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Ideological Homophily and Factional In-Group Bias in Intra-Party Interactions: A Network Analysis of UK MPs on Twitter.

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Abstract

While several studies have analysed the way in which MPs interact on social media, this literature has focused mostly on the *inter*-party ties of MPs. There is still a lack of research into the determinants of *intra*-party interactions. This dissertation analyses the Twitter interaction networks of British MPs between 2020 and 2021 utilising latent space network models. The aim of this study is to understand the role that ideological similarity and factionalism have in structuring MPs' intra-party Twitter interactions. The research finds that ideological distance – as estimated by Wordfish – is negatively associated with the number of interactions in both intra and inter party interactions. This dissertation also shows that factional co-membership is positively associated with the number of interactions - although this effect is highly heterogeneous across factions. The research highlights the advantage of using the network analysis of Twitter interactions as a means to analyse factional cooperation and conflict within parties. Throughout this research the dissertation also adds to our understanding of contemporary British party politics and the factional dynamics within the Starmer's Labour Party and Johnson's Conservative Party.

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Chapter 1: Introduction

Large heterogenous parties, like the UK's Conservatives and Labour, contain actors with a wide range of ideological positions. This internal diversity often leads to factionalism, with likeminded actors grouping together with the goal of steering the party in their preferred direction. Factionalism and intra-party conflict have been found to influence a wide range of political outcomes, from coalition formation (Bäck, 2008) to government collapse (Boucek, 2012). In British politics, conflict between factions has often proven destructive for parties' stability and electoral chances (Williams & Hickson, 2021). Studying intra-party conflict is therefore critical to better understand a range of political phenomena.

However, researching intra-party politics has traditionally encountered numerous difficulties, including a lack of available data and political parties that are outwardly unified in their legislative behaviour. The consequence of these difficulties has been an underdeveloped literature on the topic (Ceron, 2017). This has begun to change, however, as new sources of data have become available and new methods have become mainstream in political science. This research utilises one such novel approach, namely, the network analysis of politicians' social media interactions. As Weaver, et al. (2018, p.141) argue, such an approach "…can reveal fine-grained social structures in contexts where other approaches (e.g. use of voting records) do not succeed."

When using social media platforms, politicians face countless decisions on who and what to engage with. In liking, retweeting, and replying to each other, politicians are making conscious decisions on who – and who not – to interact with. The interactions between politicians can be used to form a network that, when analysed, can reveal politicians' personal relationships, as well as their political preferences. Existing research utilising this approach has predominantly focused on the interactions between parties and the partisan divides in politicians' social media networks. However, research to date has placed insufficient attention on the structure of *intra*-party networks. In this research, I aim to better understand this aspect of politicians' social networks by exploring the role that ideology and factionalism play when politicians are deciding to interact with other members of their party. In so doing, this research also gains an insight into contemporary British politics and highlights the factionalism and intra-party conflict within the UK's Labour and the Conservative parties.

To go about this, I construct a dataset comprising of dyadic Twitter interactions between British MPs during 2020 and 2021. Using this data, I test several hypotheses that seek to explain MPs' decisions to interact with each other at an intra-party level. By using latent space models, I show that even within parties, the ideological distance between MPs determines the degree of interaction. I also find that membership to several factional groupings – in particular, the COVID Recovery Group, Northern Research Group, and Socialist Campaign Group – is strongly associated with the number of interactions between their members. Lastly, I find instances of factional cooperation and conflict by studying the interactions between leadership factions. Taken together, these findings advance our understanding of the determinants of Twitter interactions at an intra-party level, as well as exposing contemporary sub-party social structures among UK MPs.

Chapter 2: Literature Review

2.1 The Promise of Social Media

In Brito et al.'s (2020, p.1) study of co-voting in the Brazilian Chamber of Deputies, they argue that "Politicians with similar voting patterns can be understood as having similar views and interests, thus can be connected in a political network". While this logic may seem intuitive, in many situations, co-voting is a poor measure of political or personal relations.

In highly disciplined legislative environments such as Westminster, analysing the legislative behaviour of politicians often results in a warped view of their relations to one another (Cioroianu, et al., 2019). In most votes, the Westminster system produces a situation where government MPs support legislation, and opposition MPs oppose it. While MPs do rebel, large rebellions are rare occurrences and party Whips pressure MPs to avoid their emergence. Most the intra-party debate and deliberation on legislation happens well before MPs vote on a Division (Owens, 2003; Cioroianu, et al., 2019). If a large selection of backbench MPs oppose legislation, it will likely never reach the voting stage as the leadership will likely back down and avoid an embarrassing defeat. The demands of party politics mean that MPs rarely vote owing to their own individual policy positions contrary to Brito et al.'s description (Hix & Noury, 2016). While MPs display a unity in their legislative actions, this hides a wide heterogeneity in the political preferences within parties. The political pressures of the First-past-the-post electoral system tend to keep these parties from splitting as there are high political costs incurred for those that break away and try and form a new party. In the UK, the few attempts at breaking the two-party system have proven disastrous for renegade MPs (Liddle, 2017; Williams & Hickson, 2021). This is why Chartash, et al., (2018) argue that Westminster systems can be characterised as displaying "high discipline, low cohesion".

In this environment, studying the votes of MPs to investigate intra-party relations is often only fruitful in extraordinary political circumstances where the authority of the Whips' Office breaks down. For example, Intal & Yasseri (2021) analysed the co-voting network of MPs after the Brexit Referendum when both main UK parties experienced persistent rebellions on Europe. Using this network, they were able to identify groups of MPs who held similar preferences and understand patterns of dissent within parties. Yet, in most circumstances, the analysis of Parliamentary Divisions produces limited insightful information on the inter- and intra-party relations of MPs. Resultantly, to study factions and intra-party conflict, alternative data sources are needed.

Social media has been offered as one such potential solution (Weaver, et al., 2018; Cioroianu, et al., 2019). When on social media, politicians can communicate and interact directly in the public's view without the same levels of discipline enforced by party Whips. Therefore, social media interactions can better reflect the personal and political relations between politicians compared to analysing co-voting. Owing to the public nature of these platforms, as researchers we have at our disposal vast quantities of useful data. This opens a host of opportunities for research into intra-party politics. As Andrae Ceron (2019, p. 189) notes when writing about the future direction of intra-party research: "… the recent developments of text analysis, web scraping and social media analysis pave the way to new opportunities to opening the black box of political parties...".

Having shown the promise of analysing social media interactions, in this next section I turn my attention to the literature directly concerned with how and why lawmakers interact on social media. Specifically, I focus on the role that ideological homophily and factional structures play in influencing these interactions.

2.2 Ideological Homophily

Homophily, or the tendency of actors to interact with those who are similar to themselves, is a foundational concept in the literature on social networks (McPherson, et al., 2001). A large body of research has shown that homophily is a powerful force on social media, with likeminded individuals coming together to form online communities (Maria Aiello, et al., 2012; Bisgin, et al., 2012). Social media platforms can also exaggerate this homophilic effect with curation algorithms that promotes content that the user is more likely to interact with.

This can result in ‘filter bubbles’ where users are mostly exposed to content that conforms with their prior beliefs (Berman & Katona, 2019).

Previous studies into the social media interactions of politicians have shown that their interactions are also influenced by homophily. Several studies across a range of political contexts have shown that politicians tend to interact on social media predominantly with members of their own political party (Boireau, et al., 2015; Cherepnalkoski, et al., 2016; Cook, 2016; Cioroianu & Coffe, 2019; Guerrero-Sole & Lopez-Gonzalez, 2019). A couple of recent comparative studies have further supported this finding by demonstrating that politicians prefer to interact with co-partisans across all the countries they studied (Praet, et al., 2021; Van Vliet, et al., 2021).

In terms of inter-party interactions, politicians tend to prefer to interact with other lawmakers from parties ideologically closer to their own. Garcia et al. (2015) and Praet et al (2021) highlight the strong effect that the ideological distance between parties has on the likelihood of politicians forming inter-party ties on social media. Boireau (2014) likewise observed that Belgian politicians tended to interact with other parties within the same ‘party family’, further providing support to the notion that ideology determines politicians’ interactions. These inter-party Twitter interactions can be informative of party positions. Cherepnalkoski, et al (2016) found that greater levels of interaction between parties on Twitter corresponded with higher rates of co-voting in the European Parliament. Likewise, Guerrero-Sole & Lopez-Gonzalez (2019) found that inter-party Twitter interactions can give insight into coalition formation between parties.

Using the fact that individuals and politicians appear to interact in an ideologically homophilic manner on social media, several studies have used social media interactions to predict individuals’ ideology (Bond & Messing, 2015; David, et al., 2016; Ecker, 2017). The most influential of these studies was by Barbera (2014) who used the Twitter follower networks of polititians and the public to estimate individuals' political ideology across a range of countries and then validated these estimates using their stated ideological positions.

While previous research supports the notion that politicians interact in an ideologically homophilic manner, there are still many unanswered questions about the role ideology plays in influencing social media interactions. One unclear question is whether the tendency to interact with other members of the same party is more a product of their ideological similarity or rather in-group bias resulting from a partisan loyalty. This is what Currarini and Mengel (2016) mean when they distinguish between 'homophily' and 'in-group bias'. Disentangling the two is tricky for researchers as members of the same party are ideologically similar.

On top of this, it is yet unclear what role ideology plays in *intra*-party interactions. The primary focus of the prior research into ideology and social media interactions has been on inter-party relations and does not attempt to answer the question below the party level. The reason for this, is likely due to the lack of data regarding politicians' individual ideological positions. The question is therefore unclear whether ideology plays a similar role *within* parties as it does *between* parties in influencing politicians Twitter interactions?

Thirdly, the ideological and partisan structure to politicians' social networks can break down due to events and policy issues that do not map easily onto Left-Right dimensions. Weaver, et al (2018), Cioroianu, et al (2019), and McLoughlin, et al (2019) all focus on the way cleavages around Brexit cut across party lines and disrupted the usual partisan divisions in politicians' social networks.

While beyond the scope of this research, other factors have also been found to influence politicians' interaction on social media. Language (Boireau, et al., 2015), gender (Boireau, et al., 2015; Cioroianu & Coffe, 2019) as well as geography (Cook, 2016) can all influence politicians' decisions to interact. The interactions between politicians on social media is, therefore, not simply a product of ideological similarity but associated with a plethora of factors.

2.3 Factional In-group Bias

Before assessing the relevant literature on role of intra-party factions in determining social media interactions. A definition of faction is needed. For the purpose of this research, I adopt the minimalist definition of faction articulated by Zariski (1960, p.33) and supported by the likes of Boucek (2012). This definition views "…a faction as any intra-party combination, clique, or grouping whose members share a sense of common identity and common purpose and are organized to act collectively – as a distinct bloc within the party – to achieve their goals." As opposed to some other definitions of faction, this minimalist definition can include a range of groups that have received a variety of other names such as 'tendencies', 'issue-groups', 'caucuses', and 'wings' with the condition that there must be a common identity and purpose.

These factions often have different aims and incentives that can be in tension with one another. As a result, intra-party conflict emerges. However, it is important to note that intra-party conflict and factionalism is multidimensional and does not always occur only along left/right lines (Gherghina, et al., 2019). While thinking of factions in terms of Left and Right is often reasonable, it can also be limiting. In the Conservative Party, for example, the largest division in recent history has been on the issue of Europe. This cleavage is not inherently belonging to the Left or Right. Similarly, rival factions may emerge from the same ideological space based on personal disagreements among key individuals. During Tony Blair's premiership, the major factional division was between 'Blairites' and 'Brownites'. While policy differences did exist between these groups, these differences were minor.

Instead, the conflict between the two factions was mostly a product of the conflicting personal ambitions of Blair and Brown (Heffernan, 2011).

To my knowledge, the literature has only placed limited attention on the role of intra-party factions in determining social media interactions. Weaver et al. (2018), do highlight the potential of social media analysis to uncover sub-party social structures like factions and analyse factional divisions based on Leave and Remain. However, the analysis does not go into detail regarding the factional topography, and they acknowledge the utility for a more detailed investigation in this area (p.140).

There has been other relevant quantitative research into intra-party factions that utilise politicians' Tweets (Ceron, 2017; Saltzer, 2020). The purpose of these studies was to estimate the ideological position of factions using computational text analysis. Saltzer (2020), for instance, uses the distance between factions' ideology estimates as a proxy measure for factional conflict. However, these studies are limited because – as mentioned earlier – factional conflict does not necessarily follow Left-Right dimensions. Factions in close ideological proximity can compete with one another while factions who are ideologically dissimilar can cooperate. Using Twitter interactions, we can more directly measure factional conflict and cooperation rather than relying on ideological distance as an imperfect proxy.

Despite the lack of research into this specific question, there is research that can help us understand the likely effects of factional membership on Twitter interactions. One of the most established findings in social psychology is that of 'in-group bias' (Hewstone, et al., 2002). Indeed, Ahmed (2007, p.326) described it as "a universal characteristic of human social life". Individuals tend to have a positive bias in their perception of in-group members at the expense of out-group individuals. As Currarini and Mengel (2016, p.40) put it, individuals "…tend to treat others of shared social identity more favourably".

In political science, one common expression of this is “partisan bias”, where individuals favourably view other supporters of their preferred party at the expense of other party supporters (Ditto, et al., 2018). It is also likely that members of factions display similar biases. As highlighted in Zariski’s (1960, p.33), factions have “…a sense of common identity and common purpose…”. This common identification and the psychological distinction between ‘them’ and ‘us’ is likely to lead to a bias in favour of interacting with in-group members at the expense of out-group individuals.

