Elite Messaging from Bella Twit(t)alia

Did Social Media Users follow m5s and Lega into their Coalition?

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Introduction

The 2018 Italian election produced one of the most unexpected governing coalitions in democratic history. Two parties, the Lega Salvini (Lega) and Movimento 5 Stelle (Five Star Movement - m5s), formed a government despite being at opposite ends of the ideological spectrum and constantly denouncing each other throughout the campaign. This outcome was certainly unexpected considering the ideological and policy distance between the two parties (Garzia 2019), and the resulting coalition presents a challenge for understanding democratic governance in Italy and beyond.

I use this unlikely outcome to investigate one aspect of democratic governance—namely, the fundamental principle of democracy that political actors represent and are responsive to the demands and preferences of supporters. Representative democracy is predicated on the idea that parties represent citizens in a bottom-up process with their preferences ultimately driving elite behavior in parliament and government. Yet, interestingly, the formation of the Lega-m5s government seems to belie that principle. The parties are on the opposite end of the ideological spectrum with few shared policy positions. Moreover, the two parties reinforced this in their rhetoric throughout the campaign. However, as the dust settled after the election, they eventually agreed to put aside their differences and form a government.

In this study, I examine how the decision to form the coalition affected partisans' levels of support for the opposing party. Did supporters follow their respective leaders and become more open and accepting of the coalition? Or were they disgruntled at the party elites' decision to form this coalition? How does this differ for the most avid supporters versus weaker supporters?

As citizens spend an increasing amount of time online, a growing amount of political opinion making occurs on the internet. Almost half (45%) of Italian citizens use online social media and networks (Eurostat 2017). Especially in the case of Italy's 2018 election, online campaigning played a central role. M5s, led by Luigi di Maio and the party with the largest electoral share, has its roots in online activism and blogging culture. In addition, the Lega, the party winning the most votes within the largest coalition after the election, ran a campaign mostly orchestrated on its leader Matteo Salvini's own social media accounts. He, as well as di Maio, made extensive use of Twitter and Facebook to conduct highly personalized campaigns, leveraged by the numbers of followers to their personal accounts (Mazzoleni 2018).

My approach focusses on the electoral campaign as it unfolded on Twitter and specifically the retweeting behaviour of users before and after the coalition agreement. Following Conover et al. (2012) and Guerrero-Sole (2017), I consider the act of retweeting from an account affiliated with a party to be an endorsement of this party. That is because the act of *retweeting* (rather than mere following) can be a costly act when the retweeted message conveys an ideological stance (Ceron, Curini, and Iacus 2015): a retweet appears in the timelines of followers to a user. There is a social cost attached to displaying oneself to be in support of a particular ideological message. While following only influences one's own information environment, retweeting signals to others one's political leanings and communicates that to one's own followers.

To test for different reactions to the coalition among party supporters I use a model based in Item Response Theory (Jackman 2012) to place social media users on a scale. Users' positions on that scale depend on the political elites they follow. Some following-connections are more important for positioning than others, so if a user follows politician from across the political spectrum, the user's position on this scale will depend on an informational "weight" attached to each politician. This non-invasive way of measurement allows researchers to determine the closeness between any user and any party. I apply a spatial theory of party ID to this case: I consider a Twitter user "close" to a specific party if the user's estimated position is close to a given party on this estimated scale.

Based on this logic of "who follows whom", I extract a measure of partisan proximity from Twitter for every user to examine political behaviour. This approach is similar to several recent approaches that have been developed to infer ideological ideal points for elites and individuals on Twitter (Barberá 2015; Imai, Lo, and Olmsted 2016). Borrowing from these approaches, I use the resulting ideal point estimates to determine their closeness to a political party. Closeness of an individual to a party is a continuous measure of partisan affinity. This measure of affinity represents users' party identification[1].

I take this degree of partisan affinity and use it to test to what extent users are willing to 'follow' an extreme right party. With this present work, I contribute to an important question about democracy in an ongoing debate over its fundamental conception: Who leads public opinion? Do voters lead with their opinion, and politicians adjust their position based on voters? Or is the exact opposite the case: Do politicians lead, and voters follow?

I use the case of Italy's general election in March 2018 to examine this question. To assess individuals' political behaviour, I analyse over 8.3 million tweets related to the election. Since these data points all carry timestamps and identifiers for specific users, I can analyse their reactions to specific events. My study examines if closeness to the Lega had a systematic effect on users' party support after the Lega/m5s coalition was announced. How was individuals' support for the Lega affected by Salvini backtracking on a central campaign-claim? Did Lega-supporters follow their party into the coalition?

My results indicate that, indeed, distance in affinity between party supporters and Lega mattered for the behaviour of users. Accounts who were close to Lega toned down their support for the party after it announced the coalition. The same pattern applied for m5s-supporters. Additionally, users sitting between both parties were less affected by the elites' interactions than staunch party supporters were. These findings indicate that, especially among strong party supporters, unequivocal following did not occur in this situation. This

[1] Barbera (2015), for example, uses this approach to investigate the *ideological* composition of the US Twittersphere. In this case of a two-party system this scale can be interpreted as ideology. The same is true for multiparty-cases where the politics is organized between two distinct ideological poles.

contradicts the idea that party supporters are merely blind followers and is in line with the expectation that voters take party cues predominantly on issues with low saliency.

Previous research has identified party identification as central to an individuals' propensity to lead or follow politicians' positions (Lenz 2012; for an overview: Johnston 2006). For my analysis, I assume active Twitter users have a higher-than-average degree of political interest and, as such, are more likely to identify with a specific party as well. After providing some background on the context of the election, I begin by discussing the role of party ID as a powerful determinant of party support and public opinion.

Background: The 2018 Election in Italy

Italy's 2018 election campaign was to a large degree characterised by two parties with highly personalised campaign styles. On the one hand was the far-right *Lega Salvini* with its leader Matteo Salvini, who had been a fixture of Italian politics for decades but ran on a staunch populist, anti-establishment, and anti-immigration platform. On the other hand, the euroskeptic, populist Movimento 5 Stelle with leader Luigi Di Maio, also ran an anti-elitist but very decentralised campaign. Ultimately, m5s gained the largest vote share, with 33% of the popular vote while Salvini's Lega received 17% of the popular vote, putting it at the top of the largest electoral coalition.

Throughout the duration of the campaign, Matteo Salvini vehemently rejected collaboration with the m5s. This position was regularly expressed publicly during the campaign. For example, during an interview with the centrist newspaper *La Stampa* on February 2, 2018, Salvini ruled out a coalition with the "unreliable" m5s. During the last leg of the campaign, Salvini reiterated his position by tweeting his own quotes from two earlier TV appearances. One was from *Porta a Porta* (a talk program broadcasted by *Rai*), on March 1, 2018, where Salvini said: "I'll never form a government with Renzi, Di Maio, Gentiloni, or Boldrini. Someone in Europe roots for confusion and hopes for chaos after the election [by claiming this]."[2] One day later, on March 2, 2018, Salvini tweeted this quote from *Bersaglio Mobile* (a talk show broadcast on *La7*): "Plainly stated: the only coalition that can have the votes for GOVERNANCE is the CENTRE-RIGHT. Whoever votes Lega chooses CLARITY, I will NEVER support governments of Renzi, Di Maio, Boschi, Boldrini or anyone else [emphases in original].'[3] This stance did not change even as results were

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[2] Original tweet by "matteosalvinimi" on 2018-03-01, 14:59:51 UTC: "Non andrò mai al governo con Renzi, Di Maio, Gentiloni o Boldrini. Qualcuno in Europa tifa per la confusione e spera nel caos dopo le elezioni."

