Float With the Current Hate: A Causal Dynamic between Twitter Hate Speech and Terrorist Attacks?

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Abstract

In the field of social media research only a few scholars have focused on a causal dynamic between Tweets and real life events. They examined rather network structures which is mostly common on a social media analyze approach. But this research will focus on a causal analysis of terrorist attacks on tweeted hate speech against refugees during the refugee crisis in Germany, 2015. I hypothesize that if a salient event occurs the hate speech will increase as well. A salient event is a terrorist attack such as the Charlie Hebdo shootings in France on the 7^{th} January. Using Tweets with anti refugee indicators in the year 2015 and the provided Data of Müller and Schwarz (2019a) I will examine anti refugee Tweet behavior. Empirically, I find that the online hate speech increase after a salient event. This result provides a further evidence that the offline and online life is linked. Additionally, one can presume that those salient events flared up the hate against refugees.

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1 Introduction

Since the internet offers social media platforms such as Facebook, Instagram, or Twitter it affect our life be it to stay in contact with long-distance friends or discuss with strangers about political, research, or cooking problems. Due to that fact researchers examined either network structures in social media platforms a lot of times or analyze the posted content by users. A causal effect of the linkage between real life incidents and social media behavior get rarely examined by researchers. Presumable because those platforms have only recently been developed, comparing to social problems since the Middle Ages (at latest) such as poverty. Nevertheless, in this term paper I investigate a causal dynamic between German Twitter hate speeches against refugees to salient events such as terrorist attacks in the year 2015. This year attracts interests because over half a million people arrived in Germany in search for protection from war and other grievances (Jaki and De Smedt, 2019). Most of the refugees came from North Africa and Muslim countries. Reported by Reuters (2016) most of them were young men and some are few ISIS fighters disguised as refugees. But this case was not only occurring in Germany but also in whole Europe. During this time Europe and other Western countries witnessed a few of violent incidents by IS sympathizers or refugees. This topic is polarizing in Germany which is shown by the federal elections in 2017. At this election the right-wing party Alternative für Deutschland (AfD, Alternative for Germany) receives a positive voting change of 8.3% compared to the election of 2013 (Bundeswahlleiter, 2017). Jaki and De Smedt (2019) certified much more Twitter hate speech to users which sympathize with the political right-wing.

My research question can therefore be outlines as follows: *"Is there a causal dynamic of salient events such as terrorist attacks on tweeted hate speech against refugees in the year 2015?"* To investigate this question I scrape Tweets with an indicator of hate speeches against refugees and set salient events such as nine terrorist attacks in Europe, the United States of America, and Australia as treatment. In the following sections the theory of rigid way of thinking is explained and embedded in the theory of echochambers. From this theoretical construct hypothesis are formulated and introduced. In the next section the literature review is following. In addition, the Data which are used and the method to analyze the data are presented. It continues with the illustration of the results and, finally, a conclusion is drawn and the faced issues and limitations are explained.

2 Theory

Since omnivores, especially the human species, suffers by the dilemma of neophobia and neophilia they fear the new but on the other hand they have also an interest on the new (Haidt, 2012). These structures differ from individual to individual. So, some are more neophobic others are more neophilic. Such trends have always been present in social life (Fischler, 1980). Schmitz (2009) argues that this phenomenon has also occurred in politics since Middle Ages at the latest. Thus, conservative (neophobia) and liberal (neophilia) parties, ideologies and people can also be found in politics.

Since conservatives and liberals are on opposite sides of the political spectrum, conservatives are on the right and liberals on the left. Conservative people are ascribed both a sense of tradition as well as a liking for the status quo (Adorno et al., 1950). On the other side liberal people criticize authorities and existent orders as well as they tend to want to reform the status quo (Adorno et al., 1950). Due to this diversity of models, the question of the psychology difference of the followers of these political tendencies is discussed several times. Following this, Adorno and colleagues (1950) have discussed the authoritarian personality. Such is characterized by conformist and extremist manifestations; it tends to follow ideologies and fascist. As a result of this, supporters of the political right (-wing) spectrum were increasingly ascribed such personality. Based on the work of Adorno et al. (1950) the *rigidity-of-the-right-hypothesis* was developed (compare to Jost et al. (2003) for example). This hypothesis presumes that people who follow a conservative ideology are more rigid in their mind compared to others. Hence, they cannot so easily change their minds, and they more quickly declare mindsets, ideologies, and approaches which are not conform to theirs to be wrong. Furthermore, this hypothesis assumes the more liberal an individual is the less rigid are their ideological thoughts (see Figure 1).

The *ideological-rigidity-hypothesis* is another, similar approach which shows that the rigidity of thinking is not such linear but rather more U-shaped (Rokeach, 1960). It is presumed here that rigidity thoughts do not only occur at the followers of the political right (-wing) but also at every individual who is not part of the political centre. A similar approach as for the other hypothesis also applies here; the further one gets from the political centre the more rigid is the way of thinking (see Figure 2).

A third approach, the *mental-rigidity-hypothesis*, is a combination of the two previous hypotheses. So, this hypothesis presumes that both political sides can exhibit a rigid way of thinking. Jost and colleagues (2003) argue that this can be distinguished as follows; the left side is less rigid as the right side (see Figure 3). This theoretical approach is well received in the literature (e.g. Smithers and Lobley, 1978; Tetlock, 1983, 1984; Tetlock et al., 1985).

