# Essays on the Political Economy of Mobilization

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To you.

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# Introduction

Mobilization is a concept underlying a diverse array of processes in society. From the turnout in elections and shows of support for a particular cause to political upheaval and the spread of violence – all of these dynamics are based on influential behavior and interdependent decisions of individuals. This dissertation sheds light on different forms and aspects of mobilization by theoretically, methodologically and empirically advancing our knowledge of the concept.

Part I approaches the political economy of mobilization from a theoretical perspective against the background of current events. Chapter 1 starts out from the observation, that numerous of western industrialized nations have experienced a notable polarization of political ideologies in recent years, and that growing numbers of individuals seemingly support extreme positions. As a result, established political parties have moved to the left or right and new parties have appeared on the fringes. But why are people with extreme political views this visible in the public debate, and how are they able to move party positions further to the margins when they should be outnumbered by a moderate majority? Contradictory to the classic literature that focuses on collective action problems, this chapter studies emerging effects from informational asymmetries. It extends a spatial voting model to include incompletely informed candidates and knowledgeable voters. Agent-based simulations suggest that only fringe voters benefit from distorting their opinions and dominating political discourse. At the same time, better informed candidates have a competitive advantage in elections no matter how strongly voters distort their positions.

After this theoretical discussion of potential mechanisms behind the escalation of extreme political opinions, the chapters in part II turn to a particular kind of mobilization and examine the spread of right-wing violence. The recent rise of xenophobic attacks against refugees in Germany has sparked both political and scholarly debates about the drivers, dynamics, and consequences of right-wing violence. But a lack of systematic data collection and data processing has inhibited the quantitative analysis to help explain this current social phenomenon. Chapter 2 therefore introduces a new georeferenced event dataset on anti-refugee violence and social unrest in Germany in 2014 and 2015 based on a public chronicle. The dataset includes information on 1 645 events of four different types of right-wing violence and social unrest: xenophobic demonstrations, assault, arson attacks, and miscellaneous attacks against refugee housing (such as swastika graffiti). After discussing how the dataset was constructed, the chapter provides a descriptive analysis of patterns of right-wing violence and unrest in Germany in 2014 and 2015.

Based on this dataset, chapter 3 offers an in-depth analysis of all recorded instances of anti-refugee violence in order to answer the following questions: To what extent can series of hate crimes be explained by contagion? To what extent are they brought about by local conditions, including the level of support for right-wing extremist political parties? Using standard non-spatial and spatio-temporal econometric models, this chapter shows that hate crimes have a strong spill-over component across different types of violence. Adopting an epidemiologic point process model, this chapter also determines the contagiousness of each type of violence.

Taking up the notion from chapter 1 that public discourse is increasingly taking place within social media, part III considers possible approaches for analyzing these oftentimes unstructured data sources appropriately. In order to look beyond the opportunities of social media and investigate the precise mechanisms of online mobilization, chapter 4 proposes a combination of automated content and network analysis to examine determinants of successful online mobilization. This approach is applied to the extended Twitter networks of organizations within the environmental and nuclear disarmament movements to demonstrate its usefulness. Results show that sentiment-laden messages receive widespread popularity, irrespective of the messenger's identity and role in the network. However, message content is subordinate to the centrality of a messenger when it comes to mobilizing more distant network members.

In addition to its focus on different varieties and aspects of mobilization, this dissertation has another underlying theme that binds the individual chapters together: Computational methods in the social sciences are being increasingly utilized and also adopted from other disciplines to the effect that we can develop more complex theories, analyze existing data in novel ways, and create entirely new data from sources never considered before. Each of the subsequent chapters contributes to this methodological diversity. Chapter 1 implements the spatial voting model in an agent-based computational framework and uses simulations in order to reconstruct emerging global effects from individual behavior. Chapter 2 demonstrates the usefulness of web-scraping and comprehensive data cleaning for collecting new data and creating scientifically usable datasets. Chapter 3 adopts statistical tools from epidemiology in order to gain new insights from spatio-temporal data. Finally, chapter 4 uses a combination of computational text analysis and graph theory to explore the vast amounts of information within social networks.

The individual chapters of this dissertation are based on the following papers:

Chapter 1: Benček, D. (2016). Opportunistic Candidates and Knowledgeable Voters – A Recipe for Extreme Views. *Under review*.

Chapter 2: Benček, D. & Strasheim, J. (2016). Refugees welcome? A dataset on anti-refugee violence in Germany. *Research & Politics 3*(4): 1–11.

Chapter 3: Benček, D. & Martin, C. (2016). Explaining hate crimes against refugees in Germany: Contagion or local determinants? *Under review*.

Chapter 4: Benček, D. (2016). Message Received: Analyzing Determinants of SMO Mobilization on Twitter. *Under review*.

# Part I

# A Theory of Extreme Views

# Chapter 1

# Opportunistic Candidates and Knowledgeable Voters – A Recipe for Extreme Views

David Benček

## 1.1 Introduction

Recently, a number of Western industrialized nations have experienced a notable polarization of political ideologies and growing numbers of individuals seemingly support extreme views on the left or right. Survey data among US American adults, for instance, show a "growing ideological distance" between parties as well as along educational and generational lines (Pew Research Center, 2014, 2016). Reacting to such shifts in preferences, established political parties have moved considerably to the left or right, and new political parties have emerged – and succeeded – on the fringes of policy space. The impact of Bernie Sanders and his supporters on the US Democratic Party's platform with regard to issues such as the minimum wage or Wall Street reform, the rise of Donald Trump as the Republican Party's presidential candidate, but also the widespread emergence of anti-immigration parties in Western Europe or the electoral successes of left-wing parties in Greece, Portugal, or Spain are examples of these trends. It seems as if extreme political views have become more prevalent in public discourse, have moved "from the margins to the mainstream" (Lowles, 2015), and have considerably influenced the face of party systems for years to come. But why are people with extreme political views this visible in the public debate, and how are fringe voters able to move party positions to the extremes when they should be outnumbered by a moderate majority?

This paper develops a spatial voting model built upon a classic Downsian framework extended by incomplete information, heterogeneous candidates and knowledgeable voters to show why fringe political views influence the political discourse to the extent observed today. The motivation underlying this approach is twofold: With such departures from the standard model this paper contributes to the theoretical literature by accounting for empirical observations in the model's assumptions. As recent studies have highlighted, notable discrepancies exist between voter preferences and candidate assessment of their constituency due to ideology or political commitments (e.g. Enos & Hersh, 2015; Broockman & Skovron, 2015) and cognitive heuristics (Miler, 2009).

Additionally, adopting an extended spatial voting model in order to comprehend widespread shifts in our political discourse can help trace the mechanisms responsible for them. Of course, a common theoretical explanation of differences between individual preferences and social outcomes is based on collective action problems among the large majority of people holding moderate views (cf. Olson, 1965). What extremists lack in numbers they make up for by dominating public discourse, while the moderate majority is trapped in a situation where no one feels urged to proclaim their views. However, we live in a time of instantaneous unlimited communication and a real-time feedback loop between politicians and their constituency; opinion polls are being conducted constantly and statistical models have become sophisticated and relatively accurate tools for predicting election outcomes. In this environment, society is conspicuously aware of the interplay of politics and political interests; and voters have an adequate understanding of democratic processes. So if there were a collective action problem inhibiting moderate views to challenge extreme opinions in public discourse, it would be identified and internalized almost immediately. By incorporating knowledgeable voters in a spatial voting framework the potential causes of discourse shifts are thus not subsumed under the umbrella of collective action but can instead be traced along the mechanisms at work.

Focusing on the combination of incompletely informed candidates and voters' interest in affecting policy, this paper argues that only voters holding fringe political views should have a justifiable interest in signalling their preferences distorted towards even more extreme positions. Voters with moderate political opinions do not benefit from similar signalling behavior due to the complex interplay of electoral competition, multiple attempts at influence, and opportunistic candidate behavior under incomplete information. Simulations of the model support this proposition and further show that better informed candidates as well as stronger electoral competition both mitigate such disparate behavioral incentives.

The remainder of this paper proceeds as follows: Section 1.2 briefly reviews the relevant literature on the interplay between voter preferences and candidate perceptions and behavior. Subsequently, section 1.3 presents a spatial voting model with informational and behavioral frictions. The formal model is used to derive the proposition that only fringe voters with preferred policies sufficiently far from the center in an $n$-dimensional issue space benefit from signalling distorted opinions, because only they can influence candidate platforms in the desired way. This proposition is then examined in section 1.4 using an agent-based simulation implemented in NetLogo. The simulation enables us to fully consider the implications of heterogeneous agents and investigate different parameter constellations regarding the informational capacity of candidates, electoral competition, and voter influence. The final section concludes and identifies avenues for future research.

## 1.2 Background

The concept of spatial competition, starting out with Hotelling (1929) and Black (1948), and popularized by Downs (1957), has produced a vast and diverse literature within the social sciences (e.g. Stokes, 1963; Eaton & Lipsey, 1975; Aoyagi & Okabe, 1993). It has especially influenced theoretical research on party policy strategies as well as empirical empirical studies of voting behavior (cf. Adams & Merrill III, 2000). Most of this literature has focused on two particular issues: First, the existence of stable or unstable equilibria in policy space under various circumstances and model assumptions has been the topic of numerous studies. For instance, Lin, Enelow, and Dorussen (1999) demonstrate that differences in equilibria exist between deterministic and probabilistic multicandidate spatial voting models; Schofield (2006) develops a spatial model with valence, in order to explain the gap between theory and empirical observations regarding equilibria in voting models, and derives general conditions under which local Nash equilibria exist in a multiparty setting; and Banks and Duggan (2005) set up a basic and common framework to unify large parts of the existing literature on probabilistic voting with two candidates. They prove the existence of equilibria in pure and mixed strategies and relate them to social optima.

Second, the spatial voting framework has also been applied to the explanation of variance in voter turnout: Plane and Gershtenson (2004) study voter alienation in US mid-term elections and find that voter indifference and alienations explain why voters abstain from casting their vote; and Geys (2006), in a meta-analysis of 83 studies on voter turnout, highlights in particular population size and election closeness as explanations for why people turn out in elections.

A very common simplifying assumption in these studies is that of perfect information of either candidates, voters or both (see e.g. Shepsle & Weingast, 1984). For instance, McKelvey and Patty (2006) use a Bayesian framework that includes game-theoretic considerations for voters in order to model strategic voting – but this implicitly assumes voters to have the capabilities to process lots of information. Stimson, Mackuen, and Erikson (1995, p. 559) are also optimistic about politicians' ability to correctly assess preferences of their constituency and describe them as "keen to pick up the faintest signals". When testing the predictions of such spatial voting models, the empirical literature takes these assumptions as given (see e.g. Schofield, Sened, & Nixon, 1998).

But empirical studies have shown noteworthy discrepancies between the assumptions underlying standard spatial voting models and actual candidate behavior: Candidates have widespread and lasting misperceptions about their constituencies. Miller and Stokes (1963, p. 56) were the first to show empirically that representatives have "very imperfect information about the issue preferences of [their] constituency". Several studies have also shown that politicians are more likely to consider information coming from specific interest groups (Bartels, 2009; Hacker & Pierson, 2010; DeCanio, 2005; Gilens, 2012). Similarly, Miler (2007) finds that candidates do not assess information from all constituents, nor from the largest constituencies, but rather from the most active and resource-rich constituents. Therefore it is not surprising that according to Page, Bartels, and Seawright (2013) the top 1 percent of US wealth-holders, which tends to be both more conservative and more politically active than the rest of the population, has a higher impact on government policies than the majority of US citizens. Miler (2009) also studies the role of incomplete or unrepresentative information in politicians' judgement and suggests the widepsread use of cognitive heuristics by decision-makers. Their effects can be found in Enos and Hersh's (2015) research who find political campaign staff overly confident and note how this limits the benefits of electoral competition.

So while there is abundant evidence of bounded rationality and the resulting systematic or incidental misperceptions, it is mostly the empirical literature accounting for them. As a result, formal theoretical models neglect the complex properties of established political systems which consist of a constant interplay of actors and can thus exhibit emerging dynamics. This paper therefore develops a formal spatial voting model that expands the standard framework with respect to three essential aspects: First, candidates do not possess complete information about voter preferences. They can only consider a subset of opinions when choosing their policy platform for elections. Second, candidates are heterogeneous with respect to the scope of information they are able to take into account. As in real elections, some candidates are more experienced, have higher quality information or more resources at their disposal, or are simply more interested in the preference structure of the electorate. Some candidates thus choose their platform based on more voter information than others. Lastly, voters in the proposed model are knowledgeable in the sense that they are aware of how the democratic process functions. Voters know that candidates try to win elections and do so by appealing to as large a share of the electorate as possible. Consequently, voters are able to signal their preferences but do not necessarily need to signal them thruthfully. The underlying rationale is to influence the candidates' perceptions and arrive at more favorable policy outcomes.