[3] Original tweet by "matteosalvinimi"" on 2018-03-02, 14:14:57 UTC: "Realisticamente parlando: l'unica coalizione che può avere i voti per GOVERNARE è il CENTRODESTRA. Chi vota Lega sceglie la CHIAREZZA, non sosterrò MAI governi in cui ci sono Renzi, Di Maio, la Boschi, la Boldrini o chiunque altro."

tallied. One day after the election, on March 5th, when asked about the prospects of a Lega/m5s coalition, Salvini told reporters: “N. O. No, underlined three times."[4]

Salvini voiced openness towards the m5s for the first time just one week later, on March 14th, as the election results had sunken in and strategic considerations were brewing. Three days after, the official Twitter account of Lega quoted Salvini with: ‘Salvini: Di Maio will call me? I’ll answer [the phone] for anyone, all right.’[5]. This shift, however, was initially rejected by Di Maio. The m5s ruled out any collaboration with Forza Italia’s Silvio Berlusconi, and Salvini was unwilling to drop Berlusconi as member of the centre-right coalition.

After almost two months of failed negotiations, however, things had changed. Italian news service ANSA reported on the morning of May 9th that Salvini and Di Maio had met for talks. From here, things developed fast; on May 14th they reached an agreement to form a coalition government. Subsequently, both parties called their supporters to the polls to cast judgement over the attained agreement. Large majorities of voters from both camps cast their ballots in favour, but the convoluted path through these consultations did not conclude there. A quarrel over the designated minister for finance and the economy, Paolo Savona, a euroskeptic and anti-Euro academic, almost ended the governing coalition before it officially began. Yet, again, a compromise was found in Savona being named Minister of European Affairs and the coalition was finalized on June 1st. More than eight weeks had passed since the election.

The confrontational way that the election campaign was conducted and the long time frame over which it unfolded offer a unique opportunity to examine and test the tendency of party supporters to follow party leaders. For one, Twitter played a key role for each of these parties throughout the campaign. Secondly, data extracted from the online platform allows to measure how supporters reacted to specific events. Lastly, the clear positioning of Lega and m5s until shortly before the coalition agreement are clear indicators of the parties’ positions towards each other. Overall, this election makes an interesting case to analyse the effects that party affiliation and partisan proximity have on potential voters and the roles each play for the expression of political opinion. In line with a large body of research the central determinate for political opinion I test here is partisan affiliation.

Partisan Affiliation - The Unmoved Mover?

Research has long noted the congruency between party identification and policy preferences among individuals. Early on, the Columbia School identified the importance of partisan loyalty, mainly imprinted through family upbringing, as central to voting

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[4] “Rival populists rule out coalition together as battle begins over right to govern Italy”, The Telegraph Online, 2018-03-05. Retrieved from https://www.telegraph.co.uk/news/2018/03/05/rival-populists-battle-right-govern-italy-hung-parliament/ on 2019-05-02.

[5] Original tweet by “LegaSalvini” on 2018-03-17, 13:50:25 UTC: “Salvini: Di Maio mi chiamerà? Io rispondo a tutti, va bene.”

behaviour (Berelson, Lazarsfeld, and McPhee 1954). Building on this work, the social-psychological perspective of the Michigan School, with large-n surveys of representative samples, quantified the central "role of enduring partisan commitments in shaping attitudes toward political objects" (Campbell et al. 1960, 135). Proponents of this stream considered party affiliation as an "unmoved mover": it is largely unchanged over time, yet party ID acts as a "filter" through which political realities are perceived in a way favourable to an individual's partisan orientation. Party affiliation shapes policy preferences and political attitudes, but remains mostly constant over time.

The 'revisionist' perspective challenged the Michigan School by considering retrospective evaluations as instrumental for party ID (Fiorina 1981). This rational choice theory adds an important component to the earlier static model of the "unmoved mover". It can not only explain why party affiliation is stable, but more importantly, why party affiliation changes over time. Voters keep a "running tally" of retrospective evaluations of party promises and government performance. So, while individuals might start out with political socialization determining their party identification (by ways of family and upbringing), over time their attachment to a party becomes increasingly a reflection of individual perceptions and evaluations of political events. Achen (1992) formalized this perspective and fit it into a framework of Bayesian Updating, i.e., voters learning from previous experience to decide on which party to support.

In cross-sectional studies this running-tally perspective allows for a benign interpretation of the democratic process — democracy works because people identify with (and subsequently vote for) the party that best represents their interests. Following a shift in individual interests, party ID and vote choice change. If enough individual shifts are registered within the electorate, party elites take note and adjust policy positioning accordingly. The causal chain in this scenario is considered good and desirable: voters lead, politicians follow. Democracy works as it should.

However, knowing whether voters actually lead politicians poses a well-known challenge for cross-sectional research designs. This is because one only has a snapshot of the two groups' proximity to one another and we cannot know for certainty who followed whom. Yet, clearly the causal ordering matters a great deal for understanding of democracy. If 'politicians lead, and voters follow", representative democracy is effectively a sham (Achen and Bartels 2017).

To resolve this empirical dilemma, Lenz (2012) uses panel data, which measures voter policy positions at multiple points in time. Matching this with elite positions, Lenz shows that contrary to the classic model of democracy, voters follow politicians on many types of issues. Moreover, this relationship is stronger for individuals with higher degrees of partisan attachment, and also appears in multi-party democracies (Slothuus 2010).

Yet, the dynamic of 'leadable' citizens does not appear to hold across the board for all parties and issues. Voters not aligned with any party are more likely to engage in issue-based reasoning (Matthews 2018). Research on voters' ideological leaning and party affiliation shows that niche parties' vote shares decline when they moderate their ideological positioning, while no such effects occur for mainstream parties (Adams et al.

2006). Supporters of niche-parties appear to disproportionately monitor and react to elite policy shifts. The relationship does not only appear for individual levels of support, but also for the ideological makeup of supporters on an aggregate level (Adams, Ezrow, and Leiter 2012). A plausible explanation is that niche party supporters are more policy-focused than supporters of catch-all centrist parties.

A second important qualifier for the parties leading public opinion is the saliency of policy issues for which the party repositions itself. Even the Michigan School acknowledged an issue-based change in partisan loyalties, with Campbell et al (1960) noting how deeply held opinions, with high personal importance and strong feelings attached to them, "must exert some pressure on the individual's basic partisan commitment. If this pressure is intense enough, a stable partisan identification may actually be changed" (p. 135).