2.4 Factionalism in Johnson’s Conservatives and Starmer’s Labour

To better understand the likely effects of factional membership on Twitter interactions, we need to delve into the context of factionalism within the modern incarnations of both the Labour and the Conservatives parties.

During the Labour leadership contest, Keir Starmer positioned himself as the ‘unity candidate’ who would end the factionalism that had plagued the Corbyn years (BBC News, 2020). However, soon after he took over as leader, factional conflict erupted over grievances concerning the removal of the Whip from Jeremy Corbyn and the firing of Rebecca Long-Bailey from the Shadow Cabinet. Martell (2020) and Williams and Hisckson (2021) describe this as a strategy of ‘marginalisation’ employed by the Starmer Leadership against the Corbynite Left. Conversely, the other factional groupings within the party have broadly supported the Starmer project. The Old Right and Blairite factions have thrown their support behind Starmer with the launch of the ‘Labour to Win’ group (Rodgers, 2021). The Soft Left has also been supportive of the Starmer leadership having received the bulk of the Shadow Cabinet positions. Ultimately, factionalism under Starmer demonstrates continuity rather than change.

While Labour seems to be undergoing an age-old factional conflict between democratic socialists and social democrats, radicals and moderates, the factional divisions within the Conservatives have been changing in novel ways under Johnson's leadership. Britain's exit from the European Union seems to have ended – or at least lessened – the 'long ideological civil war' over Europe (Gamble & Wright, 2004, p. 1). Those Conservatives that opposed Johnson's Brexit deal quickly had the Whip withdrawn and were later crushed at the ballot box (Boucek, 2013). As Jackson (2021, p.5) writes "...the Conservative Party has now cohered around support for Boris Johnson's hard Brexit. The Europhile strand of Conservatism no longer exists as a meaningful force within the party."

However, this does not mean the Conservatives are a unified party. New cleavages have emerged. For one, the 2019 election introduced a slate of new Northern MPs from formerly 'Red wall' seats. These Northern MPs have different political goals then their Southern counterparts, including a desire for a more proactive government in 'levelling up' their Northern constituencies (Jennings, et al., 2021). These MPs have cohered into the Northern Research Group to promote this end. This has produced concerns from Southern English MPs who fear focus on the 'Red wall' could come at the expense of their 'Blue wall' seats (Stewart, et al., 2021). Secondly, coronavirus has introduced tensions within the party over the management of the pandemic. The expansive role government has taken in this crisis has concerned a contingent of the party with libertarian leanings (Peele, 2021). These MPs formed the COVID Recovery Group to push for easing of government coronavirus restrictions. Unlike the doctrinaire factionalism within the Labour Party, these factions are 'issue-groups' that are predominantly oriented on single policy issues (Hine, 1982; Williams & Hickson, 2021).

Looking at Johnson's Conservatives and Starmer's Labour, both parties are factionalised and display evidence of intra-party conflict. Understanding these divisions within the parties and analysing patterns of dissent are vital to understanding the likely future of the Johnson and Starmer projects.

2.5 Hypothesising Intra-party Social Media Interactions

The Role of Ideology

Given the literature's findings regarding ideological homophily, we would also expect that MPs will interact more with other members of their party that they are closest to ideologically.

> H1: MPs interact more with MPs in their own party that they are closer to ideologically.

The effect of ideology on intra-party interactions is likely to vary across parties. This effect may be lower for the Conservative Party given that they have a reputation as being less ideologically focused then the Labour Party. The Conservatives have traditionally tried to position themselves as the 'natural party of government' that are driven by pragmatism over ideological principle (Douglas, 1983). We would expect therefore that ideological similarity will play less of a role in a Conservative MP's decision to interact with another Conservative. It must be noted however, that the depiction of an unideological Conservative Party has been strongly contested in the post-Thatcher period (Gamble & Wright, 2004).

> H1b: The magnitude of this ideological homophily effect will be larger in the Labour Party compared to the Conservative Party.

The Role of Factions

I broach the question of factions from two directions. Firstly, I focus on the many formal and informal intra-party groupings of MPs. Secondly, I approach the question by looking at the interactions of "leadership factions".

The Parliamentary parties of both Labour and Conservatives contain several sub-party groupings of MPs. In the Labour Party, there are a range of informal to formal groupings of MPs ranging from the Corbynite 'Socialist Campaign Group' to the moderate 'Labour to Win'. In the Conservative Party, the hugely influential 'European Research Group' has inspired numerous descendants, from the 'Northern Research Group' to the 'COVID Recovery Group'. These groupings are constructed of likeminded MPs who seek to shift the policy platform of their party in their preferred direction. Due to the tendency towards in-group bias covered in the literature review, I expect that:

> H2: MPs who are members of intra-party groups will prefer to interact with other faction members.

Despite, the fact that there are several such groupings in both parties, it is not always clear from journalism alone which groups are meaningful and impact the behaviour of their members. Some groups like the COVID Recovery Group and European Research Group are issue-groups and the size of their effect is likely to be tied to the salience of the issue itself. Some groups, such as the Socialist Campaign Group, represent highly cohesive and organised groupings that have distinct views across a range of policy areas. As a result, I would expect heterogeneity in the levels of in-group bias from these factions.

Along a similar vein, I would expect that MPs who endorsed the same candidate for party leader will interact more with one another. Boucek (2012, p.44) identifies leadership contests as 'key junctures' where the fault lines within parties become visible. Those that support the same candidate can be seen as being part of the same 'leadership faction'. As Hazan & Rahat (2010, p.12) argue, "…candidate selection expresses the internal make-up of the party…". Selecting a party leader tends to be a fraught process with contending factions competing to select the candidate closest to their own political preferences (Cross & Blais, 2012). In this view, leadership contests are therefore a good proxy for studying factional groupings of MPs. Furthermore, leadership contests do not only reflect party divisions, but can factionalise parties further. Bitter and closely fought leadership contests can exacerbate party divisions and shape the dynamics within the party going forward. I would therefore expect that:

> H3: MPs will interact more with other MPs who supported their preferred candidate for party leader.

However, ideological proximity is not the only factor that influences whether a MP endorses supports a certain candidate. Stark (1996) highlights three other factors in influencing the selection of party leader, ‘acceptability’, ‘electability’, and ‘competence’. Hence, an MPs decision-making when choosing the candidate is not simply about who is closest to themselves ideologically, but also about deciding who is the most likely to do a good job at winning elections and governing the party. Stark’s framework has been used to explain both the victories of Boris Johnson and Kier Starmer in their leadership contests (Heppell & McMeeking, 2021; Heppell, 2021).

One of the benefits of focusing on leadership factions is that the categories are exclusive. MPs are broken down into clear distinctive groups based on who they endorsed. We can therefore also assess how these groups of MPs interact with each other. I expect that some groups will have lower levels of interaction than others. Given the hypothesis on ideological homophily I would also expect that:

> H4: When interacting with MPs from other leadership factions, MPs will interact more with those other factions that are ideologically closer to their own.

Chapter 3: Data and Methods

To test these hypotheses, this research focuses solely on the current 58th UK Parliament. In particular, I focus the analysis to the two largest parties – the Conservatives and Labour.

While there is undoubtedly factional politics in the SNP and other minor parties, the larger number of Conservative and Labour MPs makes it easier to explore factionalism and ideological heterogeneity.

This research utilises methods of social network analysis. At its simplest, social network analysis refers to the study of nodes (representing social actors) and the edges between them (representing a relationship between two actors). There has been a growing popularity of network analysis methods to study intra-party politics. This use of network methods is no methodological fad, but a theoretically informed choice that reflects the fact that both parties (Koger, et al., 2017) and factions (Disalvo, 2010) are themselves not just hierarchical organisations but rather networks of cooperating and competing individuals and groups. Network methods can better capture this theoretical understanding and model the social and political ties between actors.

3.1 Data Collection

The first step in this research process is to assemble a dataset that measures how MPs interact with one another on social media. As mentioned previously, this research utilises Twitter for this purpose. Twitter was used over alternative social media platforms primarily for practicality purposes. Twitter is inherently dyadic in nature with MPs following, liking, retweeting, and mentioning other MPs. This easily translates to the idea of edges in network analysis. Twitter's API also makes it easy to programmatically collect large quantities of data with relatively few limitations imposed. Both these factors made Twitter the obvious choice and it is little surprise that most studies into politicians' activity on social media have utilised Twitter for their studies.

I focus on two forms of Twitter interaction. Firstly, I collect instances of when an MP 'retweets' another MP's tweet. Secondly, I also collect occasions when an MP 'likes' another

MP’s tweet. Underpinning the inclusion of these interactions is the assumption that both these functions are forms of endorsement. Whether retweeting is always endorsement has been disputed in some research (Liu, et al., 2012), but broadly, most researchers acknowledge that – in most situations – retweeting is an expression of support for a tweet (Guerrero-Solé, 2018). To test the robustness of whether likes and retweets are measuring the same type of behaviour. The appendix shows a comparison of some findings when just retweets and then just likes. Overall, using either form of interaction gives similar findings – albeit with slightly different magnitudes. This supports the assumption that both likes and retweets measure the same behaviour.

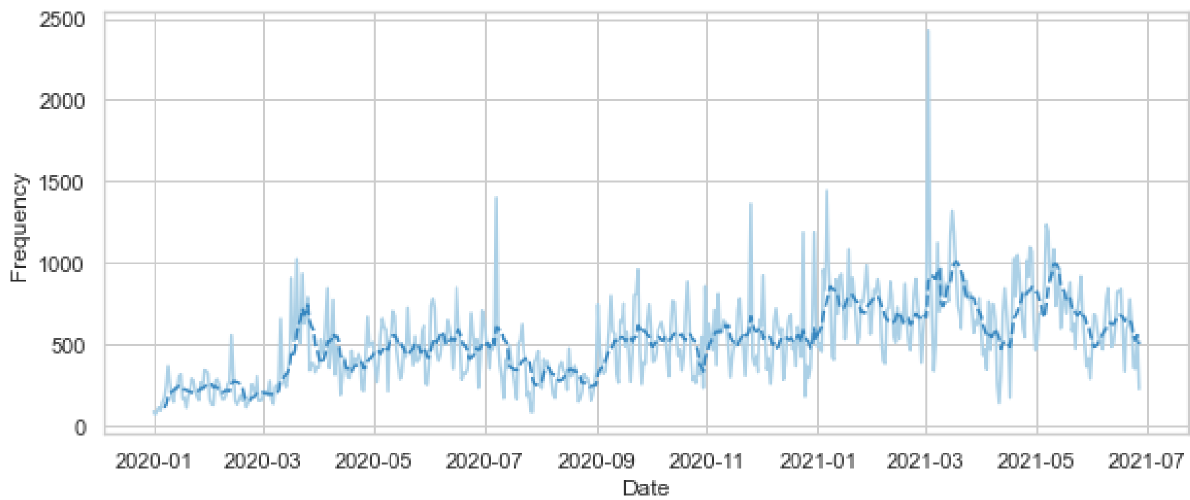
I choose to collect both retweeting and liking interactions primarily because it increases the sample size, which resultantly strengthens the certainty of the model estimates. Other forms of Twitter interaction could plausibly have been used. ‘Mentions’, for example, have been used elsewhere in the literature (Boireau, et al., 2015), as well as ‘follows’ (Barbera, 2014). Yet, both these interactions are less frequent and less obviously used as an expression of agreement.

There are some limitations to using Twitter as a source of data. For one, not all MPs are active on Twitter. 72 (11%) MPs did not have accounts during the research process and are therefore missing from this study. Moreover, this missingness is not randomly distributed. Conservative MPs seem to be less likely to use the platform. 80% of MPs without Twitter are Conservative. Nevertheless, the majority of MPs from every party do have Twitter accounts, so it is unlikely that missing data would too severely impact any findings.

Using the Python library *Tweepy*, I collected these Twitter interactions from between the 1st of January 2020 and the 28th of June 2021. This period covers most of the 58th Parliament up to the date of writing. As a result of this collection strategy, 137,618 retweets between MPs were collected. On top of this, 144,690 likes were also collected. Together this makes a total of 282,308 Twitter interactions for this research. Figure 1 below breaks down the number of tweets collected over time. The figure demonstrates a good spread of interactions collected throughout the period giving this research a broad view of the 58th Parliament to date.

Once collected, this data was used to form an adjacency matrix in which the rows and columns represent the MPs, and the values contained in the matrix constitute the total number of interactions between any two MPs. Using this adjacency matrix, I constructed a weighted, non-directed network with MPs functioning as nodes and the frequency of twitter interactions forming the weight of the edges. A visualisation of this network can be seen in the appendix to this paper.

Figure 1: Frequency of Collected Twitter Interactions Over Time.



3.2 Independent Variables

1) Measuring Ideology

To analyse whether ideological similarity influences MPs' decision to interact with other co-partisans, I use the distance between MPs' Wordfish estimates as a predictor. The Wordfish model is an unsupervised text scaling technique developed by Slapin and Proksch (2008), that positions actors on a one-dimensional latent scale. The underpinning assumption behind this, and other quantitative text scaling models, is that the ideology of an actor can be inferred from the words they use and the frequency at which they use them. The Wordfish model has achieved widespread use in political science for its simplicity and its ability to infer ideological positions across a range of actors and data sources. Importantly for this research, prior studies have demonstrated its usefulness at differentiating between sub-party actors including factions and individuals (Schwarz, et al., 2017; Ceron, 2017; Haber, 2015; Saltzer, 2020). Such a capability is vital for this study, as we need to be able to measure ideological heterogeneity within parties.

