layer. For the following layer, Newman's Assortativity Coefficient has decreased over time as well. Conversely, in the @-mention layer the ratio of same-party and different-party ties has increased and we also observe increasing values for Newman's Assortativity Coefficient over time in this layer (e.g. from 0.39 in T1 to 0.47 in T3; Table 2).

<<<Table 1 & 2>>>

Network dynamics

Before we delve deeper into our core results derived from the RSiena models, we briefly describe some noteworthy structural effects observed and the estimated covariate effects as summarised in Supplementary Material C.

Structural and covariate effects

In all three network layers we observe positive significant reciprocity effects, and they are strongest for @-mentions ($b=1.402$, $se=0.090$), likely reflecting that MPs hold small back-and-forth conversations or discussions via Twitter. Second, more active MPs are significantly less popular, as indicated by the negative outdegree-popularity parameters ($b=-0.186$; $b=-0.096$; $b=-0.271$, respectively for following, @-mentions and retweets). More prominent politicians seem to have less time to invest on Twitter but are called upon more by others. Third, all network layers show transitive closure (e.g., MPs are likely to follow MPs who are followed by MPs already being followed). The shared popularity effect was negative in all three layers but only reached significance in the retweet layer ($b=-0.014$, $se=0.005$). This finding is in line with the theory that social contagion is lower within a community because of the inherent redundancy and lack of novelty of messages within a community but contradicts the idea that tweets spread via complex social contagion (Harrigan et al., 2012).

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For our covariates, first, MPs with a better ballot position follow fewer other MPs ($b=0.542$, $se=0.154$) but are @-mentioned ($b=-0.012$, $se=0.003$) and retweeted ($b=-0.012$, $se=0.004$) more, indicating that MPs with a more favourable position on the ballot are sought out more to draw into a discussion and their tweets are pushed more by others too. Party leaders are also @-mentioned and retweeted relatively often ($b=0.129$, $se=0.092$; $b=0.122$, $se=0.079$; respectively), but they engage significantly less in debate on Twitter than non-party leaders as indicated by the corresponding negative and significant estimated ego covariate effect within the @-mention layer ($b=-0.300$, $se=0.096$). Although there are 13 different parties in parliament, we only find few significant party effects. MPs of the liberal democrats and green party are @-mentioned less often than others, and MPs of the liberal democrats and the populist radical right are significantly less often retweeted.

The further MPs sit from one another, the less likely they are to follow ($b=-0.022$, $se=0.007$) and retweet each other ($b=-0.031$, $se=0.006$). Because we already accounted for party affiliation (at the ego, alter and dyad-level), it is unlikely this result is driven by ideological distance between MPs alone. Thus, physical distance in the House seems to matter.

Party segregation and social homophily

Turning to our main variable of interest, the ‘same party’ dyadic covariate, we find positive and significant estimates in all three layers of the Twitter network (Model 1, Table 3). Thus, even if we take into account structural network effects, factors that impact MPs’ activity and popularity, and the distance between MPs within parliament, we still observe that MPs are more likely to form relations on Twitter with MPs of their own party than with MPs of different political parties. More concretely, the probability to form a follow relation with an MP of the same party versus a different party is approximately three times larger ($e^{1.088}$), for @-mentions this is approximately two-and-a-half ($e^{0.922}$) and for retweets four ($e^{1.388}$) times larger. These findings underscore our previous descriptive observations, and we thus clearly find corroborative evidence for Hypothesis 1.

More specifically, we expected to see party-based segregation most clearly in the retweet-layer and that the degree of political segregation would be lowest in the @-mention layer (Hypothesis 3a and 3b). This expected order of political segregation can indeed be observed, whereby segregation in the retweet layer is significantly more pronounced than in the @-mention layer (the difference is .468 with $se = .096$ and $t\text{-ratio } t = 4.887$, $p < 0.001$). Hence, we find corroborative evidence for the expected ordering of Hypothesis 3.

In Model 2 we assessed social inbreeding homophily (see Table 3). Besides MPs are more likely to retweet tweets of MPs of the same sex ($b=0.127$, $se=0.049$), we find no other estimates in line with the idea of social inbreeding homophily. To be clear, the sex, age and ethnic background of MPs themselves do impact twitter relations (see replication website ***). For instance, younger and female MPs are more likely to be followed than the counterparts, and younger MP follow more other MPs too. Moreover, female MP retweet more and are retweeted more, with the latter holding for younger MPs as well and the former of MPs with a visible ethnic minority status. But, there are no clear and consistent social division lines running through the layers in the Twitter network in parliament and we reject Hypothesis 2a. And with no pronounced social inbreeding homophily present, party-based segregation is not a by-product of it either. We therefore refute Hypothesis 2b too.

Understanding how twitter's layers are interrelated

We observed party-based segregation in all three layers of the Twitter network, but we did not assess yet whether, for instance, segregation in the follower network *causes* segregation in the @-mention and retweet network and vice versa. Model 3 (Table 4) does and our results reflect the digital architecture of Twitter.

