Political Anger

Evidence from Social Media Campaigns in the Italian Elections

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This Version: 13th May 2022

Abstract

The aim of this paper is to measure political anger in social media posts of political parties and candidates during electoral campaigns. To this end, we construct four text-based indicators that quantify the anger content of social media posts: the first is based on a dictionary approach, the second on the frequency of caps lock usage, and the last two based on unsupervised machine learning method. We apply these measures to 18,964 Facebook posts that Italian parties and their leaders published during the campaigns of the two most recent national elections to date. We find that our measures perform well in capturing different aspects of anger. Our evidence shows that anger is mostly targeted at attacking political opponents, mocking them and at associating the election to a battlefield. Moreover, we show that right-wing parties are more likely to publish angry content than left-wing and centrist parties across all four indicators.

Keywords: Anger, Elections, Social Media, Text Analysis, Sentiment Analysis, Machine Learning.

1 Introduction

Anger is a powerful mobilizing emotion (Carver and Harmon-Jones, 2009) and one of the most commonly felt emotions in politics (Mattes et al., 2018). Its relevance in politics and in electoral campaigns cannot be understated. Existing empirical evidence suggests that political anger matters for three main reasons. First, it mobilizes voters by increasing their attachment to a party or candidate (Finn and Glaser, 2010; Valentino et al., 2011; Sparks, 2015; Stapleton and Dawkins, 2021), boosting affective polarization. Second, it sways citizens in favor of certain political decisions (Banks, 2014), and in particular choices that have violent repercussions, such as military actions (Back et al., 2011; Huddy et al., 2005, 2007; Huddy and Feldman, 2011). Third, political anger can have negative social implications, such as higher hate crime rates (Alrababa'h et al., 2021; Müller and Schwarz, 2020). Moreover, political anger stimulate negative emotions in the electorate: Stapleton and Dawkins (2021) provides experimental evidence that exposure to an angry political debates significantly increases the amount of anger and other averse emotions, including outrage and disgust, among voters in the United States.

Political anger has relevant political and social implications also when expressed on social media. Exposure to angry political debates on Facebook makes users more engaged (Wang and Silva, 2018), and anger toward an opposing political party motivates partisan individuals to engage in social media (Hasell and Weeks, 2016). Moreover, online content, such as news and memes, that incites anger is more likely to be shared (Heath et al., 2001; Berger and Milkman, 2012; Vargo and Hopp, 2020), whereas political advertising charged with anger content has the effect of activating negative feelings toward individuals or parties that are perceived as opposing (Ridout and Searles, 2011). The impact of political anger on social media can have negative implications that go beyond online and voting behavior. Müller and Schwarz (2020) show that posts with strong anti-refugee sentiments from the Facebook page of Alternative for Germany, a far right populist party, increased the likelihood of hate crimes against migrants in areas of Germany with higher Facebook usage. More broadly, anger in social media has been a good predictor of hate crimes also in other contexts, including anger among fans of football teams (Alrababa'h et al., 2021).

The aim of this paper is to measure political anger in social media posts of political parties and candidates during electoral campaigns. To this end, we construct four text-based indicators that capture the anger content in social media posts. We apply these measures to 18,964 Facebook posts that twenty Italian parties and their leaders published before the 2013 and 2018 national elections, the most recent Italian national elections to date. The first method we implement consists of the creation of a lexicon of words that are associated to anger. The basic assumption is that the more frequent these words, the angrier the content of a social media post. The second approach is based on the count of terms that are written using caps lock. While this method could also capture the attempt of candidates to attract users' attention, it is generally used to express anger and outrage in virtual communication. The other two methods rely on unsupervised algorithm pre-trained on social media.

Compared to previous works, this paper is the first to analyze how political parties channel anger through their social media posts. Our contribution hence lies in the development of four measures that are able to capture different aspects of political anger. Thanks to these indicators, we are able to draw some stylized facts on how political parties use anger in their social media communication. First, anger is mostly used to attack political opponents, which can be identified as individual candidates or parties. Second, these attacks are linked to a wide range of political contexts, ranging from corruption scandals to responses to the opponents' declaration. Often anger is mixed with a message targeted at ridiculing the opponent. In this sense political anger seems to be very close the emotion of contempt. However, in other cases anger manifests itself in the depiction of the election as a battlefield, where voters are encouraged to mobilize to ensure the victory of their party.

By inspecting the distribution of anger across parties, we shed new light on how ideology interacts with anger. Some of these findings are in line with our expectations and confirm the strength of our indicators: the anger content is significantly higher among far right and far left parties than moderate ones. However, we also show that far right parties are on average more likely to publish angry content than left-wing parties across all the four measures. Our evidence shows that the League ('Lega') and the Brothers of Italy ('Fratelli d'Italia') are the parties that display the highest content of anger and that make the widest use of caps lock in their Facebook posts. The result for the League strengthens in 2018, as Matteo Salvini becomes the party leader. Compared to these two parties, the angry content published by the Five Star Movement is considerably lower, and drops even further in 2018, when the leadership shifts from Beppe Grillo to Luigi Di Maio.

In next section, we discuss different definitions of anger and how previous studies measured anger based on text. In Section 3 we propose four methods to measure anger based on Natural Language Processing (NLP). After briefly describing the dataset we use in Section 4, we present and discuss the empirical results in Section 5. In the last section we draw some preliminary conclusions and describe the next steps we intend to take to link political anger to economic distress.

2 Political Anger: Definitions and Measurements

2.1 Definitions of Anger

Anger is a powerful mobilizing emotion (Carver and Harmon-Jones, 2009) and one of the most commonly felt emotions in politics (Mattes et al., 2018). However, it is difficult to find a minimal common definition of anger. Even from a physiological perspective, anger escapes easy definitions. While anger is generally associated with physical reactions, such as increased heart rate and intense blood flow (Prinz and Nichols, 2010), research in neuroscience shows that anger's bodily footprint is not consistent and can often result in heterogeneous physiological patterns (Barrett, 2017).

While anger is broadly considered a high arousal emotion with a negative valence (Nabi, 2003; Vargo and Hopp, 2020), some authors underlined how anger can also have positive connotations. In particular, theoretical work described anger as an attacking emotion (Frijda et al., 1986) targeted at changing a person's, or an institution's (e.g., government or agency, political party, company...), behavior (Potegal and Qiu, 2010; Sell et al., 2009). In line with this, Lonergan and Blyth (2020) distinguish between negative and positive political anger. Negative anger stems from tribal identity, such as that which clusters together ultras football fans. Positive anger relates to moral outrage against phenomena such as corruption or socio-economic inequality. These definitions echo Aristotle, who considered anger as 'a desire accompanied by pain for an imagined retribution' (Aristotle, 2010, 1378a31–33) and conceptualize anger as an emotion that can entail a payback component (Cherry, 2022; Nussbaum, 2016).

However, it is often difficult to identify the payback component in the context of an electoral campaign. While from an optimistic point of view the payback could be a policy change desired by morally outraged citizens, political anger could take more fuzzier shapes that are difficult to capture. For instance, the payback component of an angry political post could simply be the electoral gain for the candidate that writes it at the expenses of her opponents. Against this backdrop, Mattes et al. (2018) provides a possible solution to this conundrum based on the distinction between anger and contempt. According to their distinction, anger aims at confronting an individual to change her/his behavior. In this framework, anger entails the possibility of resolution or reconciliation. On the contrary, contempt is targeted at discrediting an individual, and hence entails a deteriorating long-term impact.

2.2 Existing Text-Based Measures of Political Anger

Existing text-based measures of political anger can be categorized into three main approaches, depending on whether they rely on (1) human coding, (2) lexicons (also referred to as 'dictionaries' or 'bags-of-words'), or on (3) machine learning algorithms.

Human coding requires to manually annotate each part of text with a specific sentiment. This process can be very lengthy especially for long texts, and may be prone to subjective judgment.

To overcome this issue, many researchers rely on dictionary approaches (Alpers et al., 2005; Baker et al., 2016; Cantarella et al., 2020; Shapiro et al., 2022; Fraccaroli et al., 2022). These methods rest on the creation of a list of terms, or 'dictionary' (also referred to as 'lexicon' or 'bags-of-words'), that refer to a specific emotion. These terms are then counted in the textual data to obtain a quantitative score of the intensity of that emotion in a certain document. Sentiments scores based on dictionaries tend to display moderate positive correlations with scores based on humanly annotated data (Shapiro et al., 2022; Soroka et al., 2015), suggesting that lexicons can be an effective alternative to manual coding to capture sentiments in large textual data. However, Soroka et al. (2015) note that the performance of these methods vary depending on the type of text and emotion that needs to be captured. Works that measure anger based on dictionary approaches include Back et al. (2011), that captures anger in text pager messages on 9/11, and Soroka et al. (2015), that measures anger (alongside other sentiments) in news stories based on a dictionary approach.

Machine learning approaches represent a third group and vary substantially depending on the method. On the one hand, supervised methods proved to perform better in coding fear than anger in text from news when compared to manual classifiers (Aman and Szpakowicz, 2007; Strapparava and Mihalcea, 2008). On the other hand, training on the text of blogs proved more effective in capturing anger and joy rather than other emotions (Strapparava and Mihalcea, 2008). Overall, the comparison between dictionary and machine learning approaches suggests that dictionaries have exceptional precision but lack scope, as they rely on a limited list of terms, whereas supervised and unsupervised algorithms can expand by 'learning' unexpected terms from the text. On the other hand, machine learning approaches exhibit greater coverage but higher likelihood of misclassifying emotions (Soroka et al., 2015; Strapparava and Mihalcea, 2008). An example of a study that measures anger using a machine learning approach is Vargo and Hopp (2020), that relies on the Google Perspective API to capture anger in Facebook ads.

3 Methodology: Four Text-Based Measures of Political Anger

We implement four different methods to measure political anger. These approaches are based on dictionary, caps-lock frequency, and the last two on machine learning algorithms.

First, we use a dictionary-based approach, which consists of the creation of a lexicon of terms that are associated with anger content. This approach has been used in other works to measure anger in textual data (Soroka et al., 2015). We use the NRC lexicon of Mohammad and Turney (2013), as it provides a list of anger-related terms adapted to the Italian language. As we found a number of terms unrelated to anger in the NRC lexicon, we remove them from the list, resulting in a more parsimonious dictionary than the original NRC. Formally, for each Facebook post i of party p at time t, we compute the intensity of anger based on the following equation:

$$\psi_{ipt} = \frac{\mu_i}{N_i} \tag{1}$$

where μ is the count of angry terms present in post i. We weight μ by N, that is the total number of terms present in the post. Based on the frequency of angry terms, we obtain an indicator of the anger content of each post, ψ, which we can aggregate at party level or year level.

Second, we develop a very simple indicator based on the count of terms in caps lock. While this approach does not capture anger directly, we assume that it provides for a good proxy of an angry tone. While this is a strong assumption, we test its validity by inspecting the correlation of this indicator with the other measures. The caps lock approach is based on the same equation with the only difference that the term μ is substituted by the count of terms that are written using caps lock. We exclude from the count those words that have only one capital letter, to avoid that names (e.g., of individuals or cities) are included in the count.

Third, we use a machine learning approach which identifies the intensity of anger content. We use UmBERTo, a semi-supervised natural language model trained on a pre-classified sample of

Italian tweets and first introduced in Bianchi et al. (2021).[1] UmBERTo is constructed following the same learning approach of BERT (Bidirectional Encoder Representations from Transformers), which was developed by Devlin et al. (2019) and implemented by Google for its searches. BERT is a pre-trained algorithm that leverages on an extremely large textual corpus based on a bidirectional representation model. This means that BERT considers the context of a word in a text jointly based on the text that precedes and follows such word. In this instance, BERT differs from previous machine learning approaches that analyzed words based on the preceding text, while ignoring the following terms. In both algorithms the learning process relies on a 'masked language model' in which random terms are masked in order to be predicted by the net of terms in the document. The only difference between BERT and UmBERTo is that the latter is trained on textual data in Italian. More precisely, UmBERTo is trained on Italian text from Twitter, which makes it particularly suitable for our purpose of identifying emotions on social media. BERT is particularly fit for our purpose as it has proved to outperform other machine learning methods in the classification of social media political campaign messages (Gupta et al., 2020). The outcome of UmBERTo is a score for each post across four emotional dimensions: anger, fear, joy, sadness. In this paper, we focus on the scores related to the emotion of anger.