In brief, the model assumes that the frequency of words comes from a Poisson process. The Wordfish model as applied to this research can be summarized as below:

$$Y_{i,j} \sim Poisson(\lambda_{i,j})$$

$$\lambda_{i,j} = exp(\alpha_i + \psi_j + \theta_i \beta_j)$$

Here λ refers to the mean and variance of the Poisson distribution. The alpha refers to the fixed effect of individual *i* which controls for the fact that the length of text varies by individual MP. The parameter ψ denotes the fixed effect of word *j* which likewise controls for the fact that some words are more commonly used regardless of political ideology. The beta highlights the degree to which word *j* distinguishes between MP's texts. Lastly, Θ represents the latent position of the MP *i* on the identified dimension. For this research, I implemented Wordfish using Will Lowe's (2017) *austin* package for the R statistical programming language.

After choosing Wordfish, the question becomes which source of textual data to use. For this purpose, I use the content of MPs' Tweets over the same period as I used for MPs' Twitter interactions. The social media posts of politicians are more likely to resemble the true ideological opinions of politicians compared to their legislative speeches or official statements (Ceron, 2017). Bhattacharya (2019) found that in Parliamentary debates party leaderships often exercise tight control over the speeches made by its members. As a result, there is the potential for party speeches not to be representative of the individuals' policy positions. Because of this fact, I judge that tweets are a better source of data to capture ideology.

In total, I collected 961,777 individual tweets to feed into the Wordfish model. In terms of pre-processing, I removed hyperlinks and mentions but deliberately retained other online specific language such as hashtags and emojis as these can be important carriers of information. I also removed punctuation and stop words but did not reduce words to their stems as previous research has shown this makes little difference to estimates (Proksch & Slapin, 2009). On top of this, I removed words that were mentioned in less than 20 articles as this helps remove outliers (Saltzer, 2020).

Looking at these Wordfish estimates, the model clearly captured Left-Right variation in language use. The Wordfish latent positions of both MPs and words can be viewed in the appendix. It shows that the model ascribed Left-leaning words such as 'comrade', 'inequality', and 'solidarity' a highly negative value and Right-wing words such as 'innovation', and 'queen' a positive value. The appendix also shows the positions of MPs by party, compared to the Chapel Hill expert survey estimates from 2019. This shows that the Wordfish estimates align with the Chapel Hill estimates with only some minor variation among the smaller parties who are of less interest to this study. Taken together, the Wordfish model appears to have worked as anticipated and the latent dimension does in fact capture ideology.

Lastly, using these Wordfish estimates, I formed a matrix of ideological distances between MPs. This matrix is the same shape as the adjacency matrix of Twitter interactions that can then be used as a predictor in statistical analysis. We would therefore expect that as the ideological distance between MPs increases, it will be associated with a negative effect on MPs' Twitter interactions.

2) Factional Groupings

The collection of factional groupings of MPs is a challenge as few groups publish complete lists of members. Without the existence of such definitive lists of factional memberships, I predominantly relied on a range of qualitative sources to infer membership to factions. These membership lists are not exclusive, and many MPs were identified as belonging to multiple factional groups. The research process of inferring which MPs belonged in which faction can be viewed in the appendix. Undoubtedly, these are not exhaustive lists of factional membership and so the estimates should be viewed with a degree of uncertainty because of this.

For the Labour Party I include three prominent factional groups, the Socialist Campaign Group, Open Labour, and Labour to Win. These were chosen as they broadly represent the main ideological traditions within Labour – Hard Left, Soft Left, and Right. Labour to Win is a recent group formed from a combination of the Old Right faction, Labour First and the Blairite faction, Progress. Another Soft Left faction is the Tribune group, this group has heavy overlap with those associated with Open Labour and so is not included. However, the results are very similar when using either faction. In terms of the size of their memberships, I Identified 42 MPs associated to Open Labour, 34 with the Socialist Campaign Group, and 81 with Labour to Win.

For the Conservative Party, I included six factions that have been visible in the journalistic coverage of this parliament. This includes, the European Research Group, the Northern Research Group, the COVID Recovery Group, the Common Sense Group, the One Nation Conservative Caucus and the Blue Collar Conservatives. In terms of membership, I identify 82 members of the ERG, 38 members of the COVID Recovery Group, 41 members of the Northern Research Group, 26 members of the Common Sense Group, 62 members of the One Nation Conservative Caucus, and 87 members of the Blue Collar Conservatives.

2) Leadership Factions

To test Hypotheses 3 and 4, I collected data on which MPs nominated who for party leader. For the Labour Party this collection was a very simple process. Leadership nominations are a formalised part of the selection process and are made public. Secondly, the last Labour leadership election occurred within this parliament giving up to date information on most Labour MPs. Consequently, information is missing for only a couple of Labour MPs who did not nominate a candidate. Some of the candidates that dropped out of the race at an early date and had only a few nominations are not included in the analysis. This leaves 5 leadership candidates: Rebecca Long-Baily, Kier Starmer, Lisa Nandy, Emily Thornberry, and Jess Phillips.

Collecting the same data on Conservative leadership nominations is more difficult. For one, while Conservative MPs do vote for party leader, these votes are not made public. Resultantly, I relied on the self-reporting of MPs based off media and social media statements. A number of newspapers and websites have collated much of this information for ease of access (e.g. Goodman, 2019). A second problem is that the last Conservative leadership race took place during the last parliament in mid-2019. Since that date, there has been considerable churn within the Parliamentary Conservative Party. Resultantly, information on leadership nominations is missing for 146 (40%) of the Conservative MPs. On a more fundamental level, the Conservative Party has changed in dramatic ways since the last leadership election, it might be doubtful if the political divisions of the 2019 leadership contest are still meaningful for the modern incarnation of the Conservative Party. In a similar manner to the collection of Labour candidates, I did not include every candidate for Conservative Party leader. Rather, I included the six candidates that lasted the longest and had a sizable support from MPs. These leaves supporters of Boris Johnson, Dominic Raab, Jeremy Hunt, Michael Gove, Rory Stewart, and Sajid Javid.

3.3 The Latent Space Approach

Most of the usual statistical methods in a social scientist's toolbox assume the conditional independence of residuals. Social networks on the other hand are focused on relational dynamics, where the ties between observations influence their outcomes. To deal with this challenge to the independence assumption, a growing range of statistical tools have been developed for the analysis of social networks. This research utilises an approach known as *latent space network models* (LSMs). These models were first developed by Hoff, Raftery, and Handcock (2002) and extended to non-binary data by Hoff (2005). To get around the problem of inter-dependencies between nodes, LSMs condition on the nodes' positions in a k-dimensional latent 'social space' estimated by using multidimensional scaling methods. The Euclidean distance between two nodes in latent space indicates the probability of those nodes forming a tie. By controlling for the nodes' latent positions, we can get estimates of the covariates without the biasing effect of inter-dependencies between individuals, as these dependencies are captured in the latent space parameter.

LSMs were chosen over alternative methods for several reasons. Firstly, the idea of social space models for the transitive nature of social relations. *Ceteris paribus*, the existence of ties (i ↔j) and (i↔k) implies that j and k are close together in social space. In the case of MP interactions on Twitter, this makes intuitive sense. An MP interacting with Diane Abbot and John McDonnell will also likely be close to Jeremy Corbyn as they are more likely to have similar latent characteristics. Because of this, LSMs make theoretical sense in the context of this research. On top of this, Hoff, et al., (2002) argue that by modelling edges as transitive, the model fit is improved compared to alternative approaches.

Secondly, LSMs are simple to fit in comparison to Exponential Random Graph Models – the main alternative family of models – which require the specification of endogenous dependencies which LSMs capture in the latent space term. While this arguably brings added flexibility, it also opens room for misspecification. A good overview of the strengths of weaknesses of different approaches can be viewed in Cranmer, et al., (2017). The LSM itself resembles a generalized linear model albeit one that is "elaborately specified" (Cranmer, et al., 2017, p. 242). In the case of this research, the weights of the edges are modelled using a Poisson distribution. This model can be expressed as below:

$$Y_{i,j} \sim Poisson(\mu_{i,j})$$

$$\log\ \mu_{i,j} = \eta_{i,j} = \sum_{k=1}^{p} \beta_k X_{k,i,j} + d(z_i, z_j) + \delta_i + \delta_j$$

Here the edge weight of *y* between two nodes (*i and j*) is taken from a Poisson distribution given the mean and variance of μ. The parameter *p* represents all the covariates included in the model. The beta refers to the coefficient of these covariates. *d* refers to the Euclidean distance between nodes' coordinates (*z)* in three-dimensional latent space when conditioned on the model's covariates. Three dimensions were chosen through a process of trial and error. While Hoff, et al., (2002) suggests two dimensions usually suffice, I found that two dimensions often created counterintuitive results such as placing Sinn Fein MPs centrally – close to the Liberal Democrats – in latent space. MPs' latent space positions had more face validity when using three dimensions. δ models the sociality effects of both nodes i and j. This effect explicitly models for the fact that MPs may have different levels of activity on Twitter and are therefore more likely to form ties.

All models fitted in this paper used the R package *latentnet*. The models themselves were estimated using a maximum likelihood estimator (MLE). MLE is, admittedly, a less sophisticated approach compared to the Bayesian alternative that *latentnet* also implements. However, MLE is computationally far faster than the Bayesian alternative, especially when dealing with larger networks. MLE does, however, tend to overfit the data compared to MCMC (Hoff, et al., 2002, p. 1094). However, this problem only becomes disastrous when dealing with isolated nodes. On top of this, when I compare the two approaches, they show only minor differences in their estimates. A figure in the appendix compares the results of models when using the MLE and MCMC approaches. It shows only minor differences in the estimates. As a result, for practicality purposes, I opt for MLE as the estimator of choice for the LSM models. It is noteworthy however, that the MCMC estimation does model a higher degree of uncertainty in its estimates. It is important to therefore bear in mind that MLE may underestimate the uncertainty when viewing the results.

Latentnet Model Terms

This research makes use of three terms available in the *latentnet* package:

1. Nodematch: The nodematch term estimates the effect of nodes i and j sharing the same attribute.

2. Nodemix: While nodematch only models the effect of when attributes of i and j are matching, nodemix adds a term for every possible combination of the attribute's value.

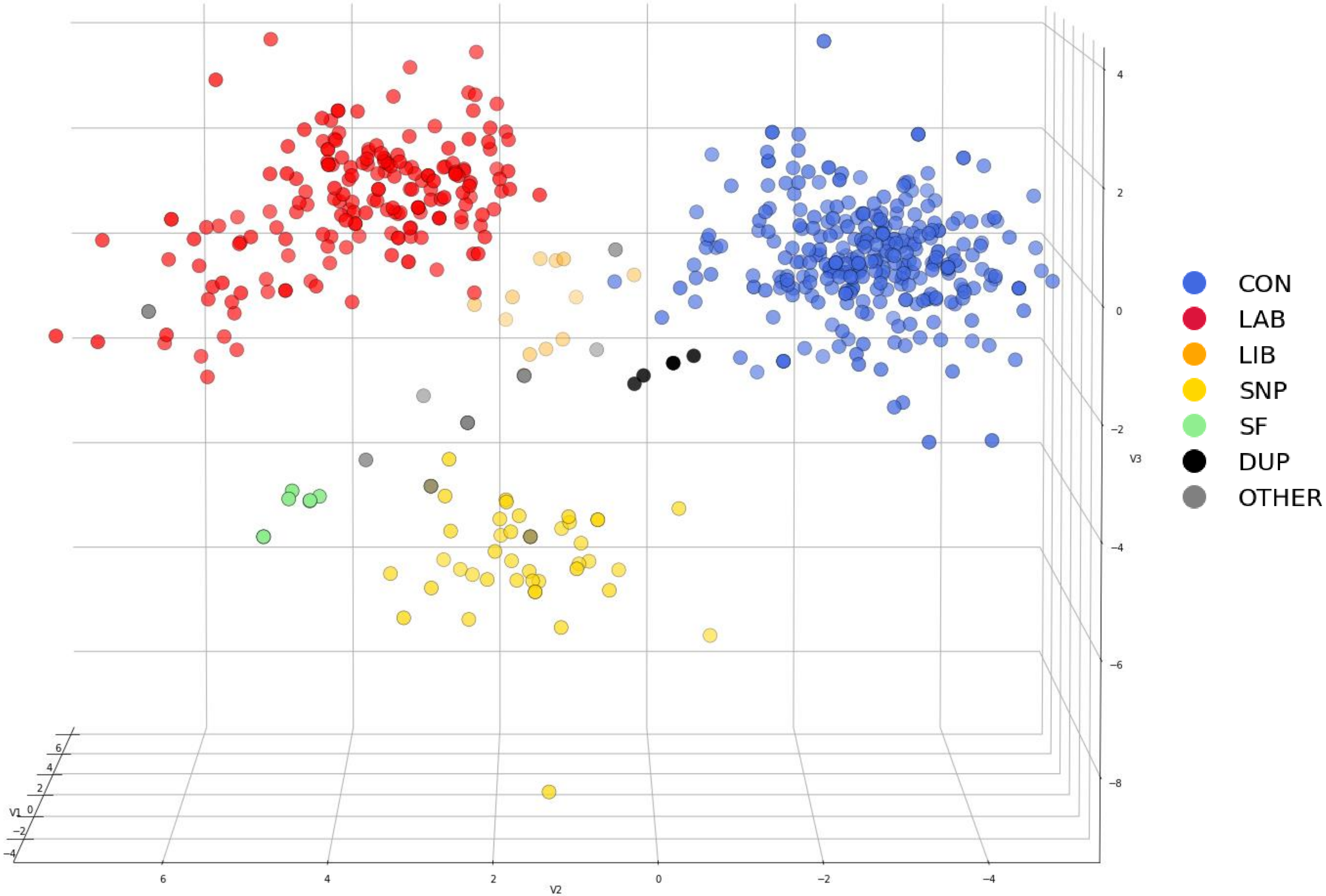
3. Edgecov: Both nodematch and nodemix model the effect of nodal attributes. The edgecov term instead estimates the effect of a quantitative edge attribute.