Following MPs and being followed also leads to @-mentioning ($b=0.400$, $se=0.072$; $b=0.158$, $se=0.066$, respectively) and retweets ($b=0.647$, $se=0.092$; $b=0.251$, $se=0.076$, respectively) later. To @-mention a colleague MP will increase the chance that your tweets will be retweeted by this MP in the future ($b=0.988$, $se=0.231$), indicating that twitter discussions cross network layers. Also, MPs are more

likely to start to follow and @-mention MPs who they retweeted ($b=1.718$, $se=0.536$; $b=0.454$, $se=0.212$, respectively) and to start following MPs by whom they were retweeted ($b=0.677$, $se=0.483$).

After taking these cross-network effects into account the ‘net party-based segregation effect’ is considerably lower; the respective probability ratio’s decreased from Model 2 to Model 3 by approximately 28, 40 and 25 percent, respectively for following ($e^{(.755 - 1.088)}$), @-mentions ($e^{(.406 - .922)}$) and retweets ($e^{(1.106 - 1.388)}$). The observed segregation along party membership lines in each respective layer of Twitter is thus in part the result of the degree of segregation in the other two layers and we hereby find corroborative evidence for Hypothesis 4.

Segregation dynamics over time

Lastly, we investigated the importance of party-based homophily over time on which we formulated Research question 1. In Table 3 we summarized the main results of Model 4, which is Model 1 with the additional interaction terms. We observe that the tendency of MPs to follow and retweet colleagues from the same party is more important for the explanation how the network developed in period 2 than in period 1. Within the @-mention layer party-based homophily has less impact on network development in period 2 than in period 1.

At first sight, these results seem to point in the opposite direction as our descriptive results discussed above. We have to keep in mind, however, that in Table 1 and 2, we described the *current* degree of segregation at three *timepoints* (i.e., states). With our RSiena models, we looked at the *development* of party based segregation in two *periods* (i.e., dynamics). To illustrate the difference, if party-based segregation – measured at the network-level – decreased faster in period 1 than in period 2, it is likely that party-based homophily – measured at the MP-dyad-level – plays a larger role in explaining network dynamics in period 2.

What might these results indicate? To understand that party-based homophily in the follow layer is more important in period 2 might be linked to our focus on the time after the elections. It might be that when a new parliament is installed, the MPs start forging between-party ties. For retweets

something similar might be the case, whereby the end of an electoral campaign might cause an additional relaxation around endorsing tweets of other parties, but towards government formation and politics as normal (i.e., period 2) this easily restores to stronger within-party preferences. This also aligns with the shift for @-mentions, as in cross-party debates seems to more important in the second period.

<<<Table 3>>>

5. Conclusion

We brought together the online network literature (Boutyline and Willer 2017; Hofstra et al. 2017; Lin and Lundquist 2013; Wimmer and Lewis 2010) with that on the political consequences of the digital architecture of social media platforms and their political use (Bossetta 2018; Jacobs & Spierings, 2016). We investigated the extent to which the network of Dutch MPs was characterized by party-based segregation in the different Twitter layers (i.e., following, retweeting and @-mentioning relations) and whether preferences to interact with socio-demographic similar others, network dynamics, and the twitter architecture in a political context could explain the observed party-based segregation patterns.

Our results, altogether, highlight the importance of combining these literatures and studying the different layers of Twitter *interrelatedly* and *dynamically*, which this paper is the first to do. It allows us to understand party-based segregation among MPs on Twitter as a function of the political rules of the game in parliament which is facilitated by the architecture of the platform, while social inbreeding homophily – an important driver of social segregation in the offline world – hardly plays a role.

Our analyses provides further evidence for conclusions from previous (mainly descriptive) studies (e.g., Del Valle and Bravo 2018; Hsu and Park 2012; Valle et al. 2022) that among MPs, Twitter relations with MPs of the same political party are substantially more common than with MPs of other parties. This holds true for *all* network layers within Twitter – followers, retweets, @-mentions – and

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at all three time points in our study, even in the Dutch context with a large number of small parties in parliament. And, our novel analyses of network dynamics also clearly demonstrated that MPs are more likely to form relations with co-party members, even if we control for endogenous and exogenous network mechanisms.

More in-depth we show that the degree of segregation in the different networks does align with how the architecture of the platform and the nature of politics are related. The segregation is strongest for retweets, then for follower ties and finally for @-mentions. Retweets mainly function as political endorsements, whereas @-mentions are more a way to hold micro discussions. Moreover, while there is ample evidence that socio-demographic factors constitute power relations and political hierarchies, this does not lead to online in-group preferences, recalling that several decades ago, (informal) female and ethnic-minority networks were a tool for MPs from marginalized groups to empower themselves (Dahlerup and Leyenaar 2013). Such cross-party solidarity seems to have waned. The results discussed in this paragraph aligns with and further substantiates the insight that Twitter is considered mainly as a campaigning tool, while the other opportunities it offers – such as creating deliberative spaces that can counter polarization – may be underutilized.