The fourth approach relies on the Google Perspective API. This tool was designed to measure the tone of online comments or posts along several dimensions, including severe toxicity, insults, identity attack and others. This tool combines a powerful transformer machine learning algorithm with millions of annotated training data to predict whether a small chunk of text is toxic, insulting or related to other negative sentiments. The Perspective API is used by the New York Times to identify and moderate language abuses in the online comment section of the newspaper. In the academic literature, this approach has been used to capture online anger in Facebook ads (Vargo and Hopp, 2020) and sexist language in Congressional speeches (Bisbee et al., 2022). Perspective API relies on six different dimensions that can be linked to anger: toxicity, severe toxicity, identity attack, insult, threat, profanity. Our anger score using this approach relies on the average of these six dimensions.

[1] To implement this algorithm, we use the `feel-it-italian-sentiment` package for Pythond developed by the MilaNLP Lab and available at the following link: https://huggingface.co/MilaNLProc/feel-it-italian-sentiment.

4 Data

Our dataset consists of 18,964 Facebook posts from 20 parties and their respective leaders that participated to the Italian elections of 2013 and 2018.[2] The dataset was first introduced in Cantarella et al. (2020) to study the effect of fake news on the voting behavior of the Italian electorate.[3] For each party, the dataset contains the text of the posts published on the Facebook pages of each party and its respective leader. For instance, we have data on the Facebook posts of both the page of the *Lega* party and its leader, Matteo Salvini. This dataset contains the universe of Facebook text posted by political candidates in the three months preceding each election. We select this period as it coincides with the electoral campaign.

Table 1 provides an overview of the data. The table displays the sum of the number of posts published by the Facebook page of the party and its leader. The frequency includes posts published both in 2013 and 2018, when a party ran in both elections.

[2]The elections took place on February 24-25, 2013 and on March 4, 2018.

[3]The original dataset covers 22 parties. We exclude from the sample the Facebook posts of the South Tyrolean People's Party and of the Die Freiheitlichen as they are linked to the German-speaking Italian community and their posts are in German language. These two parties combined account for a loss of 357 posts.

Table 1: Posts by Political Party

Party	Code	Frequency	Percentage
Five Star Movement	M5S	3,818	20.13
League	LEGA	2,435	12.84
Democratic Party	PD	1,780	9.39
Brothers of Italy	FdI	1,579	8.33
CasaPound	CP	1,588	8.37
Left, Ecology and Freedom	SEL	829	4.37
Power to the People	PaP	992	5.23
Union of the Centre	UDC	700	3.69
Forza Italia	FI	668	3.52
Civic Revolution	RCiv	607	3.20
Act to Stop the Decline	FARE	526	2.77
The Right	LaD	519	2.74
More Europe	PiuE	500	2.64
Together	IEI	486	2.56
Civic Choice	SCiv	494	2.60
Civic Popular	CIVP	429	2.26
Party of the Family	PdF	420	2.21
Free and Equal	LeU	356	1.88
Party of Freedoms	PDL	197	1.04
Party of the Value	PVL	41	0.22

Table 2 displays the correlation between the scores of the measures of anger that we implement to the posts. All correlations are positive and statistically significant, but their magnitude varies. The two machine learning approaches, BERT and Perspective API, report the highest correlation, whereas the two approaches based on frequency, dictionary and caps lock, report the lowest.

Overall, Perspective API is the method that displays the highest overall correlation with all the other indicators.

Table 2: Covariance Matrix: Measures of Anger

	Dictionary	Caps Lock	BERT	Perspective API
Dictionary	1.0000			
Caps Lock	0.0798	1.0000		
BERT	0.1485	0.2182	1.0000	
Perspective API	0.2013	0.1888	0.3585	1.0000

5 Results

5.1 Validation

First of all, we validate the accuracy of each methodology. To this end, we look at the posts that report the higher scores of anger to test whether they actually capture an angry tone. We report the five posts that have the highest anger score for each methodology in Section A.1 of the Appendix. We report the original post in Italian and the translation in English using Google Translate, which we adjusted whenever it was mistaken.

We begin with the dictionary approach, for which we present the results based on a trimmed sample (see discussion in Section A.1 of the Appendix). We notice that the top five results are associated to posts published by four far right parties (Brothers of Italy, The Right, the League and CasaPound) and one far left party (Civil Revolution), which arguably all fall under the category of populist parties.[4]

The dictionary performs well in capturing anger in most texts. We notice that the three posts of right-wing parties express anger that is explicitly directed to their political opponents. The post of The Right considers Mario Monti, the Italian prime minister at the time, as a traitor, whereas the Brothers of Italy call for the condemnation of Luigi De Magistris, the left-wing mayor of Naples at the time. The post by CasaPound attacks Matteo Ricci, a local politician from the centre-left

[4]While the League and Brothers of Italy are categorized as populist parties in the literature and in datasets on populism (Rooduijn et al., 2019), the other parties are relatively understudied due to their short life and low representation in the electorate.

Democratic Party who was mayor of the city of Pesaro. The post from Civil Revolution displays a different typology of anger. While they are not attacking a specific candidate or party, they contextualize the elections and the restoration of legality as a 'battle' or even a 'war'. This type of communication fits well with the definition of anger as a mobilizing, aggressive emotion provided in the literature (as outlined in Section 1). Finally, the post by Matteo Salvini proposes to expel the French diplomats from the Italian territory. This proposal, which went viral, refers to a debated event which took place in the city of Bardonecchia on the border with France and that was related to the refugee crisis, a topic close to Salvini's political agenda. On March 2018 five French agents irrupted in the facility of an NGO that was helping migrants to cross the border in Bardonecchia, and hence on Italian soil. This post has a particularly strong angry charge as it incites for the ejection of foreign diplomats.

Figure 1 summarizes the terms with the highest number of matches in the form of a wordcloud. Violence, fight, battle and war are among the most frequent terms (in the wordcloud these correspond to the words: 'violenza', 'lotta', 'battaglia' respectively). These terms reflect the tendency of parties to describe the elections or their policies as a 'war' or a 'battle'. Other frequent words are related to the mobilizing nature of anger: for instance the words protest ('protesta'), fight ('combattere'), denounce ('denunciare'), revolution ('rivolta'). The word anger ('rabbia') also features among some of the most frequent terms, alongside words that are linked to negative stances or judgements such as disaster ('disastro'), failures ('fallimento'), guilt ('colpa'), or simply bad ('male'). In the Appendix, we show the wordclouds for the other three approaches, that present very similar results (Figures A3-A5).

We now analyze the posts with the highest scores based on the caps lock approach. When analyzing the top five posts of the dictionary-based approach, we noticed that already two posts out of five were entirely written in capital letters, suggesting a positive relationship between anger and the use of caps lock. The posts all report a score of one since the entirety of the text is written using caps lock. While there are multiple posts with this score, we report the first five that feature in the dataset when sorting by highest score. The top five posts based on the caps lock score are dominated by the Brothers of Italy. This is also true for all the posts in the dataset that have their entire text in capital letters: out of 531 posts fully in caps lock, 444 are by the Brothers of Italy (83.62 percent) and 27 by the League (5.08 percent), the second most frequent party.

Figure 1: Wordcloud of the most common words using the dictionary approach

Similarly to the extracts based on the dictionary, also most of these posts are attacking political opponents. In the first, Salvini attacks the centre-left president of the parliament's lower chamber, Laura Boldrini, suggesting that she is not fit for covering such a relevant role and that this will not last for long as the election is forthcoming. Moreover, the post has a strong attacking connotation, as it calls for "shame" on the political opponent. In the third and fourth posts, Brothers of Italy attacks the Democratic Party (both the party and Andrea Orlando, one of its main representatives) and the Five Star Movement respectively, for issues related to corruption. In the second post, the party is referring to the paint that was thrown on some of the electoral posters of its leader, Giorgia Meloni, in the city of Naples, arguing that this act of vandalism will not stop the party's "political battle". The last post is the only one that does not contain an angry message, as it focuses on the proposal of a policy to support the Italian birth rate.

Third, we examine the posts with the highest angry scores based on BERT. Under this approach, the League dominates the top five posts, as only one of them belongs to a different party, namely the Five Star Movement. Another interesting aspect is that four out of five of these posts are actually published by the pages of the candidates, Matteo Salvini and Beppe Grillo, rather than by the parties. This is different from the previous two approaches where only one post out of ten was from a candidate's page. The top five posts show that the BERT algorithm performs well in capturing posts that contain angry terms such as 'scam', 'bullshit' or even profanities, such as 'arse-licker'. The strength of BERT compared to the dictionary approach can be appreciated in the third post, which does not contain a particularly violent lexicon, but is clearly attacking a political opponent. In this post the leader of the League is mocking his opponent Laura Boldrini, the left-wing feminist representative of Left, Ecology and Freedom, who asked to be referred to as "presidenta" ("president" in the female conjugation, which we translated with "she president") rather than "presidente". The ability of BERT to capture this sort of attacks is relevant given the definition of anger as an 'attacking emotion' that we provided in the introduction. The other relevant element to underline is all these posts but the first reflect a direct attack to an opponent. Grillo attacks those that wrongly claimed that he intended to ally with the fascists, whereas Salvini attacks (1) the left-wing politician Laura Boldrini, (2) the incumbent prime minister Mario Monti and (3) the then leader of the Democratic Party Matteo Renzi, that he calls 'The Bomb', a nickname that political opponents gave to Renzi to reflect his alleged tendency to exaggerate when talking about his achievements.

Finally, the results of Perspective API also perform well in capturing anger. The first two posts are from far left parties. The first one features the leader of Power to the People that tells to 'fuck off' to those that minimize the issue of femicide - this is a post she published on eighth March, the international women's day. The second post also contains a number of profanities, but they are actually quotes from the opposing party, the Five Star Movement, that in 2013 generally mocked its opponents by calling them "walking dead" or by insulting them in different manners. The last three posts are from the far right parties of the League and the Brothers of Italy and all refer to migration and terrorist attacks.

5.2 Party Scores

We now analyze the party performance in terms of anger scores across the different approaches. Figures 2-4 show the anger scores based on the three first approaches for the years 2013 and 2018 aggregated at party level (Figures A10 and A15 in the Appendix provide the same figures but split by election). For each party's score we report the 95% confidence interval to account for the heterogeneous sample size across parties. In these analyses we report the scores of the People of Freedom (PDL) and Forza Italia (FI) under the same label (FI-PDL), as they were both under the same leadership (that of former prime minister Silvio Berlusconi), but with different names depending on the election.

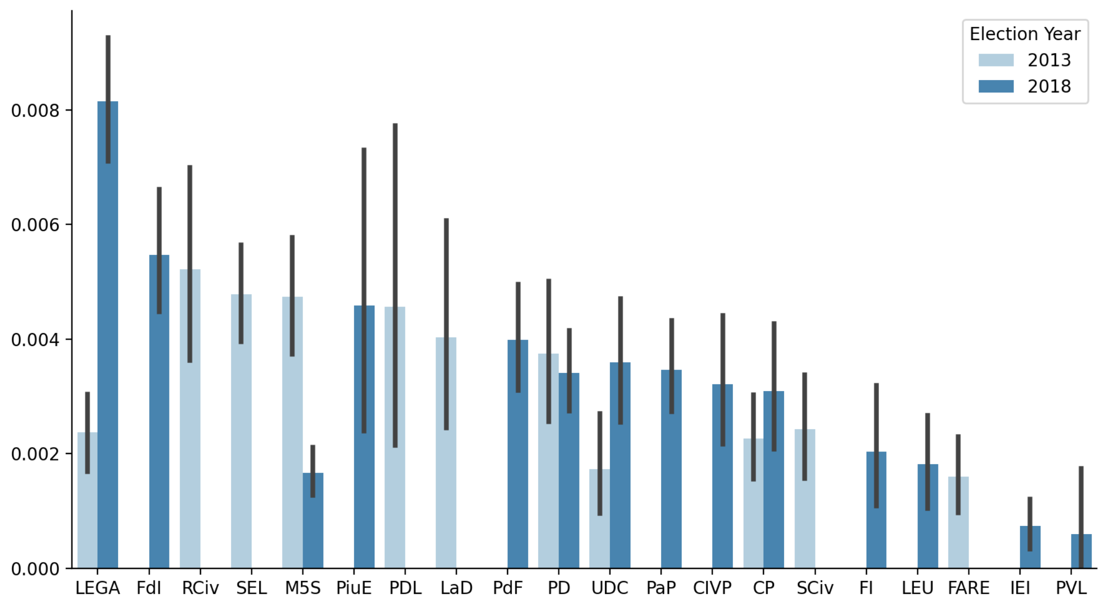
Based on the dictionary approach (Figure 2), in 2013 the parties that report the lowest scores are centrist parties: the libertarian Act to Stop the Decline (FARE), the Christian Democrats (UDC) and Civic Choice (SCiv), Mario Monti's technocratic platform. However, somewhat surprisingly, far right parties such as CasaPound (CP) and the League (LEGA) also report very low scores. The result for the League can be partially explained by the fact that its leader at the time, Roberto Maroni, belonged to the moderate wing of the party. The parties that report the highest scores in 2013 belong to the radical left: Civic Revolution (RCiv) and Left, Ecology and Freedom (SEL). These are followed by Berlusconi's Party of Freedom (FI-PDL), The Right (LaD), and the Five Star Movement (M5s). While The Right is a far right party, both the Party of Freedom and the Five Star Movement are considered as populist parties in the literature (Rooduijn et al., 2019).[5]

The major change in 2018 is marked by the rise of the League to the top of the ranking followed by the other main far right party, Brothers of Italy (FdI), which are now the two parties with the highest score in terms of anger. The third party in terms of anger score is the Party of the Family (PdF), a conservative anti-abortion party. While Civic Revolution and Left, Ecology and Freedom do not participate to the 2018 elections, the new party of reference for the radical left, Free and Equal (LEU), reports one of the lowest score in terms of anger, signalling a strong change in the communication of the left. The Democratic Party (PD) is the only party to maintain a very similar score across the two elections. Interestingly, the angry content of the Five Star Movement decreases in 2018. While the party was successful in both elections, this change can be explained by the change of leadership from Beppe Grillo, the comedian who founded the party and that characterized its rhetoric with a strong use of angry content, to Luigi Di Maio, who tried to give the party a more institutionalized communication style. In line with this, Di Maio covered several

[5]The categorization of populist may be easily extended to the party The Right. However, this party is generally absent from cross-country analyses as it received considerably less votes than the other two.