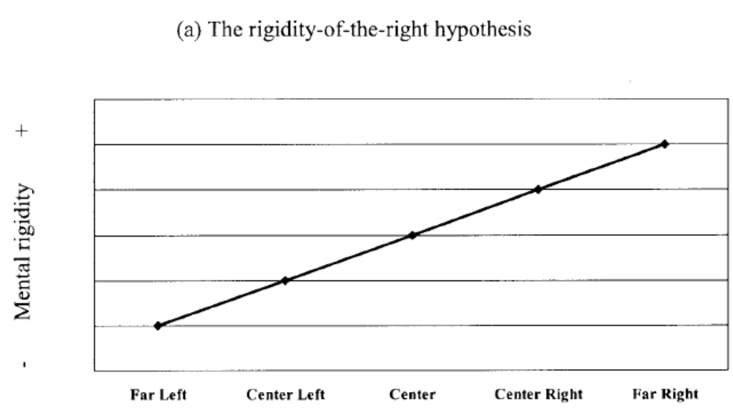

Figure 1: *rigidity-of-the-right-hypothesis* (Jost et al., 2003, S. 7)

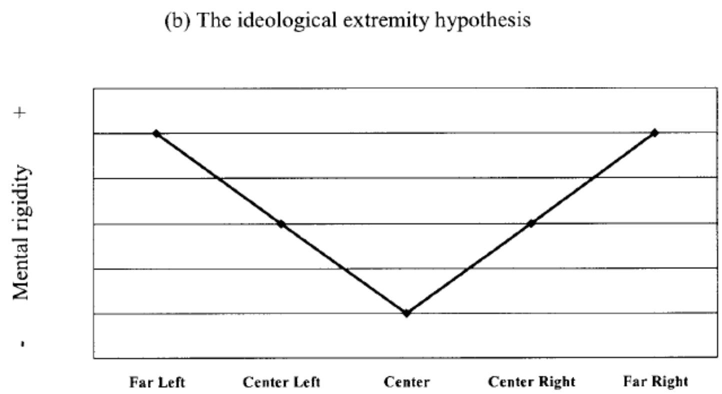

Figure 2: *ideological-rigidity-hypothesis* (Jost et al., 2003, S. 7)

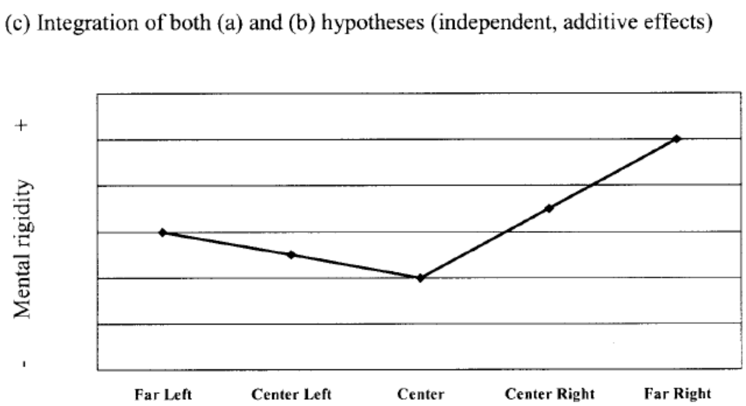

Figure 3: *mental-rigidity-hypothesis* (Jost et al., 2003, S. 7)

So, such individuals who identifies themselves more with the conservative, and right side of the political spectrum are more susceptible to be rigid in their way of thinking. As a consequence of this those individuals can be in more cognitive closed systems. According to Rokeach (1960) people can be in two different cognitive systems – the closed one and the more open one. He argues that the closer a cognitive system is the less they exhibit cognitive discrepancies (see also Festinger, 1957). Therefore, ones have fewer discrepancies between information, thoughts and actions if ones are within such a cognitive closed system. Since individuals with such similar systems meet in real or virtual life they build another system within, self-evidently, the abovementioned discrepancies are going on. As a result of this, those systems are isolated. The more a system is isolated the more only similar opinions and world views will be found within. Metaphorically it is a bubble and if one is in such a bubble one will only find the opinions and world views which are within (Rokeach, 1960). This metaphorical bubble is also called an echochamber (Jamieson and Cappella, 2008). So for example, if political right sympathizers want to inform themselves than they would receive the best, and unbiased information from the political left system or vice versa. However, there is rivalry between these two systems and therefore they would probably get any information from their own system. A real life example of this is the German word "Lügenpresse" (mendacious/lying press). This word emerged on the basis of users (real and virtual life) who are within a closed system which provides only certain information. But once these users receive information which are from the outside they declared those to be wrong (Froitzheim, 2017; Kersting and Mehl, 2018).

This example shows that the information which circulate within those echochambers are not always be right. Furthermore, such chambers serve to informal social learning i.e. a form of socialization (Bowman-Grieve, 2009). According to Hundeide (2003) communities, like political radical rights, justify violent actions and terrorism to achieve their goals. Following this it is quite obvious that political radical rights use more often hate speech (Bilewicz et al., 2017) which can be also found on social networks like Twitter (Jaki and De Smedt, 2019) and so political right (-wing) echochambers could contain more hate speech. Moreover, events which occur and are related to long discuss topics are more salient. If these events are shocking or violent, like terrorist attacks (e.g. attack on Charlie Hebdo in 2015), they also stay longer in the news (Johnson, 1996; Soroka, 2006). So, these events are also more discussed in social networks (online and offline) because of the salience (for explnation see Lebherz, 2007). Since the networks of the political right (-wing) contains more violent content and hate speech I assume that the hate speech against refugees will increase after a salient event like terrorist attack by non-whites in Western countries like Europe, the United States of America

(USA), Australia, or similar. So, the following hypothesis and their counterfactual are proposed:

H_0: If there is a salient event the lower are the hate speeches on Twitter.

H_1: If there is a salient event the higher are the hate speeches on Twitter.