Chapter 4: Findings

4.1 Visual Evidence

As a first step, I run a LSM model with no covariates to view the nodes' positions in latent space when not conditioning on any variables. Figure 2 shows the estimated positions of MPs in social space. The closer the proximity of two nodes in social space the more similar their latent characteristics and the higher the expected number of their social media interactions. I rotated the plot so that it best visualises the Left-Right variation of MPs' positions. Figure 2 shows that MPs tend to form clusters based on their party membership. This indicates that MPs prefer to interact with co-partisans – although its difficult to see if this is driven by partisan loyalty or ideological similarity. Ideological also clearly plays an important role in structuring inter-party Twitter interactions. Parties with similar ideologies are positioned closer together, for example, Labour is closer to Sinn Fein and the SNP, while the Conservatives are closer to the DUP. The Liberal Democrats are placed centrally between the Conservatives and Labour which is representative of their political centrism. However, while ideology clearly has a role, variation across V1 and V3 highlight that other factors also determine MPs' Twitter interactions. On top of this, it is difficult to assess the effect of ideology on interactions below the party level from this visualisation.

Figure 2: Node Positions in Three-Dimensional Latent Space When Conditioning on No Covariates



To better visualise the intra-party structure of MPs' Twitter interactions, Figure 3 shows a hierarchical dendrogram. This dendrogram uses the latent positions of MPs to identify the hierarchical structure in MPs social relations by applying the complete-linkage clustering method. This dendrogram enables us to better view the clustering of MPs at multiple levels – including sub-party clusters.

Figure 3: Hierarchical Dendrogram of MPs' Positions in Latent Space.

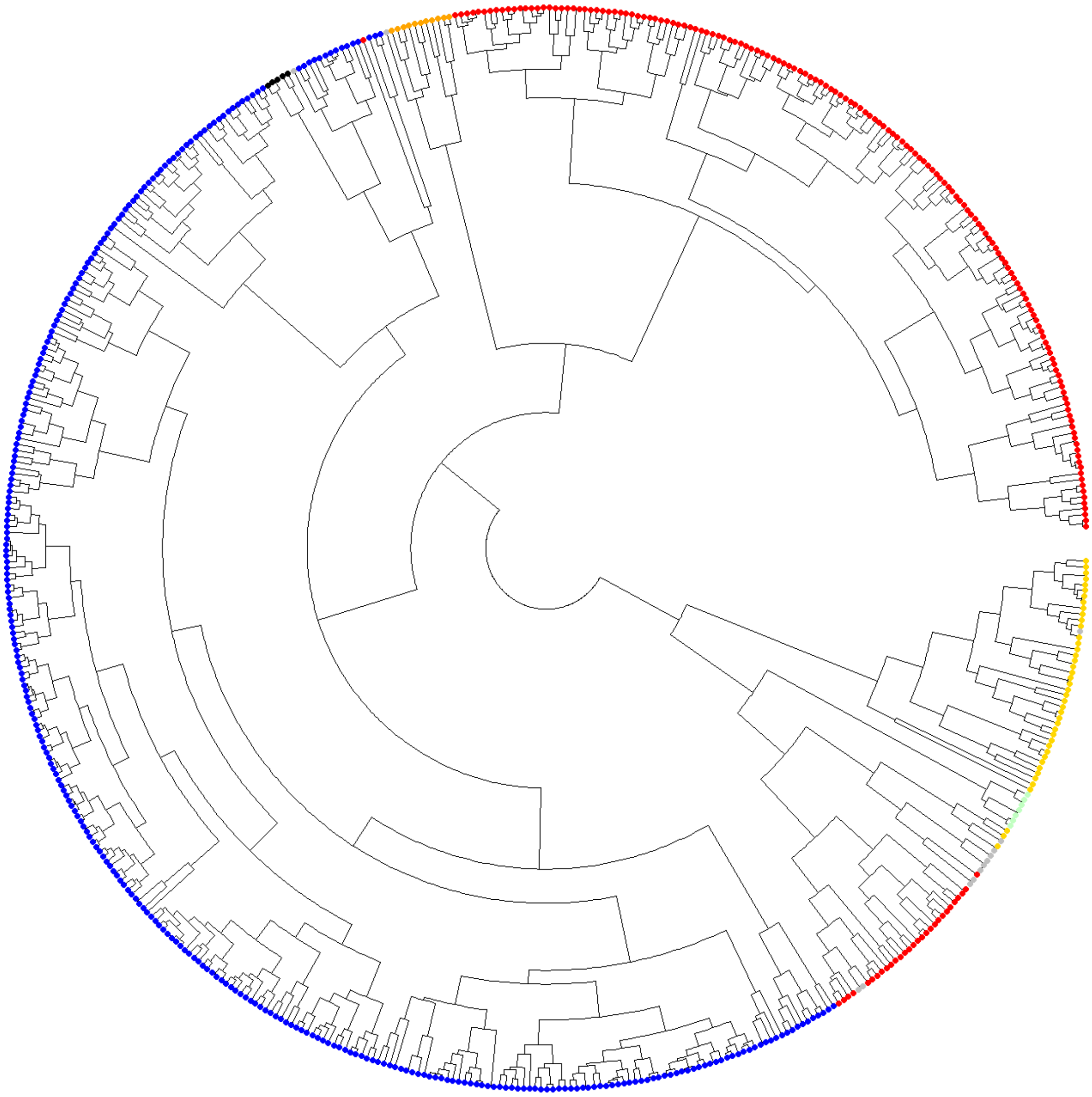


Fig.3. Dendrogram leaves coloured by same scheme as Figure 2. Clustering using complete-linkage method.

The most striking feature in Figure 3 is the division of Labour Party MPs into two clusters. The larger group of Labour MPs form a cluster close to the Liberal Democrats whilst the smaller group forms a cluster with the SNP, Sinn Fein, and others. Looking at the membership for this smaller Labour group, these MPs mostly consist of members of the 'Corbynite Left' of the Labour Party. In particular, this group contains several high-profile political allies of Jeremy Corbyn, the former Labour Party leader. John McDonnell, Diane Abbot, John Trickett, Ian Lavery, and Rebecca Long-Baily are just a few of the MPs in this cluster. Indeed, 26 out of the 28 Labour MPs in this smaller group supported Rebecca Long-Bailey for party leader and the vast majority are members of the Socialist Campaign Group. This does indicate some degree of factional divisions within the Labour Party's Twitter network. It is perhaps not surprising that supporters of Jeremy Corbyn and Rebecca Long-Bailey form a separate cluster given their reportedly sour relations with the current Labour leadership (Rodgers, 2021). The removal of the Whip from Jeremy Corbyn, the firing of Rebecca Long-Bailey from the Shadow Cabinet, and the Rightward shift of the Labour Party in general, have all contributed to a deeply antagonistic relationship between the Labour Left and Starmer's leadership. It is still noteworthy, nonetheless, that the Labour Left are clustered with the SNP and Sinn Fein rather than with the rest of the Labour Party.

The Conservative Party MPs on the other hand do not display the same degree of division compared to the Labour Party. Visually comparing this dendrogram to the one presented by Weaver, et al., (2018) it is clear that the role of Brexit divisions within the Conservative Party have reduced. Indeed, there is no visually evident clustering based on MPs' stance on Europe. Nonetheless, there are some observable sub-clusters in the Conservative Party. The dendrogram broadly sub-divides the Conservatives into two sub-clusters. The smaller group (that cluster close to the DUP) tend to be more rebellious, especially on the issue of COVID restrictions. This group contains the likes of Mark Harper, Steve Baker, William Wragg, Esther McVey, and Philip Davies who have all been critical of COVID lockdown measures and are members of the COVID Recovery Group. This indicates the Conservative Party’s network also displays some evidence of issue-based cleavages and potentially even factionalism. Yet, it is difficult to visually assess the extent of this clustering and compare it to other factional groups.

As demonstrated, some broad trends are visually identifiable. However, to get a better understanding of the magnitude and significance of these effects, statistical analysis is needed.

4.2 Estimating the Role of Ideology

I now turn to testing what role ideological similarity has on influencing MPs’ interactions with one another. Figure 4 contains four models. The first model shows the effect of party membership – i.e., the effect of two MPs being from the same party. The second model adds an edge covariate measuring the ideological distance between MPs as well as adding several control variables. This helps the model distinguish between ideological homophily and partisan in-group bias. The third and fourth models tests the effects of homophily when analysing only Conservative and Labour nodes. This is done so that we can assess whether ideology has a differential effect within each main party.

In terms of the interpretation of the models, the Poisson model uses a log link function, therefore, the exponential of the coefficient is multiplicative in its effect. Hence, In the case of the Conservative coefficient (*Model 1*), two MPs being Conservative is associated with an average edge weight 32 times higher than the intercept. In this case, it gives an average edge weight of 8.76 interactions between two Conservative MPs. The Labour coefficient is associated a 21 times higher edge weight on average – giving an average weight of 5.84 interactions. The highest estimate is given to Sinn Fein MPs, this is likely because they tend not to interact with most other Westminster MPs and so mostly communicate amongst themselves.

Model 1 conforms with both the visual evidence I presented, as well as the findings of prior research. It highlights the large effect partisan membership has in determining Twitter interactions. This effect is highly heterogeneous across parties. Particularly interesting is that the Conservative estimate is higher than the Labour estimate. This may indicate higher levels of party unity among Conservative MPs. Despite this, it is not obviously clear what is the cause of this difference. Is it because the Conservative Party is more unified? Or is it that most other parties are ideologically closer to Labour and therefore less likely to interact with the Conservatives?

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Figure 4: LSMs Testing the Effect of Party Homophily and Ideological Distance on Twitter Interactions

	Model 1 - Party			**Model 2 - Ideology**			**Model 4 - Labour**			**Model 5 - Conservative**		
	Estimate	Sig	Std. Error	Estimate	Sig	Std. Error	Estimate	Sig	Std. Error	Estimate	Sig	Std. Error
(Intercept)	-1.29	***	0.01	-0.91	***	0.01	2.88	***	0.01	1.17	***	0.01
Edgecov – Ideological Distance												
Wordfish Estimates				-0.20	***	0.00	-0.13	***	0.01	-0.23	***	0.00
Nodematch - Party												
Conservative	3.46	***	0.01	3.02	***	0.01						
Democratic Unionist Party	4.35	***	0.11	2.61	***	0.16						
Labour	3.05	***	0.01	2.40	***	0.01						
Liberal Democrat	4.52	***	0.03	4.47	***	0.03						
Scottish National Party	3.66	***	0.02	2.41	***	0.04						
Sinn Féin	7.88	***	0.06	6.83	***	0.12						
Controls	X			✓			X			X		
Sociality FE	✓			✓			✓			✓		
Nodes	568			568			186			302		
Total Edges	28697			28697			10030			14647		
Density	0.18			0.18			0.58			0.32		

*** p<.01, ** p<.05, * p<.1 – controls include *nodematch* parameters for region, gender, and parliament intake.

Model 2 shows the effect of ideological distance (as estimated by Wordfish) being entered into the model. The negative value indicates that – as hypothesised – an increase in the ideological distance between MPs is associated with a lower average number of interactions. An increase in the ideological distance between two MPs by 1 unit (Wordfish estimates vary from around -2 to 2) is associated with the weight of the edge being 22% lower on average. Again, this supports pre-existing research that finds ideological similarity is an important influence on the formation of politicians' ties. The inclusion of the ideology term and other control variables in Model 2 causes a decrease in the party effect coefficients. This implies that these other homophily covariates explain some of why MPs from the same party interact more with one another. However, the effect of belonging to the same party is still very high. This indicates that homophily is not the only driver of interactions between MPs of the same party, rather, partisan in-group loyalty seems to be an important factor when determining Twitter interactions.

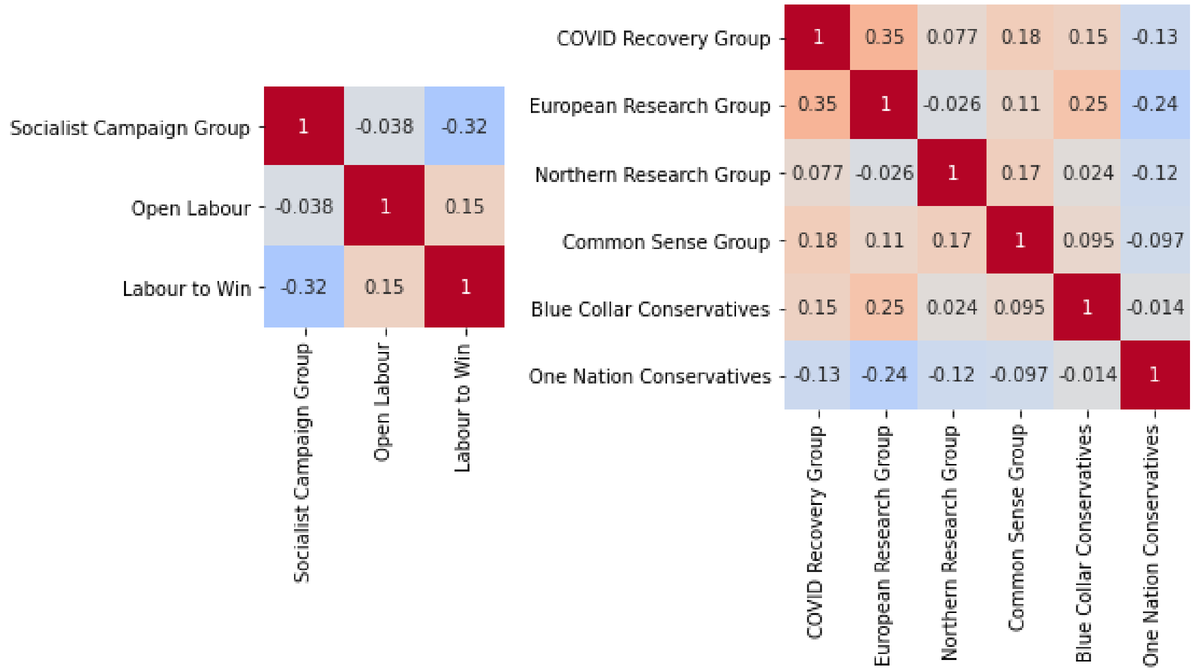
Models 3 and 4 show the effect that ideology has *within* Labour and the Conservative parties. The significant effect of ideological distance in both models indicates that, even within parties, ideological proximity is associated with the number of interactions between MPs. This provides support for Hypothesis 1. However, regarding Hypothesis 1b, the observed findings are the opposite to that hypothesised. The effect of ideological distance on Twitter interactions appears to be higher for Conservative MPs compared to Labour MPs. While a one unit increase in ideological distance is associated with a 26% lower average number of interactions for the Conservative Party, the same value for the Labour Party is only 12%.