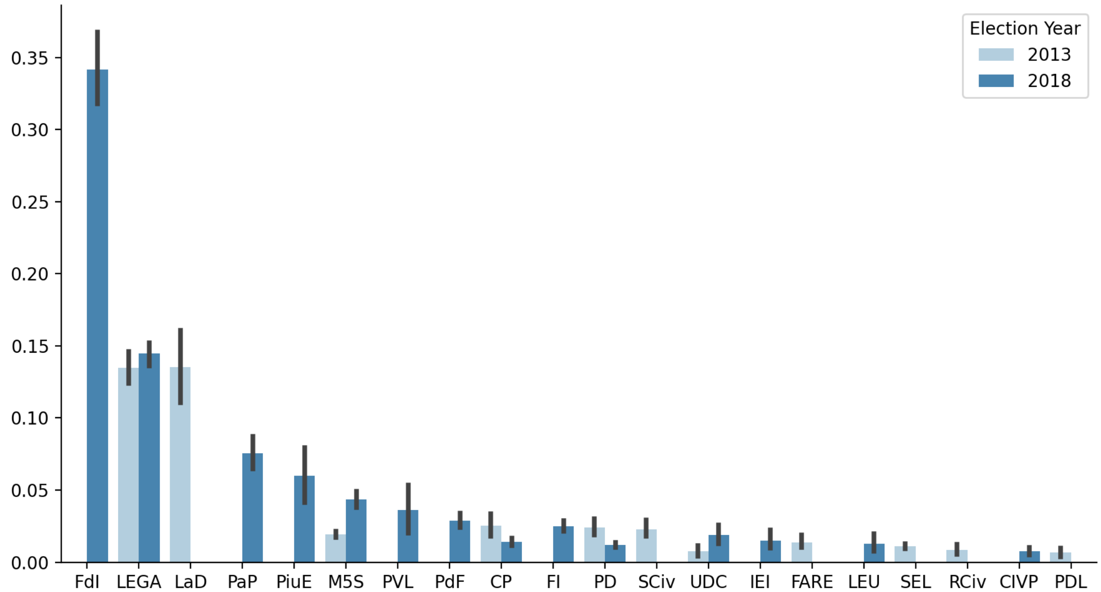
high institutional roles in different governments, including Deputy Prime Minister, Minister of Foreign Affairs, and Minister of Labor, whereas Grillo refused to undertake any role.

Figure 2: Anger scores based on dictionary approach, by party



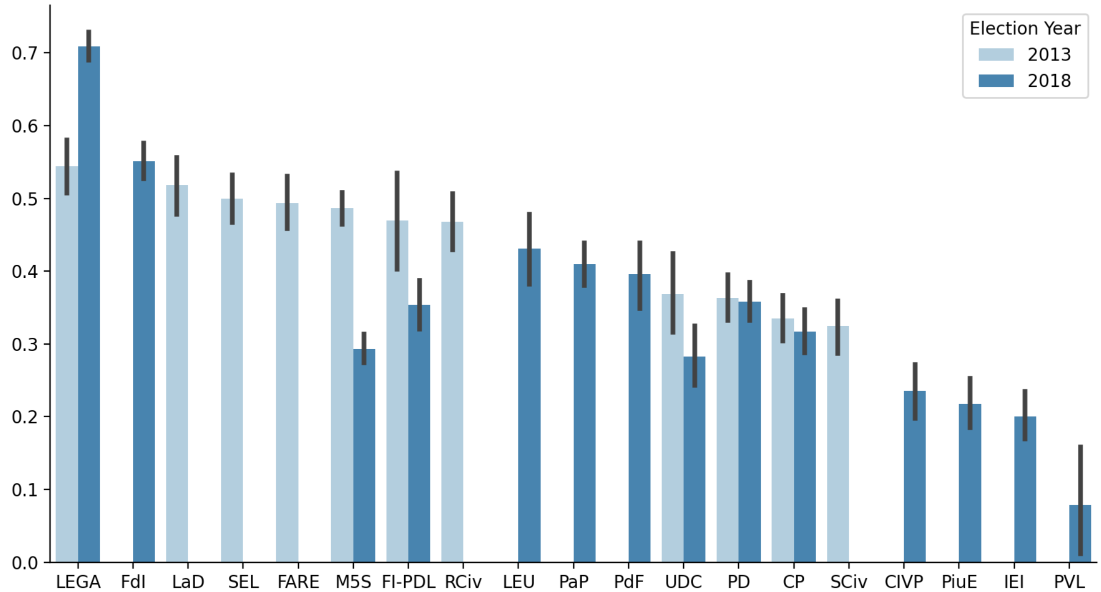
The scores based on caps lock are also dominated by the two main far right parties: the Brothers of Italy and the League. The values on the y-axis indicate that out of all the words contained in the posts of Brothers of Italy, 35 percent of them were in capital letters. In 2018 the two parties that used the caps lock the most are the Brothers of Italy and the League, whereas in 2013 those that used it the most were the League and The Right. These three parties are followed by the radical left-wing party Power to the People, the pro-European fringe party More Europe (PiuE) and the Five Star Movement (M5s). The low correlation between the dictionary and caps lock approaches (see Table 2 seems to be explained mostly by the positioning of left-wing parties such Power to the People, Civic Revolution and Left, Ecology and Freedom: the first reported a relatively low score in the first approach and a very high one in the second, whereas the opposite holds for the latters.

Figure 3: Anger scores based on caps lock, by party



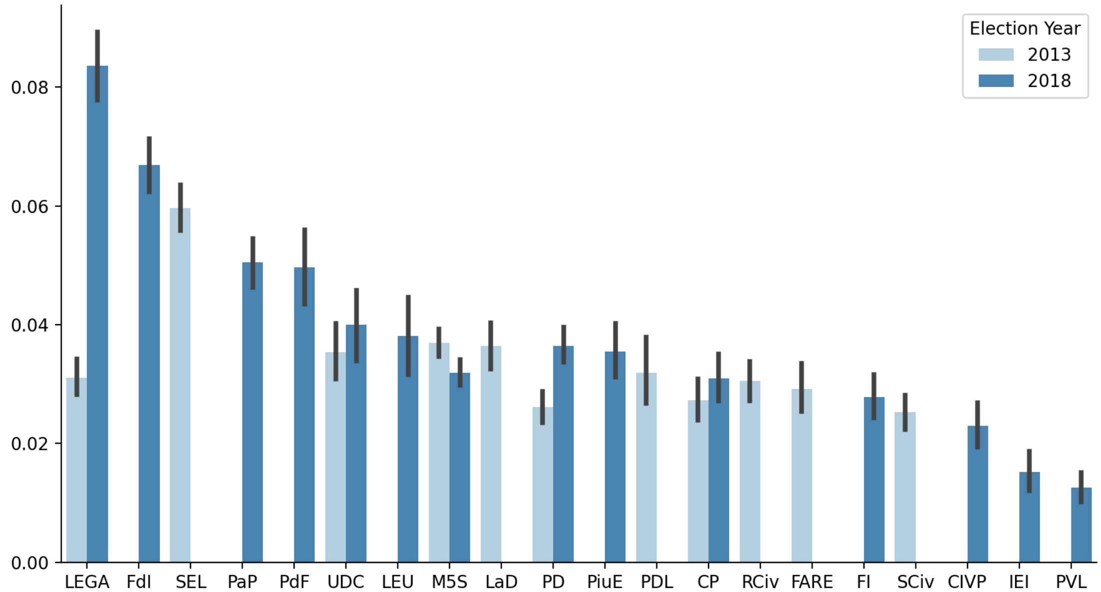
The anger scores based on BERT still display the League as the party producing the highest content of political anger on social media. However, under this approach the top three parties are all far right parties, differently from the previous methods. The League is followed by the far right Brothers of Italy, which reported high scores under the previous methods as well, but also by The Right (LaD), that had more moderate positions under the other approaches. Similarly to previous results, centrist parties report lower scores in terms of anger. These include centrist parties such as Civic Popular (CIVP), Civic Choice (SCiv), More Europe (PiuE), and Act to Stop the Decline (FARE) and the centre-left Democratic Party (PD) and Together (IEI).

Figure 4: Anger scores based on BERT, by party



The results based on Perspective API present some slight differences compared to BERT. While the League and the Brothers of Italy are the top parties in terms of production of social media anger in 2018, they are now followed by two far left parties: Left, Ecology and Freedom and Power to the People. The League in 2013 and The Right now both report very low scores relative to other parties and to their BERT scores. The Five Star Movement has a relatively high score, but still present the same pattern of decline in anger content from 2013 to 2018, with the shift of leadership from Grillo to Di Maio, that we observed across all the other methods (excluding the caps lock).

Figure 5: Anger scores based on Perpsective API, by party



How do ideological positions relate with anger? We address this question by examining the distribution of the different anger scores across party positions on the left-right axis. We categorise each party as left, right and centre. This is relatively simple as Italian parties tend to cluster in coalitions that reflect their left or right positions, whereas others tend to position in the centre and join one coalition or the other depending on the election. While this approach may be less robust than using external data sources that assign ideological scores to each party, it allows us to cover all the parties in our sample. Other databases, such as the Chapel Hill Expert Survey (CHES) or the Comparative Manifesto database, do not cover many of the parties in our sample. For robustness, we compare our results with those using the ideological score based on CHES data.

The results based on our manual classification show that right-wing parties are the most likely to produce angry content on social media (see Figures 6-9). Centrist parties are the least likely, whereas left-wing parties are in a middle position. This result is not surprising as it suggests that fringe parties are more likely to produce anger content than more moderate candidates. This fact is in line with the use of anger in politics as a mobilizing emotion: it is likely fringe parties that rest on a smaller pool of voters have a stronger incentive in boosting anger to mobilize voters and gain their support. However, this evidence on ideology unveils two non-trivial findings. First, that right-wing parties have a higher tendency to produce anger content than left-wing parties.

Second, that the gap between right-wing parties and the rest widens when we look at the caps lock indicator, meaning that the use of caps lock is substantially more frequent among right-wing candidates.