3 Literature Review

Literature Review Since online social networks have developed their prominence in recent times the research of those is rarely as well. The focus is mainly on network analysis, only a few scientists investigate the online hate speech in social networks (see Chan et al., 2016; Awan and Zempi, 2016; Hanzelka and Schmidt, 2017; Müller and Schwarz, 2019a,b; Ozalp et al., 2020). Chan and colleagues (2016) shows that the availability of broadband increases political motivated hate crime in the time period of 2001 until 2008 in the United States of America. But these crimes occurred in areas with higher levels of racism anyway. An evidence of the connection between online hate speech and real life political motivated hate crime is lacking.Awan and Zempi (2016) point out that there is an increased number of hate crime, offline and online, against Muslims after Islamic terrorist attacks in Paris and Tunisia in 2015, and in Woolwich, United Kingdom, in 2013. They also implicate that the borders between online and offline are unclear. That political motivated hate speech nearly always comes from the right-wing has shown Hanzelka and Schmidt (2017). They follow a more qualitative approach and only focused on the German anti Islam movement PEGIDA and Initiatives against Islam from the Czech Republic. Moreover, Jaki and De Smedt (2019) focus on detecting online hate speech in the German Twitter area between August 2017 and April 2018. A correlation between anti Islam Tweets and hate crime against Muslims in the US during the presidential election campaign of Donald Trump was found by Müller and Schwarz (2019b) as well as a causal effect of online hate speech on

Facebook predicts real life crime against refugees in Germany during the refugee crisis (Müller and Schwarz, 2019a). The latter is the most related study to my research topic. However, their focus was on Facebook and not on Twitter as well as only post from the right-wing party Alternative für Deutschland and not a sample of hate comments of all German users.

4 Research Design

To test the hypothesis of this term paper I constructed a new dataset which include German Twitter data, anti-refugee incidents in Germany, and a few more control variables within the year 2015. Overall, the final dataset includes information from eight different sources. So, it contains 122 days of observation in the year 2015, (1) a total number of 17557 Tweets from 8117 different user with an indicator of hate speech against refugees, (2) states based 397 incidents against refugees, and other states based information such as (3) population density, (4) foreigner density, (5) protection-seeking-people density, (6) racism level, (7) net household income, and (8) information about the digital infrastructure in each state of Germany. A statistics summary could be found at Table 1 and Table 2.

4.1 Treatment

As a treatment I choose events which are salient for users which spread hate speech against refugees, e.g. terrorist attacks mostly by non-white people such as the Charlie Hebdo shootings on the 7th January 2015. Those are salient because they provide information about the topic a user my think about on Twitter and share their (hateful) thoughts about it. So if a stimulus is highlighted out of context or provides more information about a topic which is still in mind it is therefore more accessible to the consciousness, then one speak of salience (Lebherz, 2007). I decided for nine of those

	No. Tweets	No. Inciedents	HH Income (Net)	Digital Infrastructure
No. Values	377.00	385.00	385.00	385.00
No. Zeros	0.00	0.00	0.00	0.00
No. Missings	20.00	12.00	12.00	12.00
min	54.00	1.00	14421.00	70.40
max	465.00	3.00	24026.00	99.30
range	411.00	2.00	9605.00	28.90
sum	56486.00	450.00	7882190.00	32361.30
median	145.00	1.00	19719.00	85.30
mean	149.83	1.17	20473.22	84.06
Sandard Error	3.49	0.02	94.43	0.44
Confidence Lvl (0.95)	6.86	0.04	185.67	0.86
Standard Deviation	67.74	0.43	1852.88	8.61

Table 1: Summary Statistics (1) of the final Dataset

	Population Density	Foreigner Density	Protection Seeking	Racism Level in %
No. Values	385.00	385.00	385.00	385.00
No. Zeros	0.00	0.00	0.00	0.00
No. missings	12.00	12.00	12.00	12.00
min	671489.00	79005.00	14600.00	8.00
max	17865516.00	4520000.00	252400.00	28.10
range	17194027.00	4440995.00	237800.00	20.10
sum	2577264129.00	522216020.00	32601000.00	6508.90
median	4084851.00	840000.00	42000.00	12.70
mean	6694192.54	1356405.25	84677.92	16.91
Standard Error	276734.22	77767.58	3769.31	0.36
Confidence Lvl (0.95)	544104.01	152903.59	7411.07	0.71
Standard Deviation	5429917.41	1525910.19	73959.18	7.10

Table 2: Summary Statistics (2) of the final Dataset

events in the Western World like the United States of America, Europe, and Australia. Eight of these events are at least with one lethal consequence. Three of these events take place in France: the Charlie Hebdo shootings on the 7th January, the Saint-Quentin-Fallavier attack 26th June, and the series of coordinated attacks in the area of Paris including the shootings in the Bataclan theatre at concert of the band *Eagles of Death Metal* on the 13th November (Meiser, 2017). The latter are the one with the most lethal consequences (130). Moreover, two events with a terrorist background toke place in the USA. The first one was on the 17th June in Charleston, South Carolina were a white citizen shoots nine Afro-Americans (Kreye, 2017). This is the only event with a white-racist background as a kind of control mechanism. The other one in the US happens on the 2nd December in San Bernardino, California at a Christmas party at the *Inland Regional Center* were terrorist starts a shooting with 21 lethal consequences (ZeitOnline, 2015a). Another event happened on the 2nd October in Parramatta City, Australia there a 15-year old boy killed an unarmed accountant (Time, 2020). In Copenhagen, Denmark on the 14th February three separated shootings happened with three lethal consequences including the perpetrator (News, 2015). In addition to several racist terrorist attacks on refugee hostels in Germany, there at least two other terrorist attacks which I include in my treatment series. One on the 9th September the other on the 17th September. The latter has one lethal consequence as one man attacks a female police officer with a knife (Kather and Jansen, 2017). The first one is the only one with no lethal consequence. Nevertheless, I included it in the treatment group because at this event the underground organization Partiya Karkerên Kurdistanê (PKK, Kurdistan Workers' Party) by the Kurds attacked with 25 people a mosque which was used by a hostile organization of the Turks (ZeitOnline, 2015b).