With these built-in informational and behavioral imperfections, the proposed model is detached from the focus on equlibria and instead illustrates the complex system dynamics of interdependent political behavior. The model allows for candidates to be influenced by voters to varying degrees and conditional on the underlying preferences. The following section describes the properties and dynamics of the model in more detail.

## 1.3 Model

The spatial voting model depicts the interaction of candidates and voters and the ensuing dynamics in discrete time. For reasons of clarity and legibility, the time subscript $t$ is omitted in this exposition.

### 1.3.1 Basic Structure

**Actors** The proposed model accommodates two types of actors, candidates and voters, who are scattered randomly across an $n$-dimensional, bounded policy space $Y \subseteq \mathbb{R}^n$ according to some density function $f_n^{\mathrm{c}}(\cdot)$ and $f_n^{\mathrm{v}}(\cdot)$, respectively.

Each candidate $j = 1, \ldots, M$ has a unique policy platform $\mathbf{p}_j \in Y$, represented by her position in policy space and $\boldsymbol{p} = (p_1, \cdots, p_M)$ is the vector of all candidate platforms. Candidates attempt to win elections by choosing their platform in policy space.

Each voter $i = 1, \ldots, N$ has a stationary but not necessarily unique bliss point $\mathbf{b}_i \in Y$. Voters have single-peaked, symmetric preferences according to some function $u_i(p_j)$ and their utility strictly decreases in the distance between a given policy and their ideal point. For simplicity, utility is determined by their Euclidean distance[1]

$$u_i(p_j) = -\|\mathbf{b}_i - \mathbf{p}_j\|. \tag{1.1}$$

Since voters are assumed to be utility maximizing, they will always cast their ballot in favor of the candidate closest to their bliss point. In case two or more candidates have chosen their platform at the exact same distance, he is indifferent and chooses randomly between them.

**Incomplete and Unreliable Information** Candidates do not possess complete information about voter preferences. In particular, they do not know the distribution of bliss points across policy space. In order to estimate the aggregate preference structure, they depend on voters signalling their ideal points. Candidates remain, however, incompletely informed for two reasons: First, candidates are not able to take into account signals from the entire population of voters. Instead each candidate $j$ is only able to consider $c_j$ voters in each election cycle. Heterogeneity of candidates with respect to $c_j$ may be interpreted as differences in financial endowments, infrastructure and political experience – generally, necessary prerequisites to develop and implement balanced and inclusive policies based on voter preferences.

The second reason for the persistently incomplete knowledge lies in a behavioral trait of voters: They are solely interested in policy outcomes, no matter which candidate ends up implementing them. As voters try to maximize their personal utility, they therefore always prefer a candidate to be closer to them than further away. They are furthermore aware that candidates use their signals to assess voter preferences when choosing a platform. Consequently, voters do not necessarily sig-

[1]A common alternative to this linear utility model is the quadratic utility $u_{ij} = -\|\mathbf{b}_i - \mathbf{p}_j\|^2$. The main difference between both is the stronger relative penalty that the quadratic utility places on distance. This paper follows Singh (2013), who argues that the linear formulation more accurately reflects actual election outcomes.

nal their true bliss points, but may instead distort their preferences strategically so as to pull the respective candidate closer to them. In a similar fashion as Buechel, Hellmann, and Klößner (2012) model the misrepresentation of individual opinions by non-conformists in consensus-seeking discussions, voters tend to overstate their preferences subject to the current platform the targeted candidate occupies. In particular, each voter has an innate propensity $s_i$ by which they misrepresent their signalled bliss point. So the opinion $o_{ij}$ signalled by voter $i$ to candidate $j$ is given by

$$\mathbf{o}_{ij} = \mathbf{b}_i + s_i \left(\mathbf{b}_i - \mathbf{p}_j\right). \tag{1.2}$$

Candidates receive a random sample $\mathcal{S}_j$ of voter signals each period. The signal sent by a specific voter always depends on the current platform taken up by the candidate it is intended for and will not be the same for two candidates unless $\mathbf{p}_j = \mathbf{p}_k$. Candidates therefore receive skewed information that depends on their current platform, as well as the voters' unobserved position and propensity to misrepresent their preferences.

In each period, this randomly drawn sample of size $c_j$ provides a candidate with a temporary set of opinions $\omega_j = \{o_{ij}\}_{i \in \mathcal{S}_j}$, which serves as a basis for assessing the preference structure of the voter population.

**Candidate Behavior** Candidates seek to be elected and therefore try to maximize their expected vote share. But they cannot be sure about exact voter preferences (especially since they estimate them using a sample of voters). This would, however, be required to model candidates' estimates of voting probabilities as a discontinuous step function that only takes the values $\{0, 1\}$, depending on whether or not the candidate is closest to a particular voter's bliss point. Furthermore, voters might not necessarily be perfectly informed about candidate positions and thus perceive them within a margin of error. Therefore even perfect knowledge of voter preferences would not enable candidates to clearly demarcate regions of winning platforms.

In light of this, it is more realistic to base candidate decisions on a probabilistic voting model, in which their likelihood of receiving a vote increases as their platform approaches a voter's ideal point. In order to preserve the generality of the model, utility and not simply distance is considered in the likelihood function, because there may be additional factors such as loyalty or ideology that influence voter decisions. For simplicity, however, the utility function is reduced to distance in this exposition. As explained above, candidates are imperfectly informed about voter preferences and use $o_{ij}$ as a proxy for $b_i$, which may or may not coincide. The utility function of any voter $i$ in a candidate's maximization rationale is thus

$$v_i^j(p_k) = u_i(p_k \mid b_i = o_{ij}) = -\|o_{ij} - p_k\|. \tag{1.3}$$

This denotes candidate $j$'s estimate of voter $i$'s expected utility given candidate $k$'s platform. The fact that voters may communicate different bliss points to different candidates, i.e. $p_j \neq p_k \iff o_{ij} \neq o_{ik}$ if $s_i > 0$, makes this superscript necessary to indicate whose estimate is being considered.

In order to determine voting probabilities, a standard contest success function is used and from the perspective of candidate $j$, the probability of receiving a vote from voter $i$ is

$$\pi_{ij}(\boldsymbol{p}) = \frac{e^{\alpha v_{ij}^j}}{\sum_{k=1}^m e^{\alpha v_{ik}^j}} \quad \text{with } \alpha > 0. \tag{1.4}$$

This way of modelling the probabilistic voting scheme in conditional logit form goes back to a difference-based contest success function (Tullock, 1967, 1980; Hirshleifer, 1989; Coughlin, 1992) and has been applied in empirical studies on voting (e.g. Adams & Merrill III, 2000; Merrill III & Adams, 2002).

Each candidate seeks to maximize her expected vote share $\frac{1}{n}\sum_{i=1}^n \pi_{ij}$. But since probabilities can only be estimated for those voters included in the candidate's own sample $\mathcal{S}_j$, the objective function is limited to

$$\max_{p_j} \pi_j(p_j \mid \boldsymbol{p_{-j}}) = \frac{1}{c_j} \sum_{i \in \mathcal{S}_j} \frac{e^{\alpha v_{ij}^j}}{\sum_{k=1}^m e^{\alpha v_{ik}^j}} \quad \text{s.t. } p_j \neq p_k \text{ for all } k \in P, \tag{1.5}$$

conditional on all other candidate platforms $\boldsymbol{p_{-j}} = (p_1, \cdots, p_{j-1}, p_{j+1}, \cdots, p_M)$. This implies that the candidate-specific set of voter opinions is treated by each candidate as if it were representative of the entire voter population.

### 1.3.2 Model Dynamics

From an individual voter's perspective a biased disclosure of preferences attaches a higher weight to his utility in the candidate's decision-making process and therefore also raises the expected utility from potential future policy. It is easy to show by combining equations 1.2 and 1.3 that candidate $j$'s evaluation of voter $i$'s utility becomes $v_i^j(\mathbf{p}_j) = (1+s_i)u_i(\mathbf{p}_j)$. Thus strategic opinion distortion should increase the weight attached to his true utility in candidate $j$'s estimate by $(1+s_i)$. But whether or not this actually increases the weight of his likelihood contribution in the candidate's maximization rationale depends on the spatial distribution of (i) the other candidates and (ii) the other voters in the candidate's polling sample.

Because a distorted communication of opinion $s_i > 0$ not only affects the respective candidate's estimate of voter utility given her own policy platform, so that $v_i^j(p_j) \neq u_i(p_j)$, it also changes the candidate's estimate of the voter's utility given other candidates' platforms: $v_i^j(p_k) \neq u_i(p_k)$. This affects the relevant part of candidate's objective function in the following way:

$$\pi_{ij} = \frac{e^{-\alpha(1+s_i)\|b_i - p_j\|}}{\sum_{k=1}^{m} e^{-\alpha\|(1+s_i)b_i - s_i p_j - p_k\|}} \tag{1.6}$$

As voter $i$'s opinion is distorted to pull candidate $j$ closer to $b_i$, it also depends upon the relative positions of other candidates $k$ whether this actually increases $\pi_{ij}$ compared to a non-distorted signal. The relative positions of other parties, in turn, depend on the overall distribution of voters.

**Proposition 1** *Whether or not a voter can benefit from distorted opinion signalling depends upon her true bliss point in policy space. Only if it is located sufficiently far from the center will the signalled opinion affect the candidate in the desired way and increase the weight of the true opinion.*

Due to the complexity created by the heterogeneity of actors in conjunction with the multi-dimensional policy space, there is no closed-form analytical solution of the model and we need to rely on numerical methods. The next section therefore describes the approach taken to simulate the spatial voting model and presents the results.

## 1.4 Simulation

In order to examine its dynamics and allow for emerging global behavior, the proposed model was implemented as an agent-based model in NetLogo (Wilensky, 1999). For this simulation the number of policy dimensions is set to 2. Other relevant parameters were varied between runs in order to be able to assess their effects and see whether observed results are stable. Table 1.1 summarizes the ranges used for each model parameter. Their permutations lead to 147 distinct parameter constellations used in simulating the model. Each simulation run lasted 150 elections

***Table 1.1:*** *Parameter ranges of simulation*

| Parameter | Values |
|---|---|
| Candidates | 2-8 |
| Voters | 203 |
| Sample Size | 5%, 20%, 100% |
| Distortion | 0%, 20%, 80% |
| Distorting Voters | 1, 20, 81 |
| Voter Distribution | $\mathcal{N}_2(0, 25)$ |
| Policy Dimensions | 2 |
| Size of Policy Space | $101 \times 101$ |

and each parameter set was replicated 30 times. During each run, data on voter and candidate behavior as well as on election ourcomes were recorded for subsequent analysis.[2]

Using the simulated data, a closer look at potential differences in the utility levels of voters with and without distorted signals becomes possible. For this purpose, a simple OLS-regression of after-election utility among voters who signalled their opinions on their level of distortion can be estimated:

$$u_i(p_e) = \alpha + \beta s_i + \gamma r_i + \eta s_i r_i + \varepsilon_i, \tag{1.7}$$

where $p_e$ identifies the policy platform elected by the majority of voters and $r_i$ denotes the distance of voter $i$'s bliss point from the center of policy space. Since simulations were performed with normally distributed voters around the center, controlling for the voter-specific distance is necessary. The interaction between distortion and distance is of main interest here, since according to proposition 1, only voters with extreme opinions, i.e. voters whose bliss point is located further away from the center of policy space, should benefit from opinion distortion.

Estimation results of equation (1.7) are shown in table 1.2. As one would expect, a higher distance of a voter's bliss point from the center decreases utility on average. Distorting preference signals for candidates does not generally lead to higher utility levels. However, the significant and positive interaction effect of distortion

[2]For a better understanding of the computational implementation details and in order to enable the interested reader to replicate the results, an ODD description of the model is included in the appendix (cf. Grimm et al., 2010).

***Table 1.2:*** *OLS estimation of voter utility*

| | Utility |
|---|---|
| High Distortion | $-0.383^{***}$ |
| | (0.040) |
| Radius | $-0.866^{***}$ |
| | (0.0003) |
| High Distortion × Radius | $0.009^{***}$ |
| | (0.001) |
| Constant | $-6.763^{***}$ |
| | (0.009) |
| N | 7 447 400 |
| Adjusted $R^2$ | 0.542 |

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

and distance clearly shows benefits of distorted signals for voters with extreme opinions. On average, they seem to be able to influence candidates in a way that reduces their distance compared to other voters within the same radius around the center of policy space who do not distort their signals.