Later research built on this modified Michigan perspective to investigate issue-based party conversion and found that the saliency of the issue is relevant: Layman and Carsey (2006) find that both party-based issue change (following) and issue-based party change (leading) take place. Which of the two processes ensues is dependent on the saliency an individual assigns to the issue in question. On one side, individuals for whom the issue is not particularly salient tend to realign their issue position to be in line with party ID, they are following the parties. On the other, for an issue which is considered salient, the process mirrors issue-based change in party affiliation. This is the process by which, in aggregate, voters lead political parties. Issue salience appears to nudge the "unmoved mover".

The effects also appear when tested over longer periods of time. When saliency of an issue changes from one period to the next, then the effect of that issue for party identification differs between eras. To investigate this over a longer timeframe, Highton and Kam (2011) make use of fluctuations in issue importance between 1970 and 2000. Their findings suggest that the relationship between an individual's party affiliation and their attitudes, usually measured as issue-preferences, is conditioned by the importance ascribed to the issue and appears to be affected by a larger "political context" in the long run. While in an earlier period (1973-1982) partisanship takes precedent over issue positions, the causality switches for a later era (1983-1997) when the issue position of an individual is more predictive of partisan affiliation. Somewhat surprisingly, Highton and Kam find no systematic effect of political sophistication for the switch of causality.

Overall, these previous findings paint a nuanced picture. Citizens take cues from parties to determine their own position on an issue, but only as long as that issue is of lesser importance to them. Here, elite messaging can be a good heuristic for voters. Simply following the leaders can be an effective informational shortcut for a citizen, given strong individual partisanship. Strategic party elites can make use of the heuristic when re-aligning their own positions.

This also means, however, strategic use by elites is only effective given low importance of an issue. If a citizen cares a great deal about a topic, they are less likely to adjust their opinion to make it compatible with 'their' party. Instead, the individual is more likely to shed party affiliation and switch ID.

Elites can of course be effective at changing the saliency of an issue (Zaller 1992), but doing so becomes a double-edged sword. Stressing a topic can lead to a strengthening of party affiliation amongst a party's supporters, but it increases the risk later on should the party see the need to change its position on the issue, thus risking the loss of persuaded supporters.

I test these co-dependencies on non-traditional data. Because campaigning around the Italian Election of 2018 was to a large degree conducted online it presents an opportunity to use data collected from Twitter. Instead of focusing on the content of specific tweets, I focus on the underlying structure of connections on the platform. Previous research has found that low-threshold political engagement on social media in Italy is a good predictor of other modes of political activity (Vaccari et al. 2015). Based on this, I assume users who engage with politics on Twitter are above-average interested in politics and to a large degree feel aligned with a specific party or electoral alliance.

The relationship between party ID and party support, moderated by issue position and saliency, lead me to test two hypotheses:

- *H1*: During the campaign, partisan proximity of a user to the Lega has a positive relationship with the expression of party supports (expressed per retweets). The closer a twitter user is to the source-party of the tweet, the higher the probability of retweeting.

This relationship should be reversed after the coalition is announced: Users with high partisan affinity (close ideal points to the party) should feel disappointed that a central point of Lega's campaign was withdrawn. But we should expect to see that users *closer to m5s* now start to display higher degrees of support for Lega-affiliated accounts. Overall, this leads to the following hypothesis H2:

- *H2*: With announcement of the coalition, partisan proximity of a user to the Lega is negatively related to party support (measured in retweets). The greater the distance between source-account and user, the higher the probability of a retweet.

Model and Dependent Variable

The model I propose tests the effect of party closeness on party support at two different time points: during the electoral campaign, and after the coalition between Lega and m5s was announced. My analysis is based on an OLS-regression with the outcome variable rate-of-retweet of a party for each user. The rate-of-retweet is the number of retweets in one of the time frames divided by the total number of tweets in the same time frame. Thus, it is a proportion between 0 and 1 for each user which indicates the support of this user for the respective party.

An individual retweeting a message from any account affiliated with the Lega is an act of endorsement in my model. This perspective, however, is not without its detractors. For some authors, a retweet is an ambiguous practice which can serve multiple communicative purposes and cannot explicitly be understood as a message of support (Boyd, Golder, and

Lotan 2010; Nagler et al. 2015; Guerra et al. 2017). When seen in context of a political campaign, however, where clear ideological messaging is sent from partisan accounts, a retweet becomes a costly act and it is likely to express party support or even vote intention (Ceron, Curini, and Iacus 2015; Ceron and Adda 2016). I explicitly understand a retweet to be an endorsement, since it intentionally aids visibility and increases reach of an elite message by sharing it to another part of the social network. The more retweets a user sends, the more support she shows for the party.

Methodological Approach

I test this relationship using non-traditional social science data extracted from Twitter: To determine party support I use tweets, to identify party affinity I use follower networks. Previous research has shown that the follower networks for political elites on Twitter allow for estimating ideological ideal points (Barberá 2015) for both elites as well as for individual users. Barbera uses a Bayesian Spatial Following model, developed from Item Response Theory modelling, to place political elites in a latent space. At the core of this approach is a probabilistic model for the act of "following". For these approaches, the chance of a user following a certain member of a political elite is as a function of three separate parameters: A) The ideological position of the user, B) the ideological placement of the elite, and C) the popularity of the elite. Using Bayesian simulation and repeated draws from predetermined probabilities, this model places both users and elites in a previously unobserved space. While this allows for robust estimations, it has limited scalability due to the slow pace of the underlying sampler.

For the present work, I use an approach proposed by Imai, Lo, and Olmsted (2016), which is optimized for large-scale follower matrices and produces reliable estimates. Unlike a Bayesian Spatial Following model, their proposed expectation-maximization algorithm does not return likelihood distributions, but maximum-likelihood point estimates. It is a very fast implementation and allows for the estimation of latent ideal points for 348 Italian politicians and almost 653,000 Italian Twitter users who were active during the 2018 Italian election campaign. To produce data on individuals' tweeting behaviour, I used the R-packages "streamR" (Barberá 2018), and "rtweet" (Kearney 2019) to collect tweets related to politics in Italy between February 7 and June 4, 2018 and extracted followers of political accounts (details about this process can be found in the Appendix). The resulting dataset contains over 46 million tweets.

For the analysis below, I focus on 8.3 million tweets (17.9% of the raw data) which were sent by my sample of ideologically placed politicians and users. 5.4 million tweets (65.3% of tweets by scaled users) in this collection are retweets. To identify the twitter user handles of Italian politicians I relied on a list compiled by the Italian newspaper *La Repubblica*[6]. Since I extracted follower lists after the end of the campaign and coalition

[6] This list can be found at https://twitter.com/repubblica/lists/politici-italiani

building, my estimations work off an approximation of follower lists for February 2018, a timespan roughly three weeks before the election of March 6th.

Model Specification

To determine a difference between party supporters' behaviour *before* the election and *after* the coalition announcement, I fit a bivariate OLS-regression model. My dependent variable is the rate-of-retweet of a user for a party. The independent variable of my model is ideological distance between the user and the weighted party mean. I use an interaction term to account for timing (*before* election and *after* the coalition announcement). Moreover, I fit two models for each party, one for users whose ideal points are *above* the weighted party mean for position and a second for users whose ideal points are *below* it.