Figure 6: Anger scores based on dictionary by party ideology

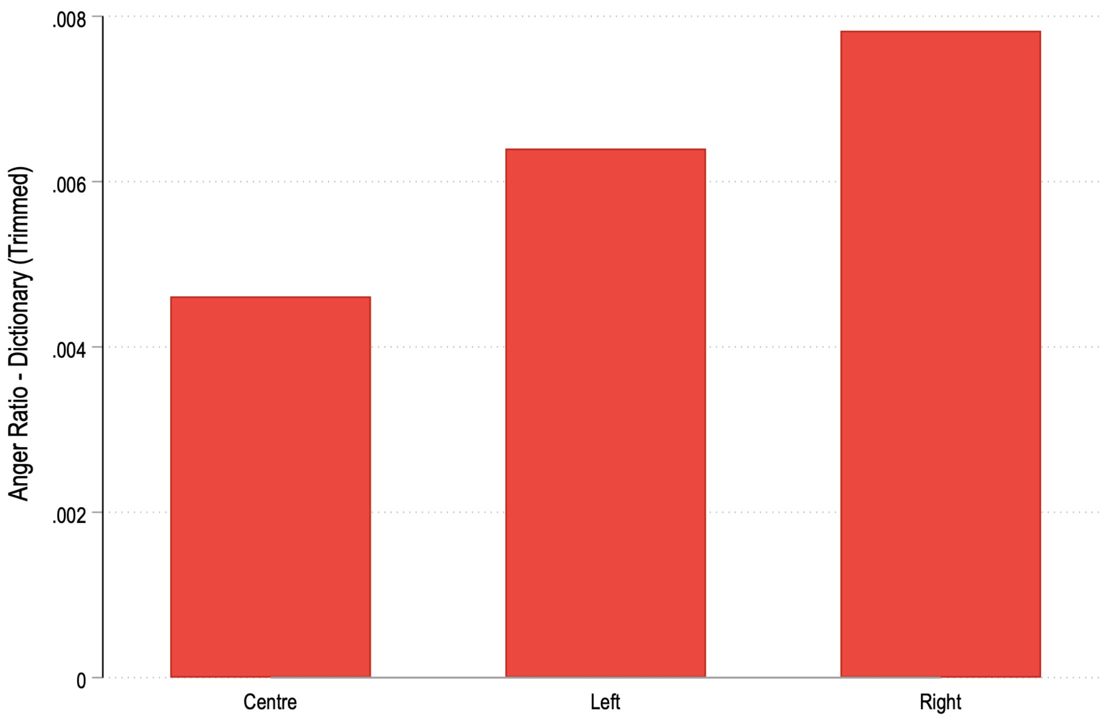


Figure 7: Anger scores based on caps lock by party ideology

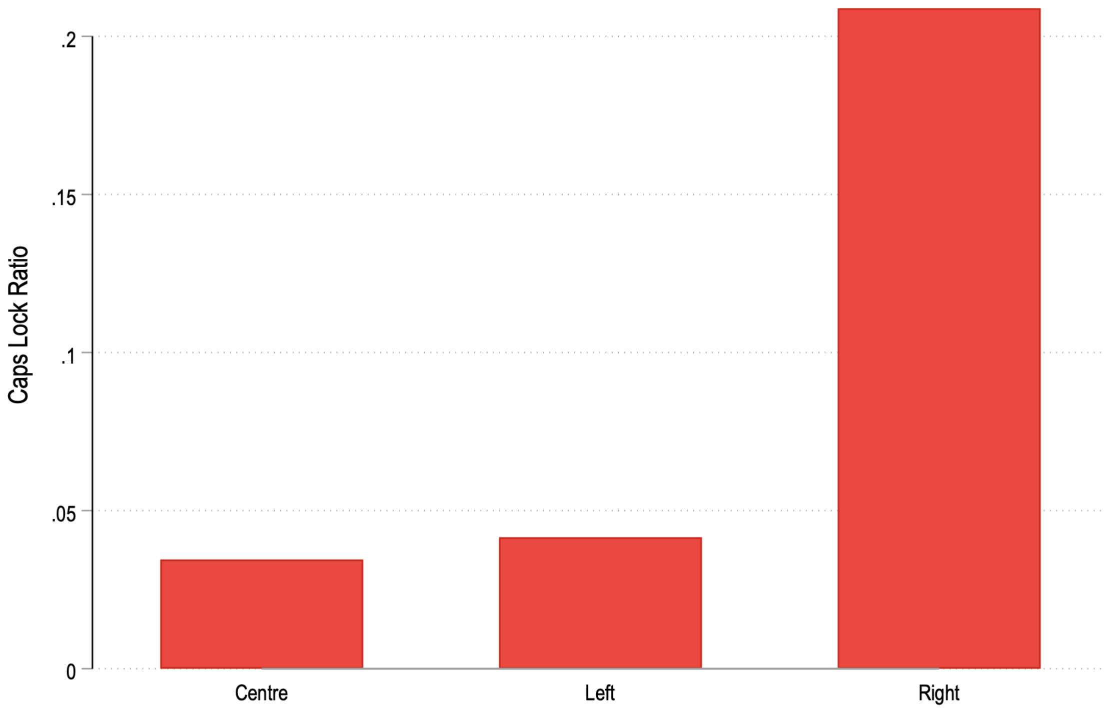


Figure 8: Anger scores based on BERT by party ideology

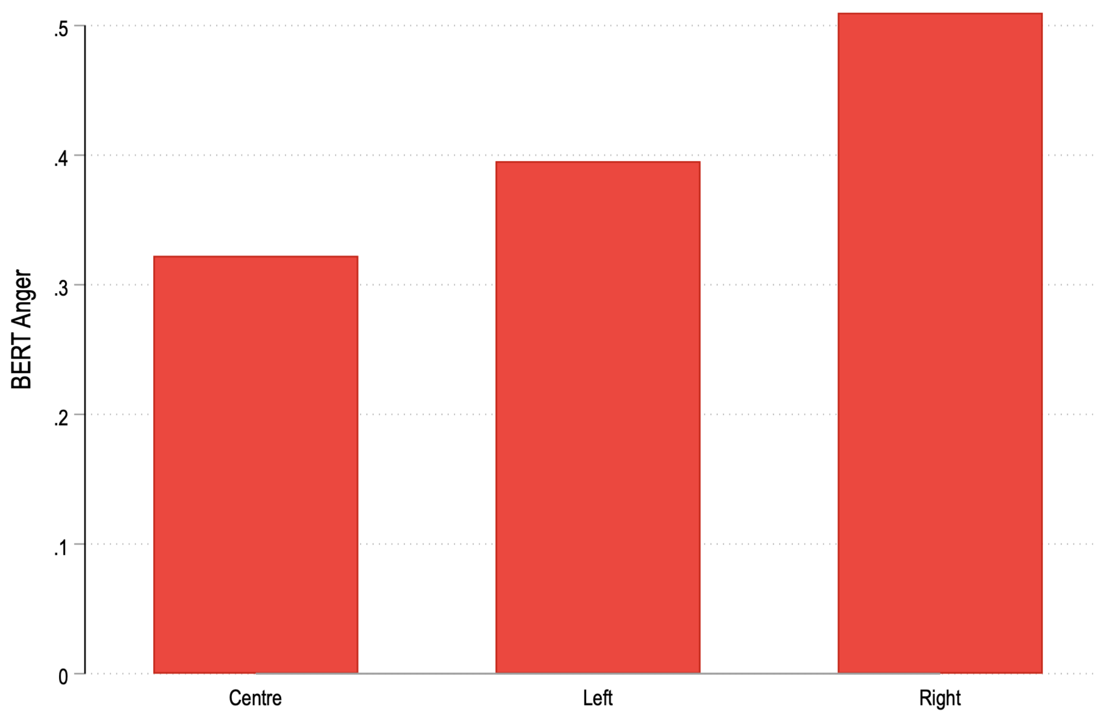
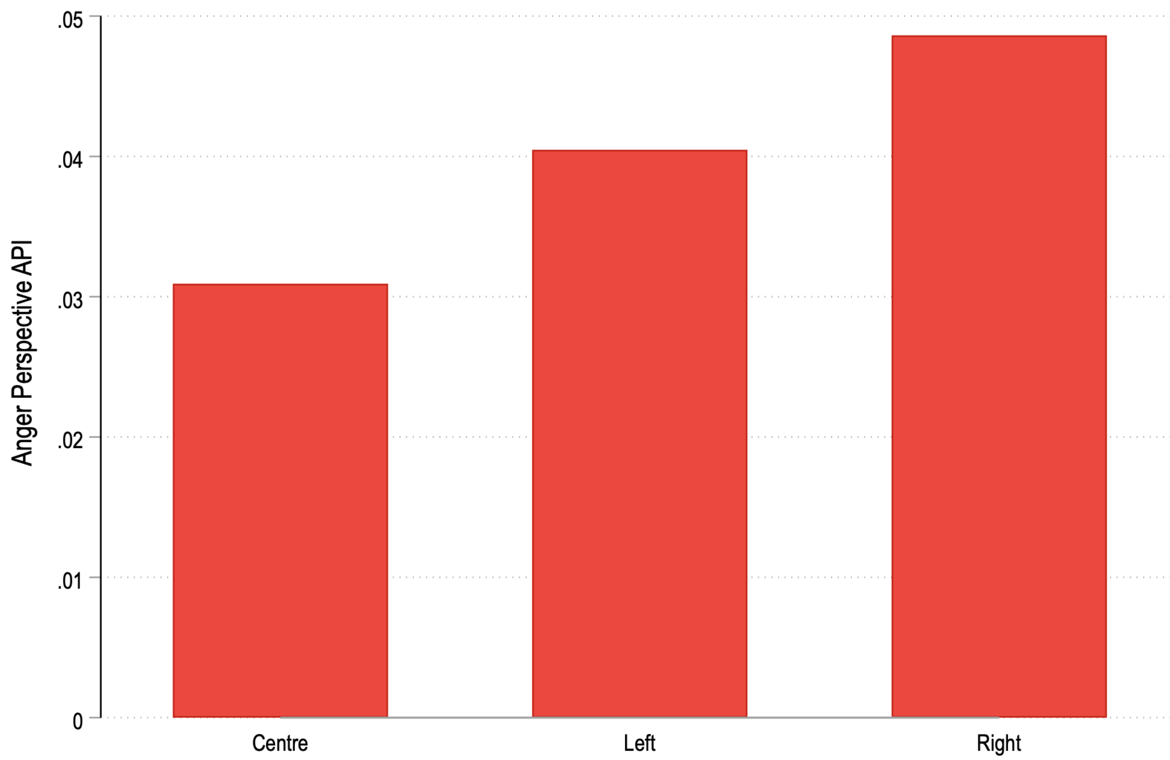


Figure 9: Anger scores based on Perspective API by party ideology



The relationship between anger and right-wing stances is robust when we replace our ideology classification with the scores based on CHES data, which we display in Figures A6-A9 in the Appendix. For each party, we select the values of the election years 2013 and 2018, which correspond to the survey waves of 2014 and 2019. We notice that there is no significant correlation between ideological stances and anger based on the dictionary approach (Figure A6). However, the approaches based on caps lock, BERT and Perspective API display a positive relationship in line with the previous estimates (Figures A7, A8, and A9 respectively). The more a party is on the right-wing spectrum of politics, the more it tends to communicate with caps lock and the more it uses an angry language.

6 Conclusions

In this paper we develop four text-based measures to capture political anger on social media campaign messages. The application of these measures to a unique and novel dataset of Facebook posts sheds new light on the political use of anger on social media. Our findings show that parties channel anger to attack political opponents on the basis of accusations, corruption scandals, or public speeches that their opponents delivered. Anger is often associated with contempt and with the derision of the opponent. Moreover, anger presents itself also as a mobilizing emotion, resting on the depiction of the election as a battle that the candidate and her/his voters have to fight against their opponents.

Overall, the empirical evidence we presented highlights some interesting stylized facts. While some findings are not surprising, by being trivial they are strengthening our prior that these measures are able to capture political anger. These include the fact that far right and far left parties report higher angry scores than more moderate parties. Moreover, as we would expect, we notice that the change of leadership from 2013 to 2018 in the League and the Five Star Movement affects the angry content published on social media. On the one hand, when Matteo Salvini replaces Roberto Maroni at the helm of the League, the anger content skyrockets, making the party the highest in terms of anger scores. On the other hand, when the leadership of the Five Star Movement shifts from comedian Beppe Grillo to the more institutionalized Luigi Di Maio, who will later undertake several governmental roles, the anger content drops.

From an ideological perspective, we show that right-wing parties are more likely to produce angry content on social media than left-wing and centrist parties. In particular, the results are dominated by the League and the Brothers of Italy, that report the highest angry scores across all four methodologies. However, anger is concentrated also in other right-wing parties, such as The Right of Berlusconi's Forza Italia, as well as among left-wing parties such as Power to the People, Civic Revolution and Left, Ecology and Freedom.

An unexpected result concerns the neofascist party CasaPound (CP), that reports very low scores across all four measures. This party has arguably more extreme positions than other far right parties such as the League, the Brothers of Italy or The Right, and made a wide use of social media - it is the fifth largest party in the sample by number of posts.

In the next steps of this work we aim to combine this indicators with electoral and economic data. While we have already provided an overview of the relationship between anger and electoral results at national level, our aim is to use more granular information at municipality level. We intend to combine this data with subnational economic indicators, such as unemployment and inequality. Our aim is to investigate whether those voters that experience harsher economic conditions tend to shift in favor of those parties that make more frequent use of an angry rhetoric.

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A Appendix

A.1 Top Facebook Posts

We report the Facebook posts with the highest scores based on each methodology. At the beginning of each post we report the name of the party or of the leader, depending on which page has published the post, alongside the election year and the anger score.