As the regression is run as a pooled model over different parameter constellations, these represent average results. In order to further analyse the effects, figure 1.1 additionally depicts the benefits from opinion distortion conditional on the number of candidates competing in elections as well as on the informational advantage, i.e. the sample size, of one of the candidates. Since it is necessary to control for the negative linear effect of distance on utility here as well, utility is depicted in relative terms compared to voters within the same radius corridor around the center of policy space. The upper row of figure 1.1 shows this relationship if all candidates use little information and receive signals from 5% of the electorate. Only voters whose true bliss point is located outside a radius around the center of more than 50% of the maximum possible distance have an incentive to distort their signalled opinion. With increasing electoral competition, these incentives are reduced and the radius beyond which benefits from distortion can be observed increases. The middle and lower rows of figure 1.1 furthermore highlight decreased incentives when the sample size of one of the candidates is larger and thus platforms are chosen based on better information.

Lastly, the effects of better information on the behavior of candidates and elec-

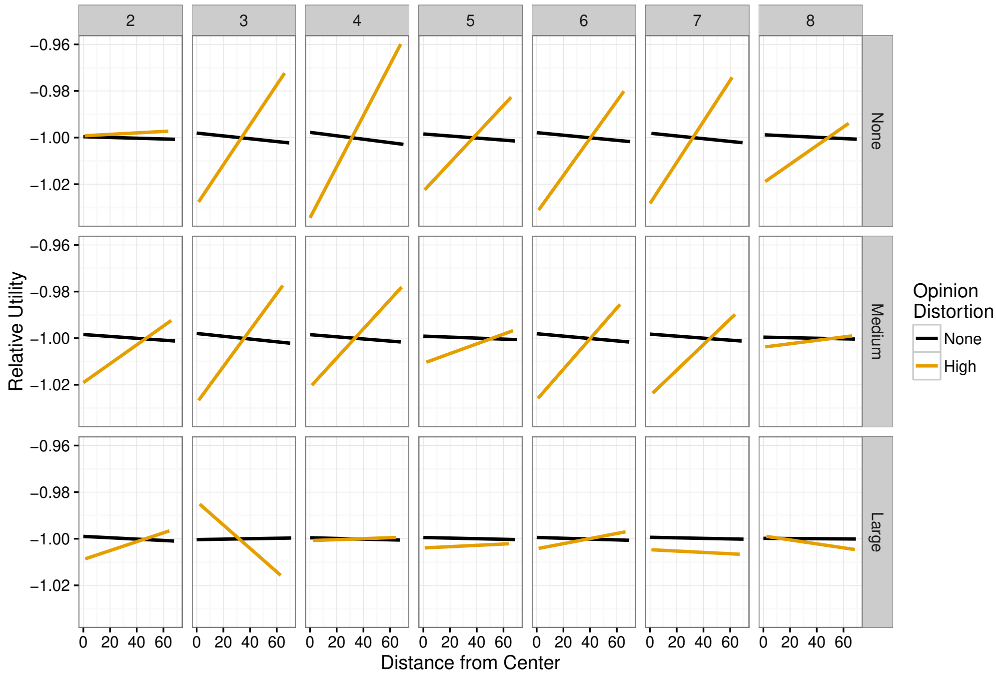


***Figure 1.1:*** *Benefits from opinion distortion by number of candidates and sample size*

toral competition can be seen in figure 1.2. The number of election wins is significantly higher if candidates can choose their platform based on a larger sample size. This advantage holds up until 5 candidates compete in elections. Beyond this threshold, choices of better informed candidates seem susceptible to randomness in the model, i.e. their maximization of expected votes may at times be too exact and thus minor deviations of anticipated behavior by voters or other candidates lead to defeat.

## 1.5 Conclusion

This paper has developed a spatial voting model that incorporates incomplete and unreliable information based on empirical research highlighting cognitive heuristics and systematic misperceptions among politicians. Furthermore, an essential property of the model concerns the behavior of voters: In an age of constant, unlimited communication and sufficient experience with the democratic process, voters

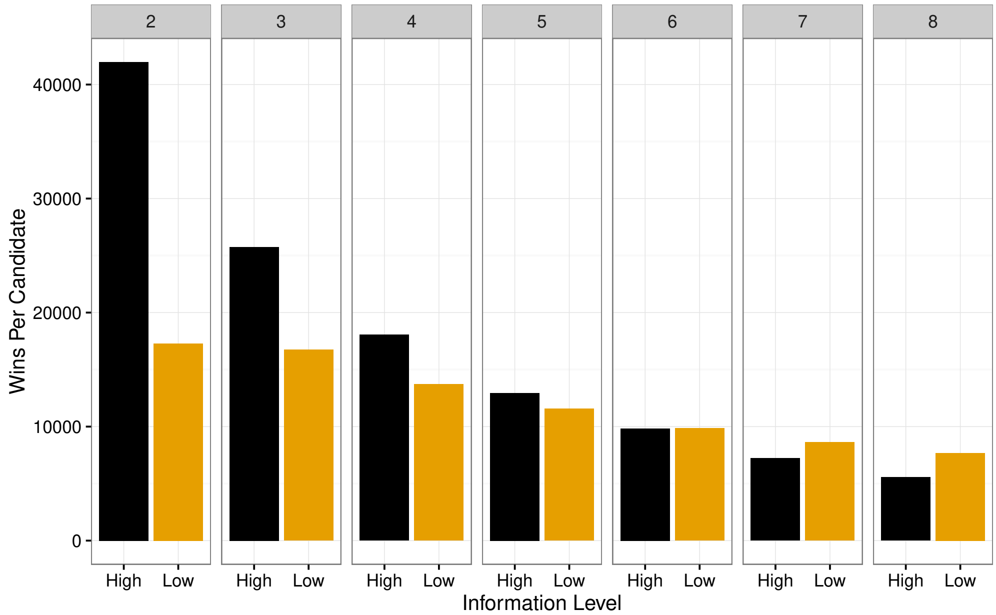


***Figure 1.2:*** *Benefits from more voter information by number of candidates*

can be expected to try to influence policy platforms to better suit their preferences. Internalizing this interplay of voter preferences and electoral competition has lead to the proposition, that only fringe voters with extreme opinions actually have an incentive to signal their views in an attempt to influence policy platforms in elections. Agent-based simulations of the proposed model support this proposition and show that these incentives for communicating extreme views are especially strong under low electoral competition (i.e. with a small number of political candidates) and when candidates base their decisions on little information.

These results may help explain the widespread shifts in public discourse we observe in recent years. If only supporters of extreme political views have an incentive to proclaim their opinions because only they can reasonably expect to have the desired impact on eventual policy, it is not surprising that the language and topics of public discourse have gotten more extreme. With voters knowledgeable of the mechanisms underlying the democratic process and candidates prone to considering only easily attainable information, moderate views do not benefit from efforts to take over the discussion. Unfortunately, the logic of the proposed model also implies that only after extreme views have succeeded to propagate extreme policies and not only preference signals but elected platforms have shifted to extremes would the moderate majority of voters have an incentive to dominate the political discussion in an attempt to influence policy. The question is thus: How extreme a shift is necessary to jolt the majority from its lethargy?

Even though the theoretical model presented in this paper takes up behavioral properties from the empirical literature to inform its underlying assumptions, its implications require empirical testing. For one, the moderating effect of the number of candidates produces a testable hypothesis: Can we observe much more extreme opinions dominating the political discourse in two-party systems compared to multi-party systems? Does this effect, for instance, also occur in the context of simple yes or no referenda? Are presidential elections more susceptible to an extreme discourse than parliamentary elections? Furthermore, since the model shows decreasing incentives with better informed candidates, newly established democracies should exhibit a more polarized political discourse than consolidated democracies. Finally, as the feedback loop of preference communication and platform evaluation is at the center of the theorized mechanism, further research should also take into account the political discourse in social media. The role of communication bots and fake user profiles in shaping discussions or simulating support deserves further analysis if we want to trace the mechanisms by which extreme views can end up feeling familiar.

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# Appendix

## 1.A Simulation Description – ODD-Protocol

### 1.A.1 Purpose

The simulation explores the effects of frictions in a spatial voting framework: incompletely informed candidates encounter voters that may signal their opinions in a strategically distorted way. Is it generally beneficial for voters to distort their signals strategically or only under certain circumstances? Do effects differ between two-candidate and multi-candidate systems? Should candidates try to gain more detailed knowledge about voter preferences or is there a threshold beyond which more information is useless (or even harmful)?

### 1.A.2 Entities, State Variables, and Scales

There are two types of actors, voters and candidate, who both inhabit a location on a grid of $101 \times 101$ cells. For voters, this location is fixed and represents their most preferred policy (bliss point); candidates may change their location once per time step, it represents their policy platform in an election. Furthermore, candidates are heterogeneous in the number of voter signals they are able to consider per time step. In each time step, they assess the preference structure of voters based on the signals they receive. Voters, have a heterogeneous propensity to strategically distort their true bliss point. In order to perform elections, voters each have one vote that indicates one of the competing candidates. Each voter also determines after each election his personal level of satisfaction given the election winner. One time step represents one election cycle and simulations were run for 150 cycles.

### 1.A.3 Process Overview and Scheduling

The following actions are executed once per time step:

- Candidates receive signals from a subset of voters, the size of which depends on their respective ability to process signals. Candidates receive their signals consecutively and in a random order (see submodel *signalling*).
- Voters signal their true or distorted bliss point (see submodel *opinion*).
- The set of signals to each candidate informs their current assessment of the preference distribution in policy space.
- Candidates maximize their number of expected votes according to this estimated preference structure by changing their location (see submodel *choose platform*).
- An election takes place, in which all voters cast their vote for their preferred candidate (i.e. the one being closest to them); the candidate with a simple majority of votes wins (see submodel *election*).
- Voters determine their level of satisfaction given the elected candidates's platform.

### 1.A.4 Design Concepts

The following concepts and theories were taken into account for performing the simulation:

- spatial voting in two dimensions
- bounded rationality
- strategic communication/preference distortion
- spatial tessellation

### 1.A.5 Initialization

A specified number of voters (203 in the simulation runs) and candidates (simulations were performed with 2 – 8) are initialized. Voters are scattered across the 10201 patches according to a bounded two-dimensional normal distribution with zero mean and a standard deviation equal to 25% of the range in each dimension. Candidates are placed randomly on an empty patch with uniform probability.

Each agent's location at once defines their bliss point (voters) and current platform (candidates). For all voters except of a subset the strategic propensity $s_i$ is set to zero. The size of the subset is user-specified and their strategic propensity is set to a chosen value between zero and one (simulations were performed with 1, 20 and 80 agents receiving a strategic propensity of either 0.2 or 0.8). Voters are chosen randomly to belong to the subset at the start of each simulation.

Candidates are assigned the number of voter signals they are able to consider per time step: In one set of simulations, all candidates were only able to consider 5% of the population in each period. Further sets of simulations were run, that had all but one candidate still relying on 5% of opinions and one randomly selected candidate having a competitive advantage. This advantage was being able to consider either 20% of opinions or even the entire voter population.

### 1.A.6 Input Data

No input from external models or data files is used.

### 1.A.7 Submodels

The following submodels are employed by agents at certain points in the simulation process:

In order to create their list of bliss points for a subset of voters, candidates use the submodel *signalling* in a random sequence. This lets them choose randomly a certain number of voter signals from the entire population. Exactly how many signals a candidate receives is determined by the candidate-specific variable $c_j$. Each chosen voter is then asked for her bliss point, in reaction to which voters use the submodel *opinion*. The signals are stored by the candidate as a list and used in the submodel "choose platform" as an assessment of the spatial preference distribution.

The submodel *opinion* is employed by voters to signal their (possibly distorted) bliss point. In case the voter is not currently at his preassigned bliss point, he moves to its location. If he has no strategic propensity, he then simply signals his location $(x, y)$. If, however, his strategic propensity $s_i$ is positive, the voter will face the candidate targeted to receive the signal, move backwards by a fraction $s_i$ of the Euclidean distance to the candidate and report the resulting location. Since policy space is bounded, a situation may occur in which the voter cannot move as far away from the candidate as his strategic propensity would make him wish to. In that case the voter will distort her position as much as possible, i.e. move to and signal a location on the boundary of policy space.

In the submodel *choose platform*, candidates calculate the expected share of votes for each possible platform in policy space, then move to the location with the highest share. They calculate the expected share for a single location by determining the sum of likelihoods of receiving a vote over all voters they have received signals from. The likelihood is given by a logit function that uses Euclidean distance from the respective voter at the platform being considered. This submodel is the numerical solution to the maximization problem stated in equation 1.5.