Main Independent Variable

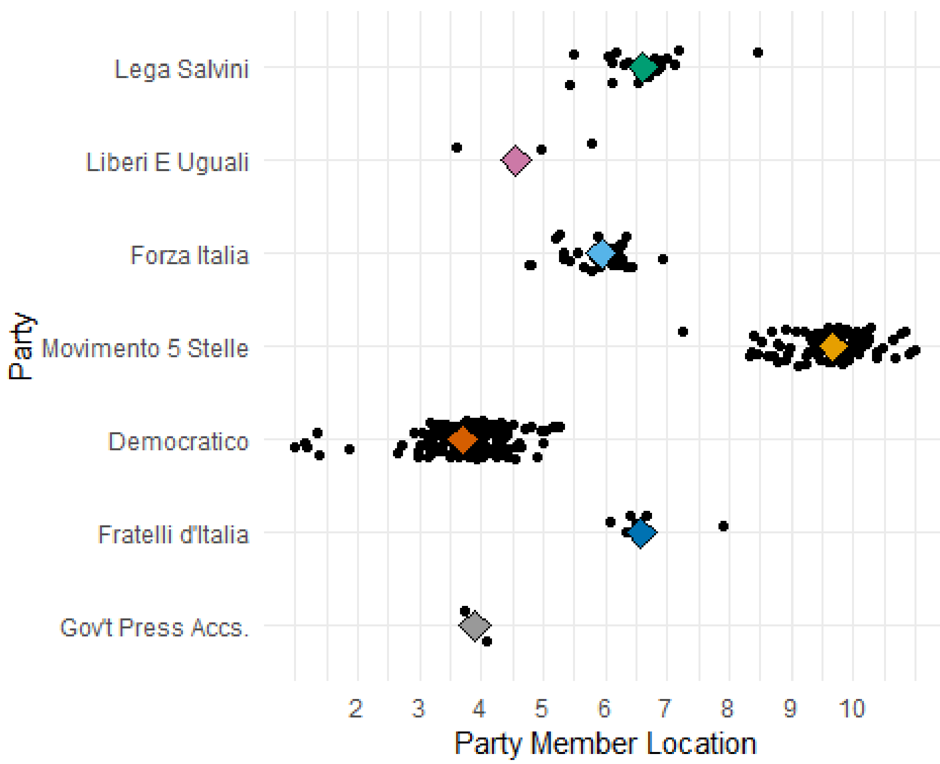

Figure 1: Estimated Elite Ideal Points with Party Means

To assess closeness of users to parties my approach places each user (individuals as well as party elites) on a scale ranging from 1 to 11. For the placement to be informative, a minimal political interest of each user is a prerequisite. To this end, I estimate an ideal point for each user which follows five or more political elites, using the maximum-likelihood estimation approach by Imai, Lo, and Olmsted (2016), as implemented in Imai, Lo, and Olmsted (2017).

Figure 1 illustrates the results of the estimation for political elites in Italy. The order of the two major electoral coalitions is in line with their political alignment: the centre-left coalition of PD and Liberi&Uguali as the moderate, left-leaning block; the rightwing coalition of Lega, Fratelli d'Italia, and Forza aligned to the right of the leftist government-coalition. The leftist-populist m5s is located on the outer end of the latent space. Party means are indicated within the scattered points of each elite account and weighted by the logged number of followers of each party-affiliated account.

The order of the estimates, if taken at face value, does not make ideological sense. In the common understanding of left-right-ideology, m5s is not more extreme right-wing than the Lega, but in this latent scale it appears to be. How can this be explained?

The utilized algorithm reduces any *n* dimensional political space into a one-dimensional scale. Similar to survey questions asking individuals to fit themselves & parties on a left-right spectrum, this estimation procedure simplifies issue-positions and reduces dimensionality. It collapses many opinions across issues and projects it to just one scale. It projects well for a one-dimensional or two-dimensional policy space but fails to appropriately conflate multi-dimensional scales. These ideal points are not in line with prior expectations in this case because there are multiple axes being reduced to just one. The underlying latent space has at least two dimensions: one differentiating between government (centre-left) and opposition (centre-right), for which the estimates presented here are what we would expect.

But there is a second axis which scales "established" Italian politics (PD, LeU, FdI, Forza, Lega) against "anti-establishment" (m5s). I offer this clarification since the estimation of ideal points *without* m5s produces ideological rank-ordering that is better in line with typical left-right expectations. Adding m5s into the model (as shown) "tacks" it onto the outer edge. It is of note that m5s is not placed on the centre-left camp (left side of the graph), but instead at the rightward end, in closeness to the Lega. This illustrates the Lega's curious appeal as an anti-old guard party, despite being around for almost 30 years. For my statistical model I do not rely on users'/elites' numerical position on this scale, but instead on users' distances from the weighted mean of Lega and m5s. By focusing exclusively on this distance between either party, I avoid the complications arising from the multiple dimensions of the underlying scale.

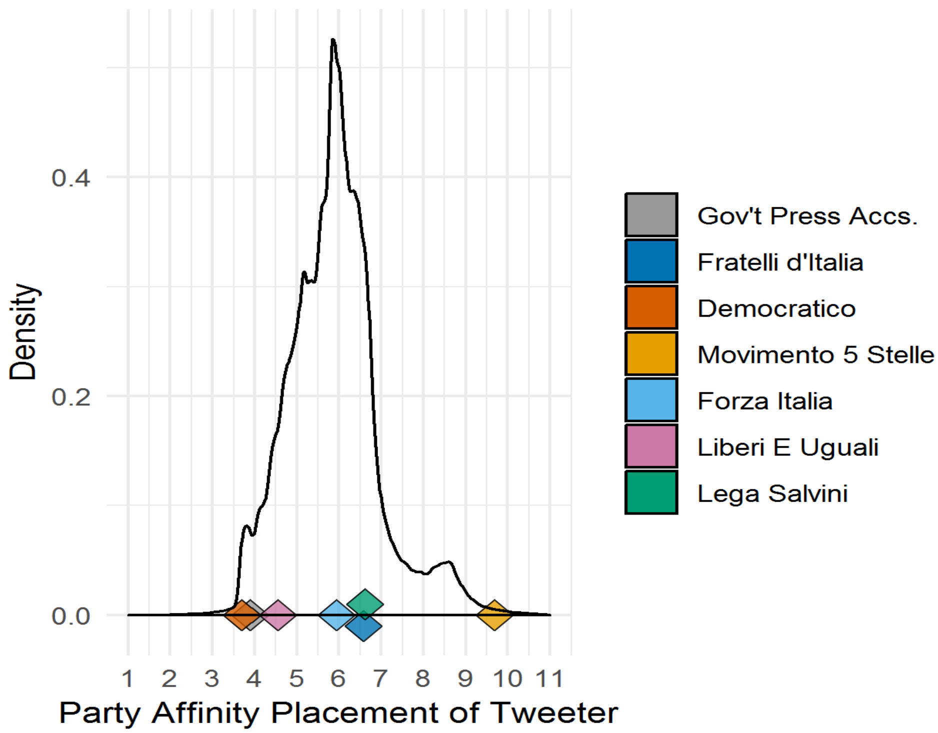

Figure 2: Affinity Scale Position of Tweeters, with Party Means

Figure 2 shows the overall distribution of twitter-users' ideal points derived from the estimation. It appears slightly right-skewed, but not unlike a normal distribution. The central peak, where most Twitter users fall ideologically, is about 5.7. Overall mean for the ideological position of users is 6.13, the median 6.14. 73.9% of Twitter users are within one standard deviation (1.08) from the mean, with 15% being placed above of this window and 11% below.