A.1.1 Anger Lexicon

The dictionary approach presents a problem when applied to a textual database such as social media posts that stems from the heterogeneous length of the textual documents. Since some documents are very short and contain only a few words, the presence of a single term associated to anger has the potential to inflate the anger score, creating some noise at the tails of the anger score distribution. To overcome this issue, we trim the corpus with a lower bound of three tokens and an upper bound of 500 tokens. We select these values based on the outliers that we identify in the distribution of scores before the trimming (see Figures A1 and A2 in the Appendix). We display the results for the trimmed corpus.

(i) **Brothers of Italy, 2018, Score: .333.** *ELEZIONI, DONZELLI: GRAVE INTIMIDAZIONE NAPOLI, ATTENDIAMO CONDANNA DE MAGISTRIS*. Translation: ELECTIONS, DONZELLI: SERIOUS INTIMIDATION NAPLES, WE WAIT A CONDEMNATION FOR DE MAGISTRIS.

(ii) **Civil Revolution, 2013, Score: .333.** *La vostra battaglia, la nostra battaglia.* Translation: Your fight, our fight.

(iii) **The Right, 2013, Score: .286.** *MONTI TRADITORE, TRADITORE TRE VOLTE: ladestra.com* Translation: MONTI TRAITOR, TRAITOR THREE TIMES.

(iv) **Matteo Salvini (League), 2018, Score: .250** *Salvini, espellere diplomatici francesi* Translation: Salvini, let's expel the French diplomats.

(v) **CasaPound 2018, Score: .231.** *Caso Palmulli, CasaPound denuncia Ricci per abuso d'ufficio e diffamazione CasaPound Italia's photo.* Translation: Palmulli case, CasaPound denounces Ricci for abuse of office and defamation CasaPound Italia's photo.

A.1.2 Caps Lock

(i) **Matteo Salvini (League), 2018, Score: 1.** ++ *QUESTA SAREBBE (PER FORTUNA ANCORA PER POCO) LA TERZA CARICA DELLO STATO... VERGOGNA!* ++ Translation: ++ THIS WOULD BE THE THIRD [HIGHEST] OFFICE IN THE STATE (LUCKILY NOT FOR LONG)... SHAME!

(ii) **Brothers of Italy, 2018, Score: 1.** *ELEZIONI, A NAPOLI VERNICE ROSSA CONTRO LA MELONI. CIRIELLI: INTIMIDAZIONI NON FERMERANNO NOSTRA BATTAGLIA POLITICA* Translation: ELECTIONS, IN NAPLES RED PAINT AGAINST MELONI. CIRIELLI: INTIMIDATIONS WILL NOT STOP OUR POLITICAL BATTLE.

(iii) **Brothers of Italy, 2018, Score: 1.** *GIUSTIZIA, MELONI: DA PD E ORLANDO REGALI A DELINQUENTI, CON FDI AL GOVERNO TORNERÀ LA CERTEZZA DELLA PENA* Translation: JUSTICE, MELONI: FROM THE DEMOCRATIC PARTY AND ORLANDO GIFTS TO THE CRIMINALS, WITH BROTHERS OF ITALY IN GOVERNMENT THE CERTAINTY OF THE PENALTY WILL BE RESTORED.

(iv) **Brothers of Italy, 2018, Score: 1.** *RIMBORSI M5S, TRANCASSINI: VIENE MENO L'ULTIMA RAGIONE PER VOTARE I GRILLINI* Translation: REIMBURSEMENTS FIVE STAR MOVEMENT, TRANCASSINI: THE LAST REASON TO VOTE FOR THE FIVE STAR MOVEMENT HAS BEEN LOST.

(v) **Brothers of Italy, 2018, Score: 1.** *GOVERNO, MELONI: CON FDI AL GOVERNO FAREMO IL PIÚ IMPONENTE PIANO A SOSTEGNO DELLA NATALITÁ DELLA STORIA* Translation: GOVERNMENT, MELONI: WITH BROTHERS OF ITALY IN GOVERNMENT WE WILL SET UP THE MOST IMPRESSIVE PLAN TO SUPPORT THE BIRTH RATE IN HISTORY.

A.1.3 BERT

(i) **League, 2018, Score: .9994408.** *LA DENUNCIA DI TELENUOVO Giovani favorevoli, anziani no: sentono odore di fregatura e parlano di "stangata".* Translation: TELENUOVO'S (local

TV station) DENUNCIATION: YOUTH IN FAVOR, ELDERLY AGAINST: THEY SMELL A SCAM AND SPEAK OF A BLOW.

(ii) **Beppe Grillo (Five Star Movement), 2013, Score: .9994397.** *SECONDA BALLA: "Grillo ha aperto a Casa Pound, vuole allearsi con i fascisti..." chi lo ha scritto è in totale malafede, un leccaculo del Sistema. Io non ho aperto a nessun partito e non sono fascista né simpatizzante del fascismo. Ma chi credete di prendere per il culo? Invece ho detto e ribadisco che il M5S non è un movimento ideologico.* Translation: SECOND BULLSHIT: "Grillo opened up to Casa Pound, he wants to ally with the fascists..." the person who wrote this totally did so with hypocrisy, he is an arse-licker of the System. I have never opened up to any party and I'm not fascist nor a sympathizer of fascism. But who do you think you can jerk around? On the contrary, I said and I repeat that the Five Star Movement is a non-ideological movement.

(iii) **Matteo Salvini (League), 2018, Score: .9994389.** *DA CHE PULPITO VIEN LA PREDICA... Cosí disse la "presidenta" al 3% di voti, che in ogni sua uscita pubblica ha avuto parole sempre e soltanto per gli immigrati...* Translation: LOOK WHO'S TALKING... So the "she president" said to her 3% of voters that in every public speech she spent words always and only in favour of the migrants...

(iv) **Matteo Salvini (League), 2018, Score: .9994381.** *PREMIER SULL'ORLO DI UNA CRISI DI NERVI Il Premier a Davos fa campagna elettorale e spara a zero contro Lega e Berlusconi. E si inventa un'Italia ricca e in buona salute, che esiste solo nei suoi sogni.* Translation: THE PRIME MINISTER ON THE BRINK OF A NERVOUS BREAKDOWN The prime minister in Davos continues the electoral campaign and launch an invective against the League and Berlusconi. And he makes up an Italy that is rich and in good health, that exists only in his own dreams.

(v) **Matteo Salvini (League), 2018, Score: .9994379.** *STRACCI VOLANTI PRE-ELETTORALI Il Bomba: "Noi siamo gli amministratori che non falsificano i bilanci, non mettono cinque milioni in più a penna". La sindaca s'incazza.* Translation: PRE-ELECTORAL FLYING RAGS[1] The Bomb: "We are those administrators that do not falsify the balance sheets, that do not add up five millions with a pen". The mayor loses her shit.

[1]Flying rag is slang for 'flying insults'. In this context it is used to describe a situation of pre-electoral partisan brawl.

A.1.4 Perspective API

(i) **Viola Carofalo (Power to the People), 2018, Score: .5530197.** *Eh però degli uomini uccisi dalle donne non parlate mai ma che è sto "femminicidio" un omicidio è un omicidio. Andate affanculo. Una donna uccisa ogni 60 ore. 18 vittime dall'inizio dell'anno https://m.huffingtonpost.it/2018/03/20/una-donna-uccisa-ogni-60-ore-18-vittime-dallinizio-dellanno_a_23390216/ #MarielleFrancoPresente #8marzo*

Translation: Ah, but you never talk about those men that are killed by women. But what is this "femicide"? A homicide is [simply] a homicide. Fuck you all. A woman is killed every 60 hours. There have been 18 victims since the beginning of this year https://m.huffingtonpost.it/2018/03/20/una-donna-uccisa-ogni-60-ore-18-vittime-dallinizio-dellanno_a_23390216/ #MarielleFrancoPresente #8march

(ii) **Left, Ecology and Freedom, 2013, Score: .5394207.** *Ai suoi «vaffanculo!» rispondiamo con «reddito minimo garantito». Ai «che facce da culo!» rispondiamo con «legge sul conflitto d'interessi e legge anti-corruzione». Ai suoi «siete tutti morti!» rispondiamo con «riduzione delle spese militari e diritti uguali per tutti e tutte». Ai suoi «Arrendetevi!» e «dimettetevi!» rispondiamo con «nuova legge elettorale»* Translation: To his "fuck off" we respond with "guaranteed minimum wage". To his "shit faces" we respond with "law on the conflict of interest and anti-corruption law". To his "you're all dead!" we respond with "reduction of military expenditure and equal rights for all men and women". To his "surrender!" and "resign!" we respond with "new electoral law".

(iii) **Brothers of Italy, 2018, Score: .5383262.** *IMMIGRAZIONE, MELONI: DA M5S COME DA PD ESCAMOTAGE PER IMPEDIRE RIMPATRIO CLANDESTINI* Translation: IMMIGRATION, MELONI: BOTH THE FIVE STAR MOVEMENT AND THE DEMOCRATIC PARTY USED AN ESCAMOTAGE TO HINDER THE REPATRIATION OF ILLEGAL MIGRANTS.

(iv) **Matteo Salvini (League), 2018, Score: .5345199.** *STAZIONE CENTRALE. ESPELLERE TUTTI GLI IMMIGRATI CHE IERI HANNO LANCIATO BOTTIGLIE SU POLIZIOTTI. PREFETTO SI SVEGLI, MANDI VIA QUESTI CRIMINALI* Translation: CENTRAL [TRAIN] STATION. THOSE IMMIGRANTS THAT YESTERDAY THREW BOTTLES TO THE POLICE SHOULD

BE EXPELLED. THE PREFECT SHOULD WAKE UP AND KICK OUT THESE CRIMINALS.

(v) **Brothers of Italy, 2018, Score: .5315421.** *TORINO, LA RUSSA: BOMBE CARTA CON CHIODI COME NEGLI ATTENTATI JIHADISTI, CERTEZZA DELLA PENA PER QUESTI CRIMINALI* Translation: TURIN, LA RUSSA: PAPERS BOMBS WITH SPIKES LIKE IN JIHADISTS TERRORIST ATTACKS, CERTAINTY OF THE PENALTY FOR THESE CRIMINALS.

A.2 Distribution of dictionary-based anger scores and number of words

Figure A1: Distribution of dictionary-based anger scores and number of words before trimming

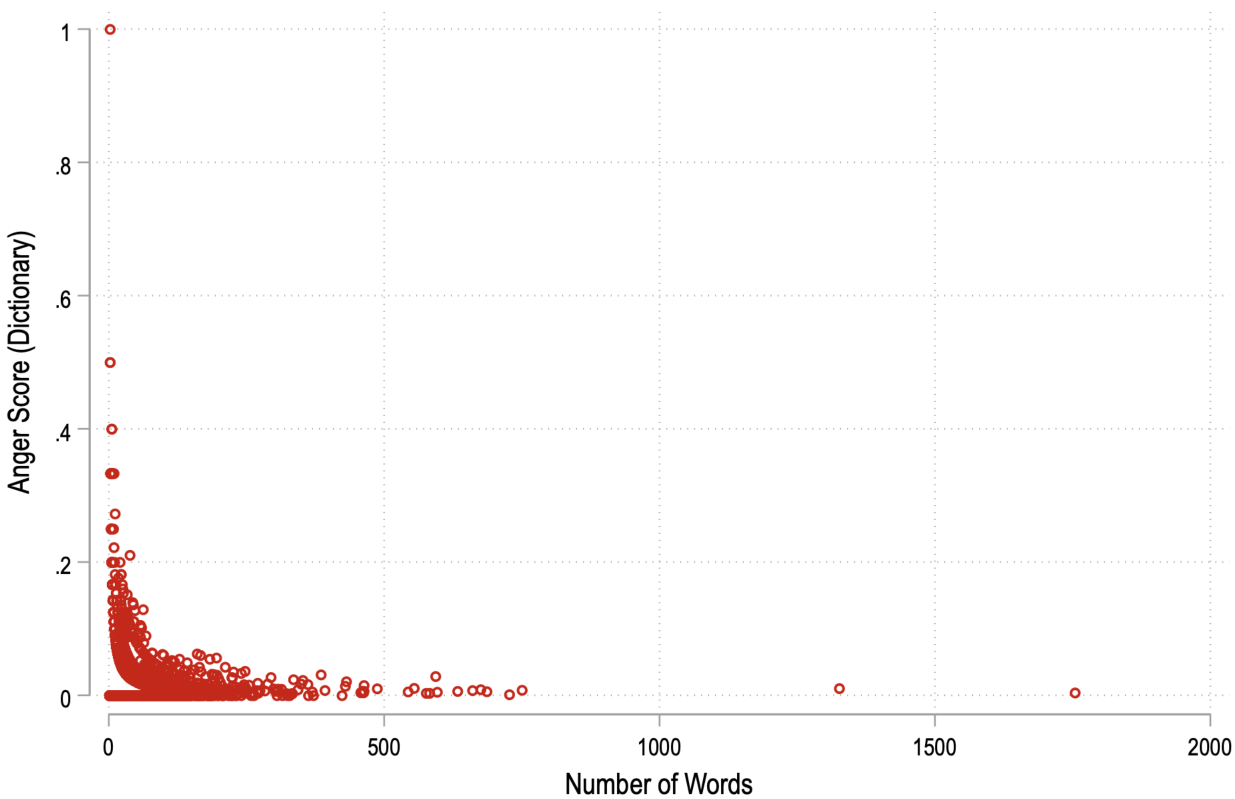


Figure A2: Distribution of dictionary-based anger scores and number of words after trimming