Despite this, we should not rush into any hasty conclusions regarding the hypotheses. The validity of these findings rests upon the validity of the Wordfish estimates. There are a number of limitations with using Wordfish estimates as a predictor in the LSM. For one, the uncertainty of the Wordfish estimates themselves are not integrated into the latent space models. This means that there is a large degree of uncertainty not reflected in the results. Because of this, comparison between the Labour and Conservative estimates should be treated with a higher degree of uncertainty than is reflected in the standard error. Nevertheless, while we should be reticent to fully reject Hypothesis 1b, the findings do provide evidence for the fact that ideology structures MPs' intra-party interactions. Future research will be needed to better understand the differential role that ideology plays in both Conservative and Labour intra-party interactions. This future research should make use of alternative measures of individual MPs' ideologies in order to ascertain the robustness of these findings.

4.3 Factionalism in Social Media Interactions

These findings support, strengthen, and extend the literatures findings regarding the role of ideology. I now turn my attention to the role of factional structures and dynamics within the Conservative and Labour parties' social media networks. This section tests Hypotheses 2 by looking at how membership to different factional groupings within the Conservative and Labour parties influences MPs' decisions to interact with one another. As mentioned in the methodology, I focus on six groupings within the Conservative Party and three groups within the Labour Party. MPs are not limited to belonging to one group. Indeed, many MPs are members of several factional groupings. For example, the Conservative MP William Wragg, is a member of the Common Sense Group, the European Research Group, and the COVID Recovery Group. To get a better look at how the memberships of these groups overlap, Figure 5 shows correlation matrices that measure the degree to which different factions' memberships align.

Figure 5: Matrices Showing Correlations of Factional Group Membership.



For the Labour Party, Figure 5 shows that the highest level of membership overlap is between Open Labour – representing Soft Left MPs – and Labour to Win – representing the Labour Right. Labour to Win membership has a strong negative correlation with that of the Socialist Campaign Group which is to be expected given they represent opposite ideological traditions within the Labour Party.

Likewise, many of the factional groups within the Conservative Party have overlapping memberships. The highest membership correlation is between the COVID Recovery Group and the European Research Group. Wagner and Bale (2020) argue that Euroscepticism and lockdown-scepticism are views that make easy bedfellows as they both share a common libertarian ideological foundation. Both groups also share a significant membership with the Common Sense Group, who focus on social conservative issues – “nationhood, community, migration, the rule of law and public order” (The Common Sense Group, 2021, p. 1). The Blue Collar Conservatives similarly have a high level of overlapping membership with the European Research Group. The One Nation Conservative Caucus, on the other hand, has little overlap with other groups, its membership tends to occupy the more Europhile, economic interventionist wing of the party.

To assess how membership to these intra-party factional groupings impacts MPs' Twitter interactions, I include them as *nodematch* parameters in various latent space models. Figure 6 shows a coefficient plot of four models. Two of the models focus on the Conservatives and two on the Labour Party. I also show the results with no controls and results when controlling for ideology and other variables. The full models can be viewed in the Appendix to this paper.

Figure 6 highlights that co-membership to many – but not all – of these factions has a positive effect on the average edge weight between members. The factional groups with the highest magnitude include the Socialist Campaign Group for Labour and the COVID Recovery Group for the Conservatives. The effect of two MPs being in the Socialist Campaign Group is associated with a 2.86 times higher average number of interactions. For the COVID Recovery Group this value is 2.53. Evidently, members of these factional groups have a very strong preference to interact with other faction members.

It is, however, unclear as to why these groups have higher effects compared to others. To speculate, Peele (2021) argues that the coronavirus pandemic has introduced new divisions in the Conservative Party over the unprecedented role that government has taken in order to limit the spread of the pandemic. Due to much of Twitter discourse being centred on the issue of COVID, it is understandable that Twitter interactions are structured based on MPs' opinions on the issue. This is similar to Weaver, et al.'s (2018) findings during the Brexit Referendum. As Brexit was the dominant issue of the time, divides between Leave and Remain structured the interactions between MPs. Given that these factions are issue-based one would expect their effect size to be tied to the salience of the issue itself. This provides a good explanation as to the high magnitude of the COVID Recovery Group observed in Figure 6.

Figure 6: Coefficient Plot Showing Factional Determinants of Twitter Interactions – 95% confidence intervals shown

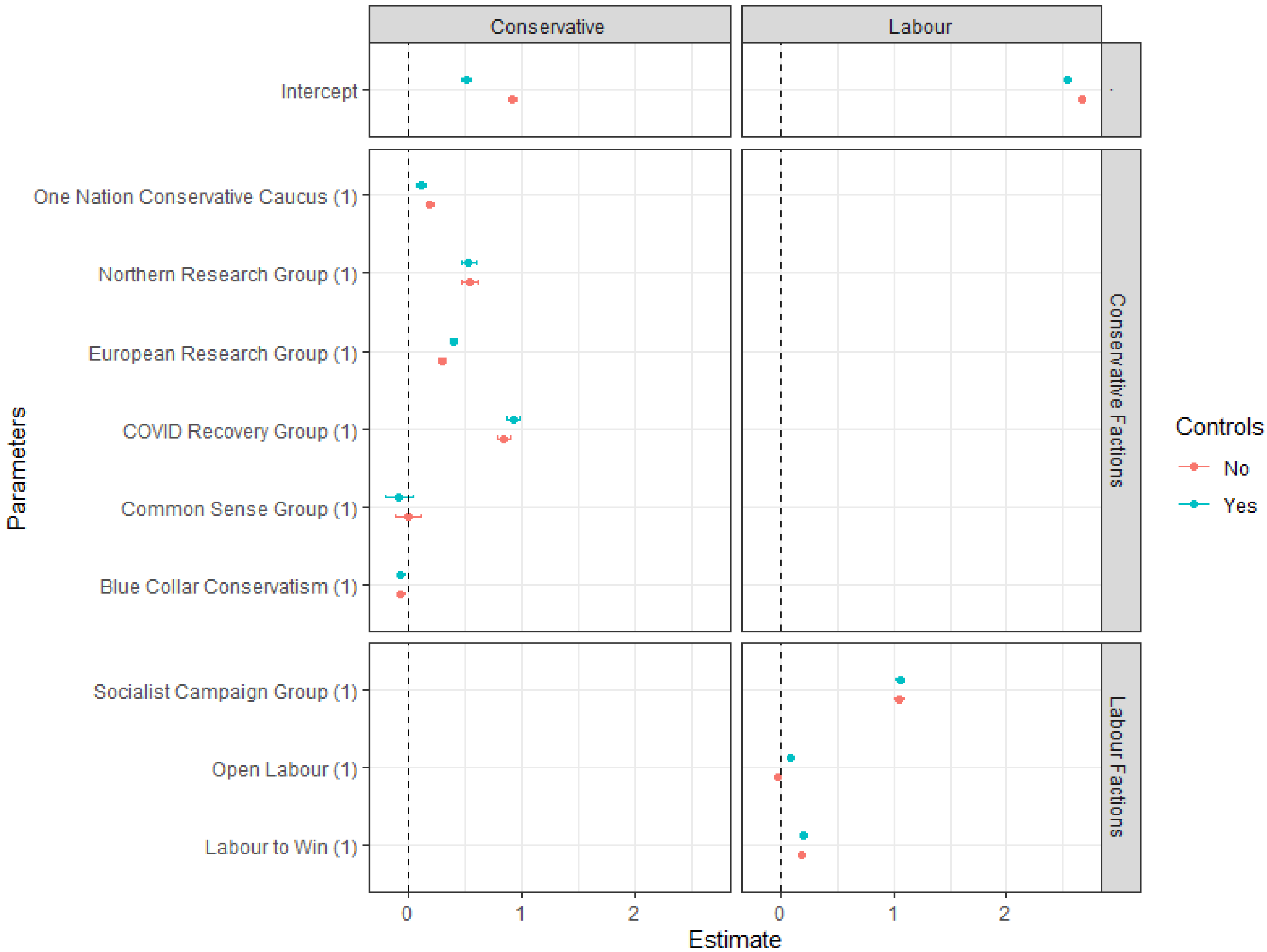


Fig 6: controls include nodematch parameters for region, gender, and parliament intake and edgecov parameters for ideological distance.

For the Socialist Campaign Group, the high effect of co-membership on interactions is potentially because the Socialist Campaign Group is a highly formalised and cohesive grouping that has been in existence for a long period of time. This likely means that many of these MPs have strong personal relationships as well as political similarities.

Other factions such as the European Research Group, the Northern Research Group, and Labour to Win also display relatively strong effects. Even though Brexit has been enacted and its political salience has declined, members of the ERG – the “most influential [faction] in recent political history” (Payne, 2020) – still display a preference to interact with other ERG members. It would be interesting for future research to compare the size of this effect over time, in order to see if this ERG in-group bias has declined since Brexit and at what speed. The Northern Research Group (NRG) is largely comprised of Northern English MPs who push for a ‘levelling up’ agenda for the Northern regions. Despite controlling for regional and ideological homophily, members of this group still display a high preference to interact with other members, signalling that they may have developed a factional identity and in-group bias.

On the other hand, the Blue Collar Conservatives, One Nation Conservatives, Common Sense Group, and Open Labour are all estimated to have little to no effect on MPs’ choice of who to interact with on Twitter. To speculate as to the reason for this, despite being one of the largest intra-Conservative groupings of MPs, the Blue Collar Conservatives has no real binding programme or policy aim other than the vague goal of being a ‘champion [of] working people’ (Blue Collar Conservatives, 2021). As a result, it appears to be less of a political faction and more of a loose collection of MPs that share a common working-class identity.

Similarly for Open Labour, the organisation is deliberately broad, aiming to cut across factional divisions. Because of this, the group comprises of a wide range of politicians from both the Corbynite and moderate wings of the party. Correspondingly, there is likely no binding identity of being associated with Open Labour unlike the Socialist Campaign Group. I repeated the models using the Tribune Group of MPs – another Soft Left faction – instead of Open Labour. Again, the group displayed little preference for interacting with other members. This may indicate that the Soft Left is not a cohesively organised faction. Sienna

Rodgers (2021), the editor of LabourList, described the Soft Left within the Labour Party as being “organisationally weak”. These findings seem to provide some supporting evidence for this claim.

Overall, factional membership does seem to influence how MPs interact. There is, however, a wide heterogeneity in the magnitude of this effect. While some groups display very high levels of preference to interact with other co-members, others display little to no effect. This heterogeneity also provides interesting information into contemporary party politics and the factional landscape within the main parties. It is difficult to assess from journalism and other qualitative sources alone which factional groupings are tight-knit, organised factions and which are more diverse groups with less of a common identity and purpose. This research shows that by studying the interactions of MPs we can better understand the factional lay of the land within parties.

4.4 Cooperation and Conflict Between Leadership Factions

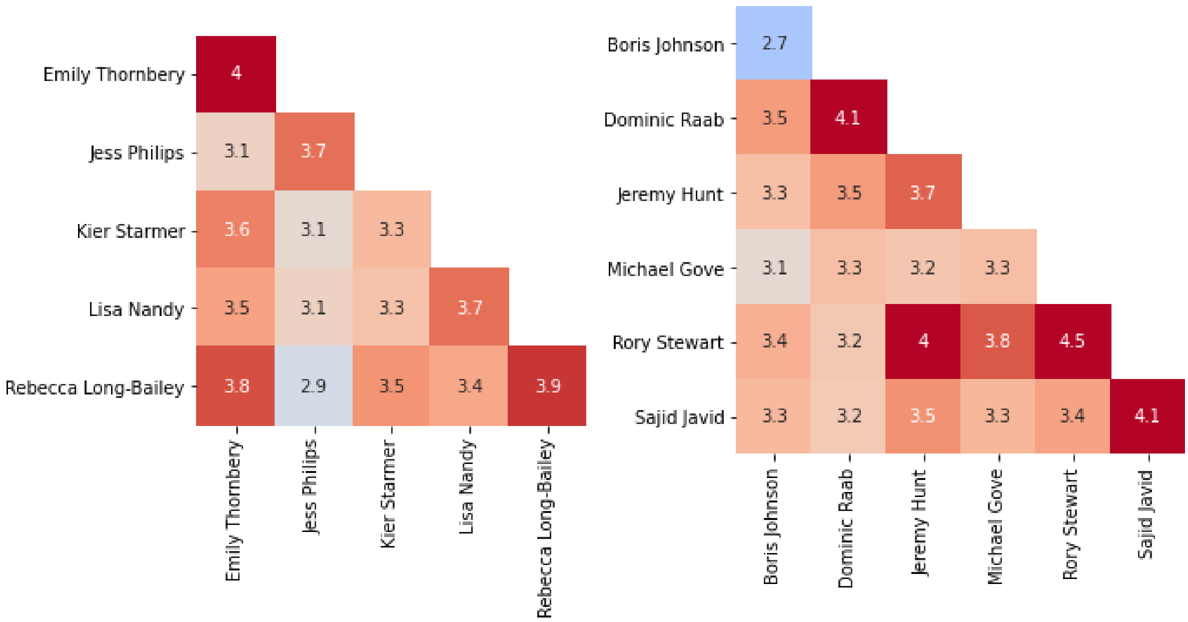
While factional group membership does appear to influence MPs intra-party social networks, the previous analysis doesn’t allow us to measure how these factions interact with one another. These previous factional groups are not exclusive and therefore the *latentnet* nodemix term could not be implemented. By focusing on leadership factions – groups of MPs who supported the same candidate for party leader – we can better understand factional dynamics within parties.