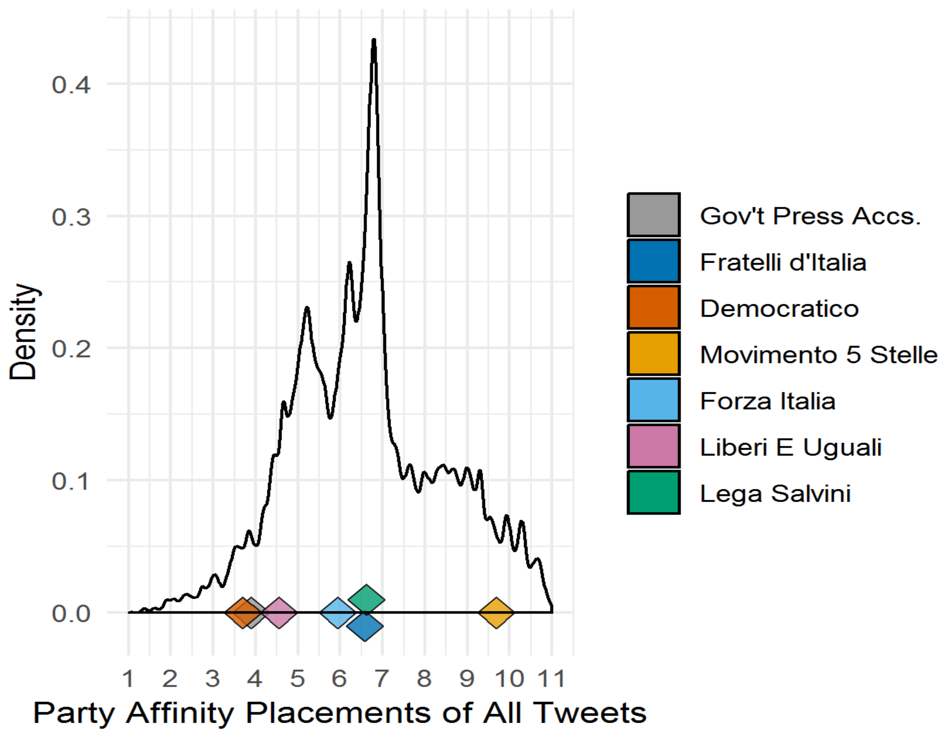

Figure 3: Affinity Scale Position of All Tweets, with Party Means

Figure 3 provides a first link between my central independent variable (ideological ideal points) and individual users' behaviour. The figure shows in which areas on the latent scale the most active users are placed by plotting the distribution of tweets over the ideological position of the tweeting accounts. The resulting curve has two distinct peaks, with a distinct right skew - meaning that users on the anti-establishment end of the scale punch above their weight in terms of tweeting-volume. 66.6% percent were sent from accounts within one Standard Deviation (1.79) from the mean (5.39). 15% of all tweets were sent from accounts which are more than one Standard Deviation above the mean. For my regression I calculate the distance between each retweeting user and the weighted party mean.

Dependent Variable

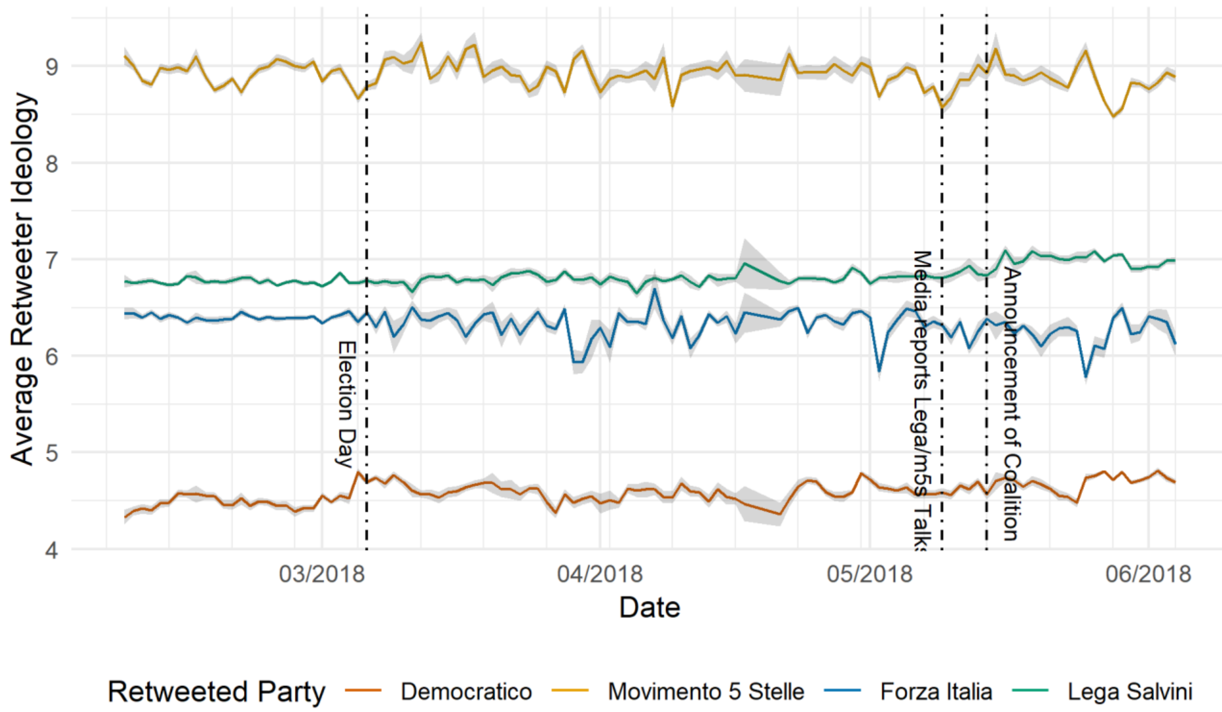

Figure 4: Daily Mean of Retweet-Ideal Points by Party

My focus of interest is on the degree of support from Twitter users closely affiliated with Lega and, to a certain extent, a different set of users affiliated with m5s, during the campaign and after the coalition between both was announced. Again, I understand retweets to be endorsements. Figure 4 presents the average ideological score of retweets for each party per day. Three vertical lines indicate days with central events: The election held on March 6th, the first media reports about talks held between Salvini and Di Maio on May 9th, and finally the announcement of the coalition between Lega and m5s on May 14th. Of special note is the average daily ideology of retweeters of the Lega: Low in variance, with an aggregate mean of 6.77 before the election, it starts to increase on the day of media reports about coalition talks, and remans slightly elevated with a mean of 6.96. This is a first indication of a change in tweeting behaviour amongst supporters of the Lega after the coalition-announcement.