Our novel focus on the interrelatedness of the network layers and how they form segregation patterns turned out fruitful: following and being followed stimulated the other interactions; @-mentioning another MP increases the chance of a retweet of that MP; retweeting a colleague is linked to start following and @-mentioning that colleague (i.e. coming across a post worth retweeting feeds into more interaction); and being retweeted increases the likelihood to start following the retweeting MP. Crucially, these interrelations between the layers also lead to more segregation. The observed party-based segregation in each of the respective Twitter network layer is partly the result of the degree of segregation in the other network layers and the interrelatedness between them.

While it are of course the MPs who decide who to engage with online, the structure of Twitter and the functioning of politics strengthen the preference for own-party connection and pushing messages of fellow party member. In other words, political culture and twitter architecture dovetail in

contributing to the maintenance of echo chambers. While this might not sound surprising, it is noteworthy as overview studies and voter studies have concluded that political echo chambers are far from established or even argued against their existence (Del Valle et al., 2022; Jeroense et al., 2021; Matuszewski & Szabó, 2019).

Lastly, we added to the literature by exploring to what extent segregation patterns change over time. We observed that segregation decreased in the following layer and increased in the @-mention layer. Paradoxically, focusing on network *dynamics*, we reached the conclusion that preferences to form ties with co-party members became more important to explain changes in the following and retweet layer, but less important in the @-mention layer. As discussed more elaborately above, these patterns align with the logic of politics, elections cycles, including government formation (i.e. stress the importance of the institutional context of a multiparty system [see also Praet, Martens & Van Aelst, 2021]).

The above also brings us to one of the main limitations of this study. While introducing a unique longitudinal perspective to the MPs' Twitter network literature, our time frame was restricted. The moment in the political cycle matters and seems to go beyond the 'campaign time' versus 'peace time' distinction. Observing the networks at more time-points over a longer time period would be a valuable next step. Similarly, making the big data of Twitter thick with publicly available information on (offline) collaboration networks (e.g., being member of the same committee), or with MP survey data could provide important new avenues for research.

Altogether this paper sheds new light on the degree and origin of party-based segregation of MPs on twitter, which is not only of academic relevance, but also has direct bearing on democratic politics. Most importantly, while Twitter offers much democratic potential in terms of forging new connections, also to dissimilar others, the medium does not live up to this potential among MPs.

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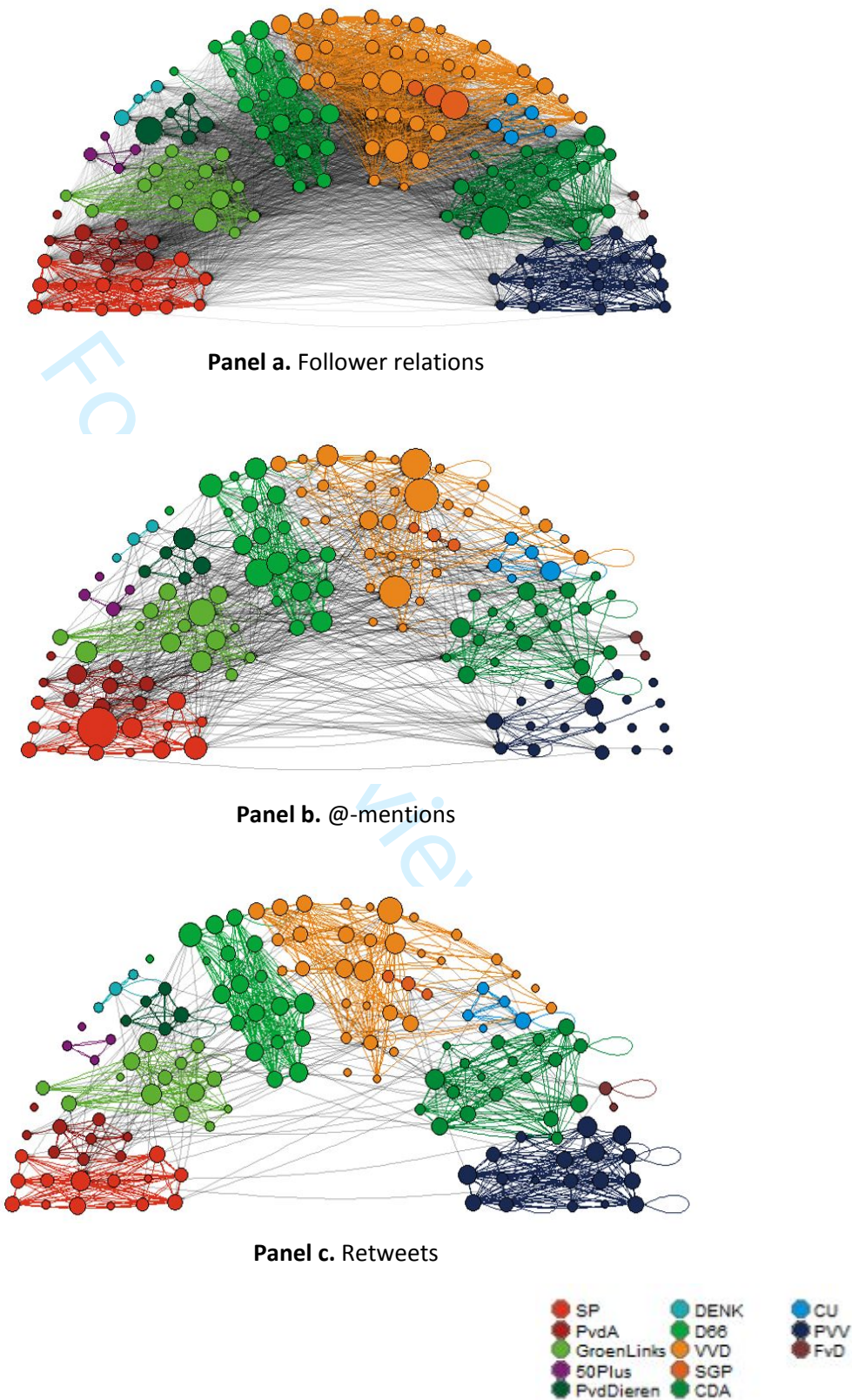