During the submodel *election*, the positions of all agents are fixed and voters determine, which candidate is closest to their bliss point. This is achieved by dividing up policy space into Voronoi polygons, using an algorithm by Wilensky (2006). Candidates act as generator points of the Voronoi polygon and their cells comprise their respective constituency. Voters sense whose cell they lie in and set their vote to reflect their preference for that candidate. Candidates then count the number of their votes and the election winner is determined according to a simple majority rule. A coin toss breaks potential ties.

# Part II

# Eruptions of Right-Wing Violence

# Chapter 2

# Refugees Welcome? Introducing a New Dataset on Anti-Refugee Violence in Germany, 2014–2015

David Benček and Julia Strasheim

## 2.1 Introduction

In 2015, an ever rising number of refugees made their journey to the European Union (EU) to seek asylum in one of the EU's member states. According to the United Nations High Commissioner for Refugees (UNHCR), as of early 2016, most asylum applicants in Europe were Syrian citizens fleeing military advances by both their government as well as the Islamic State (48 per cent of arrivals), closely followed by refugees from Afghanistan (21 per cent), where a withdrawal of foreign troops has led to a resurgence of Taliban control (UNHCR, 2016). Most refugees have sought asylum in Germany and Sweden, and particularly the German government's reaction towards incoming refugees has sparked international attention. By the end of summer 2015, when other EU member states began closing their borders, Chancellor Angela Merkel publicly pledged that Germany would offer temporary residence to all incoming refugees. Her government also suspended applying the EU's Dublin III Regulation that determines the member state responsible to examine asylum applications. In addition to this "open-arms policy" (Hockenos, 2015) of the German Chancellor, television footage of cheering citizens welcoming refugees at the Munich train station stood out in comparison to increasingly restrictive policies towards refugees across the EU.

Not everyone welcomed refugees to Germany. The *Christlich-Soziale Union* (Christian Social Union, CSU) – the Bavaria-based sister party to Merkel's *Christlich-Demokratische Union* (Christian Democratic Union, CDU) and a partner in the national coalition government – soon openly challenged Merkel's descisions, an act previously unthinkable in German consensus politics. Simultaneously, the new right-wing party *Alternative für Deutschland* (Alternative for Germany, AfD) started to attract an increasing number of voters in polls.[1] In addition to these political reactions, xenophobic violence directed against refugees and their supporters was on the rise throughout 2015 (Deutsche Welle, 2015). This violence reached a tragic climax in October 2015, when Cologne city official Henriette Reker was stabbed in the neck over her position towards refugees during an electoral campaign event.

Anti-refugee violence and social unrest is not new to post-Cold War Germany, and a number of scholarly analyses have shed light on this phenomenon in the past. To name a few prominent examples, Koopmans and Olzak (2004) study the causal links between public discourse and xenophobic violence in Germany, analyzing over 11 000 public statements in the period from 1990 to 1999 (cf. also Koopmans, 1996). Their findings suggest that media attention to right-wing violence affects both the precise targets of such attacks as well as these attacks' temporal and spatial distribution (cf. a similar analysis on xenophobic violence in the Netherlands by Braun, 2011). Krell, Nicklas, and Ostermann (1996) also investigate the links between rising numbers of asylum seekers in Germany during the early 1990s and anti-refugee violence, presenting both a typology of the perpetrators as well as studying the explanatory power of various theories in order to account for the rising number of attacks. And Willems similarly focuses on the perpetrators of right-wing violence in Germany by analyzing police data on their biographical and socio-demographic characteristics (Willems, 1995a) as well as public opinion polls, arguing inter alia that anti-refugee activist groups are far too heterogeneous "to be sweepingly labeled as racists" (Willems, 1995b). These studies tie into a broader literature on how immigration links to the rise of right-wing extremism and xenophobia in the Western world, that has in the past particularly been driven by studies modeling the emergence of extreme right-wing populist parties and voting behavior (e.g. Betz, 1993;

[1] In March 2016, the AfD gained a significant share of votes in regional elections and entered three state parliaments.

Rydgren, 2005; Arzheimer & Carter, 2006; Lubbers, Gijsberts, & Scheepers, 2002; Green-Pedersen & Odmalm, 2008) as well as of anti-immigration movements (e.g. Fetzer, 2000; Brown, 2013).

The recent spread of anti-refugee sentiments in German politics and society has already sparked academic interest, but investigations have thus far overwhelmingly concentrated on explaining the rise of the right-wing anti-immigration movement Pegida (*Patriotische Europäer gegen die Islamisierung des Abendlandes*, or Patriotic Europeans against the Islamization of the Occicent) that flourished in late 2014 (e.g. Dostal, 2015; Vorländer, Herold, & Schäller, 2016). A lack of systematic data collection and data processing of the recent anti-refugee events in Germany has thus far inhibited a thorough quantitative investigation of this phenomenon, its patterns, dynamics, drivers, and consequences. This paper therefore introduces a new geo-referenced event dataset on Anti-Refugee Violence and Social Unrest in Germany (hereafter ARVIG) during 2014 and 2015.[2] Our dataset is based on information collected by two civil society organizations that we process to make it usable for statistical research. The dataset identifies in total 1 645 events of four different types of right-wing violence and social unrest: demonstrations, assault, arson attacks, and miscellaneous attacks against refugee housing. In the following sections we first present data sources, discuss the categorization of different types of right-wing violence, and describe the process of constructing the dataset, before we outline the variables included in the dataset. Afterwards we discuss initial descriptive statistics of patterns of anti-refugee violence and social unrest in Germany. We conclude the paper by outlining several potential uses of the dataset in future research.

## 2.2 Creating the Dataset

In order to create the ARVIG dataset, we rely on information released on the website *Mut Gegen Rechte Gewalt* or Courage against Right-Wing Violence (MGRG), a project that was started in August 2000 by the Amadeu Antonio Foundation and the weekly magazine Stern. This website provides a public chronicle of anti-refugee violence and social unrest since 2014 and we include all available entries between 01.01.2014 and 31.12.2015 in the dataset.[3] The chronicle provided by the

[2]The ARVIG dataset is made available as an R data package and can be found along with installation instructions at https://github.com/davben/arvig.

[3]Quarterly updates of the dataset are planned, provided that MGRG keeps publishing the information.

MGRG project is itself based on information collected by two civil society organizations. The first is the Amadeu Antonio Foundation itself that was named after Angolan citizen Amadeu Antonio Kiowa, who was one of the first victims of right-wing violence in reunified Germany when he was beaten to death by extremist youths in 1990. The foundation was started in 1998 with the explicit goal to strengthen German civil society activism against right-wing extremism, racism, and anti-Semitism (Amadeu Antonio Stiftung, 2016a). The second organization is PRO ASYL, founded in 1986, shortly after significant restrictions were introduced to the German asylum law that resulted in greater difficulties for people persecuted in their home countries to secure lasting protection in Germany (Förderverein PRO ASYL e.v., 2016). Both the Amadeu Antonio Foundation and PRO ASYL belong to the largest and most respected pro immigration advocacy organizations and closely work together with international human rights organizations, which increases our confidence in the quality and transparency of their data collection.

### 2.2.1 Categories of Right-Wing Violence

The chronicle provided by the MGRG project documents four different types of attacks and unrest against refugees and refugee housing in Germany: demonstrations, assault, arson attacks, and miscellaneous attacks against refugee housing. The collection is based on a variety of sources, including public reporting in newspaper articles, press releases by the German police, parliamentary interpellations as well as publicly accessible reports by local and regional organizations offering advice and consultation for victims of right-wing violence (Amadeu Antonio Stiftung, 2016b).

The first type of violence and social unrest reported by MGRG are events of anti-refugee demonstrations, such as the rallies staged by Pegida since December 2014. The causes and dynamics of xenophobic protests have in the past been thoroughly studied by researchers interested in social movement theory (see e.g. Della Porta, 2000; Holdt & Alexander, 2012), and our data thus provides the opportunity to test existing theories on a new case. To give one example of the demonstrations the MGRG project reports, on 14 March 2015, 180 people protested against the construction of a new refugee shelter in the city of Flöha in Saxony. The demonstration was registered by Pegida-spokesperson Steffen Musolt and at least one man was reported shouting "Sieg Heil!" (Freie Presse, 2015). Notably, MGRG points out that because anti-refugee demonstrations and rallies have been on the rise in recent years, it is impossible to collect information on every single one of them. Thus, demonstrations can be expected to be under-reported in the chronicle – and thus also in the dataset presented here.[4]

The second type of violence reported by the MGRG project concerns physical assaults and bodily injuries. For instance, on 12 January 2015, a Libyan asylum seeker was heavily injured in Dresden. He had been asked for cigarettes by "men wearing bomber jackets," and after he did not understand the question, one of the men reportedly poured hot liquid over his face, shoulders, and arms, making it necessary for him to seek medical treatment (Morgenpost, 2015). There exist some limitations to the reporting of this type of violence as well: MGRG notes that information on assault is only recorded in the chronicle if an individual with refugee status is targeted. Assault of, for instance, left-wing and pro-refugee protesters, volunteers helping incoming refugees, or journalists covering xenophobic rallies, are not recorded. Furthermore, and resembling a problem faced by many criminal statistics, MGRG points out that the actual number of assaults – irrespective of the victim's status – is likely to be much higher than what is reported in the chronicle (Amadeu Antonio Stiftung, 2016b).

The third and fourth type of anti-refugee violence reported by MGRG provide information on arson attacks against refugee housing, as well as on miscellaneous attacks against such shelters. For instance, on 23 March 2015, a group of unknown attackers was reported trying to set fire to a school in Berlin-Kreuzberg that houses refugees (Berlin Online, 2015). Miscellaneous attacks against refugee housing comprise instances of rocks thrown at shelters or xenophobic graffiti. For example, on 8 January 2015, unknown attackers painted swastikas on the walls of a house in Hausberge/Porta Westfalica (North Rhine-Westphalia) that was supposed to be turned into a refugee shelter (Mindener Tageblatt, 2015).

In addition to these four distinct categories, some of the reported events include mixed forms of anti-refugee attacks, such as demonstrations in the course of which refugee shelters were attacked: On 6 March 2015, an anti-asylum demonstration of 1500 people in Freital (Saxony) not only attacked police officers and journalists with pyrotechnics, but some demonstrators also forced their way to a refugee shelter and reportedly vandalized the building (Tagesspiegel, 2015). A small number of events in the dataset is not categorized as they do not belong to any of the four basic event

[4]MGRG also notes that under-reporting has become a problem mostly since January 2016, at which point the Amadeu Antonio Foundation and PRO ASYL have limited themselves to reporting demonstrations that specifically disregarded German law, meaning that the demonstration was illegal and not registered with the authorities beforehand, the demonstration included assaults against journalists or police, or demonstrators were reported using hate speech (*Volksverhetzung*) (Amadeu Antonio Stiftung, 2016b).

***Table 2.1:*** *Frequencies of event categories*

| Category | N |
|---|---|
| Demonstrations | 443 |
| Assault | 195 |
| Arson attacks | 157 |
| Miscellaneous attacks | 763 |
| Arson & miscellaneous attacks | 8 |
| Demonstrations & assault | 8 |
| Demonstration & miscellaneous attacks | 16 |
| Demonstration & miscellaneous attacks & assault | 1 |
| Miscellaneous attacks & assault | 29 |
| Other | 25 |

types. Examples include the distribution of xenophobic leaflets or public banners with right-wing extremist slogans. Table 2.1 summarizes the frequencies of all observed event types as reported by the MGRG project. Figure 2.1 offers a geographic overview of all recorded events. For a more concise presentation, multi-category events have been split and counted once in each of their respective categories.