Oftentimes, leadership factions closely resemble existing factional groupings. For example, most supporters of Rebecca Long-Bailey came from members of the Socialist Campaign Group. Similarly, most of Jess Phillips supporters came from the Blairite group Progressive Britain. In the Conservative Party, Dominic Raab drew much of his support from the ranks of the European Research Group while Rory Stewart supporters originated from the One Nation

Conservative Caucus. Other candidates such as Boris Johnson, Jeremy Hunt, and Kier Starmer drew more diverse coalitions together comprising of MPs from multiple factional groups.

To measure how MPs from the same and different leadership factions interact, I specify a model which uses the *nodemix* term to see the interaction coefficients of each pairing of leadership faction. In this model I also control for the effect of party membership. This is done as we are interested in whether these leadership factions display an in-group preference significantly different from that displayed at the party level. Due to the large number of coefficients, the full results of this model are shown in the appendix. Figure 7 shows two matrices containing the leadership faction coefficients, I added these to the party effect coefficients so that the values can be compared across Labour and the Conservatives.

Figure 7: Matrices of Leadership Faction Coefficients Showing Association with Twitter Interactions.



The diagonal of the heatmaps show the in-group effect of belonging to the same leadership faction. MPs who supported, Dominic Raab for example, are estimated to share an average edge weight of 25.6 interactions. Many of the leadership factions display a preference towards interacting with other MPs who supported their preferred candidate for party leader. This is especially true for Dominic Raab, Sajid Javid, and Rory Stewart supporters as well as Emily Thornberry and Rebecca Long Bailey supporters. Indeed, most leadership factions display some in-group positive effect.

The exceptions to this are supporters of Kier Starmer, Boris Johnson and Michael Gove. Interestingly, the estimated number of interactions between Boris Johnson supporters is very low with only 6.4 interactions on average. The potential reason for this is that Johnson was perceived as an electoral winner by many Conservative MPs, thus, many MPs endorsed Johnson not out of ideological conviction but rather a pragmatic electoral calculus. Those MPs wanting to further their own political career may be keen to attach themselves to the campaign of the likely winner to try and secure a government position. Resultantly, Johnson's supporters are unlikely to be ideologically homogenous, but instead come from all wings of the party. Even so, the fact that this represents the lowest value is striking and may signal that the Conservative parties' starkest divides are hidden *within* Johnson's supporters and not *between* leadership factions.

The Kier Starmer leadership faction likewise displays low in-group bias in their Twitter interactions. Given Starmer was – from an early stage – the favourite in the leadership contest, the rationale used for Johnson could also apply here. Indeed, his supporters contained MPs from across the Centrist and Soft Left wings of the party and are not a cohesive faction. Both these facts conform with Stark's (1996) thesis of party leadership contests, that stresses the importance of electability in selecting the winning candidate. Further research will be needed to assess whether this finding is replicated in other contexts both temporal and geographic.

Looking now at the interactions between Labour leadership factions, the lowest estimated level is between supporters of Rebecca Long-Bailey and Jess Phillips with an estimated 7.8 interactions on average. This is not surprising given that Rebecca Long-Bailey and Jess Phillips are at opposite ideologically extremes of the Labour Party. Rebecca Long-Bailey's candidacy was widely seen in the media as the 'continuity candidacy' for Corbynism (The Economist, 2020). Whilst Phillips, on the other hand, was a long-time critic of Corbynism (BBC News, 2020) and many of her supporters are figures associated with the Labour Right including Margaret Hodge, Liz Kendall, Ian Murray, and Rachel Reeves. As a result, the lack of communication between Rebecca Long-Bailey's and Jess Phillips' supporters was anticipated. This conforms with Hypothesis 4 and highlights the role of ideological differences in creating factional conflict.

Rebecca Long-Bailey's supporters appear closest to those of Emily Thornberry. Emily Thornberry was 'faultlessly loyal' to the Corbyn leadership and held the Shadow Foreign Secretary post under his leadership (Stewart, 2019). Many of her supporters in the leadership were also from the Left of the party – albeit more towards the Soft Left – and were supportive of Corbyn's leadership. This includes the likes of Dawn Butler, Rachael Maskell, and Nadia Whittome. In this view, the close relationship between Rebecca Long-Bailey's and Emily Thornberry's supporters is understandable and reflects the relative ideological proximity of the two factions.

Turning now to the Conservative Party, Figure 7 also highlights some interesting factional dynamics. The model estimates that Boris Johnson supporters interact the most with those of Dominic Raab with an estimated 14.1 interactions on average. This is likely because both Raab's and Johnson's supporters tend to come from the Eurosceptic, Thatcherite wing of the party. Dominic Raab himself later endorsed Johnson's candidacy during the campaign. The supporters of Jeremy Hunt – the main competition to Johnson in the leadership contest – are estimated to interact the most with supporters of Rory Stewart. Both Rory Stewart and Jeremy Hunt served within David Cameron and Theresa May's governments, and were Remain voting. Both candidates can be seen as coming from an economically conservative and socially liberal branch of Conservativism. After being knocked out of the race, Rory Stewart went onto endorse Jeremy Hunt for the leadership. Unsurprisingly, Rory Stewart's supporters have far less contact with Johnson's and Raab's supporters. This indicates that ideology too does play a factor in the factional interactions within the Conservative Party. However, Rory Stewart's faction was effectively destroyed after Johnson took power – only three of his formerly 14 backers remain in the party. As a result, the uncertainty attached to these estimates is far higher than the other factions.

This model supports the hypothesis that co-membership to a leadership faction is associated with higher levels of interaction. MPs tend to interact more with others that supported the same candidate. It is important to note that this effect is highly heterogenous and depends on which leadership group you look at. On top of this, there is evidence that interaction between leadership factions follows ideological lines. With ideologically dissimilar leadership factions having less interaction. Further research should focus on longitudinal intra-party networks during leadership contests to better assess the emergence and persistence of leadership factions and the dynamics between them.

While political scientists tend to shy away from prediction. Using MPs interactions on social media could be used to predict MP intra-party behaviour such as leadership endorsements. Latent space models could be particularly useful in this regard, as you could see how 'similar' MPs – who are close to each other in social space – are behaving and use this to predict the behaviour of unknown MPs. Undoubtedly, further research exploring such a possibility is needed, but the abundance of real-time social media data, in combination with network analysis, opens potential for predictive political science at an intra-party level.

Chapter 5: Discussion

5.1: Evaluating the Hypotheses

So why do some MPs choose to interact with some members of their party more than others? This research has demonstrated that ideological homophily and factional intergroup bias both play a role in influencing Twitter interactions. In terms of ideology, within both parties, ideological distance was seen to be negatively associated with Twitter interactions. This provides support for Hypothesis 1 of this study. However, the findings do not support Hypothesis 1b, in fact the model suggests that ideological distance has more influence in the Conservative Party than in the Labour Party. However, as mentioned, these findings rest upon the validity of the Wordfish estimates and so we should acknowledge a higher degree of uncertainty than represented by the model.

In terms of Hypothesis 2, I demonstrated that co-membership to a variety of factional groups was found to be a good predictor of Twitter interactions. This effect was heterogeneous however, and some groups were estimated to have a low – or zero – effect. It is also not entirely clear about the causal mechanism. It is not clear whether membership to the group itself causes a preference to interact with other members, or whether a similarity of policy views is what causes this. In the analysis I only controlled for ideological homophily in the traditional Left-Right sense, to unpick the relationship between homophily and in-group bias it would be better to control for many different policy opinions such as Euroscepticism, Authoritarian-Libertarian, Economic and Social Conservativism. Only then would we be able to truly distinguish between the influence of factional in-group bias and homophily in political preferences.

Similarly, I also showed that MPs tended to favour interacting with other MPs who supported the same candidate for party leader. This evidence broadly supports Hypothesis 3 of this study. However, like Hypothesis 2, this effect is heterogenous. Some leadership factions displayed a large in-group bias while others display low or negative in-group bias when interacting. It is also unclear as to whether differences over the choice of candidate for party leader itself has any effect on MP interactions, or whether these leadership factions are just proxies for other cleavages and factions within the parties. By analysing the interactions between leadership factions, I was also able to assess the inter-factional dynamics within the parties and measure factional cooperation and conflict. In general, ideology seems to play and important role in structuring the interactions of leadership factions. With ideologically similar factions having higher degree of interactions and *vice versa*. This supports Hypothesis 4 as well as providing additional support to Hypothesis 1.

5.2 Contribution to the Literature

By testing these hypotheses, this research has added a valuable contribution to the literature. The vast majority of the prior research in this area has focused on the inter-party interaction of politicians on Twitter. As a result, only limited attention has been placed on studying intra-party interactions and their determinants. This research has helped address this gap. When analysing the role of ideological similarity, prior research has relied on party estimates of ideology. This research has used individual estimates of ideology instead to show the role of ideological similarity at an intra-party as well as inter-party level. It has also investigated the role of factions in influencing Twitter interactions, not only has this research assessed how factional membership influences interactions with other members, it has also assessed how factions interact with each other by investigating the interactions of leadership factions.

On top of this, through testing these hypotheses, I have also added to the research on contemporary UK politics by highlighting the key factions and cleavages within the main UK parties. While many of these findings may not be surprising to those that pay close attention to UK politics it is remarkable nonetheless that this intra-party politics can be studied in a systematic way by utilising Twitter interactions. For a long time, research on factionalism and intra-party politics has suffered from a dearth of data and has relied on interviews, memoirs, and other qualitative information. Now novel sources of data and methods are continuing to open up the black box of political parties.

5.3 Limitations & Future Research

There are, however, a few limitations to this research that should be acknowledged. Many of these limitations I have already covered – e.g., uncertainty with using Wordfish estimates, imperfect data on factional membership – and will not rehash here. However, there are some broader limitations that it’s important to cover.

For one, this research focuses on the interactions network of MPs without capturing the network’s changes over time. This somewhat limits the research’s ability to distinguish association from causation as I was not able to measure the development of factional groupings. For example, the Labour leadership contest happened at the start of this Parliament, I could have measured how divisions emerged and developed during and after this process to better understand factional development and dynamics. Similarly, other factional groupings such as the Northern Research Group and COVID Recovery Group were formed during this Parliament, it would have been insightful to measure how its members’ interactions changed over this period in order to better disentangle the effect of policy preference homophily and factional in-group bias in determining Twitter interactions.

Secondly, the approach used in this paper can only measure the effect of known factional groupings. The factions that were included in this analysis were dependent on them receiving decent levels of journalistic coverage. It is likely that several informal groupings of MPs exist but don’t receive journalistic attention and therefore do not enter this study. Future research could develop improved clustering methods that are better able to uncover intra-party sub-structures. Current community detection algorithms for networks – such as the Leiden and

Louvain algorithms – struggle to distinguish sub-party clusters due to the dense network of interactions. Similarly, when using hierarchical clustering methods, such the one employed in this paper's dendrogram, it is unclear how far down the tree to focus on. At which level does the clustering constitute a faction. Such questions are not easily answered. Nevertheless, future research could potentially detect the existence and development of factions in real time independent of journalistic coverage.

Thirdly, it would be interesting to extend the analysis away from how MPs interact, in order to also look at how other party actors interact. As the literature on party networks points out, party networks are comprised not only of politicians, but also include, activists, interest groups, think tanks, journalists, and consultants – to name but a few (Koger, et al., 2017). To better understand factional intra-party politics, a broader net should be cast in future research to extend the analysis beyond Westminster. For example, internal Labour elections for positions on the National Executive Committee are some of the most factionally divisive, but it's an area that has avoided systematic study due to an absence of data (Massey, 2021). By using Twitter interactions, we would be better able to assess the ideological and factional competition in such elections.

Finally, while I won't be the first to note the predictive potential of social media in the social sciences (for an overview see Rousidis, et al., 2020). This research highlights a possibility for prediction in intra-party politics. Future research could test the successes of predicting intra-party behaviour such as endorsements in leadership contests, defections from the party, or leadership challenges. A latent space approach is particularly useful here as it captures the transitive nature of social relations and positions MPs based on their latent similarity. The distances of MPs from one another could then be used to infer their likely behaviour.