Figure 1. Directed twitter relations between Dutch MPs (2017)

Notes: Node size based on degree. Edge color based on Party affiliation, black if MPs from different party

Table 1. Inter- and intra-group densities within the three Twitter layers among Dutch MPs (2017)

	following	following	following	@-mentions	@-mentions	@-mentions	retweets	retweets	retweets
	T1	T2	T3	T1	T2	T3	T1	T2	T3
total	0.25	0.28	0.28	0.05	0.04	0.01	0.05	0.03	0.03
same party	0.71	0.73	0.74	0.20	0.14	0.06	0.34	0.25	0.25
different party	0.19	0.22	0.22	0.03	0.02	0.01	0.01	0.01	0.01
same sex	0.26	0.29	0.29	0.05	0.04	0.01	0.05	0.03	0.03
different sex	0.24	0.27	0.27	0.04	0.03	0.01	0.05	0.03	0.03
same age (<6)	0.29	0.31	0.31	0.06	0.04	0.01	0.05	0.04	0.04
different age (>5)	0.24	0.26	0.26	0.04	0.03	0.01	0.04	0.03	0.03
same ethnicity	0.27	0.29	0.29	0.05	0.04	0.01	0.05	0.03	0.03
different ethnicity	0.21	0.24	0.24	0.05	0.03	0.01	0.04	0.03	0.03

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Table 2. Newman’s Assortativity Coefficient within the three Twitter layers among Dutch MPs (2017)

	following	following	following	@-mentions	@-mentions	@-mentions	retweets	retweets	retweets
	T1	T2	T3	T1	T2	T3	T1	T2	T3
party	0.22	0.20	0.20	0.39	0.39	0.47	0.82	0.83	0.83
sex	0.04	0.03	0.04	0.10	0.04	0.06	0.01	-0.01	0.02
age	0.05	0.04	0.04	0.09	0.02	0.12	0.02	0.01	0.06
ethnicity	0.06	0.05	0.05	0.08	0.02	-0.07	0.09	0.02	0.04

Table 3. Multiplex RSiena model to predict twitter relations among (147) Dutch MPs in 2017: summary of main results from Model 1, 2, 3 and 4

	b	se	b	se	b	se
	<i>following</i>		<i>@-mentions</i>		<i>retweets</i>	
<i>Model 1</i>						
same party	1.083	0.146	0.918	0.054	1.386	0.078
<i>Model 2</i>						
same party	1.088	0.150	0.922	0.064	1.388	0.099
same sex	0.129	0.086	0.054	0.054	0.127	0.049
(absolute) age difference	0.035	0.007	0.000	0.003	0.001	0.004
same visible ethnic minority status	-0.390	0.152	0.073	0.055	0.121	0.083
<i>Model 3</i>						
same party	0.755	0.189	0.406	0.106	1.106	0.093
same sex	0.130	0.087			0.115	0.056
(absolute) age difference	0.034	0.007				
same visible ethnic minority status	-0.410	0.145			0.134	0.094
retweets	1.718	0.536	0.454	0.212		
reciprocity with retweets	0.677	0.483	0.245	0.181		
following			0.400	0.072	0.647	0.092
reciprocity with following			0.158	0.066	0.251	0.076
@-mentions					0.801	0.228
reciprocity with @-mentions					0.988	0.231
<i>Model 4</i>						
same party	1.215	0.157	0.804	0.060	1.386	0.079
period*same party	0.957	0.278	-0.448	0.099	0.265	0.056

Notes:

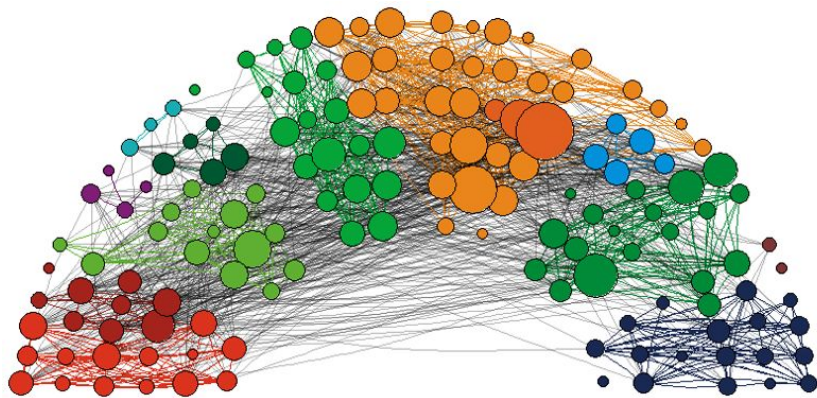
Parameters estimates with a *t*-value smaller than one were dropped to obtain an acceptable model fit. The full results of these models can be accessed via our replication website (***).