By including events from this broad set of categories, our dataset covers a wider range of anti-refugee violence than some previous studies on the topic. For instance, studying right-wing violence against asylum seekers in the Netherlands, Braun (2011) relies on data on the timing and location of events provided by the *Anne Frank Stichting*, which defines right-wing violence as "[purposive] infliction of material or physical damage to targets, chosen because of their different cultural, national, ethnic, racial or religious background" (cited in Braun, 2011). In our categorization, Braun's conceptualization of anti-refugee violence would thus only cover the "assault" category. We however prefer our broad conceptualization of anti-refugee violence and social unrest for two reasons: First, a broad concept that also includes demonstrations and attacks against property allows researchers not only to distinguish between different types of xenophobic attacks, but also to study degrees of severity. In that regard, our dataset can be used to help answer research questions that deal with the escalation of xenophobic extremism over time. Second, our broad conceptualization also relates more closely to other recent event data collections on global instances of violence and social unrest, such as the Social Conflict Analysis Database (SCAD) that covers protests, riots, strikes, inter-communal

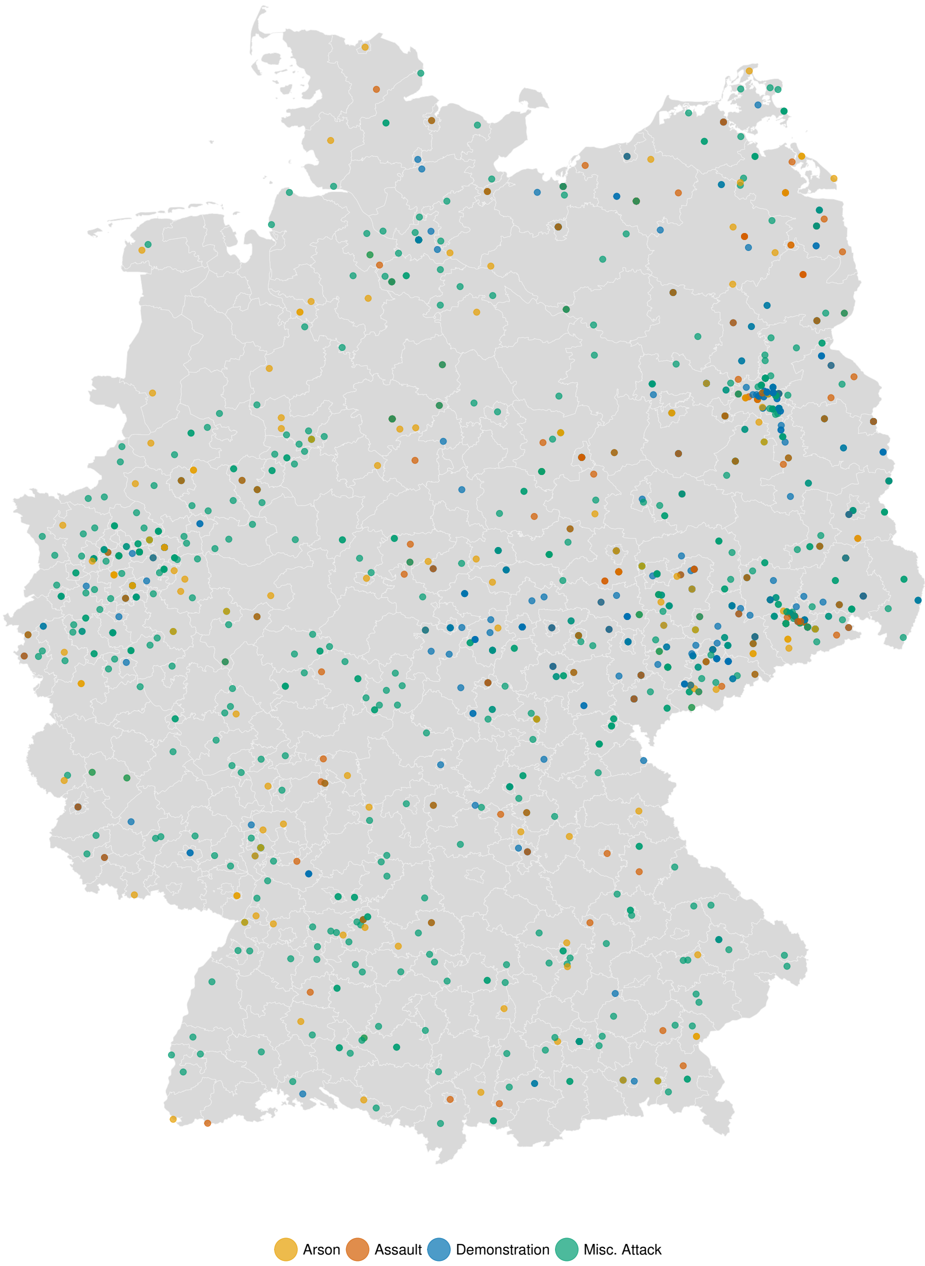


***Figure 2.1:*** *Geographic overview of events by category*

conflict, and government violence against civilians in Africa and Central America (Salehyan et al., 2012).

### 2.2.2 Webscraping and Geocoding

To construct the ARVIG dataset, we primarily relied on webscraping the information available in the MGRG chronicle. This is possible for all events from 1 January 2015 onwards as they are neatly separated in the HTML code of the MGRG website, and we used the rvest package in the software environment R that was designed to harvest data from HTML web pages (Wickham, 2015). For the 2014 events, webscraping proved insufficient, because the entries on the MGRG website are not as neatly structured in the HTML code. Hence, we manually copied the 2014 events, cleaned the data and merged it with the 2015 events.

Next, we extracted the information on the location and the respective federal state from the dataset and used the Google Maps API to geocode the location. It proved necessary to take both location and federal state, in order to avoid confusion between two locations with the same name, such as Friedberg (Hessen) and Friedberg (Bayern). Each event is thereby mapped to a longitude and latitude with municipality-level precision. This enables us to place each event on a high resolution map of Germany that includes geospatial information on all 11 306 German municipalities (*Gemeinden*) and determine the corresponding official 12-digit Community Identitification Number (*Regionalschlüssel*).[5]

### 2.2.3 Variables and Patterns

The ARVIG dataset contains 10 variables that characterize each recorded event. First, we provide the exact *date* at which an event of interest occurred. Currently, all dates lie between 1 January 2014 and 31 December 2015. Events were recorded on 563 of the 730 days covered by the dataset (cf. the frequency distribution in figure 2.2). The date for which the highest number of events was recorded is 29 August 2015, with a staggering count of 17 anti-refugee events, including six demonstrations, ten miscellaneous attacks against refugee shelters, as well as one instance of assault occurring in Halle (Saale), where a refugee from Guinea-Bissau was insulted, beaten and kicked by six to eight individuals.

[5]The partition of municipalities in Germany is constantly changing – our dataset classifies the events based on the status of 1 January 2015.

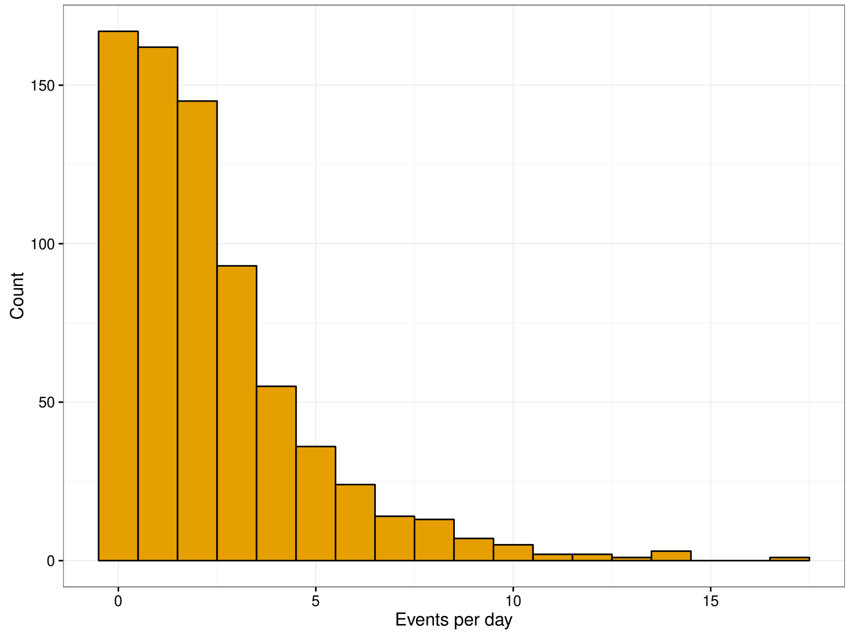


***Figure 2.2:*** *Histogram of events per day*

Next our dataset specifies the *location* and *federal state* of events as reported by MGRG (in German writing, thus including umlauts). All federal states of Germany have seen right-wing violence and social unrest in 2014 and 2015, but with strong variation in the number of events. By far the highest number of anti-refugee violence and unrest was recorded in Saxony, with 394 events in the 24 months under analysis, followed by North Rhine-Westphalia (231 events) and Berlin (210 events). The traditionally left-wing governed Bremen (where all State Premiers since 1945 have belonged to the Social Democratic Party), on the other hand, saw only 2 events in the past two years: two arson attacks on 26 October 2015 and 26 September 2015. If we control for state inhabitants, the densely populated North Rhine-Westphalia drops out of the top three and is replaced by Mecklenburg-Vorpommern – a federal state that has a history of xenophobic violence against asylum seekers, for instance when between 22 and 24 August 1992, several hundred violent protesters in the Lichtenhagen district of Rostock threw stones and petrol bombs at a refugee shelter and were applauded by an even larger crowd of bystanders. Figure 2.3 depicts the number of events per 100 000 inhabitants for all federal states and shows a clear divide between West and East Germany in their treatment of refugees.

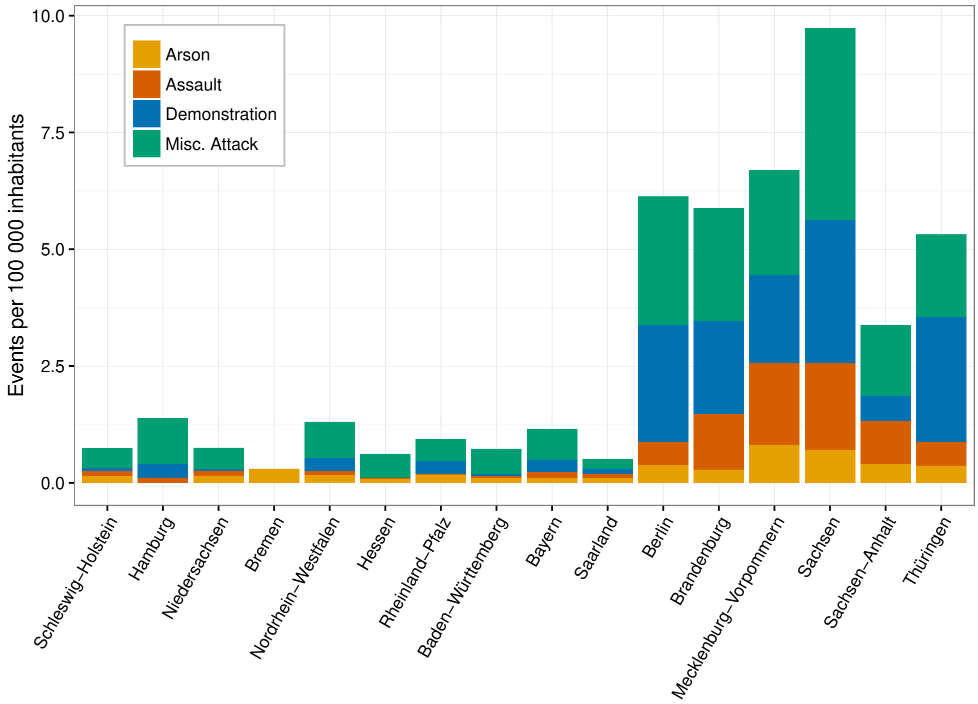


***Figure 2.3:*** *Events per 100 000 inhabitants by state and category*

Figure 2.4 additionally depicts this relationship at the district level. This map again highlights the high number of anti-refugee events taking place in East Germany, with a particularly high count in the district of Saxon Switzerland-East Ore Mountains (*Sächsische Schweiz-Osterzgebirge*). This district had in total 67 events of anti-refugee violence, including 10 instances of assault, 5 instances of arson, and 21 miscellaneous attacks in 2014 and 2015, while being sparsely populated with only 245 954 inhabitants – fewer than cities such as Mannheim, Karlsruhe, or Bonn.