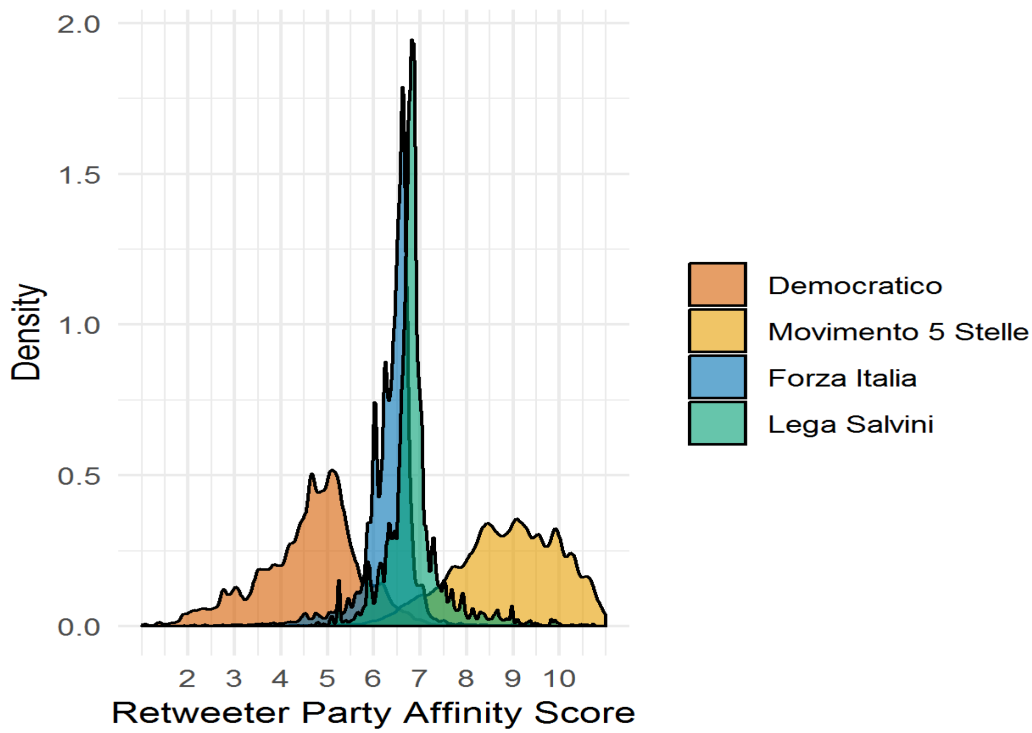

Figure 5: Affinity Scale Position of All Retweets, by Party

This seemingly small move of the average retweet-ideology warrants an investigation into the distribution of the underlying measure. Figure 5 presents the overall composition of ideological source position of all retweets by party.

Frequent retweeters of Lega (and its coalition partner Forza Italia) are mostly placed in a narrow band in the middle of the ideological scale. These vocal supporters are more concentrated than the supporters of m5s. As a reference of volume of retweets, the Democratic Party is included in this graph as well. Over the course of the whole time frame, Lega received the bulk of its support from accounts near the centre of the latent space, yet, as figure 4 illustrates, after the coalition announcement the structure of the party's twitter support appears to change.

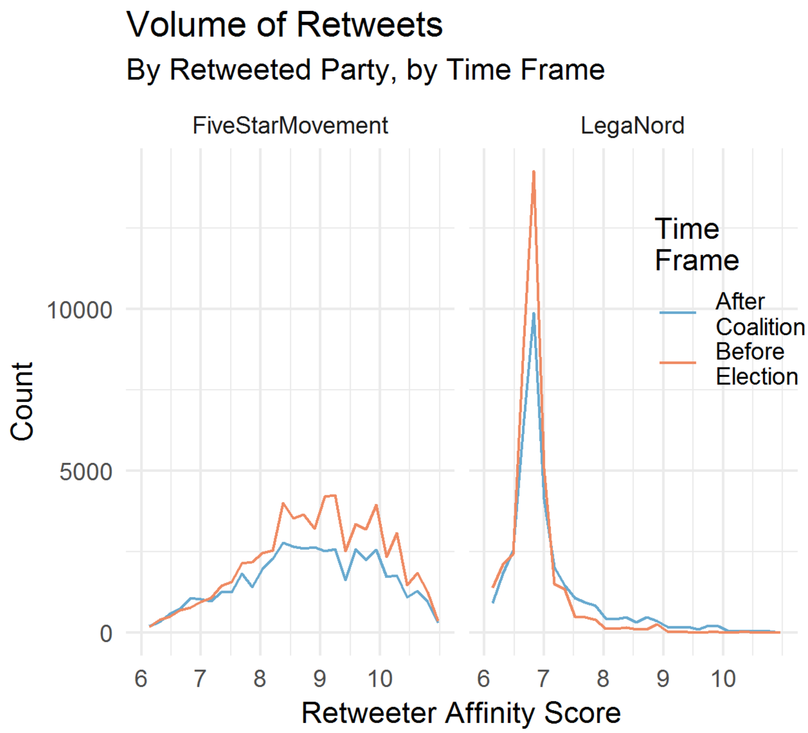

Figure 6: Affinity Scale Position of All Retweets for Lega & m5s, by time frame

Figure 6 gives an overview of absolute counts of retweets for both parties of interest. As is to be expected there is a difference in volume of tweets during the campaign and after the coalition announcement. While electioneering was ongoing, the engagement of users with either parties is generally larger, with levels dropping after the coalition announcement. It is of note that after announcement Lega received a larger number of tweets from users leaning towards the m5s-end of the scale. This difference, though, is marginal at best. It does not give any indication if this means that previous Lega-supporters have changed their behaviour. This is what my analysis below focusses on.

To account for a possible change in the rate of activity before the election and after the coalition announcement the model below considers not absolute counts of retweets, but rate-of-retweet instead. This measure describes which share of all tweets sent by a user during each of the two-time frames were retweets of a party. It is the proportion of party-retweets over the total number of tweets.

Having established these descriptive statistics about tweets and retweets around the Italian Election and coalition building in 2018, I now turn to the investigation of the behaviour of party supporters before the election and after the coalition announcement.

Results

I focus on the reaction of Lega-supporters to the formation of Lega/m5s coalition. My model predicts a user's rate-of-retweet for each party from the user's ideological ideal point estimation, both before the election and after the coalition announcement. The analysis rests on two models per party, for a total of four models overall. The first model for each party tests effects of timing for users whose ideological scores are *below* the respective party mean. The second model is fitted only on users whose ideological scores are *above* the respective party mean. My model specification includes interaction-terms between "time frame" and "ideological distance between user and party mean." Full regression results can be found in the appendix, my interpretation here focusses on the plots of predicted values for each model-specification.