Supplementary Material A. Composition of parliament in the Netherlands (2017)

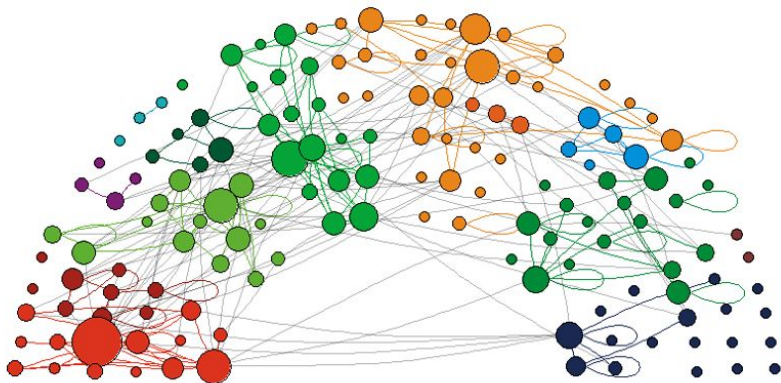
Political Party	social dimension	N / mean	prop. / SD
<i>gender</i>			
parliament	male	96	0.64
parliament	female	54	0.36
<i>age</i>			
parliament		45.13	9.32
<i>minority status</i>			
parliament	no visible minority	134	0.89
parliament	visible minority	16	0.11
<i>political party</i>			
parliament	VVD: People's party for Freedom and Democracy	33	0.22
parliament	PVV: Party for Freedom	20	0.13
parliament	CDA: Christian Democratic Appeal	19	0.13
parliament	D66: Liberal Democrats	19	0.13
parliament	GroenLinks: GreenLeft	14	0.09
parliament	SP: Socialist Party	14	0.09
parliament	PvdA: Labour Party	9	0.06
parliament	CU: Christian Union	5	0.03
parliament	Partij voor de Dieren: Party for the Animals	5	0.03
parliament	50Plus: 50Plus	4	0.03
parliament	DENK: THINK	3	0.02
parliament	SGP: Reformed political Party	3	0.02
parliament	FvD: Forum for Democracy	2	0.01
<i>gender</i>			
VVD	male	23	0.70
VVD	female	10	0.30
PVV	male	14	0.70
PVV	female	6	0.30
CDA	male	13	0.68
CDA	female	6	0.32
D66	male	12	0.63
D66	female	7	0.37
GroenLinks	male	6	0.43
GroenLinks	female	8	0.57
SP	male	9	0.64
SP	female	5	0.36
PvdA	male	4	0.44
PvdA	female	5	0.56
CU	male	3	0.60
CU	female	2	0.40
PvdDieren	male	2	0.40
PvdDieren	female	3	0.60
50Plus	male	2	0.50
50Plus	female	2	0.50
DENK	male	3	1.00
SGP	male	3	1.00
FvD	male	2	1.00

Supplementary Material A. continued

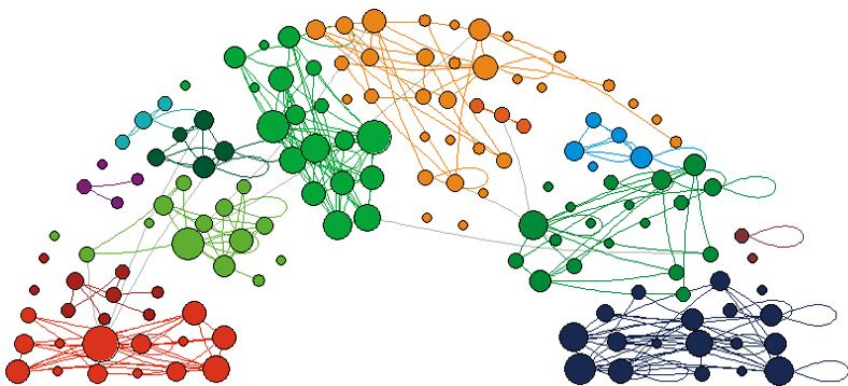
	<i>age</i>		
VVD	age	44.03	6.72
PVV	age	46.05	10.09
CDA	age	44.79	7.84
D66	age	43.84	10.16
GroenLinks	age	47.14	10.08
SP	age	38.36	6.99
PvdA	age	44.89	7.99
CU	age	46.80	4.38
PvdDieren	age	45.20	8.26
50Plus	age	64.75	8.02
DENK	age	42.33	5.51
SGP	age	52.33	7.57
FvD	age	53.50	27.58
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	<i>minority status</i>		
VVD	no visible minority	30	0.91
VVD	visible minority	3	0.09
PVV	no visible minority	19	0.95
PVV	visible minority	1	0.05
CDA	no visible minority	18	0.95
CDA	visible minority	1	0.05
D66	no visible minority	17	0.89
D66	visible minority	2	0.11
GroenLinks	no visible minority	11	0.79
GroenLinks	visible minority	3	0.21
SP	no visible minority	12	0.86
SP	visible minority	2	0.14
PvdA	no visible minority	8	0.89
PvdA	visible minority	1	0.11
CU	no visible minority	5	1.00
PvdDieren	no visible minority	5	1.00
50Plus	no visible minority	4	1.00
DENK	visible minority	3	1.00
SGP	no visible minority	3	1.00
FvD	no visible minority	2	1.00