In order to facilitate disaggregated analyses of the data, the ARVIG dataset also contains the 12-digit *Community Identification Number* of the respective municipality each event has occured in. This standardized identifier is taken from official statistics and thus makes it easy to merge highly disaggregated data from other sources with the ARVIG dataset. The data show that 640 individual municipalities within Germany experienced right-wing extremist violence and social unrest against refugees in 2014 and 2015. With a total of 215, Berlin has seen the largest

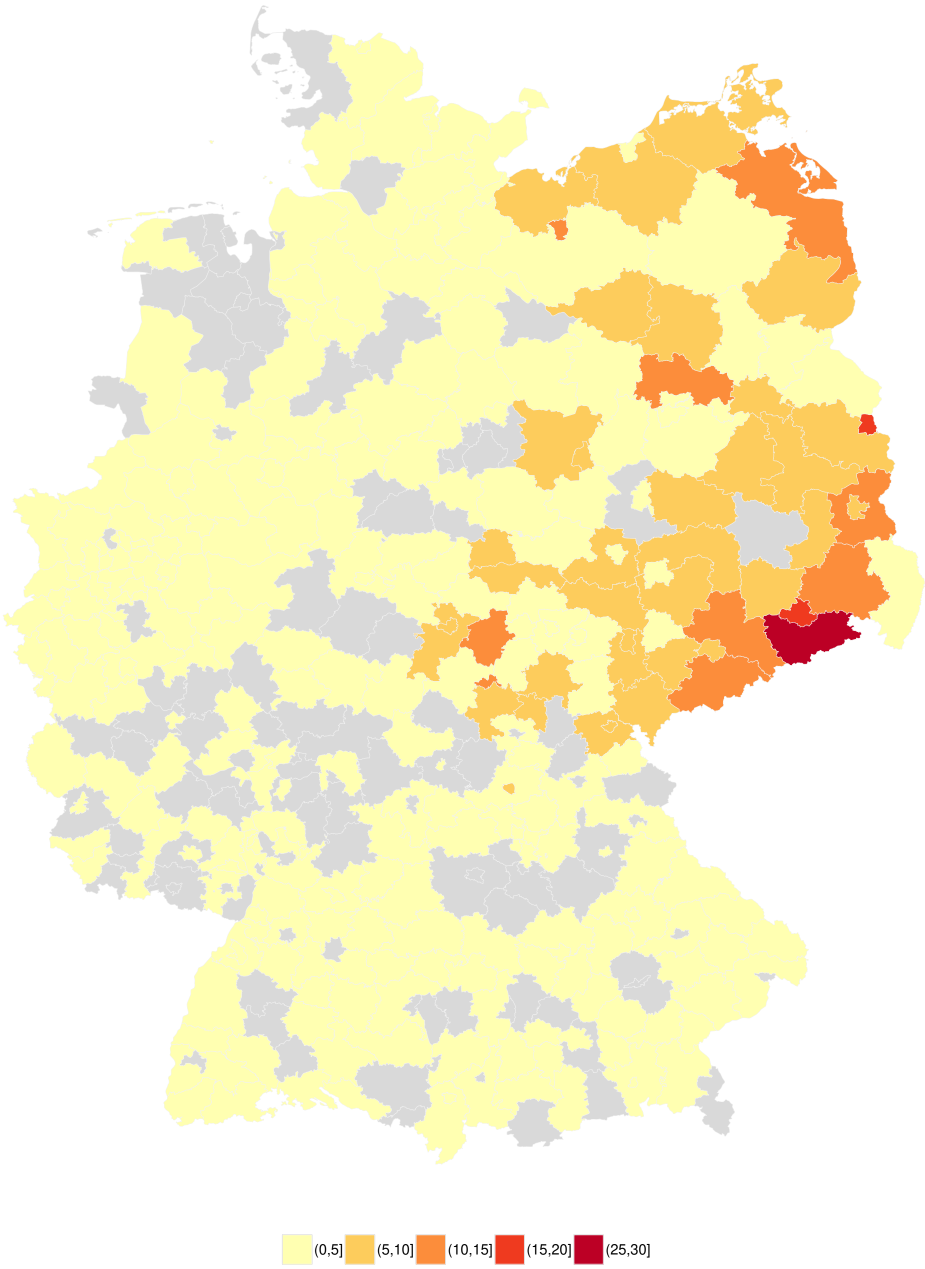


***Figure 2.4:*** *Events per 100 000 inhabitants by district (districts with zero events are grey)*


***Figure 2.5:*** *Events by weekdays and category*

number of events, 40% of which were demonstrations and 44% were miscellaneous attacks. For more detailed spatial analyses we also provide *longitude* and *latitude* of the respective event location.

The dataset furthermore contains the *event category* provided by MGRG both in German and in English. This enables us to observe an interesting variation as to when events occurred when we analyse each type of event separately: For Figure 2.5 we again split up multi-category events and added them once to each of their respective categories. We can observe that in terms of their distribution over weekdays, assault, arson and miscellaneous attacks behave quite similarly: They are relatively evenly distributed over all seven days of the week, with minor spikes on the weekends (more prominent for assault and miscellaneous attacks on Saturdays). Demonstrations, on the other hand, show a very strong spike on Saturdays. This could indicate that while demonstrations are planned and organized – they must be registered with the police beforehand, after all – the other three types of anti-refugee violence and unrest occur more spontaneously. This distribution is at least to some extent suprising because past research has found that acts of right-wing violence in Germany occur disproportionately often on weekend nights (Braun & Koopmans, 2010), a finding that is usually linked to alcohol consumption of young men. Also Braun (2011) has found that weekend nights – and summer periods – are strong predictors for an increased hazard of xenophobic violence in the Netherlands, and (as we have mentioned above) Braun does not even include demonstrations in his categorization of anti-refugee violence, which seems to be the main driver of weekend occurrences in our dataset.

***Table 2.2:*** *Sample event from the ARVIG dataset*

| Variable | Sample |
|---|---|
| date | 2015-03-06 |
| location | Freital |
| state | Sachsen |
| community_id | 146280110110 |
| longitude | 13.6512413 |
| latitude | 51.0008667 |
| category_de | Kundgebung/Demo & Sonstige Angriffe auf Unterkünfte |
| category_en | demonstration & miscellaneous attack |
| description | Am Freitag gab es in Freital die erste Anti-Asyl-Demonstration unter dem Motto “Freital wehrt sich. Nein zum Hotelheim”. Daran beteiligten sich etwa 1500 Personen. Einige Teilnehmende versuchten die geplante Route zu verlassen. Sie attackierten die Polizei mit Pyrotechnik, um zum Leonardo-Hotel zu gelangen, wo seit Mittwoch die ersten von bis zu 200 Flüchtlingen untergebracht sind. Nur mit Mühe konnte die Polizei die gewaltbereiten Asylgegner aufhalten. Laut Twitter hat einer von ihnen einen Brandanschlag gegen die Unterkunft angedroht. Außerdem wurde von einem übergriff auf einen Fotojournalisten berichtet. Dieser sei bepöbelt, bedrängt und geschubst worden. Zuvor soll eine Person auf Facebook folgende Botschaft gepostet haben: “Dann komme ich heute Nacht wieder und zünde das Ding an”. |
| source | http://www.tagesspiegel.de/politik/attacken-und-proteste-in-gera-freital-hoyerswerda-neonazis-und-besorgte-buerger-gegen-fluechtlingsheime/11472054.html |

Finally, a *description* of the event (in German language) as as well as a *source* of this description, such as a link to a news website is provided. To illustrate this set of variables, Table 2.2 provides a sample record from the dataset.

## 2.3 Conclusion: Using the Dataset

This paper introduced new georeferenced event data on anti-refugee violence and social unrest in Germany in 2014 and 2015. Based on a public chronicle provided by the *Mut Gegen Rechte Gewalt* project, we webscraped and processed the available information so as to make them accessible for statistical research on anti-refugee violence. The dataset complements existing research on the determinants and effects of anti-refugee attacks in Germany and Western Europe with new and systematic data. The event-based coding as well as the adherent information on event-locations make the data useful for a variety of analyses, both event-based or aggregated to German administrative units such as the municipalities (*Gemeinden*) or districts (*Kreise*). In that regard, the data presented here offer a starting point to analyze the recent rise in anti-refugee violence from different disciplinary backgrounds, including, but not limited to, criminology, sociology, political science, or economics.

For instance, and as we have outlined in the introduction to this article, a number of studies have reflected upon the determinants of anti-refugee violence in the 1990s: (youth) unemployment, the success of right-wing political parties, and media discourses have been identified as strong predictors of violent outbursts. It would be interesting to examine if the recent rise of anti-refugee attacks adheres to the same old pattern, or whether different predictors have stronger explanatory power.

Kuechler (1994) has for instance argued that in the early 1990s an analysis of survey data indicated "strikingly similar patterns of hostility towards foreigners" between citizens in East and West Germany. Yet our data show a clear divide of anti-refugee violence and unrest between East and West Germany. What factors explain this variation? And what effects does this variation in anti-refugee violence have on other variables, such as patterns of social cohesion within German municipalities, or patterns of integration of asylum seekers? Since we include the Community ID (*Regionalschlüssel*) in our dataset, researchers have the opportunity to merge ARVIG easily with all official German statistical data in order to explore any underlying relationships.

Similarly, our descriptive and preliminary analysis of patterns in anti-refugee violence in Germany in 2014 and 2015 already pointed to a surprising finding, namely that besides the occurrence of demonstrations, other types of anti-refugee violence are spread evenly across weekdays. As this goes directly against previous findings on the issue, more research on why this is the case would be advantageous. Can we detect, for instance, similar developments for other types of crime?

Further, events that have gained a lot of media attention have shaped public and political discourse. As the impact of public discourse on the outbreak of violence has been established by previous research (Koopmans & Olzak, 2004), our event-based data enable researchers to identify key events that may have increased or decreased the ensuing level of violence. Is anti-refugee violence, for instance, a direct reaction to fears of terrorist violence in Europe? Does it increase after terrorist attacks (and the subsequent media reports), or are these events unrelated?

Finally, our dataset is also valuable to scholars conducting qualitative or mixed-methods research on the causes and consequences of anti-refugee violence. ARVIG enables scholars to carry out systematic case selection, for instance if they aim to compare municipalities with high levels of anti-refugee violence and unrest with municipalities with low levels of such violence.

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# Chapter 3

# Explaining Hate Crimes Against Refugees in Germany: Contagion or Local Determinants?

David Benček and Christian Martin

## 3.1 Introduction

Western Europe has recently witnessed a massive inflow of asylum seekers, refugees, and migrants. In Germany alone, an estimated 1.1 Mio refugees arrived during the year of 2015 (Bundesministerium des Innern [BMI], 2016a). Parts of the German populace reacted with shows of civic engagement and support. However, as data published recently by the German Federal Office for the Protection of the Constitution (*"Bundesamt für Verfassungsschutz"*) show, attacks on refugee shelters increased fivefold between 2014 and 2015 (BMI, 2016b, pp. 26-28). These attacks were by no means the only shows of xenophobic sentiment. Rallies organized by groups like "Pegida" (*"Patriotische Europäer gegen die Islamisierung des Abendlandes"* – "Patriotic Europeans against the Islamization of the Occicent") drew ever larger numbers of supporters with some participants advocating lynching members of a federal government they viewed as incapable of handling a perceived refugee crisis or whom they outright accused of a plan to "replace" the German population (Vorländer, Herold, & Schäller, 2016). The AfD (*"Alternative für Deutschland"* – "Alternative for Germany"), a party that after some splits and leadership quarrels now clearly presents itself as a right-wing populist party, attracted large numbers of voters with a platform of anti-Islam and anti-immigration sentiments.

This is the context against which this paper investigates the determinants of three types of right-wing violence in the years 2014 and 2015, namely assault on refugees, attacks on refugee shelters, and a specific type of attack, arson. We are interested primarily in whether these events can be explained by local conditions (for example levels of unemployment) or if they are driven by spill-overs from prior events. The underlying question is, then, one about the dynamics that drive right-wing extremist violence: Does it spread or is it locally determined and, thus, locally contained? The answer to this question is both theoretically interesting and politically relevant. We argue that, unlike other crimes, hate crimes against refugees carry a political message. While a perpetrator might act out of motives that are in part locally determined, the act of right-wing violence itself goes beyond the immediate target of the attack. For example, a perpetrator might act because he is unemployed and uneducated (Krell, Nicklas, & Ostermann, 1996) and fears competition from refugees at the lower end of the labor market (McLaren, 1999), and has had limited exposure to foreigners (Steinmayr, 2016). The crime itself however, to the extent that it is observed by others, could increase the probability that a potential perpetrator somewhere else will act, too. The reason for this is the informational externality that emanates from the crime. Others will learn from it or will emulate the action because an act of right-wing violence has been committed somewhere else.

More generally, in a setup like this, actors are not independent from one another but their utility functions are connected. We draw on a simple theoretical model that allows for interdependence between actors in the style of Granovetter (1978) or Kuran (1997). In these and other models like them, actors base their cost-benefit calculation of a specific action (e.g. participating in an anti-immigrant demonstration; firebombing a refugee shelter) in part on the decisions of others to do the same thing. Every individual has a threshold that is a function of the proportion of actors in a population who have to do the same thing in order for the individual to act accordingly. This basic model setup can give rise to spill-overs in the absence of any exogenous change in preferences (which makes these models attractive to attempts at parsimoniously and non-trivially explaining switching behavior in populations).

We argue that not all kinds of anti-immigrant actions can be expected to exert the same spill-over dynamics. Rather, the influence on other actors hinges upon the generalizability of the action perpetrated. Against this backdrop we show that assault exerts the strongest spill-over dynamics in the sense that it is the most generalizable form of hate crime, positively and significantly influencing the occurrence of other forms of physical attacks like arson and miscellaneous attacks on property.