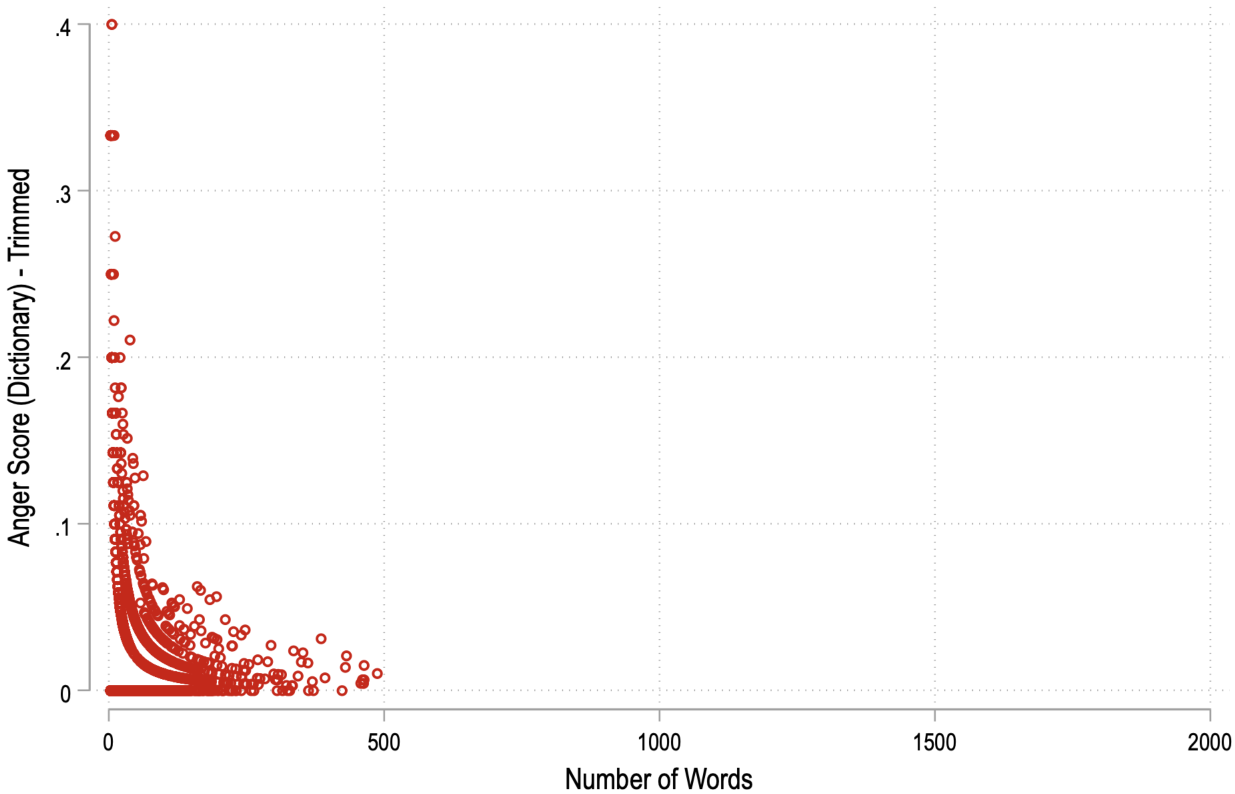
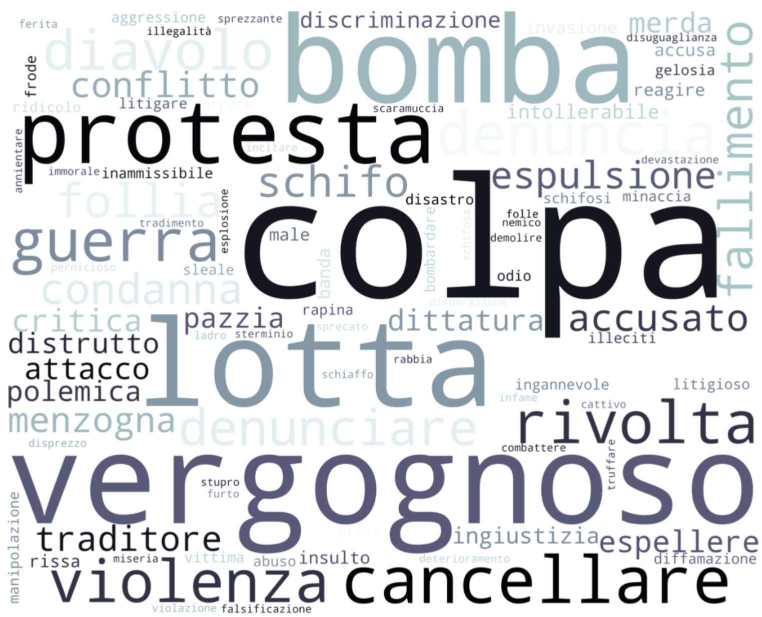


Figure A3: Wordcloud of the most common words using the caps lock approach

Figure A4: Wordcloud of the most common words using BERT



A.3 Word Clouds

A.4 Anger and Ideology based on CHES data

Figure A6: Anger score based on dictionary approach and left-right ideology based on CHES data

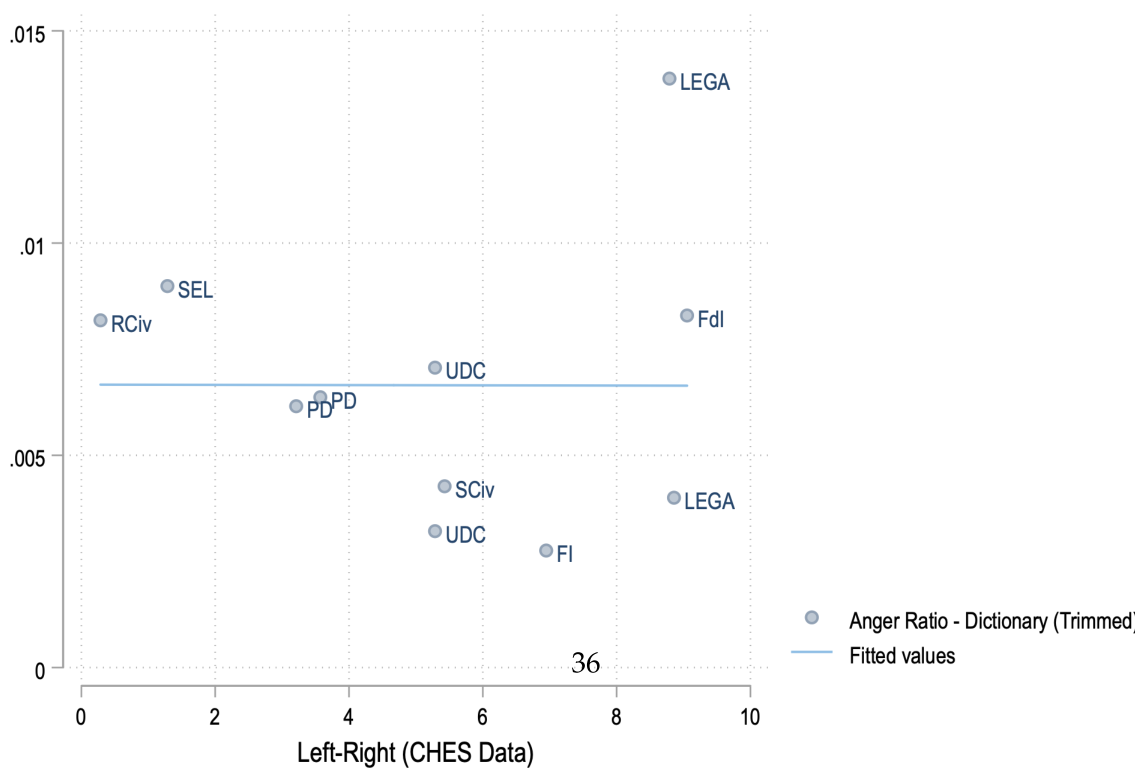


Figure A5: Wordcloud of the most common words using Perspective API

Figure A7: Anger score based on caps lock and left-right ideology based on CHES data