Panel a. Follower relations



Panel b. @-mentions



Panel c. Retweets



Supplementary Material B. Reciprocated twitter relations between Dutch MPs (2017)
Notes: Node size based on degree. Edge color based on Party affiliation, black if MPs from different party

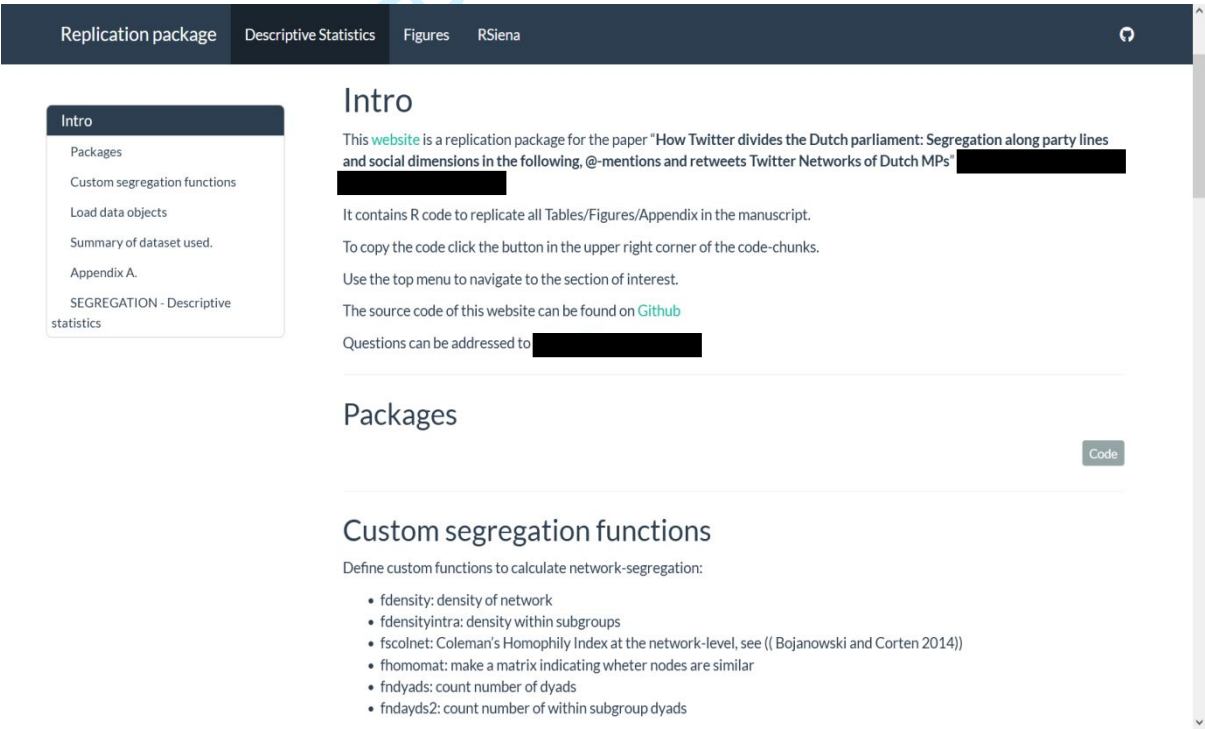
Supplementary Material C. Multiplex RSiena model to predict twitter relations among (147) Dutch MPs in 2017: full results Model 1