Chapter 6: Conclusion

The importance of social media platforms for political communication continues its seemingly inexorable rise. This trend has only been intensified during the COVID pandemic where traditional means of doing politics temporarily ground to a halt. As politicians continue to migrate to social media, the importance of studying their behaviour on these platforms will only continue to grow. This research has contributed to studying politicians' behaviour on social media by looking at their intra-party interactions. It has found evidence of ideological homophily and factional in-group bias in the intra-party interactions of MPs. Such findings expand the literature's underdeveloped understanding of intra-party social media networks. In the process of testing these hypotheses, this research also undercovers much about the cleavages and factions within contemporary UK politics.

Evidence of ideological division and factionalism in current UK parties is important. As Françoise Boucek writes (2012, p.206), "For Britain's Conservatives, big election defeats had always been caused by party splits…" Despite Boris Johnson's large majority in the House of Commons, factional divisions can quickly turn a seemingly strong position on its head. Members of the COVID Recovery Group, Northern Research Group, and European Research Group all display high in-group bias when interacting. Similarly for the Labour Party, Starmer's road to power rests upon his ability to manage the factional tensions within his party. In 1979, the academic and former MP, David Marquand (1979, p. 17) wrote that, "To pretend, in this situation, that socialists and social democrats are all part of the same great Movement … is to live a lie. But it is a lie which the Labour Party has to live if it is to live at all." This statement remains as true as it did in 1979. Success for both parties, therefore, relies on how well they hold their diverse and divided coalitions together. The network analysis of social media data can provide a window into the 'black box' of political parties and opens a wealth of opportunity for future research into intra-party politics and factionalism.

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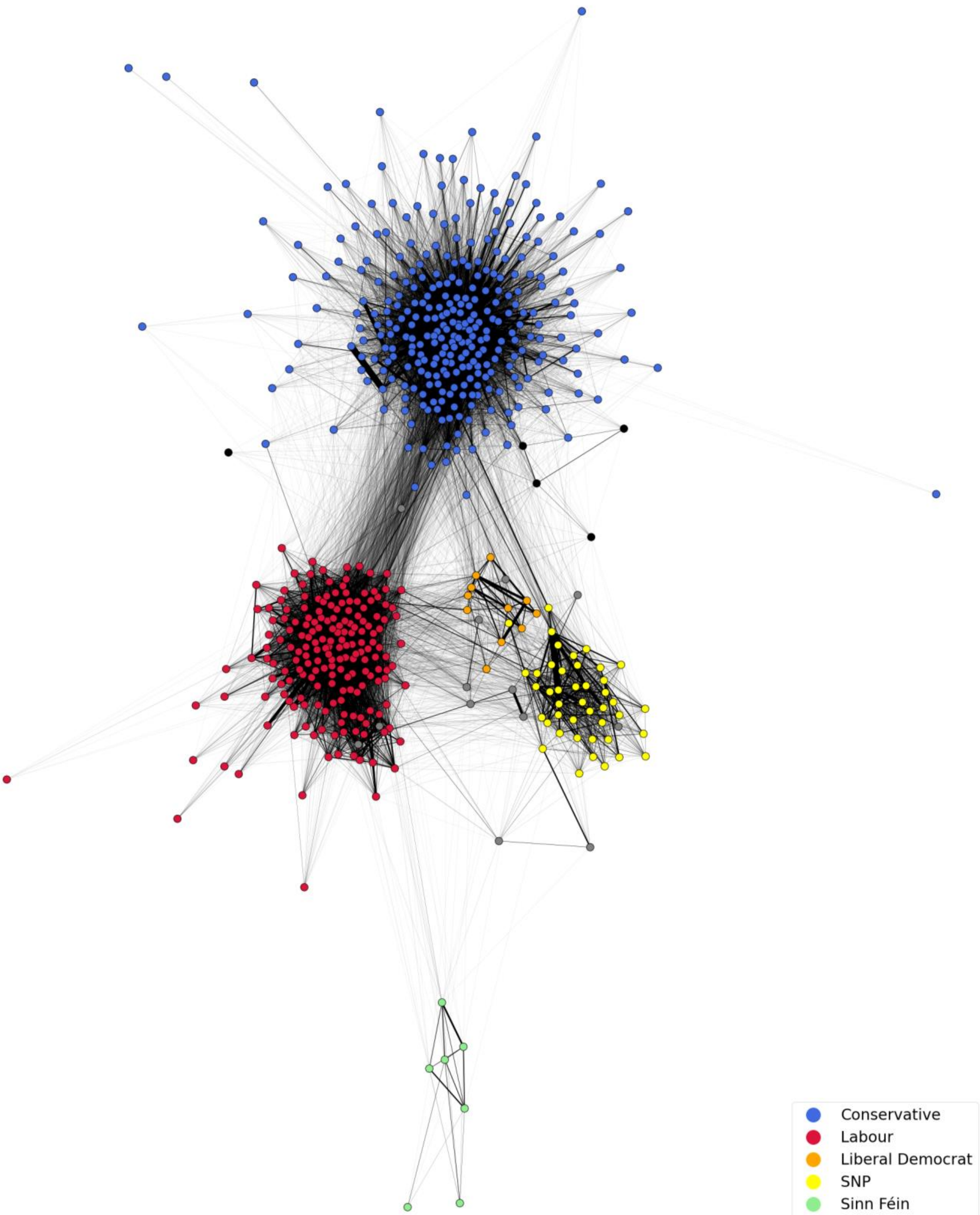
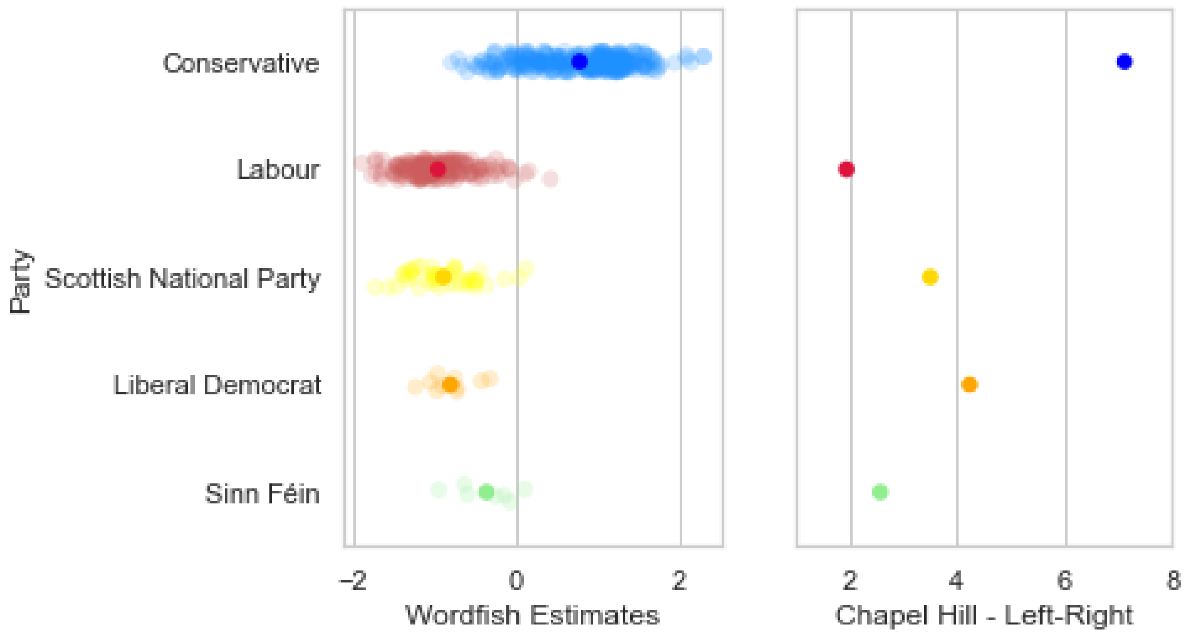
Appendix

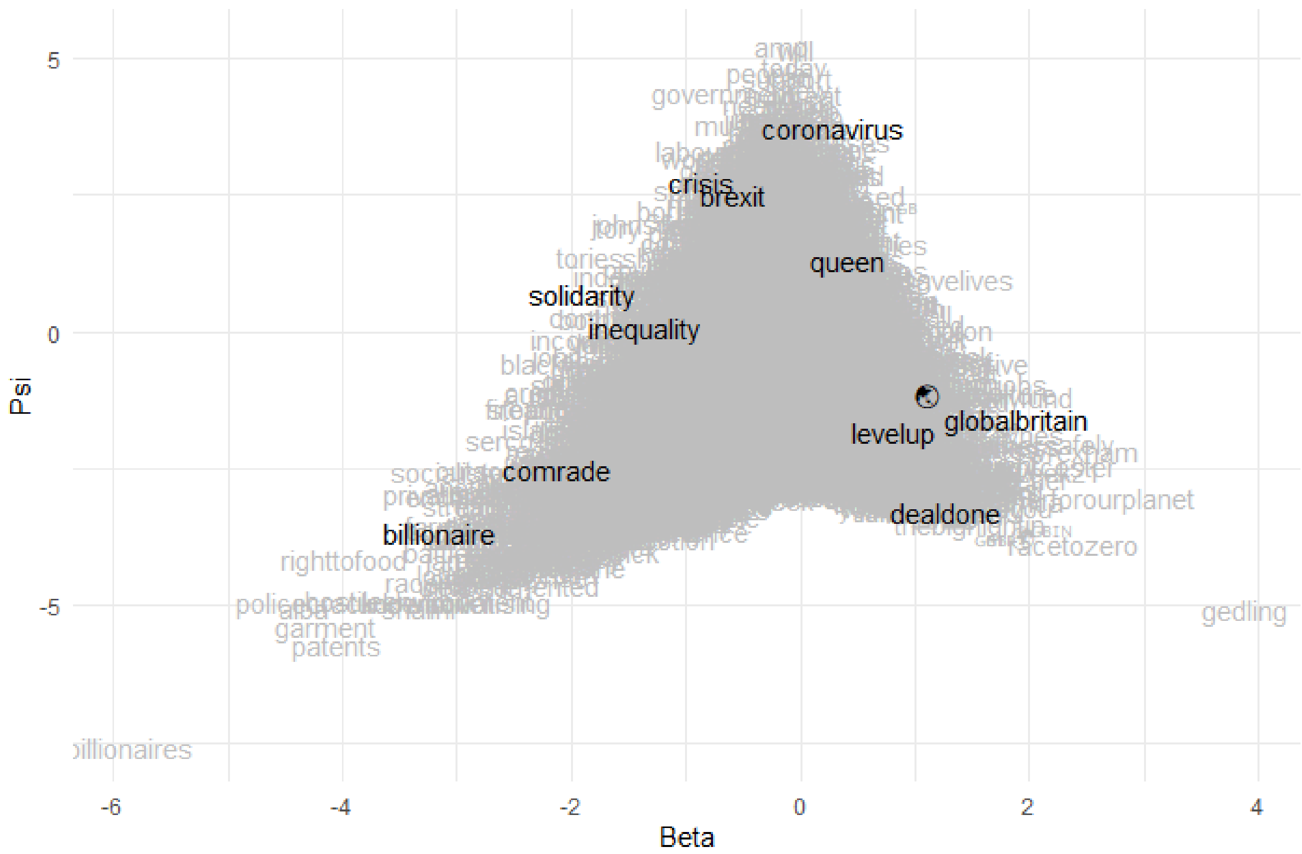
A.1: Twitter Interactions Network



A.7: Layout using Fruchterman Reingold force-directed algorithum. Edge thickness indicates weight of edge. 500 iteractions used.