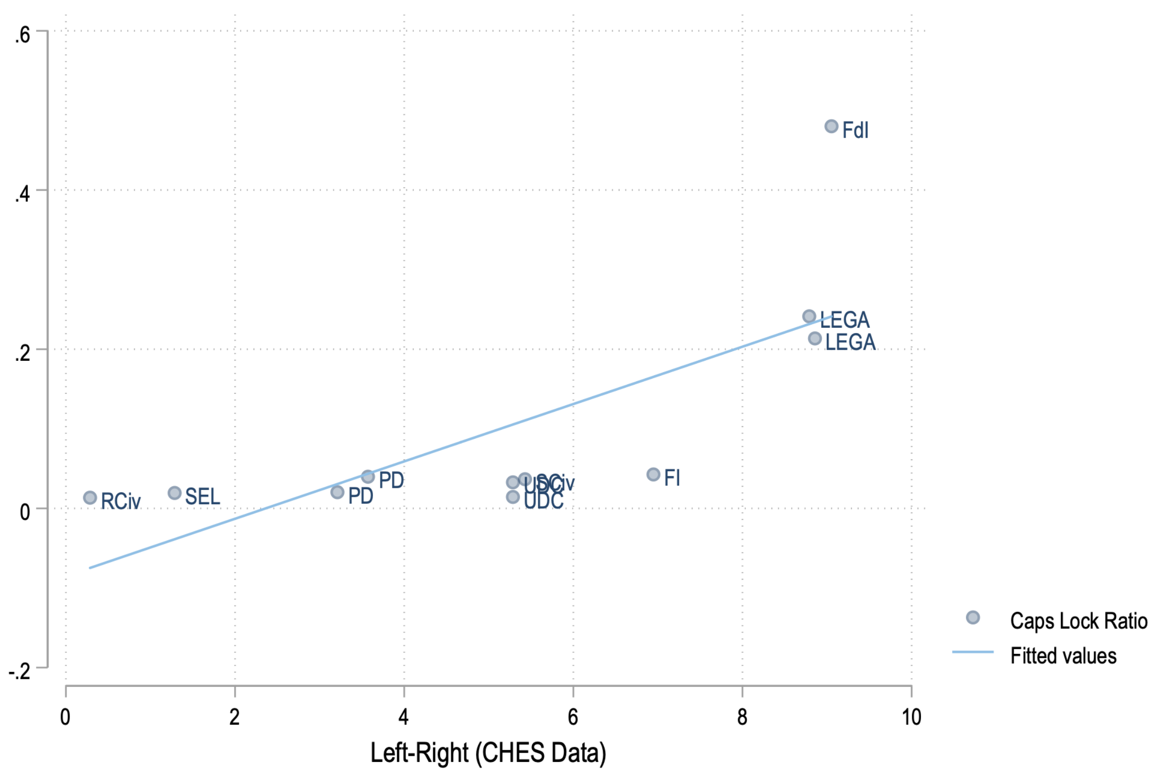


Figure A8: Anger score based on BERT and left-right ideology based on CHES data

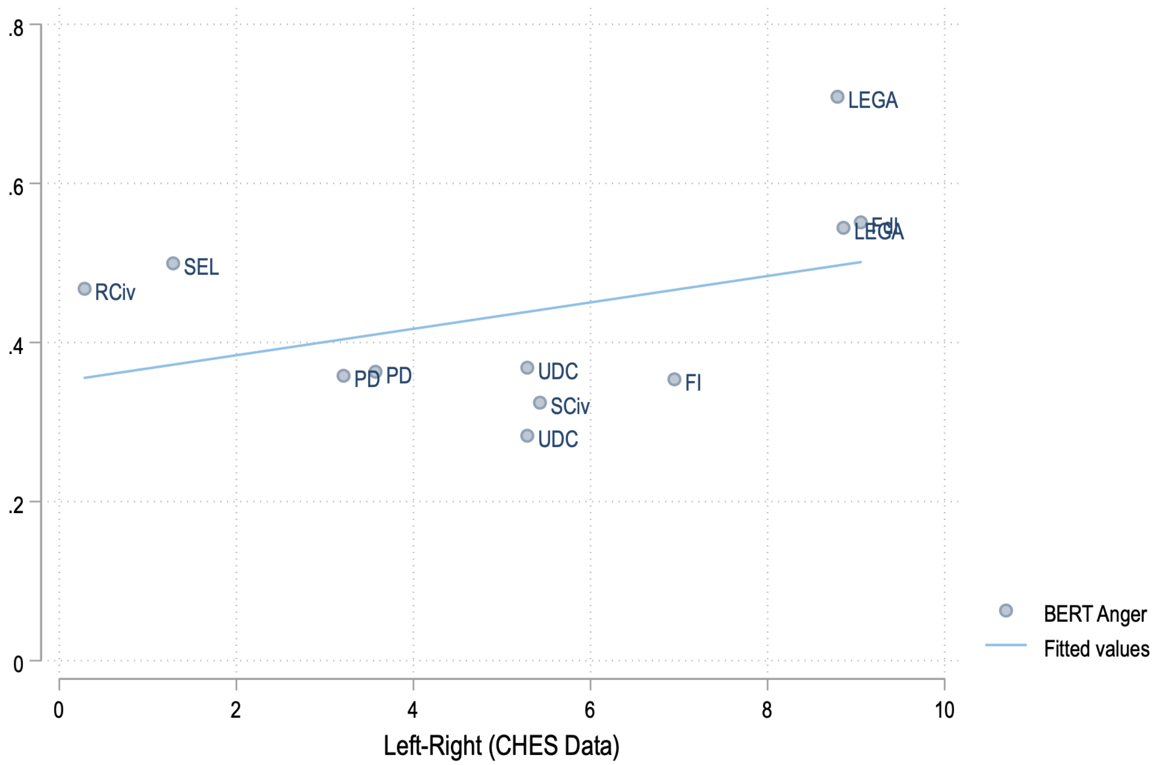
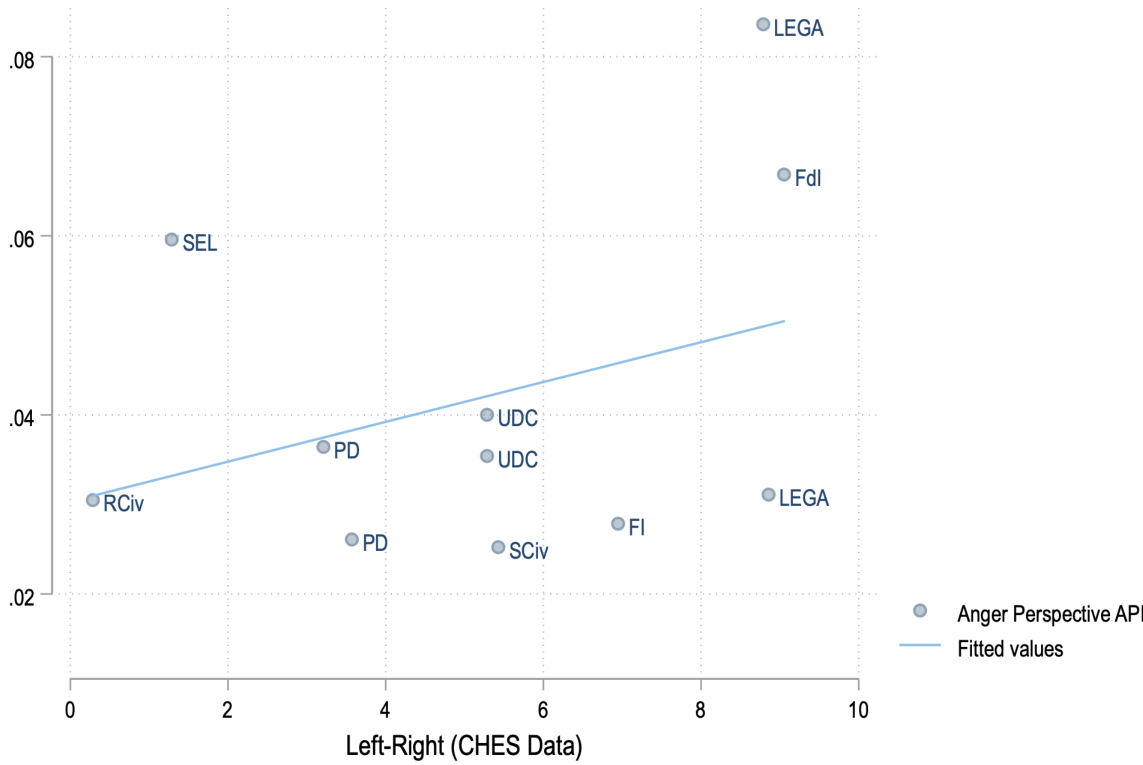


Figure A9: Anger score based on Perspective API and left-right ideology based on CHES data