	b	se	b	se	b	se
	<i>following</i>		<i>@-mentions</i>		<i>retweets</i>	
<i>rate parameters</i>						
period 1 (April – June)	4.626	0.293	66.540	48.362	18.468	1.760
period 2 (June – September)	2.035	0.130	13.365	0.943	17.263	1.437
<i>structural effects</i>						
outdegree	-13.307	1.871	-4.215	0.140	-3.923	0.164
reciprocity	0.847	0.114	1.402	0.090	0.615	0.094
transitive triplets	0.037	0.007	0.066	0.036	0.157	0.025
shared popularity	-0.001	0.000	-0.008	0.010	-0.014	0.005
indegree - popularity (sqrt)	0.351	0.062	0.395	0.051	0.393	0.045
outdegree - popularity (sqrt)	-0.186	0.034	-0.096	0.039	-0.271	0.059
outdegree - activity (sqrt)	1.328	0.250	0.256	0.025	0.162	0.027
<i>ego characteristics</i>						
Liberal Democrats					-0.427	0.074
Populist Radical Right					-0.180	0.084
Green party			0.135	0.070		
party leader			-0.300	0.096		
incumbent					-0.114	0.045
position on election ballot	0.542	0.154				
<i>alter characteristics</i>						
Liberal Democrats			-0.104	0.071		
Green party			-0.171	0.084		
Incumbent	-0.507	0.087			-0.082	0.046
position on election ballot			-0.012	0.003	-0.012	0.004
party leader			0.129	0.092	0.122	0.079
<i>dyad characteristics</i>						
same incumbency status	0.165	0.083				
seating distance	-0.022	0.007			-0.031	0.006
same party	1.083	0.146	0.918	0.054	1.386	0.078

Notes: Overall maximum convergence ratio: 0.2471; parameter estimates with a *t-value* < 1 have been dropped.

Screenshots of replication website hosted at github

We strongly endorse the principles of open science. We therefore constructed an elaborate an detailed replication website on which all used data, R code and reported findings in the manuscript can be found. This website also allows researchers to assess our findings robustness for alternative modelling strategies. To guarantee the double-blind review process we cannot share the link to the github website/repository at this point in time. We therefore provide the reviewers with some example screenshots.



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Descriptive Statistics
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RSiena

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Appendix A.
SEGREGATION - Descriptive statistics

Load data objects

Data objects:

- key: information on all politicians on election list
- twitter
 - keyf: information on all 147 MPs with twitter handle
 - mydata: RSiena object with all kind of goodies inside
 - seats: seating coordinates of HoP (used for plotting)

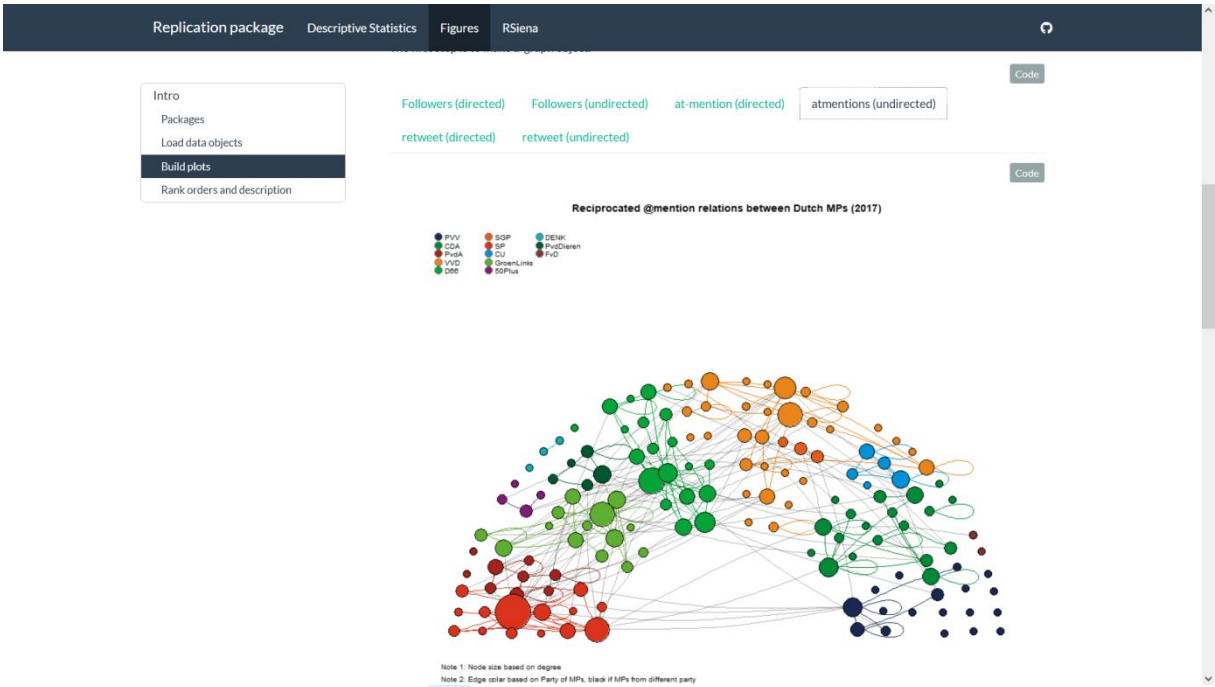
Code

Summary of dataset used.