4.2 Twitter Data

I scraped Tweets via Pythons Twitterscraper in 18 weeks in 2015, especially, from the 1st January until the 14th January, 7th February until the 21st February, 10th June until the 24th June, 19th June until the 3rd July, 2nd September until the 16th September, 12th September until the 24th September, 25th September until the 9th October, 6th November until the 20th November, and from the 25th November until the 9th December. This is due to the fact that Twitter has a scrape limit to 18,000 Tweets every 15 minutes and usually one could only scrape Tweets up to seven days ago. Therefore, I used Pythons Twitterscraper package to avoid the latter limitation, but the limitation to 18,000 Tweets remain in force. But these 18 weeks still provide a sample of 17557 Tweets from 8117 different users which contain indicators for hate speech. The indicators are slurs which are against Muslim refugees or refugees from North Africa (see Table 3). Jaki and De Smedt (2019) show that those slurs are mostly used for German hate speech against refugees. Therefore, I assume that the most of these Tweets contain hate speech which is also proofed by the sentiment analysis of the Tweets. But those slurs can also be used in an ironic or informative sentiment. So, the general sentiment of these Tweets is computed. Figure 4 shows that the dataset is more negatively polarized, since there are almost twice as many negative as positive sentiments (56 negative vs. 29 positive). Moreover, those negative sentiments are more weighted as the positive ones.

4.3 Anti-Refugee Incidents

Unfortunately, the German government or the German federal criminal police office (BKA, Bundeskriminalamt) do not provide any public data of political motivated crime like the Uniform Crime Report (UCR) in the United States of America, only some annual report as a PDF and news account (Bundeskriminalamt, 2020). So, I got the data of the anti-refugee incidents from Müller and Schwarz (2019a). These dataset

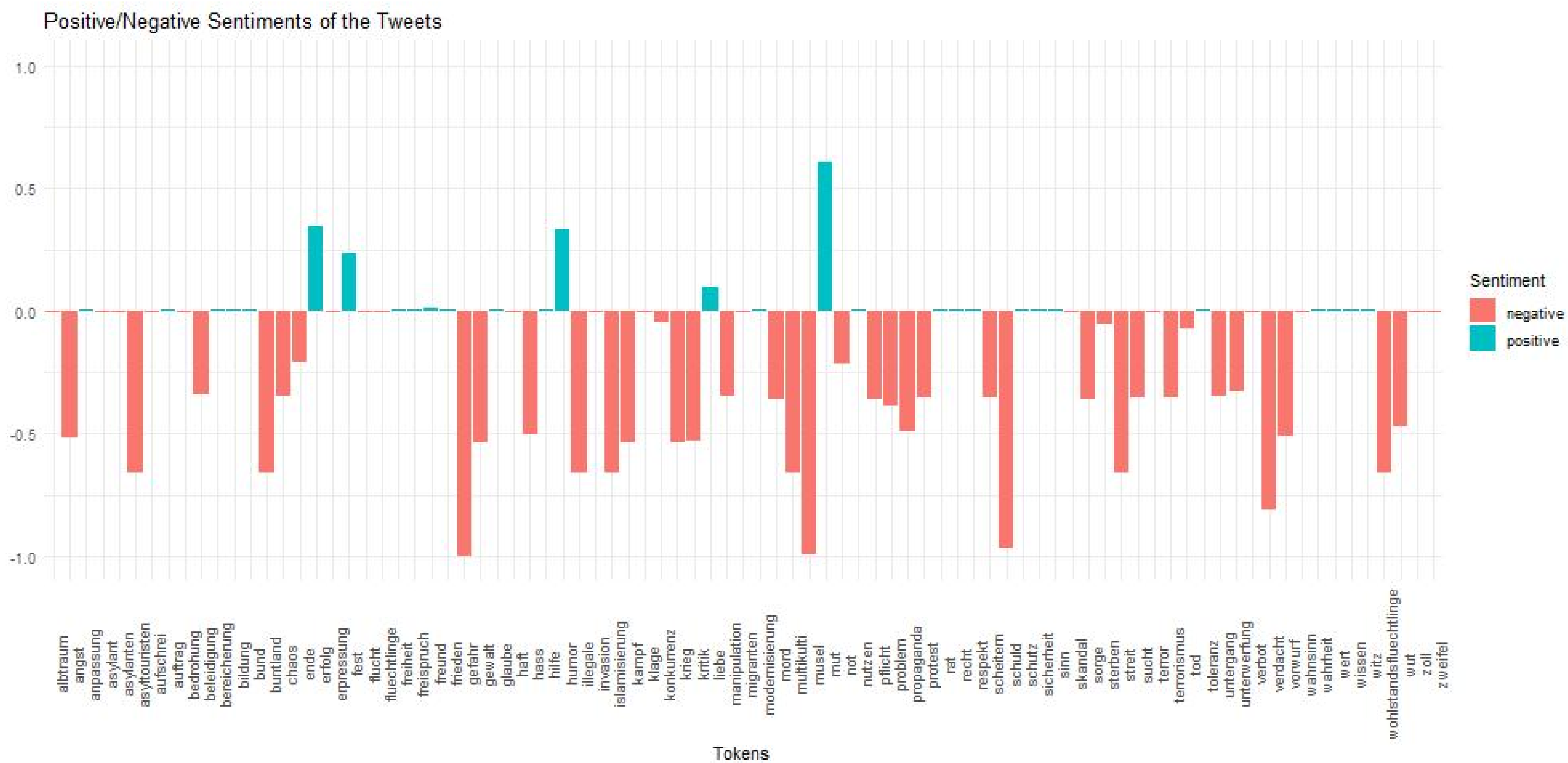

Figure 4: Sentiments of the Tweets

Word
Islamisierung
Multikulti
Nafris
Asyltouristen
Merkel-Gäste
Illegale
Wohlstandsflüchtlinge
Zudringlinge
Musel
Salafistenschwestern
Kampfmuslimas
Burka-Frauen
Kloneger
Buntland
Dummstaat
PlemPlemLand
Schandland
Bundeskloake