A.5 Anger Scores, by Party and Year

Figure A10: Anger scores based on dictionary approach, by party, year 2013

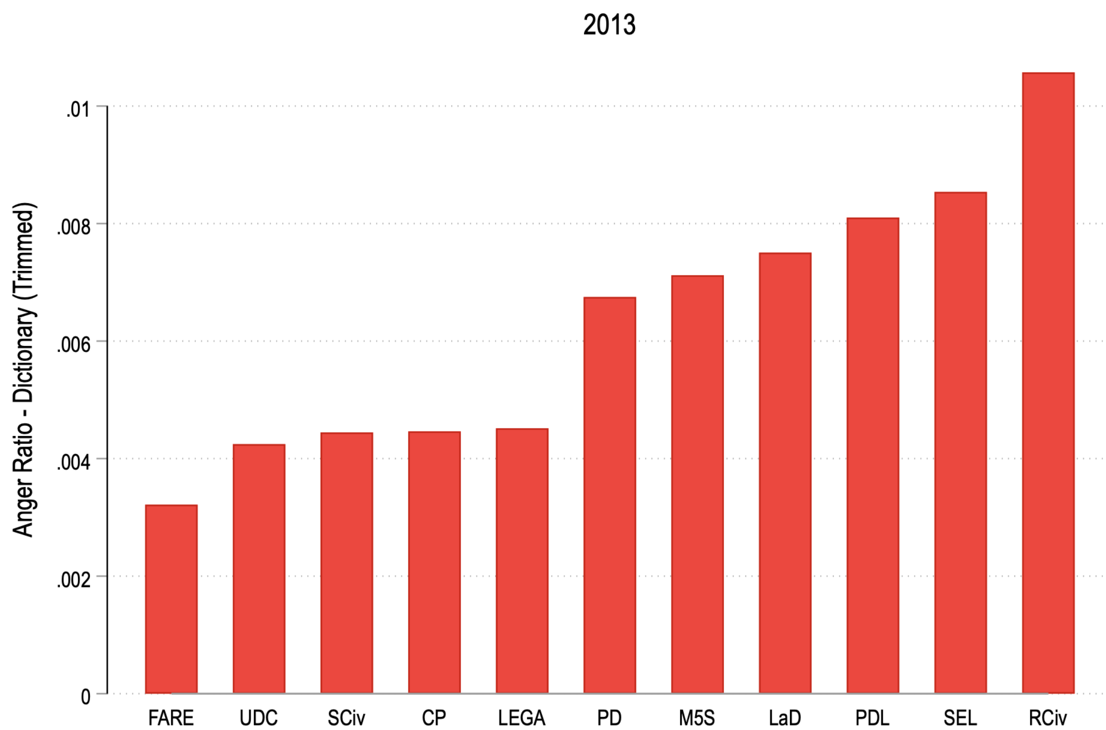


Figure A11: Anger scores based on dictionary approach, by party, year 2018

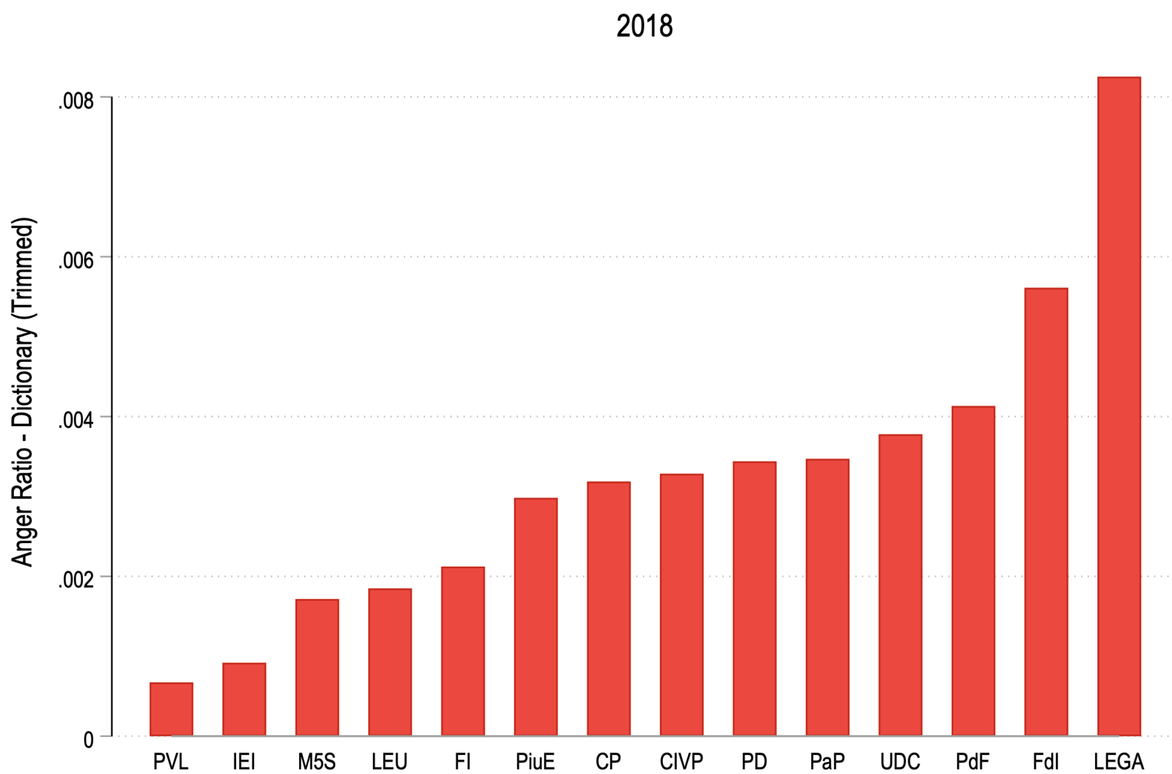


Figure A12: Anger scores based on caps lock, by party, year 2013

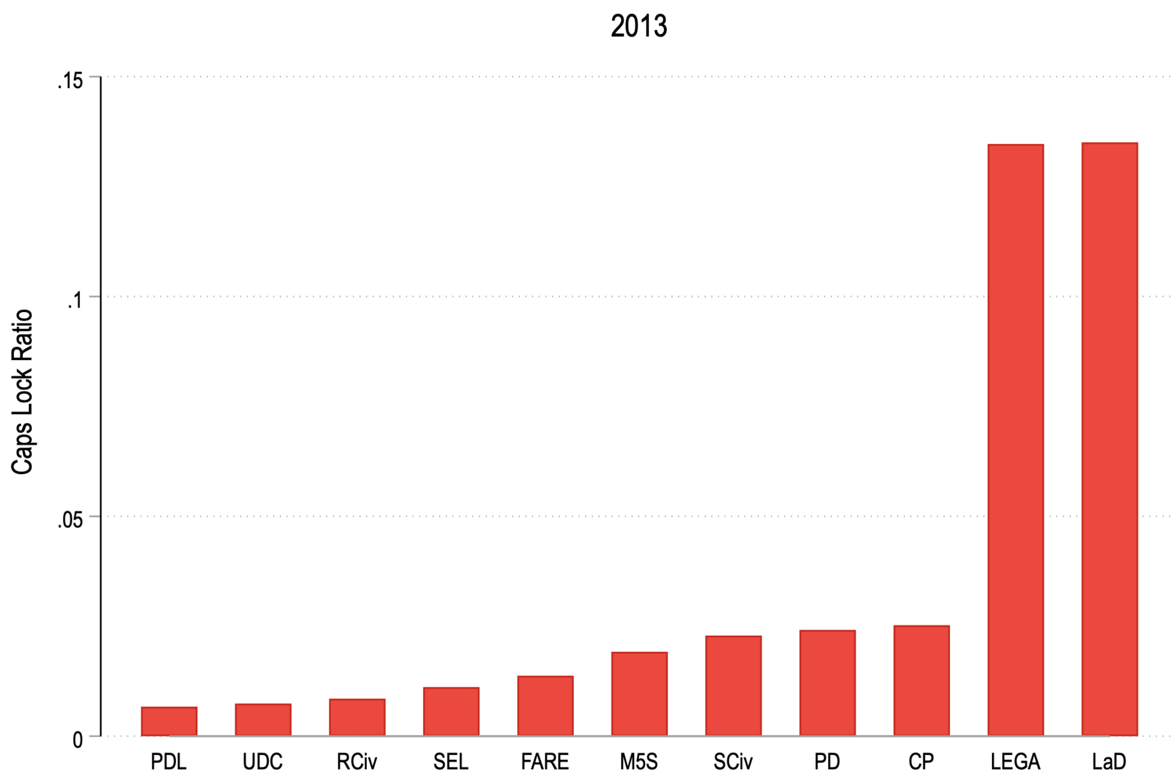


Figure A13: Anger scores based on caps lock, by party, year 2018

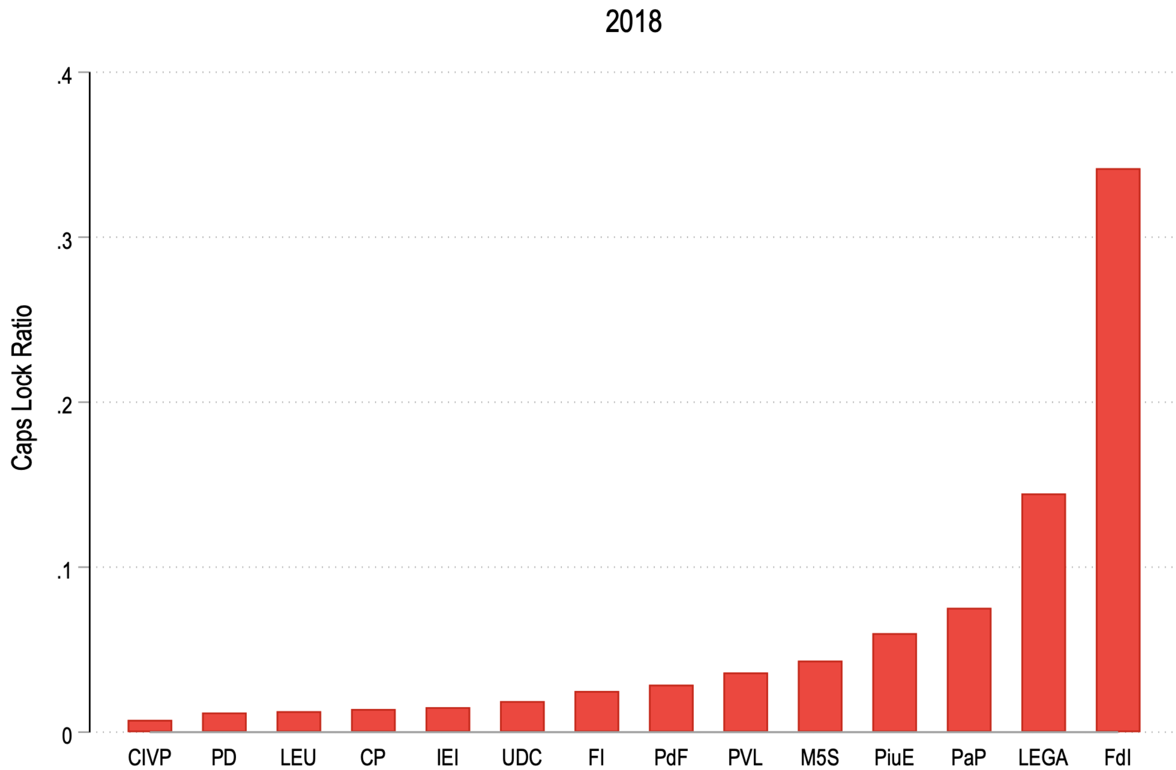


Figure A14: Anger scores based on BERT, by party, year 2013

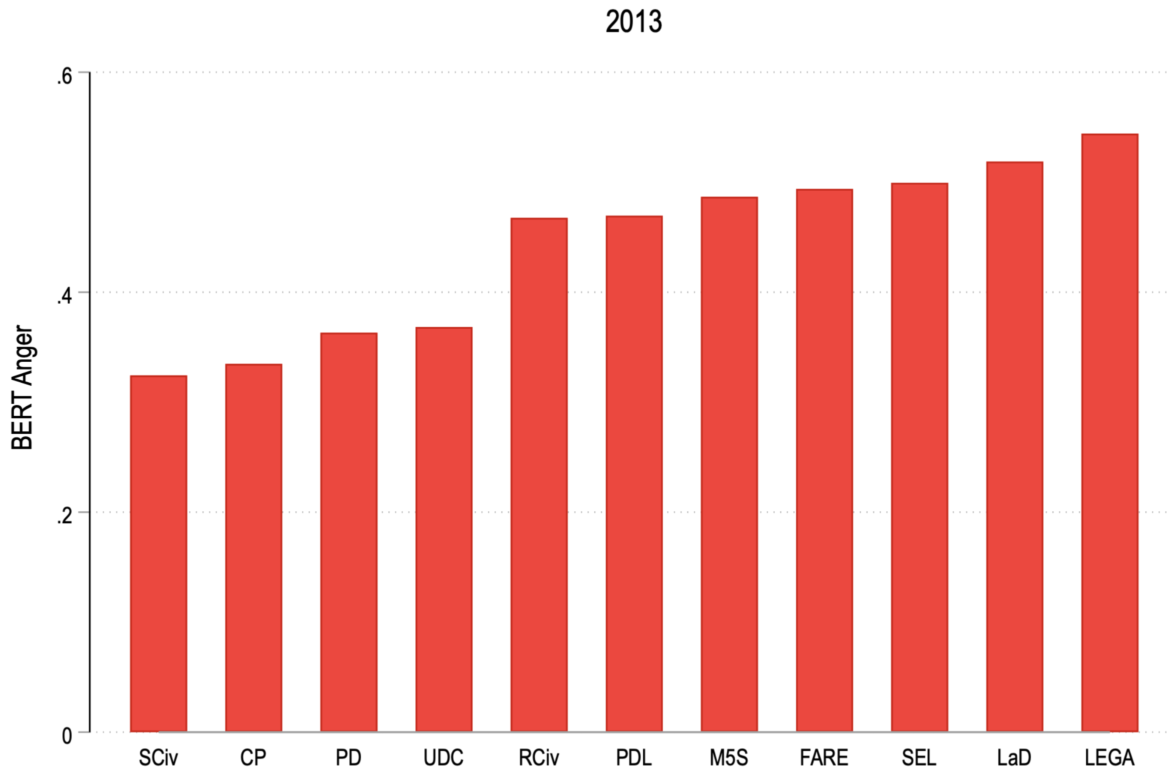


Figure A15: Anger scores based on BERT, by party, year 2018

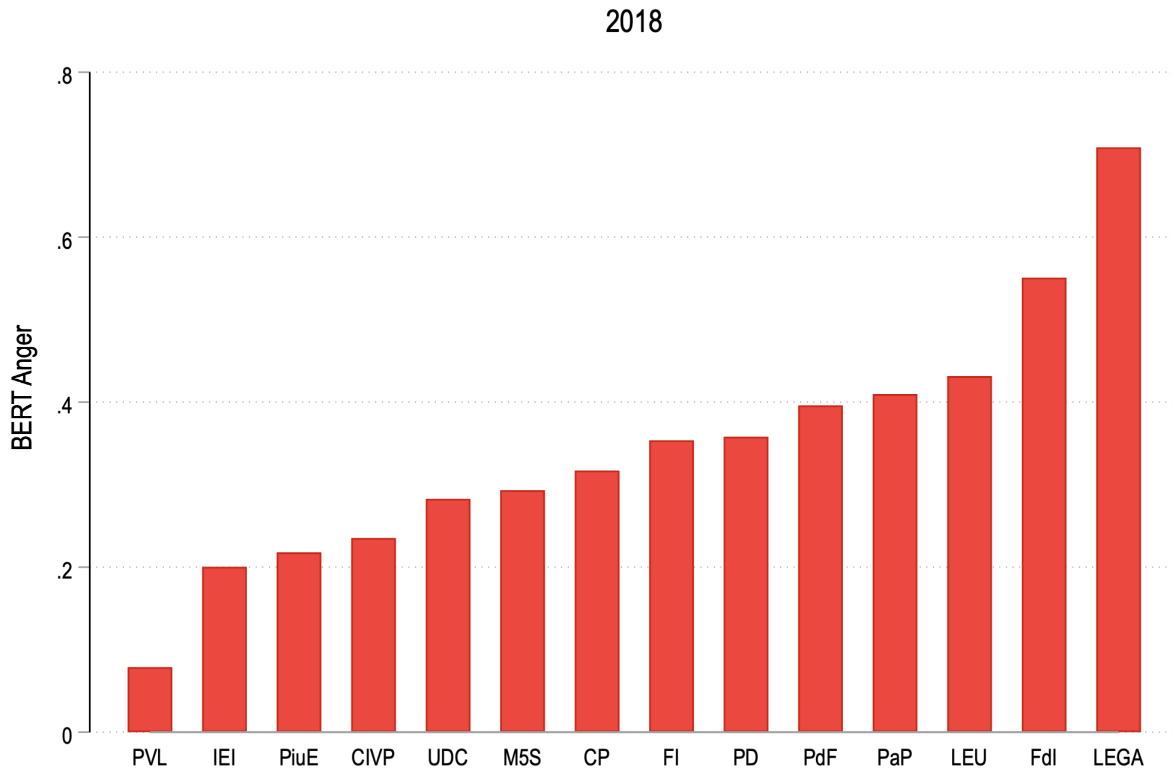


Figure A16: Anger scores based on Perspective, by party, year 2013

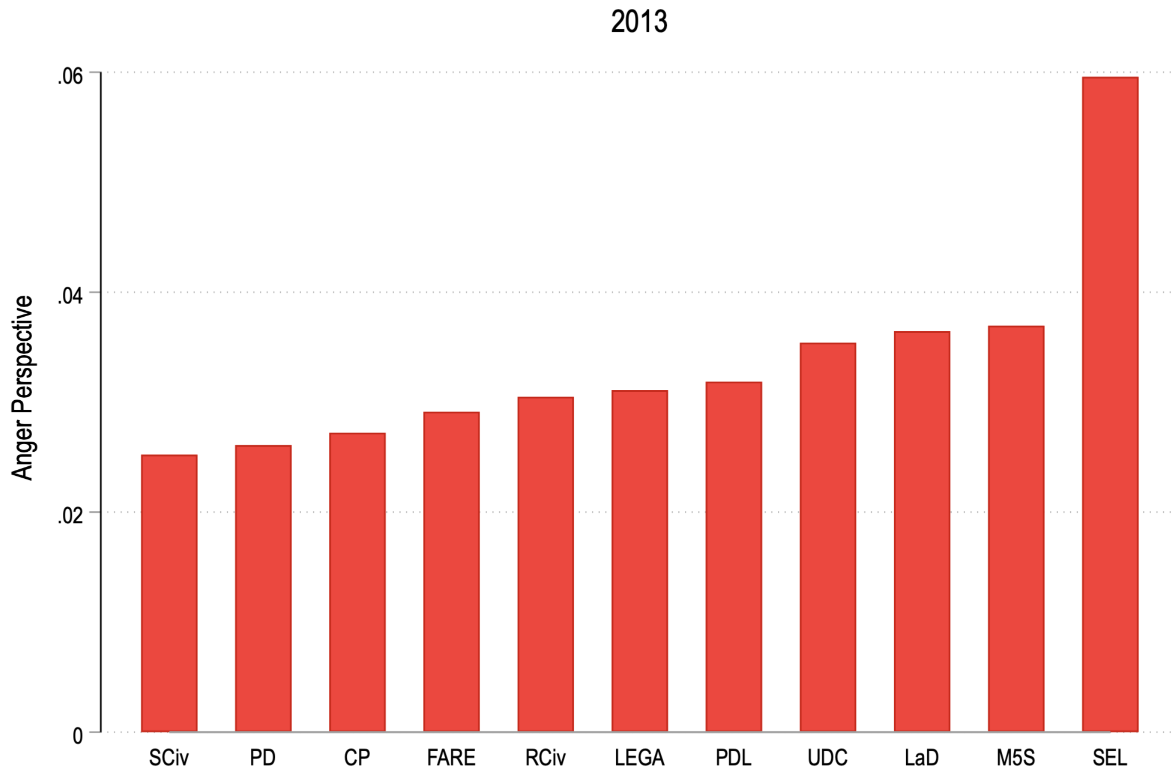


Figure A17: Anger scores based on Perspective, by party, year 2018