Code

Dataset summary

Name	Party	Sex	Birth Year	Visible Minority	List Position	Incumbency status	Seating Segment	Seating Row	Seating Column	X-coord.	Y-coord
Agema, Fleur	PVV	female	1976	0	2	1	1	1	2	7.9	-2.9
Amhaouch, Mustafa	CDA	male	1970	1	15	1	2	3	1	9.5	1.3
Arib, Khadija	PvdA	female	1960	1	2	1	6	6	3	-16.1	-0.8
v. Ark, Tamara	VVD	female	1974	0	4	1	3	2	1	3.9	3.5
Azmani, Malik	VVD	male	1976	1	10	1	3	3	2	3.7	5.5
Beertema, Harm	PVV	male	1952	0	10	1	1	4	1	13.6	-4.5
Belhaj, Salima	D66	female	1979	1	14	1	4	4	3	-3.3	7.4
Bergkamp, Vera	D66	female	1971	0	6	1	4	3	4	-4.6	5.0



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Model 2

Social inbreeding homophily

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```
myeff <- getEffects(mydata)
myeff_m1 <- myeff

# according to suggestion of rsiena manual
myeff_m1 <- includeEffects(myeff_m1, inPopsqrt, name = "fnet")
myeff_m1 <- includeEffects(myeff_m1, inPopsqrt, name = "atmnet")
myeff_m1 <- includeEffects(myeff_m1, inPopsqrt, name = "rtnet")

myeff_m1 <- includeEffects(myeff_m1, outActsqr, name = "fnet")
myeff_m1 <- includeEffects(myeff_m1, outActsqr, name = "atmnet")
myeff_m1 <- includeEffects(myeff_m1, outActsqr, name = "rtnet")

myeff_m1 <- includeEffects(myeff_m1, outPopsqr, name = "fnet")
myeff_m1 <- includeEffects(myeff_m1, outPopsqr, name = "atmnet")
myeff_m1 <- includeEffects(myeff_m1, outPopsqr, name = "rtnet")

myeff_m1 <- includeEffects(myeff_m1, transTrip, name = "fnet")
myeff_m1 <- includeEffects(myeff_m1, transTrip, name = "atmnet")
myeff_m1 <- includeEffects(myeff_m1, transTrip, name = "rtnet")

myeff_m1 <- includeEffects(myeff_m1, sharedPop, name = "fnet")
myeff_m1 <- includeEffects(myeff_m1, sharedPop, name = "atmnet")
myeff_m1 <- includeEffects(myeff_m1, sharedPop, name = "rtnet")

myeff_m2 <- myeff_m1

#kamerlid2016' 'pleklijst' 'pleklijst1'

myeff_m2 <- includeEffects(myeff_m2, interaction1 = "kamerlid2016", altX, name = "fnet")
# myeff_m2 <- includeEffects(myeff_m2, interaction1 = "kamerlid2016", altX, name = "atmnet")
myeff_m2 <- includeEffects(myeff_m2, interaction1 = "kamerlid2016", altX, name = "rtnet")

# myeff_m2 <- includeEffects(myeff_m2, interaction1 = "kamerlid2016", egoX, name = "fnet") myeff_m2
# <- includeEffects(myeff_m2, interaction1 = "kamerlid2016", egoX, name = "atmnet") myeff_m2
# <- includeEffects(myeff_m2, interaction1 = "kamerlid2016", egoX, name = "rtnet") myeff_m2
```

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#> Estimates, standard errors and convergence t-ratios

#>		Estimate	Standard Error	Convergence t-ratio
#>	1. rate constant fnet rate (period 1)	4.6699 (0.3148)		-0.0025
#>	2. rate constant fnet rate (period 2)	2.0351 (0.1208)		-0.0196
#>	3. eval fnet: outdegree (density)	-13.8927 (2.4679)		0.0059
#>	4. eval fnet: reciprocity	0.8624 (0.1487)		0.0436
#>	5. eval fnet: transitive triplets	0.0380 (0.0074)		0.0166
#>	6. eval fnet: shared popularity	-0.0007 (0.0003)		0.0159
#>	7. eval fnet: indegree - popularity (sqrt)	0.3507 (0.0599)		0.0138
#>	8. eval fnet: outdegree - popularity (sqrt)	-0.2056 (0.0373)		0.0125
#>	9. eval fnet: outdegree - activity (sqrt)	1.4265 (0.3490)		0.0030
#>	10. eval fnet: afstand	-0.0230 (0.0067)		-0.0074
#>	11. eval fnet: same partij	1.0876 (0.1498)		0.0171
#>	12. eval fnet: same ethminz	-0.3905 (0.1522)		-0.0125
#>	13. eval fnet: vrouw alter	0.2413 (0.0911)		0.0440
#>	14. eval fnet: same vrouw	0.1293 (0.0863)		-0.0225
#>	15. eval fnet: lft alter	-0.0166 (0.0053)		-0.0025
#>	16. eval fnet: lft ego	-0.1400 (0.0541)		0.0116
#>	17. eval fnet: lft abs. difference	0.0353 (0.0068)		0.0213
#>	18. eval fnet: kamerlid2016 alter	-0.4018 (0.1030)		0.0063
#>	19. eval fnet: same kamerlid2016	0.1786 (0.0909)		0.0127
#>	20. eval fnet: pleklijst ego	0.5931 (0.2065)		0.0027
#>	21. rate constant atmnet rate (period 1)	66.2628 (6.9214)		0.0626
#>	22. rate constant atmnet rate (period 2)	13.3240 (0.9697)		-0.0232

Code