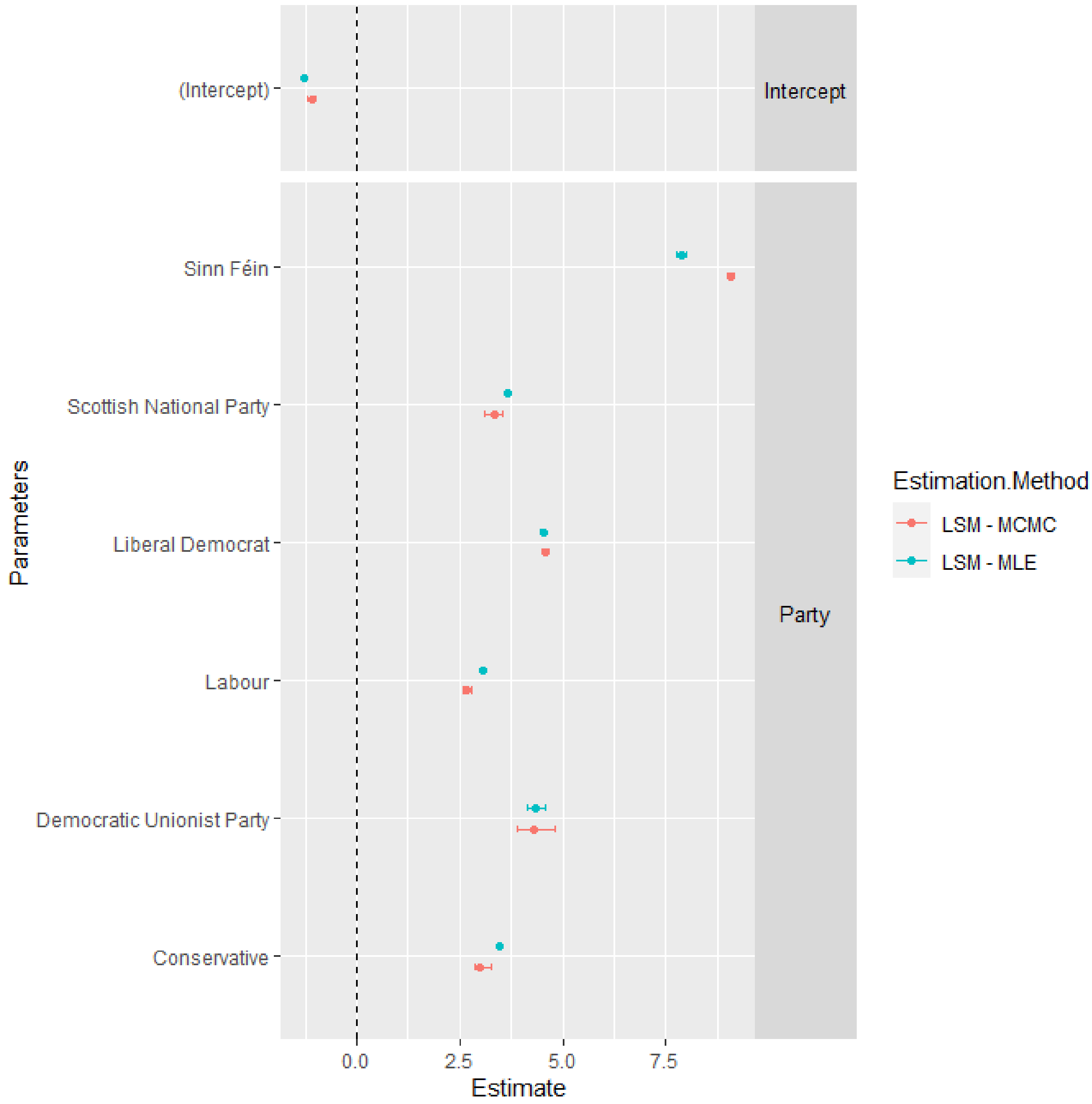
A.2: Wordfish Estimates





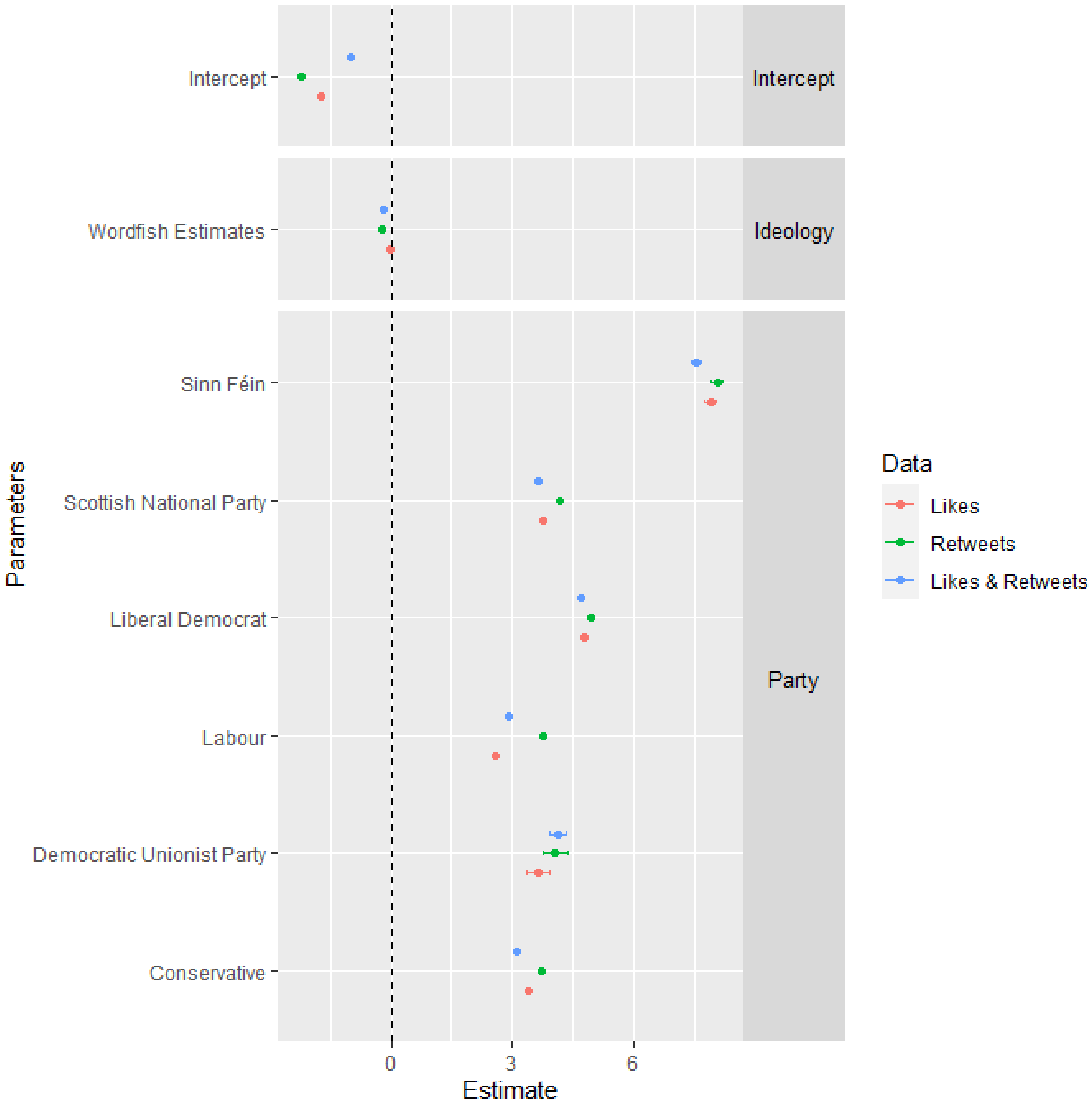
A.3: Robustness Check – Comparing MLE and MCMC Estimation

95% Confidence/Credible Interval Shown



A.4: Robustness Check – Retweets vs Likes

95% Confidence Interval Shown



A.5: Leadership Faction Predictors of Twitter Interactions

	Model 1		
	Estimate	**Std. Error**	**Sig**
(Intercept)	-0.8547	0.007921	***
Nodematch - Party			
Conservative	3.29897	0.009206	***
Labour	2.63471	0.01378	***
Nodemix - Labour Leadership Candidates			
Emily Thornberry - Emily Thornberry	1.39606	0.043079	***
Emily Thornberry - Jess Phillips	0.51309	0.032407	***
Jess Phillips - Jess Phillips	1.0509	0.023136	***
Emily Thornberry - Kier Starmer	0.98229	0.01707	***
Jess Phillips - Kier Starmer	0.43269	0.016195	***
Kier Starmer - Kier Starmer	0.6856	0.014063	***
Emily Thornberry - Lisa Nandy	0.82152	0.027488	***
Jess Phillips - Lisa Nandy	0.50814	0.023315	***
Kier Starmer - Lisa Nandy	0.6256	0.015545	***
Lisa Nandy - Lisa Nandy	1.0505	0.02478	***
Emily Thornberry - Rebecca Long-Bailey	1.17033	0.029243	***
Jess Phillips - Rebecca Long-Bailey	0.30031	0.044187	***
Kier Starmer - Rebecca Long-Bailey	0.89573	0.018004	***
Lisa Nandy - Rebecca Long-Bailey	0.79193	0.026116	***
Rebecca Long-Bailey - Rebecca Long-Bailey	1.26353	0.018652	***
Nodemix - Conservative Leadership Candidates			
Boris Johnson - Boris Johnson	-0.6292	0.010218	***
Boris Johnson - Dominic Raab	0.18708	0.01462	***
Dominic Raab - Dominic Raab	0.82301	0.05103	***
Boris Johnson - Jeremy Hunt	-0.0157	0.014302	
Dominic Raab - Jeremy Hunt	0.18608	0.041063	***
Jeremy Hunt - Jeremy Hunt	0.43893	0.047208	***
Boris Johnson - Michael Gove	-0.2299	0.018877	***
Dominic Raab - Michael Gove	-0.0091	0.054429	
Jeremy Hunt - Michael Gove	-0.0577	0.049185	
Michael Gove - Michael Gove	-0.0058	0.091865	
Boris Johnson - Rory Stewart	0.08096	0.035108	***
Dominic Raab - Rory Stewart	-0.0728	0.108622	
Jeremy Hunt - Rory Stewart	0.70208	0.065574	***
Michael Gove - Rory Stewart	0.4765	0.088281	***
Rory Stewart - Rory Stewart	1.17608	0.210004	***
Boris Johnson - Sajid Javid	0.01658	0.014209	
Dominic Raab - Sajid Javid	-0.0906	0.045371	***
Jeremy Hunt - Sajid Javid	0.23525	0.034888	***
Rory Stewart - Sajid Javid	0.04425	0.045321	
Michael Gove - Sajid Javid	0.14774	0.083168	*
Sajid Javid - Sajid Javid	0.76276	0.040246	***
Sociality FE		X	

Control Variables	✓
Nodes	568
Total Edges	28697
Density	0.18

*** p<.01, ** p<.05, * p<.1

A.6: Faction Group Predictors of Twitter Interactions

Conservative Factions	**Model 1**			**Model 2 - Controls**		
	Estimate	Std. Error	Sig	Estimate	Std. Error	Sig
(Intercept)	0.92	0.02	***	0.51	0.021	***
European Research Group (0)	0.08	0.01	***	0.07	0.01	***
European Research Group (1)	0.30	0.02	***	0.40	0.02	***
COVID Recovery Group (0)	-0.20	0.01	***	0.03	0.01	**
COVID Recovery Group (1)	0.84	0.03	***	0.93	0.03	***
Northern Research Group (0)	0.07	0.01	***	0.02	0.01	**
Northern Research Group (1)	0.54	0.03	***	0.54	0.03	***
Blue Collar Conservativism (0)	0.04	0.01	***	0.02	0.01	**
Blue Collar Conservativism (1)	-0.07	0.02	***	-0.07	0.02	***
One Nation Conservative Caucus (0)	0.16	0.01	***	0.22	0.01	***
One Nation Conservative Caucus (1)	0.19	0.02	***	0.11	0.02	***
Common Sense Group (0)	-0.03	0.01	**	0.00	0.01	
Common Sense Group (1)	0.00	0.06		-0.08	0.06	
Sociality FE	✓			✓		
Control Variables	X			✓		
Nodes	306			306		
Total Edges	14647.00			14647.00		
Density	0.32			0.32		

Labour Factions	**Model 1**			**Model 2 - Controls**		
	Estimate	Std. Error	Sig	Estimate	Std. Error	Sig
(Intercept)	2.67	0.01	***	2.53	0.01	***
Socialist Campaign Group (0)	-0.11	0.01	***	-0.09	0.01	***
Socialist Campaign Group (1)	1.05	0.02	***	1.06	0.02	***
Labour to Win (0)	-0.16	0.01	***	-0.23	0.01	***
Labour to Win (1)	0.18	0.01	***	0.21	0.01	***
Open Labour (0)	0.01	0.01		-0.03	0.01	***
Open Labour (1)	-0.03	0.01	**	0.09	0.01	***
Sociality FE	✓			✓		
Control Variables	X			✓		
Nodes	186			186		
Total Edges	10030			10030		
Density	0.58			0.58		

*** p<.01, ** p<.05, * p<.1 – Controls include *edgecov* term for ideological distance and *nodematch* terms for region, gender, and intake parliament

A.7 Internal Party Groupings Data Collection

Conservative Party Factions

European Research Group

For simplicity I follow the Financial Times list of 90 ERG members. Seen here: https://ig.ft.com/brexit-tory-tribes/

COVID Recovery Group

The membership of the CRG is not well publicised with only its leaders – Mark Harper and Steve Baker – frequently named in the news coverage. However, there are reportedly around 50-70 MPs that are part of this group. To infer the CRG's membership I collected which Conservative MPs frequently rebelled against the government on key COVID divisions. In total, I identify 38 MPs who are very likely CRG members. While I could identify more likely CRG members the surety of these inferences would decline.

Northern Research Group

The MPs who are members of the NRG was collected from the signatures to an open letter written to Boris Johnson in October 2020. Seen here: [Over 50 Tory MPs in northern England press PM for roadmap out of lockdown | Coronavirus | The Guardian]. There are 41 Conservative MPs that signed this letter However, several other NRG members reportedly remained anonymous and so this is not an exhaustive list of NRG membership.

Common Sense Group

Likewise, for the Common Sense Group, I identify membership from an open letter. 27 Common Sense Group MPs signed an open letter to the Telegraph in November 2020. Seen here: https://www.edwardleigh.org.uk/news/letter-telegraph. However, this is not a list of all Common Sense Group MPs, the group purports a membership of 59 MPs.

Blue Collar Conservatives

The collection of Blue Collar Conservative members was very simple as an list of Blue Collar Conservative MPs are available from their website. Seen here: https://www.bluecollarconservatism.co.uk/team .This gives 87 MPs, although reportedly their full membership extends to 130 MPs.

One Nation Conservatives Caucus

The One Nation Conservative Caucus' membership is relatively difficult to infer despite it being one of the largest Conservative groupings with over 100 members. To identify members, I collected all MPs who have been authors in their many publications and policy proposals. On top of this, I also identified those who have been named as members by the One Nation Conservative's Twitter account. This gives an identified membership of 62 MPs.

Labour Party Factions

Socialist Campaign Group

The Socialist Campaign Group of MPs were identified from a list of MPs posted on the groups Twitter Account. List seen here: @socialistcam/Campaign Group MPs / Twitter . This comprises of 34 MPs.

Open Labour

I identify 42 Open Labour MPs. This was constructed from MPs named on their website as well as MPs who have retweeted – or have been by – the Open Labour Twitter account.

Labour to Win

As Labour to Win was a joint endeavour of both Progressive Britain and Labour First, I collected MPs who have been associated with either of these organisations. This includes journalistic evidence, from their own websites as well as Twitter links. In total 81 MPs were included in this group.