Table 3: Slurs against refugees which are an indicator pf hate speech ((Jaki and De Smedt, 2019))

includes 3,335 incidents of "anti-refugee graffiti, arson of refugee homes, assault, and incidents during protests in Germany between January 2015 and early 2017" (Müller and Schwarz, 2019a, p. 8f.). Since I just observe the year 2015 I cut this data down to the incidents within the weeks around the treatments, therefore I got 397 incidents. A distribution of all incidents is shown in Figure 5.

Although this data were produced by the Amadeu Antonio Foundation and the Non-Government Organisation "Pro Asyl" it is a high quality dataset, because more than half of the data were reported by the federal government, other were reported by the police, and national/local media outlets (Müller and Schwarz, 2019a). This dataset comes along with a short description of the incidents, geo-codes, source, date of incident, state, and they are also classified in four groups (arson, incidents at demonstrations, other attacks on accommodations, assaults, and some incidents which are still under investigation). Since I am not interested in all of those variables I select just the date

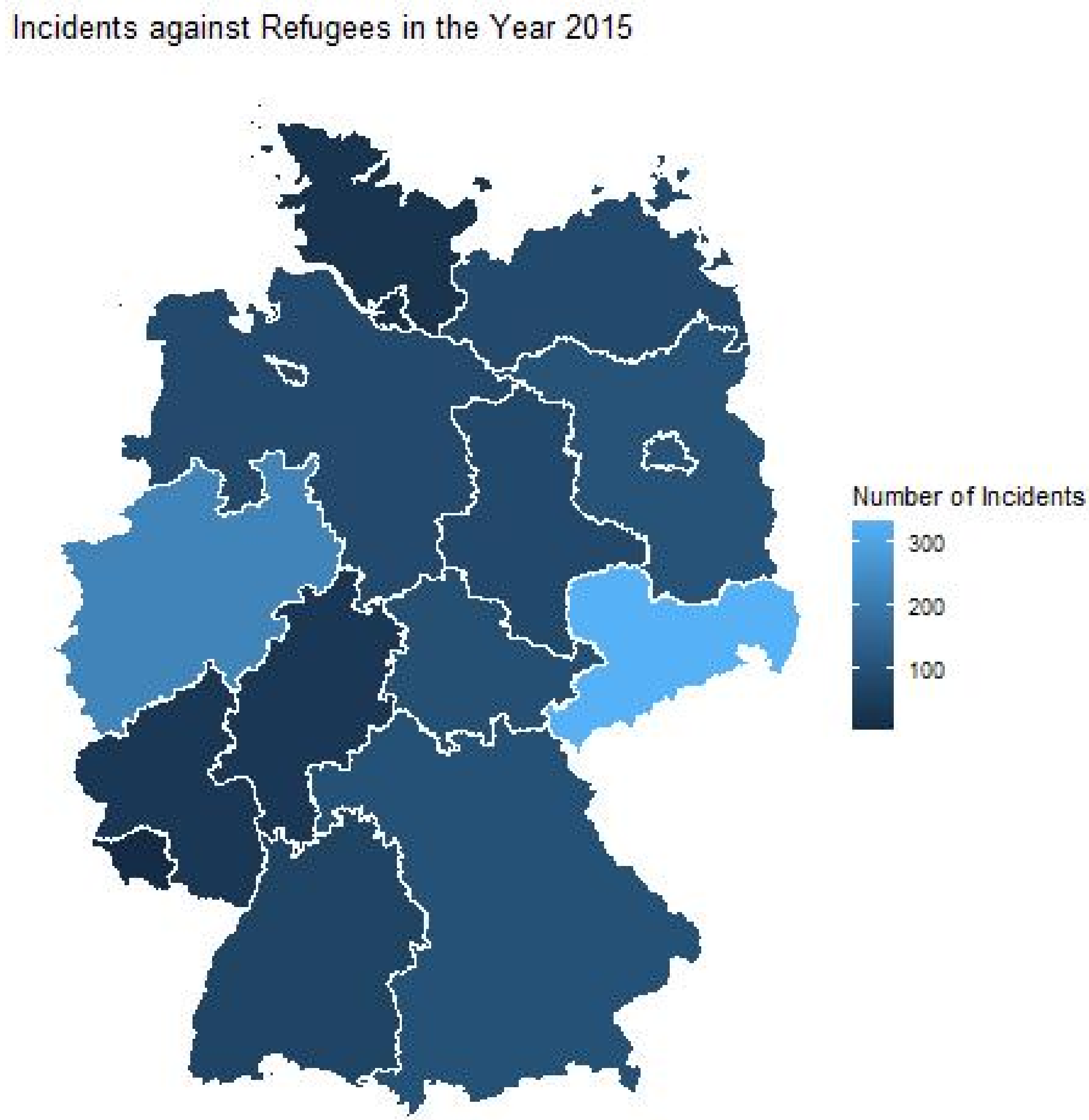

Figure 5: Number of Incidents against Refugees in the all year 2015

of incident, the state, and the number of incidents per day. The latter I calculate with grouping per date and counting the number of incidents. A distribution of Tweets and the occurrence of Tweets which contain indicators of hate speech can be seen at Figure 6.