Distinguishing between local and regional determinants on the one hand and spill-over dynamics on the other hand, we will first test hypotheses about local and regional conditions that have been argued in the literature (see below) to be potential drivers of anti-immigrant hate crimes. These local and regional hypotheses are, first, concerned with a possible backlash against globalization and modernization in the form of a new cleavage that has emerged over the last three decades, second, the deprivation hypothesis and competition hypothesis, i.e., respectively, labor market and overall economic conditions (deprivation), as well as their relation to the overall immigrant population (competition), and, lastly, the contact hypothesis, i.e. the idea that more exposure to immigrants may lead to a reduction in anti-immigrant sentiment and, consequently, hate crimes.

We will first test these hypotheses by using standard non-spatial and spatio-temporal econometric models. In an additional step, we import a methodological innovation from epidemiology into political science, namely the point process model proposed by Meyer, Elias, and Höhle (2012). To the best of our knowledge, this is the first time that this continuous space-time model has been used in political science.

The remainder of this paper proceeds as follows: Section 3.2 describes our theoretical framework for explaining hate crimes against refugees based on the relevant literature and distinguishes between local determinants and the mechanism of violence diffusion. We present the dataset for our empirical analysis in section 3.3 along with a detailed description of specific variable operationalizations. Section 3.4 contains the empirical models and discusses their results while section 3.5 concludes with a summary and perspectives for future research.

## 3.2 Theoretical Perspectives

This section distinguishes between two different drivers of hate crimes. We will first look at local determinants before turning to spill-over and diffusion effects.

### 3.2.1 Local Determinants

There is a vast literature on delinquency and, more generally, deviant behavior from sociology and criminology. Roughly speaking, these can be grouped into approaches that focus on structural conditions to explain crime, and others that focus on the individual level. In the latter group, psychological approaches can be found that treat delinquency, and hate crimes more specifically, as possibly pathological phenomena pertaining to disturbed individuals (e.g. Craig, 2002; Perry, 2001). We will not cover those here and rather focus on rational actor assumptions underlying the explanation of hate crimes.

In a sense, hate crimes are unlike other crimes since they are hard to grasp within a non-trivial and non-redundant rational actor framework. Whereas a burglar's actions can be readily explained by asessing his net expected pay-off, this logic of explanation seems less adequate in the case of hate crimes.

Against this backdrop, explanations center on the relative deprivation of individuals and their feeling of frustration that are brought about by factors like unemployment and dissatisfaction with the political system (Runciman, 1966). Constructing a connection between structural change and individual preferences are theories that point to the emergence of "post-materialist" values as a by-product of modernization processes (Inglehart, 1977). Post-materialist individuals seek self-actualization in the form of self-determination. They eschew authoritarian values and are therefore less prone to the allure of right-wing political parties. Drawing on the initial work of Lipset and Rokkan (1967), numerous scholars have pointed out that the rise of green parties can be explained by this new societal cleavage (e.g. Alber, 1989; Dolezal, 2010).

Using the same logic, a new cleavage has been argued to have emerged over the last two decades as a consequence of economic and political integration, namely a cleavage line that – broadly speaking – separates winners and losers of globalization and technological change (e.g. Bornschier, 2010). Along this new cleavage, right-wing authoritarian and populist parties have garnered support and made their way into most of Western Europe's party systems. More generally, according to this view, right-wing extremism can be attributed to losers of modernization processes in advanced societies (Heitmeyer, 1993).

These factors can be hypothesized to influence the probability of an anti-refugee or ant-immigrant hate crime occurring. With higher unemployment and more support of right-wing parties as signs of deprivation and the relevance of a pro- and anti-globalization cleavage, this probability can be excepted to rise. On the other hand, strong support for green parties as a sign of cultural change towards more openness should reduce anti-immigrant sentiment and – possibly – hate crimes.

While there is no straightforward connection between anti-immigrant sentiment and hate crimes against refugees, the probability of a hate crime occurring can be plausibly expected to rise if anti-immigration sentiment is higher. Reasons for this might be that low-skilled workers fear labor market competition from refugees with the same skill set (e.g. McLaren, 1999). Such competition models have recently been tested more rigorously. For example, Helbling and Kriesi (2014) have tested attitudes towards high- and low skilled immigrants in Switzerland using an online survey. They reject the labor market competition model and find an anti-immigrant effect that is conditional upon an individual's economic situation and tax burden.

Their findings are compatible with results from a study on right-wing political party support in Austria (Steinmayr, 2016). Using a natural experiment where the treatment is settlement of refugees in Austrian municipalities, Steinmayr (2016) shows that contact with refugees decreases support for the right-wing populist FPÖ party. This is in line with a long standing argument from social psychology, namely the contact hypothesis which states that contact between different groups leads to a decrease in conflict between these groups (Allport, 1954; Pettigrew, 1998).

Steinmayr's (2016) results are, however, in contrast to findings in the literature on crimes committed against immigrants. Connecting demographic change with hate crimes against immigrants, Green, Strolovitch, and Wong (1998) find that hate crimes against ethnic minorities in New York were most pronounced in those mostly white neighborhoods that had recently witnessed immigration of minorities. This result is mirrored by Grattet (2009) who finds similar effects for predominantly white neighborhoods, but not for neighborhoods that are predominantly non-white.

Overall, the results on local determinants of anti-immigrant and anti-refugee sentiment as well as anti-immigrant crimes are mixed. A possible explanation for the inconclusiveness of the evidence is that only local determinants are considered. If there are spill-over effects that are present but not considered, this may result in omitted variable bias that could cloud the results. Therefore, in the next section, we turn to a theoretical consideration of external effects, diffusion and spill-over dynamics.

### 3.2.2 Spill-over Effects and Diffusion

The vastly diverse literature on interdependence and diffusion (of policies, cultural practices, innovations, and otherwise) is predicated upon a common tenet, namely that events "here" can be partially explained by the same or similar events occurring "there". "Here" and "there" are mostly defined in geographical terms; in political science, this is frequently cast as jurisdictions influencing one another. The four basic mechanisms of diffusion discussed in the literature are coercion, competition, learning, and emulation. With respect to hate crimes, the latter two of these four – learning and emulation – seem to be most relevant. Actors in a territorially defined unit $i$ observe actions that occur in units $j$. This induces them (causally) to act as well. Note that this is best understood in a probabilistic framework where something happening in $j$ influences the probability of something happening in $i$.

Applying a threshold model in the vein of Granovetter (1978), an individual in unit $i$ will take action if "enough" individuals in unit $j$ will take the same action or similar actions. More generally, actions are not independent from one another. Thus, they are not only determined by local conditions to which an individual is subjected, but are rather co-determined by the choices other people make. Therefore, dynamics may ensue that cannot be explained by local determinants alone. This is the basic insight of models of collective dynamics. Just what it is that diffuses is hard to pin down exactly. While it is fairly easy to show empirically that events or policies are spatially interdependent, identifying causal mechanisms that link $i$ to $j$ is a matter of theory. For the context of this paper, we surmise that different types of hate crimes have different informational content that trigger different types of reactions across actors. More specifically, an actor contemplating whether to participate in an anti-refugee protest will take his or her clues from other people doing the same thing elsewhere. An anti-refugee protest in $j$ can give an informational clue to an individual in $i$ that changes an individual's expected utility from participating in a protest in $i$. This may pertain to the perception of social acceptability of anti-refugee protests as well as more rational calculations about the marginal effect of one's showing at a protest.

Unlike protests, acts of violence are individual rather than collective. There is no utility from a mob setting fire to a refugee shelter. Rather, an individual deciding on whether or not to commit an act of arson will consider his or her chances of getting away with this action. Therefore, violent actions in other units can serve as an informational clue in $i$ that there are more of these actions and the individual probability of being caught is smaller, assuming constant efforts by law enforcement agencies.

Both types of actions are independent and follow a threshold logic with nonlinear dynamics and switching points. But the empirical implications are different: Whereas the occurrence of anti-immigrant demonstrations is likely increased by anti-immigrant demonstrations in other units alone, acts of violence can be seen as substitutes with respect to their informational content. Therefore, we expect them to exert a stronger diffusion influence since their informational content is more generalizable to other acts of violence than the informational content of demonstrations which pertain to demonstrations alone.

This also implies that estimating different types of events and the interdependence of one type of event across units separately in an empirical model will not tell the whole story. Rather, depending on the type of event, interdependence may occur between different types of events. If different events are interdependent but their interdependence is not taken into account, local determinants as well as the interdependence between the same type of event may be upwardly biased (Genovese, Kern, & Martin, 2016).

While the literature on policy diffusion generally distinguishes between four different mechanisms of diffusion (coercion, competition, emulation, and learning (Dobbin, Simmons, & Garrett, 2007)), for this paper, we consider only the latter two, emulation and learning. While learning fits rather easily into a rational actor framework with incomplete information, the case is different with emulation. An actor emulating an action that has been taken elsewhere does not to do so because of an incentive emanating from that action. Rather, he copies the action because of the action itself. That is, there are no (positive or negative) externalities stemming from the event elsewhere. The motivation to copy the action must be found in the actor himself, his psychological or pathological makeup that is somehow triggered into taking action because somewhere else someone else has taken the same action. Events can then become "contagious" as they spread across different spatially defined units, for example municipalities or counties. Of course, not the event itself spreads but the actions taken by individuals or groups.

Empirically, this does not make a difference since the exact mechanism of diffusion cannot be modeled anyway.[1] The researcher is left with assuming diffusion mechanisms and modeling the connection between different units based on these assumptions.

The next sections put these theoretical considerations to an empirical test.

## 3.3 Data and Operationalizations

Our primary data source on hate crimes against refugees is the ARVIG dataset by Benček and Strasheim (2016) which comprises $1\,645$ georeferenced events of anti-

[1]More technically, empirically modelling the connectivity between $n$ units would at the least require $n(n-1)/2$ observations. This is impossible except for the most trivial of cases. Therefore, researchers must assume specific connections between units, geographic or otherwise.

*Table 3.1: Event counts of anti-refugee violence by type*

| Type | N |
|---|---|
| Arson | 165 |
| Assault | 233 |
| Demonstration | 468 |
| Miscellaneous Attack | 817 |

refugee violence and demonstrations in Germany between 1 January 2014 and 31 December 2015. The dataset distinguishes between four types of events: Arson at refugee shelters, assault against refugees, right-wing demonstrations, and miscellaneous attacks on refugee shelters. Among all events there are 62 that are attributed to more than one category, e.g. demonstrations during the course of which a refugee was assaulted. For analytical tractability we split these multi-category events and attribute them to each relevant category. As a result our data comprise 1 683 events. Table 3.1 shows the overall frequencies of events for each category in our observation period and figure 3.1 depicts their cumulative counts over time.

While the overall number of events is high given that the observation period only covers two years, the data may still represent an incomplete account of anti-refugee violence in Germany. But since the dataset is based on information from a large array of sources including official police statistics, parliamentary interpellations, newspaper articles, as well as reports from organizations engaged with victims of right-wing violence, we do not assume any systematic selection bias with regard to the time, region or type of violence.

The event-based nature of the data enable us to perform a highly disaggregated analysis: While events are precise at the level of municipalities and days, such detailed information is not available for the set of independent variables and we thus choose districts across time as our unit of analysis. As there are 402 districts in Germany this level of aggregation preserves sufficient regional variation to estimate determinants of violence. The time dimension remains disaggregated by day, enabling us to capture the diffusion of violence between individual events.

**Dependent Variable** In order to be able to distinguish varying effects of local determinants across the different types of violence against refugees, we initially estimate separate models for the categories arson, assault and miscellaneous attack. Demonstrations are not included as a dependent variable since we focus on active

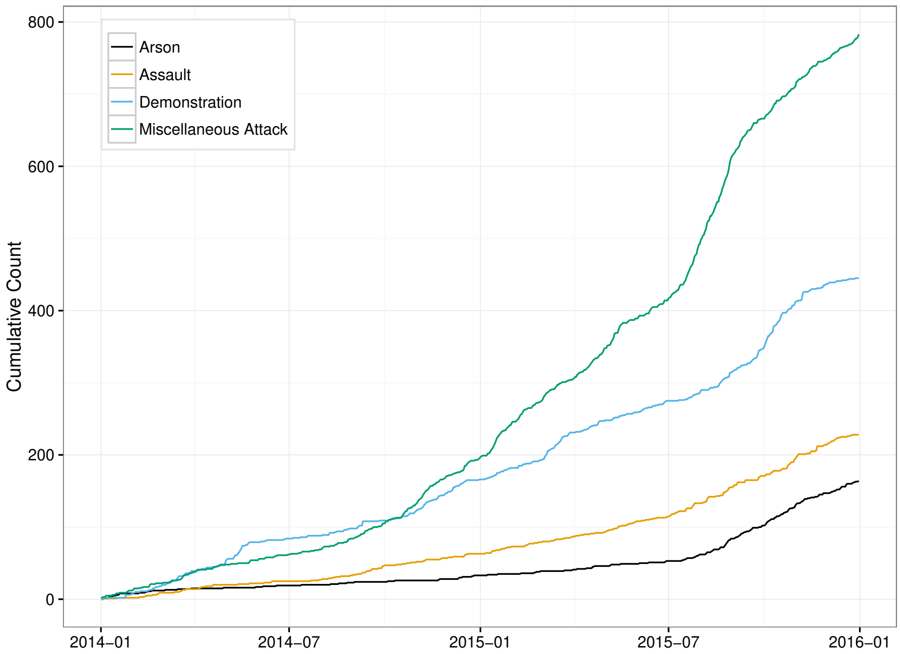


***Figure 3.1:*** *Cumulative event counts during observation period*

violence. They are, however, included as a potential source of diffusion as explained below. Despite the large number of 1 215 violence events during the observation period, the unit of analysis being district-days for each category leaves us with an even larger number of zero-observations. More importantly, only few observations have experienced more than one event of the same category. Event counts, while highly interesting, would thus lack almost entirely in variance.[2] Instead of a count as the dependent variable we therefore choose a binary value indicating whether or not at least one event of a given category has occured on a particular day in a given district.