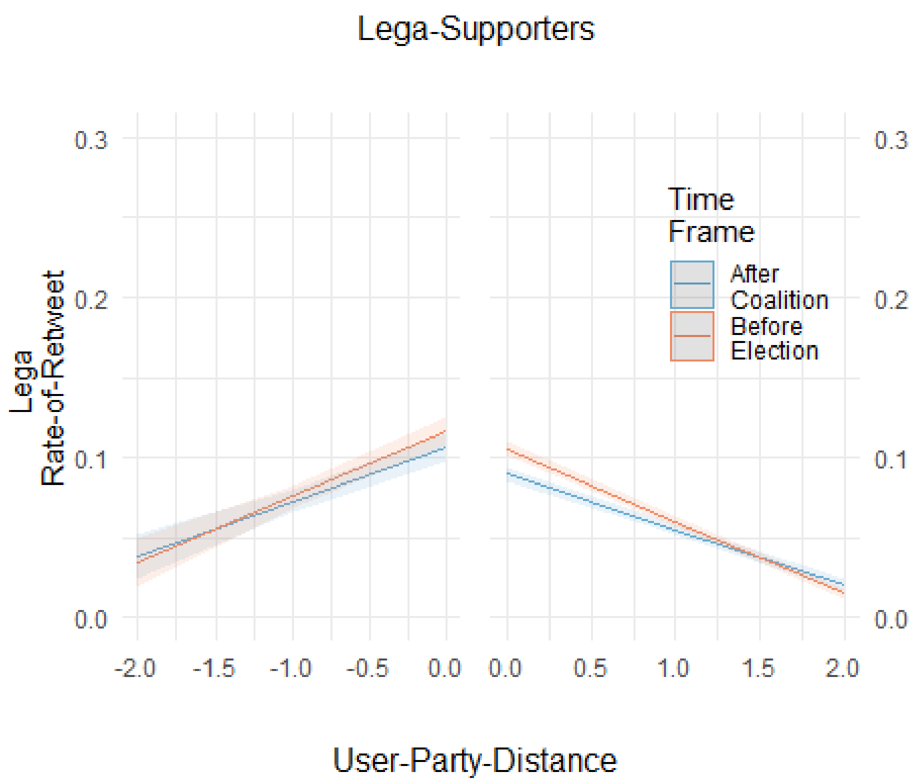

Figure 7: Effect Sizes and Direction for Affinity Distance on Rate-Of-Retweet for Lega Supporters

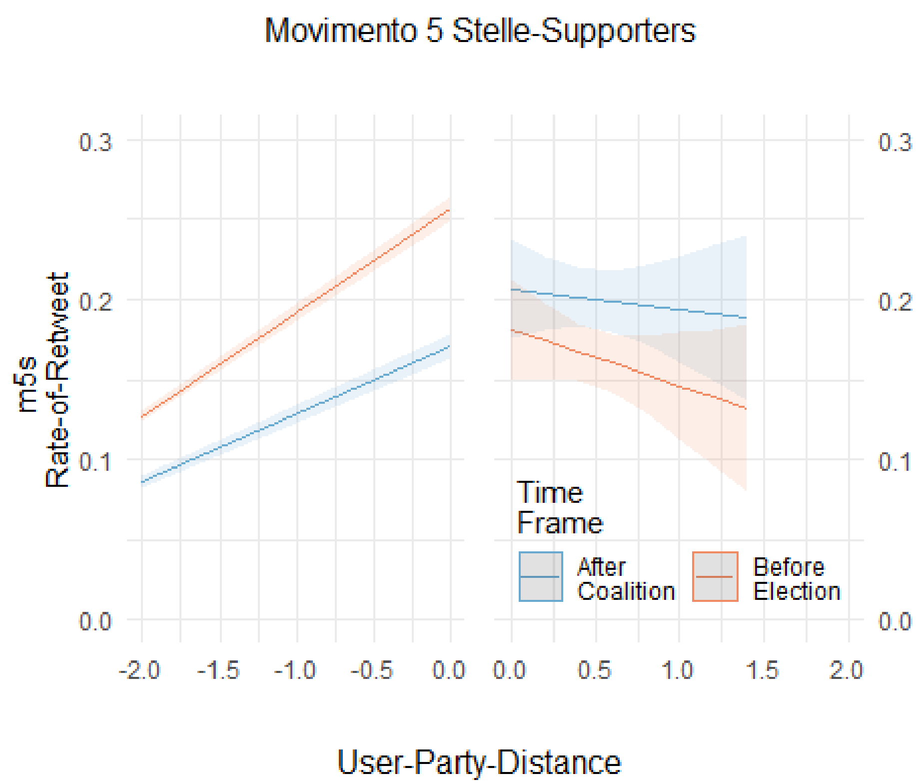

Figure 8: Effect Sizes and Direction for Affinity Distance on Rate-Of-Retweet for Movimento 5 Stelle Supporters

Figure 7 represents the predictions from the regression model for Lega-supporters only. These are users that retweeted at least one of the messages sent by any Lega-affiliated twitter account at any point during either of the two timeframes. Overall, differences in rates-of-retweets before and after are not sizeable, but they are systematic. For users whose ideological positions are below the party-mean (left side of the panel), no changes in party-supportive behaviour can be inferred between the two time frames. This opposes hypothesis H2.

For the users in the right panel of figure 7, however, the model does predict a change in behaviour. These users, who are located between the party means of Lega and m5s, appear to be affected slightly differently by the announcement of the coalition. Users closer to the party-mean of Lega reduce their expressions of support after the coalition announcement. Users further away from Lega (and thus closer to m5s) do so as well but at a lesser extent, before reaching a threshold. Beyond this threshold of about 1.5 points ideological difference their behaviour does not seem to differ between 'before' and 'after'. This is in line with hypothesis H2: The less staunch a party supporter is, the more likely is her support be unaffected by party activity. "Following" is more likely than "leading" and even though these due to their small effect sizes results are not flat-out confirmation of the proposed process, the observed effects do show the opposite.

An additional piece of evidence lies in the behaviour of m5s-supporters. Figure 8 presents the results of a similar analysis as performed for Lega retweeters. Again, the effects are different for users on either side of the party. For individuals scoring *higher* than the weighted party mean (figure 8 's right half) the model's standard errors are too high to determine a difference in effects. The same does not apply to users on the left side of the panel. For users with ideological scores between m5s and Lega, there appears a substantial difference in the rate of retweet before the election and after the coalition. Not only is the overall willingness to express support lower after May 14. The strength of association between ideological placement and rate-of-retweet (as measured in the slope of both lines) is slightly lower *after* the coalition. Compared to the *before*, the ideological distance between user and party matters less for the expression of support. Again, this implies support for H2. More moderate party supporters rely more on their party affinity to determine issue positions.