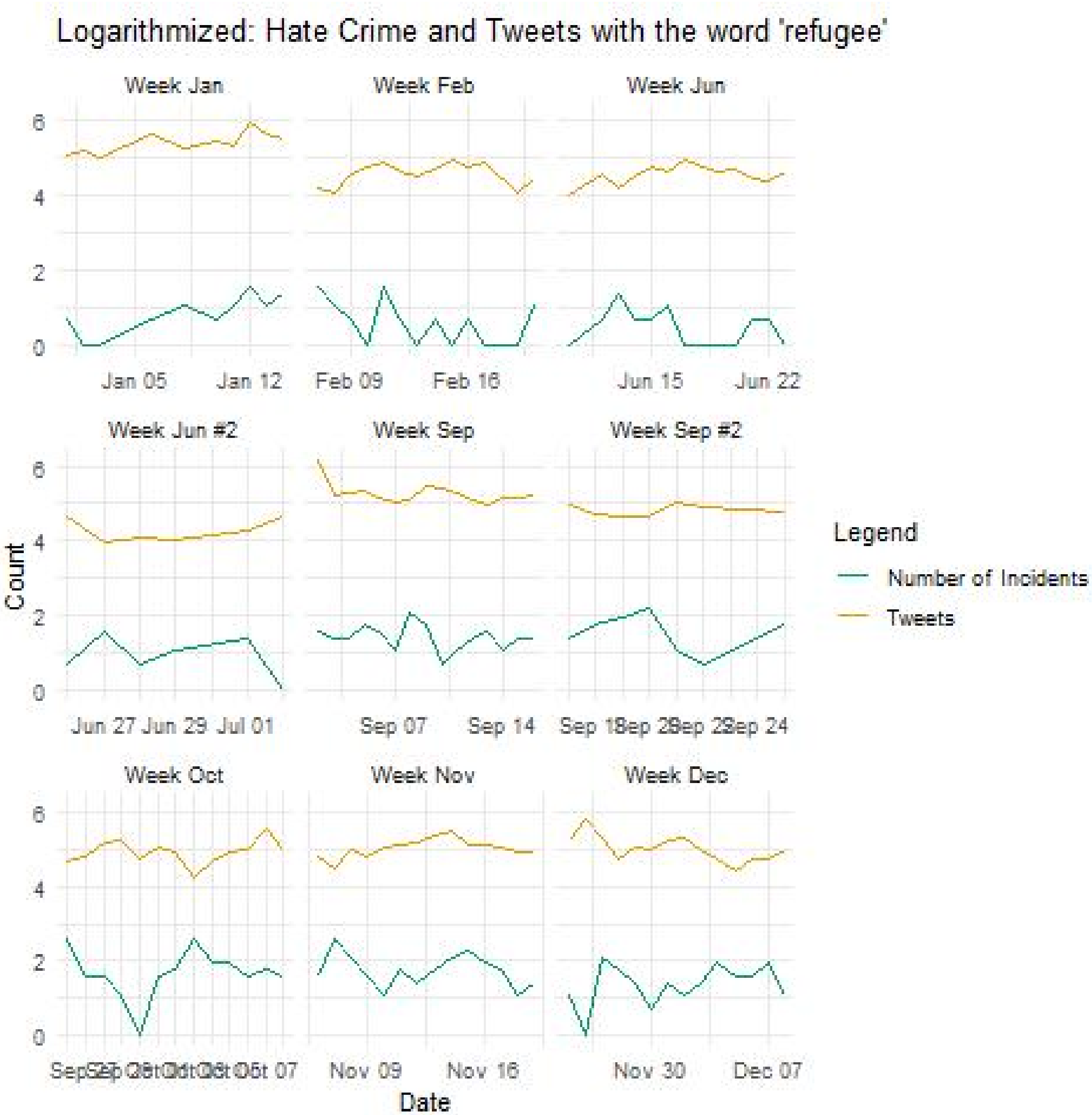

Figure 6: Logarithmized Distribution of Hate Crime against Refugees as well as the Tweets with an Indicator of Hate Speech. Note: The logarthim was used to display the distribution proper.

4.4 Additional Control Variables

As above mentioned I control also for further six auxiliary variables. These are information about the federal states such as population density, foreigner density, or the density of people who are seeking for protection. Those information I receive from wikipedia.de, sozialpolitik-aktuell.de, and the Integration Report from 2019. Moreover, I added an indicator for a general racism level by each state. To calculate this level I sum up the proportion of the second vote of the right-wing parties Alternative für Deutschland and the Nationale Partei Deutschlands (NPD, National Party of Germany) at the parliamentary elections for the Bundestag in 2017. This can be found at Bundeswahlleiter (2015).The second vote is the vote for candidates at the Landesliste (list of party candidates for election at the level of a state), so they are the direct delegates of a state. Furthermore, for the net household income per capita of each state is controlled as well as the digital infrastructure. The information of the latter I received from the Bundesministerium für Verkehr und digitale Infrastruktur (Federal Ministry of Transport and Digital Infrastructure, (für Verkehr und Digitale Infrastruktur, 2015)). I focus on the middle of the five available speed accesses of household – the 16 Mbit/s access. This is due to the fact that Müller and Schwarz (2019a) show that this access has the highest correlation "[...] with publicly available survey data on individuals' internet use" (Müller and Schwarz, 2019a, p. 15). So, these further auxiliary variables are rather an additional control mechanism for the number of incidents against refugee than for the number of tweets. Since Twitter information about the location of a user are usually biased because user can indicate that they are on the moon, for example, or at another location instead of the actual.

4.5 Method

A difference-in-difference analysis seems necessary since the outcome of interest is a difference of the number of Tweets before and after a salient event occurs. An ideal experiment for this term paper would be that I can state if a user spread and hate speech against refugees, and if so how often, or if they do not. The latter would be than the control group where each user gets a topic about which the user has almost consistently to Tweet. Therefore, the frequency of the Tweets would be the units of measurement. Additionally, the baseline of measurement would be the sentiment and frequency of Tweets one week before the treatment which would be compared to the sentiments and frequency one week after. If and when a treatment occurs would also be the decision of the constructor. Moreover, ideally would be if I have all information about the participants to control for such as personal socio-demographics, political views, social media behavior, etc.

My constructed dataset is, therefore, a kind of natural experiment since I collected data over time with a natural randomization. This randomization is take place by the users themselves because either they spread hate speech via Twitter or they do not. As above-mentioned I scraped Tweets with an indicator of hate speech.

I calculate the sentiments of those to be sure that the most are a kind of hate speech during removing German stopwords (e.g. für (for), ist (is), und (and), etc.) and classify them into negative and positive sentiments. For the latter I used the *SentiWS* from the *Wortschatzprojekt* by the University of Leipzig (Remus et al., 2010). This dataset contains over 34,000 words (16,000 positives and 18,000 negatives) with a polarization of the sentiments in an interval form -1 to +1. As I previous mentioned that dataset is mostly negative polarized (see Figure 4), therefore I assume that probably many of those contain hate speech. Furthermore, the salient events occurrence is not in the hand of the constructor but rather they occur also natural, because whether they are there or they are not. Unfortunately, I do not have all personal data from each user. Due to that fact, I control for some general measurements in each time period such as number of incidents against refugees which I also control by the aforementioned auxiliary variables. To calculate the difference within the Tweet behavior of hate speech occurrence I use the difference-in-differences analysis. This analyze is a kind of regression where the dependent variable is the difference of the values before and after the treatment with some control variables, so this regression can be modeled as follow:

$$y_t - y_{(t-1)} = \beta_0 + \beta_{treated} + \beta_{control_1} + \ldots + \beta_{(control_n)} + \epsilon \tag{1}$$

At this formula the $y_t - y_{t-1}$ describes the difference of the tweet behavior before and after a salient event. The treatment variables states at which time point the treatment started due to that it is encoded as a dummy variable where 0 = before a salient event, and 1 = after a salient event is. Additionally, I include the above-mentioned control and auxiliary variables such as number of incidents against refugees ($\beta_{control_1}$), population density, foreigner density, etc. The unobserved noise term of this regression is described as ϵ at formula (1). This noise term could include some unobserved heterogeneity such as variables which cannot be measured, or an omitted variable bias.

5 Results

To test the hypothesis if hate speech against refugees is lower with an absence of salient events I applied a difference-in-differences analysis on nine different salient events. Table 5, Table 7, and Table 9 show that the treatment effect is on every event positive and significant on a 1% level since $p < 0.01$. Therefore, I reject my null hypothesis that the salient event has no effect on the hate speech on Twitter. The largest effect is shown by Charlie Hebdo shootings on the 7th January 2015 with 432 more Tweets on average after that event, followed by Germany on the 9th September with 188 more Tweets on average, the events in France on the 13th November and in Denmark on the 14th February with 161 and 159 more Tweets on average, after the events in Australia on the 2nd October and the USA on the 2nd December occur 117 and 110 much more Tweets on average as before, and the events in Germany on the 17th September, the USA on the 17th June, and in France on the 26th January produce 104, 98 and 61 much more Tweets on average with hate speech as before. The control and auxiliary variables are nearly all insignificant which implies that the numbers of incidents against refugees explain not the Tweet behavior around the treatment events but rather the treatment only explain this.

Nevertheless, the model around the treatment of the event in Denmark has two slightly significant negative auxiliary variables effects: the household income per capita (net) and the digital infrastructure. So, the numbers of Tweets will decrease by 0.01 on average if the household changes by 1 unit which is significant on a 10% level ($p < 0.1$). Since this effect is very small it is negligible. The same applies on the digital infrastructure – the Tweets on average would decrease by 3% if the broadband access with 16 Mbit/s changes by one unit. This effect is also very small and negligible even its significance is on a 5% level ($p < 0.05$). Same applies equally on the treatment event in Germany on the 17th September, therefore if the household income per capita changes by one unit it has a positive effect on the Tweets with 0.024 on average which is also just on a 10% level significant and can negligible. The most significant auxiliary variables can be found at the model around the coordinated shootings around Paris, France on the 13th November 2015. The population density, the number of people who are seeking for protection, the household income per capita, and the digital infrastructure are all on a 1% level significant. The household income and the number of people who are seeking for protection have a positive impact on average on the Tweets with contain an indicator of hate speech. 0.028 more Tweets could occur on average if the household income changes by one unit and if the people who are seeking for protection will change by one unit it would be increase the number of Tweets by 0.002 on average. These numbers are again very small just as the negative effect of the population density which has a significant negative effect of 0.00002 on the Tweets if this density changes by one unit. Also, if the digital infrastructure will change by one unit it would decrease the number of Tweets by 2.54% on average. Although these numbers are very small and can already negligible the numbers of incidents against refugees have in this model a significant positive effect on the Tweet behavior. So, if the numbers of incidents change positively by 1, 17.6 more Tweets will occur on average after the treatment behavior, but this is just significant on a 10% level ($p < 0.1$).