Taken together these effects do support the hypotheses of different kinds of users being more prone to follow the party line. The fact that only the effects for users with ideology score between the means of Lega and m5s is a good indicator that the effects are related to the parties' activities, rather than a mere 'campaign effect' of mobilization before versus after an election. This can be further affirmed by a simple validation of the model. Applying the same regression to the other parties and their supporters reveals that systematic effects like these do not appear in another constellation. Moreover, the model specification I chose is prone to underestimate true effects. Examination of the overall data (Cf. figure 6) suggests that a logarithmic scale of effects would provide a better fit of the model. However, this would bring a tradeoff for model specification and interpretability. Thus, I present the results from linear regressions here. Furthermore, my model is conservative since in cases where a user does *not* tweet or retweet in one of the time frames, my analysis does not count the observation as 'missing' but pastes a 'zero' to the dependent variable. This might reduce effect size in the model, but is a conservative estimate to avoid "false positive" type 1 errors. Nonetheless, the different associations of ideological distance and retweeting-behaviour stand. Not only are the effects contingent on direction of distance to Lega and m5s, they also appear exclusively for these two parties.

Further Research and Conclusion

With this present work I contribute to an important question about democracy: Do politicians follow voters or do politicians lead voters? I use the Italian election of 2018, with its unlikely coalition formation, as a test bed. My examination of non-traditional social science data extracted from Twitter suggests that not all voters are equally willing to be lead and follow.

Overall, my investigation established two findings. Firstly, after the coalition announcement Twitter activity favouring Lega and m5s moved closer together. Secondly, usage patterns of individuals affiliated with either party was different between time frames and dependent on their own ideological position. As previous literature suggests, for a highly salient topic more staunch party supporters of the Lega (and m5s) do not appear as willing to follow into the coalition with the m5s. The announcement of the collaboration between both parties put off these users, and their rate of endorsement decreases. For individuals with a larger distance between party position and own ideological placement, the effects depend on the direction of the distance. Users falling between Lega and m5s on the latent scale were affected differently by the coalition than users on the outside of the parties' range.

This inquiry confirms previous findings about the relationship between niche parties and their followers. Unlike a free-wheeling dynamic where the party leads, and ideologically blinded, devout followers mimic every step of the way, supporter retention is not a given for parties like the Lega and m5s. Instead, and in line with Adams et al. (2006) and Adams, Ezrow, and Leiter (2012), staunch supporters of extreme parties appear to be more sensitive to policy shifts of 'their' parties. My results suggest this to be the case for Twitter users as they express support for the Lega.

Building on this present work, an important extension would be to establish the underlying structural changes in activity across Twitter users. My analysis focused on the difference in party support between *before* and *after* for a set of users, but does not deliver insights about the *overall* makeup of retweets for either party in different time frames. While I effects effects of ideology on support for the same party before and after, further research in this area should deliver insights about party _switchers_ and their ideological distance. These switchers have potential to serve as fruitful extensions of my argument if the propensity to switch is related to both the ideological distance of either party, and the time frame at which switching is examined. Especially when considering switchers not just between Lega and m5s, but, for example, Lega and its electoral alliance partner Forza Italia, the effects of ideological distance on expression of political support can be determined in more detail.

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Appendix A - Search Terms for Twitter Query

All tweets sent between containing any of the following keywords were collected for my analysis:

“elezioni2018”,“elezionipolitiche2018”,“voto”,“macerata”,“4marzo2018”,“elezioni”,“4marzo”,“berlusconi”,“forzaitalia”,“4marzovotoforzaitalia”,“centrodestra”,“forza_italia”,“liberi_uguali”,“liberieuguali”,“pietrograsso”,“piu_europa”,“piueuropa”,“civicapopolare_”,“civicapopolare”,“renzi”,“matteorenzi”,“pdnetwork”,“programmapd”,“sceglipd”,“avanti”,“iovotopf”,“squadrapd”,“ilmioimpegno”,“partitodemocratico”,“centrosinistra”,“m5s”,“grillo”,“beppe_grillo”,“mov5stelle”,“dimaio”,“dimaiopresidente”,“votiamolivia”,“partecipa”,“scegli”,“maipiupd”,“leganord”,“legasalvini”,“matteosalvinimi”,“salvini”,“4marzovotolega”,“salvinipremier”,“lalegatifrega”,“fratelliditalia”,“centrodestrait”,“votagiorgiameloni”,“giorgiameloni”,“4marzofdl”,“giorgiapresidente”,“melonipresidente”,“Sinistra_europa”,“Articolounomdp”,“patriotiDitalia”,“socialistarturo”,“oravotocasapound”,“direzioneparlamento”,“accettolasfida”,“CasaPound”,,“mattarella”,“cottarelli”,“#politiche”,“#politiche2018”,“#montecitorio”,“#politico”,“#parlamento”,“#governo”,“#sovranità”,“#sivota”,

Keywords below were added 4/4/2018

LEGA

“#votare”,“#elezioni”,“#leganordpadania”,“#autonomia”,“#primaglitaliani”,“#labuonapolitica”,“#salvinipremier”,“#stopinvasione”,“#matteosalvini”,“#andiamoagovernare”,“#noiussoli”,“#lacittadinanzanonsiregala”,“#sbarchi”,“#immigrati”,“#immigrazione”,“#centrodestra”,“#napolitano”,“#leggeelettorale”,

M5S

“#alessandrodibattista”,“#movimento5stelle”,“#5stelle”,“#politica”,“#movimento”,“#dibattista”,“#onestà”,“#grillino”,“#beppegrillo”,“#deputato”,“#bepopular”,“#onorevole”,

FAR RIGHT

“#casapound”,“#osa”,“#cambiamento”,“#forzanuova”,“#ipasvi”,“#vota”,“#lista”,“#fiamma”,“#tricolore”,“#forza”,“#nuova”,“#sala”,“#milano”,“#forzanuova”,

Keywords below were added 5/21/2018
“andiamoagovernare”,“quirinale”,“Consultazioni2018”,“m5slega”, “legam5s”, “salvinidimaio”, “dimaiosalvini”, “governom5slega”, “governolegam5s”, “contrattodigoverno” , “governo”, “giuseppeconte”,“maratonamentana”

Appendix B - Regression Table

OLS-Results

	Rate-of-Retweet			
	Lega-Dist < 0	Lega-Dist > 0	m5s-Dist < 0	m5s-Dist > 0
	(1)	(2)	(3)	(4)
Lega-Distance	0.034***	-0.034***		
	(0.005)	(0.001)		
m5s-Distance			0.042***	0.042***
			(0.001)	(0.001)
Time Frame: Before	0.010	0.016***	0.086***	0.086***
	(0.006)	(0.003)	(0.005)	(0.005)
Lega-Dist * Before	0.007	-0.011***		
	(0.007)	(0.002)		
m5s-Dist * Before			0.023***	0.023***
			(0.002)	(0.002)
Constant	0.107***	0.090***	0.171***	0.171***
	(0.004)	(0.002)	(0.004)	(0.004)
N	8,236	19,381	26,504	26,504
R^2	0.014	0.079	0.116	0.116
Adjusted R^2	0.014	0.079	0.116	0.116
Residual Std. Error	0.202 (df = 8232)	0.138 (df = 19377)	0.175 (df = 26500)	0.175 (df = 26500)

*p < .1; **p < .05; ***p < .01