Furthermore, the R^2 and adjusted R^2 are all over 50% which provides the evidence that more than 50% of the within variance could be explained with this data. This declares overall a high explanation of the dataset on my hypothesis. Since I include seven control and auxiliary variables it would make sense to look at the adjusted R^2 because the more independent variables one include the higher could be the normal R^2. The adjusted R^2 computes the reliability of the model and includes also the independent variables. As a consequence of this the adjusted R^2 will always be smaller or just equal with the R^2. The highest reliability of the models could be found at the one around the attack on the mosque in Bielefeld, Germany on the 9th September with 95% and the attack in Charleston, South Carolina, USA on the 17th June with 96.2%.

In addition it could be said that the not only terrorist attacks by non-white people increase the Tweet behavior of hate speech but also the terrorist attack with nine Afro-American deceased. Hence, the hate speech against refugees in the German Twitter area will increase if people who look similar to refugees are involved. These results show that there can be found a causal dynamic between salient events such as terrorist attacks and Tweets which contain hate speech against refugees.

6 Discussion

This term paper investigates if there is a causal dynamic between German Tweets which have an indicator of hate speech against refugees and certain salient events, terrorist attacks for example, in the year 2015. According to the results, tweeted hate speech will increase if events such as the Charlie Hebdo shooting in France, the attack on a police woman in Germany, the San Bernardino (USA) shootings, and similar occur. So, there

Table 4: Regression Results France

	Dependent variable:		
	Tweets		
	France 7^{th} Jan	France 26^{th} Jun	France 13^{th} Nov
Treatment	432.440***	61.094***	161.265***
Number of Incidents	−30.868	20.851	17.608*
Population Density	−0.0001	−0.00001	−0.00002***
Foreigner Density	0.0001	−0.00002	−0.00002
People who are seeking for protection	0.004	0.001	0.002***
Racism Level in Percentage	10.479	1.853	0.065
Houshold Income (Net)	0.060	0.016	0.028***
Digital Infrastructure	−7.025	−0.642	−2.535**
Constant	−894.490	−329.201	−351.021**
Observations	23	23	76
R^2	0.780	0.785	0.822
Adjusted R^2	0.655	0.662	0.800
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Results of the Difference-in-Differences Regression on the France Treatments

Table 6: Regression Results Europe 2

	Dependent variable:		
	Tweets		
	Denmark 14^{th} Feb	Germany 9^{th} Sep	Germany 17^{th} Sep
Treatment	159.835***	188.653***	104.541***
Number of Incidents	−51.264	6.892	−21.935
Population Density	0.00001	0.00000	−0.00002
Foreigner Density	0.00001	0.00001	−0.00002
People who are seeking for protection	−0.001	−0.0003	0.002*
Racism Level in Percentage	−3.796	1.072	3.415
Houshold Income (Net)	−0.010*	−0.0001	0.024*
Digital Infrastructure	−3.008**	0.682	−0.516
Constant	476.992**	−80.108	−458.965*
Observations	30	57	56
R^2	0.907	0.957	0.754
Adjusted R^2	0.871	0.950	0.712
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: Results of the Difference-in-Differences Regression on the Denmark and Germany Treatments

Table 8: Regression Results USA and Australia

	Dependent variable:		
	Tweets		
	USA 17^{th} Jun	USA 2^{nd}Dec	Australia 2^{nd} Oct
Treatment	98.157***	110.357***	117.703***
Number of Incidents	0.907	4.850	−5.584
Population Density	−0.00001	0.00001	−0.00001
Foreigner Density	0.00002	−0.00000	−0.00000
People who are seeking for protection	−0.0001	−0.001	0.001
Racism Level in Percentage	−1.549	−2.002	0.454
Houshold Income (Net)	−0.002	−0.012	0.004
Digital Infrastructure	−1.757	0.646	−0.719
Constant	241.017	221.635	−21.168
Observations	21	60	74
R^2	0.977	0.686	0.612
Adjusted R^2	0.962	0.637	0.564
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9: Results of the Difference-in-Differences Regression on the USA and Australia Treatments

is a causal dynamic between German online hate speech against refugees and salient events even if the event does not occur in Germany but in other Western countries while people who are looking similar to refugees are involved. To the latter point it does not matter if they are perpetrators or victims. This is shown at the model of the Charleston, USA attacks on the 26th June (see Table 9).

Unfortunately, this term paper faces some limitations. On the one hand I have no proper identifier of hate speeches against refugees and on the other hand is the sample for a proper generalization to small. To identify German online hate speech one had to discover prominent racial slurs e.g. from books, interviews or other. A machine learned program has to be developed by those slurs to identify hate speech against refugees. Tweets also have to be scraped and those with hate speech get detected by the program. Thus, a control group would also coexist to the treatment group. I have the Tweets separated into temporal emerge to create a control group but Tweets without hate speech are missing in my data. So, a proper control group in this term paper is lacking. Moreover, I consulted just nine events as a treatment and investigate just Tweets of one week before and one week after. So, the generalization of the results is questionable as well. But for these events in 2015 under the aforementioned conditions Tweets will increase. In addition, I have used a difference-in-difference regression that may not be entirely appropriate for my data because this tool is usually applied on wide-format data, but mine are time series long-formated. Due to the lacking of time resources I could not switch to another analyze tool such as a frequency domain analysis or similar.

Nevertheless, I get significant results for a positive causal effect of salient events on the hate speech Tweet behavior. So, this is a further proof of a direct linkage from the real world on the behavior in the internet. Furthermore, one can assume that those events flared up the hate against refugees and future research could investigate if this hateful Tweet behavior has an impact on the real world as well. For instance, if the hateful Tweet behavior increase does the number of incidents against refugees also increases?

Further Notes

You can find all data and the replication code *here*.

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