**Diffusion** As we are interested in the possible contagiousness of violence against refugees, the general approach is to estimate the effect of individual events on the likelihood of further violence. The dataset allows for a distinction of effects between the four types of events. We furthermore use the dates and geospatial information

[2]Among the 293 460 observations (402 districts $\times$ 730 days) there are in total 48 instances of event counts larger than 1, the maximum of which is 4.

to take into account the spatio-temporal distance between events. The different approaches to operationalize diffusion are described in more detail in the respective subsections of section 3.4 below.

**Independent Variables** We use two measures in order to account for possible socio-economic deprivation: the district-level disposable income per capita in 2012 (which is the latest data complete for all 402 districts) as well as the yearly average rate of unemployment of each district for 2014 and 2015 (Statistische Ämter des Bundes und der Länder, 2016d, 2016c). Based on the theoretical arguments presented above, deprivation in the form of a low disposable income and a high rate of unemployment should increase the likelihood of violence against refugees.

The perceived level of labor market competition has probably increased to a large extent during the observation period, driven by the unprecedented number of refugees and asylum seekers that has arrived in Germany. We use monthly data published by Eurostat (2016) that contain the number of first time asylum applicants. Germany applies a strict quota system based on population shares and tax base to distribute the total number of applicants between the federal states. This enables us to determine the monthly increase in asylum seekers by state. The ethnic competition hypothesis suggests a positive relationship between the number of asylum seekers and instances of violence against refugees.

We measure the level of previous contact with foreign nationals in each district by the share of foreigners relative to the entire district population in 2013, i.e. the year before the observation period (Statistische Ämter des Bundes und der Länder, 2016a). According to the contact hypothesis, more experience with foreigners (a higher share) should reduce the chances of violence against refugees.

To account for regional differences in political preferences we use municipality-level election data from the 2009 federal election. The results are aggregated to the district level to determine vote percentages for all parties as well as the turnout rate for each district. We expect a strong support for extremist right-wing parties to increase the chances of violence against refugees. At the same time, a high voter turnout, which we interpret as trust in political institutions, should reduce them.

**Control Variables** In spite of more than two decades of convergence since the reunification of Germany, East and West are still distinctly different in many respects such as political preferences, economic and social indicators. We therefore include a dummy variable East to measure systematic differences that are not explained by other variables. We furthermore use the share of lower secondary school graduations in all graduations of 2014 to operationalize the average level of education in each district (Statistische Ämter des Bundes und der Länder, 2016b). The district-level population is also included to control for the fact that events of violence are more likely to occur in regions with higher population. Finally, in order to control for varying crime rates across districts, we draw on federal crime statistics as a robustness check of our results. The data distinguish between 40 different kinds of criminal offences per $100\,000$ inhabitants (Bundeskriminalamt [BKA], 2015).

Table 3.2 gives an overview of all independent and control variables and lists descriptive statistics. The different numbers of unique observations signal the level of aggregation at which a particular variable is available. All variables with $N = 402$ vary between districts and with $N = 804$ also by year. Data on asylum applications is state-level data on a monthly basis.

***Table 3.2:*** *Descriptive statistics of independent and control variables*

| Variable | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| log(Disp. Income) | 402 | 9.900 | 0.126 | 9.631 | 10.594 |
| Unemployment Rate | 804 | 6.142 | 2.826 | 1.300 | 15.400 |
| Unemployed Persons | 804 | 7080.961 | 12 107.900 | 887 | 202 927 |
| 1st Time Asylum Applicants | 384 | 1601.484 | 1860.947 | 95.744 | 12 330.490 |
| Applicants per 100k Inhabitants | 384 | 32.660 | 18.354 | 12.221 | 85.784 |
| Applicants per Unemployed | 9648 | 0.838 | 1.105 | 0.003 | 10.171 |
| Foreigner Share | 402 | 7.079 | 4.611 | 0.860 | 31.271 |
| NPD Votes | 402 | 1.612 | 0.939 | 0.353 | 5.854 |
| Grüne Votes | 402 | 9.611 | 3.636 | 3.148 | 24.648 |
| Turnout | 402 | 66.006 | 7.068 | 49.723 | 80.046 |
| log(Population) | 402 | 11.957 | 0.655 | 10.437 | 15.046 |
| Lower Sec. Education Share | 402 | 17.558 | 5.572 | 7.239 | 43.292 |
| East | 402 | 0.192 | 0.394 | 0 | 1 |

## 3.4 Empirical Modelling and Results

### 3.4.1 Simple Model: Capturing Spillovers

In a first step we approach possible predictors of violence against refugees by testing existing hypotheses about local determinants for all three types of violence in our dataset using a logistic regression model. We then add variables to capture potential spillovers from previous events depending on their spatio-temporal distance: For this purpose we determine the number of events $\eta_{c,\tau}$ from category $c$ that have taken place during the $\tau$ days prior to any given date from the observation period and contained within the disc $b_{i,r}$ with radius $r$ around the centroid of each district $i$. The resulting model describing the odds of a given type of violence against refugees is as follows:

$$\log \frac{P(\mathbf{y}_c)}{1 - P(\mathbf{y}_c)} = \beta_0 + \mathbf{X}\beta + H\gamma, \tag{3.1}$$

where $\mathbf{X}$ is a matrix of local determinants $x_{i,t}$ and $H = (\eta_{c,\tau})$ contains all counts of potential sources of diffusion. Table 3.3 shows descriptive statistics for a selection of these diffusion variables given a set of radii. All estimations were performed with a temporal horizon of $\tau = 14$ days. The following subsections describe the estimation results for each type of violence.

#### Arson

As the estimates in table 3.4 show, the odds of arson in East Germany are between 2 and 4 times higher than in West Germany across all models. This finding remains robust no matter which other characteristics are controlled for. With regard to local determinants of arson, we find no evidence supporting the deprivation hypothesis: Neither disposable income per capita nor the average rate of unemployment in a district serve as significant predictors. Rising refugee numbers, however, strongly increase the odds of arson. In line with the competition hypothesis the number of first time asylum applicants per $100\,000$ inhabitants of a state has a significant and positive effect. This result still holds when we interact the asylum applicants with the economic situation in each district and use the number of applicants per unemployed persons as a predictor: The odds of arson increase by 40% when the measure rises one standard deviation above its mean. The only moderating effect among the considered variables comes from the existing share of foreign nationals living in a district, thus supporting the contact hypothesis.

***Table 3.3:*** *Descriptive statistics of diffusion variables*

| Type | Radius | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Arson | 10 | 293 058 | 0.004 | 0.074 | 0 | 5 |
| Arson | 50 | 293 058 | 0.070 | 0.331 | 0 | 5 |
| Arson | 100 | 293 058 | 0.227 | 0.625 | 0 | 8 |
| Arson | 200 | 293 058 | 0.727 | 1.329 | 0 | 12 |
| Assault | 10 | 293 058 | 0.007 | 0.091 | 0 | 4 |
| Assault | 50 | 293 058 | 0.070 | 0.310 | 0 | 8 |
| Assault | 100 | 293 058 | 0.247 | 0.631 | 0 | 10 |
| Assault | 200 | 293 058 | 0.866 | 1.430 | 0 | 14 |
| Demonstration | 10 | 293 058 | 0.015 | 0.155 | 0 | 7 |
| Demonstration | 50 | 293 058 | 0.182 | 0.686 | 0 | 13 |
| Demonstration | 100 | 293 058 | 0.567 | 1.408 | 0 | 23 |
| Demonstration | 200 | 293 058 | 1.824 | 3.039 | 0 | 35 |
| Miscellaneous Attack | 10 | 293 058 | 0.023 | 0.204 | 0 | 13 |
| Miscellaneous Attack | 50 | 293 058 | 0.323 | 0.909 | 0 | 15 |
| Miscellaneous Attack | 100 | 293 058 | 1.084 | 1.867 | 0 | 21 |
| Miscellaneous Attack | 200 | 293 058 | 3.541 | 4.238 | 0 | 35 |

As expected, political preferences seem to shape the encounters with refugees – at least in negative ways: The percentage of votes cast for the right-wing extremist NPD serves as a strong predictor of arson. However, this result mainly reflects differences in political preferences between East and West Germany since the NPD in general only receives high vote shares in the newly-formed federal states. NPD vote percentages and the dummy variable for East Germany therefore exhibit an extremely high correlation coefficient of $0.78$. If we run the estimation separately for East and West Germany, there is not sufficient variation in the predictor left to produce any significant effect. Other political preference variables such as the percentage of Green Party votes or the turnout in the 2009 federal election do not influence the odds of arson in any significant way.

Using the significant local determinants we finally estimate a diffusion model which includes measures for each type of event within a radius of 10 kilometers (see figure 3.2 below for the variation of estimates under an increasing radius). This shows that arson tends to take place in clusters as the number of previous arson attacks serves as the most influential predictor. But besides that, assault also increases the odds of arson significantly. Demonstrations and miscellaneous attacks

***Table 3.4:*** *Logit estimations of arson*

| | Baseline | Deprivation | Competition I | Competition II | Contact | Preferences | Diffusion |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| log(Population) | 0.958*** | 1.005*** | 0.881*** | 1.051*** | 1.404*** | 1.647*** | 1.289*** |
| | (0.067) | (0.080) | (0.058) | (0.078) | (0.138) | (0.142) | (0.141) |
| LSE-Share | −0.020 | −0.024 | −0.027 | −0.038* | −0.033* | −0.039** | −0.033* |
| | (0.022) | (0.023) | (0.022) | (0.022) | (0.019) | (0.019) | (0.019) |
| East | 1.217*** | 1.288*** | 1.153*** | 1.290*** | 0.806*** | | 0.705*** |
| | (0.217) | (0.267) | (0.165) | (0.267) | (0.269) | | (0.257) |
| log(Disp. Income) | | −0.534 | 0.327 | −0.290 | | | |
| | | (1.383) | (0.929) | (1.126) | | | |
| Unemployment Rate | | −0.059 | | | | | |
| | | (0.062) | | | | | |
| Applicants per 100k Inhabitants | | | 0.040*** | | | | |
| | | | (0.007) | | | | |
| Applicants per Unemployed | | | | 0.348*** | 0.365*** | 0.405*** | 0.344*** |
| | | | | (0.059) | (0.059) | (0.065) | (0.058) |
| Foreigner Share | | | | | −0.105*** | −0.072** | −0.110*** |
| | | | | | (0.032) | (0.034) | (0.033) |
| NPD Votes | | | | | | 0.228* | |
| | | | | | | (0.121) | |
| Grüne Votes | | | | | | −0.056 | |
| | | | | | | (0.042) | |
| Turnout | | | | | | −0.020 | |
| | | | | | | (0.016) | |
| Arson (10km) | | | | | | | 1.223*** |
| | | | | | | | (0.121) |
| Assault (10km) | | | | | | | 0.565*** |
| | | | | | | | (0.188) |
| Demonstration (10km) | | | | | | | 0.171 |
| | | | | | | | (0.157) |
| Misc. Attack (10km) | | | | | | | −0.165 |
| | | | | | | | (0.149) |
| Constant | −19.249*** | −14.098 | −22.959** | −17.486 | −23.946*** | −25.389*** | −22.495*** |
| | (0.807) | (13.673) | (9.120) | (11.119) | (1.452) | (1.708) | (1.497) |
| N | 293460 | 293460 | 293460 | 293460 | 293460 | 293460 | 293058 |
| Log-likelihood | −1300.87 | −1299.94 | −1246.12 | −1294.09 | −1286.93 | −1282.18 | −1267.23 |
| AIC | 2609.74 | 2611.88 | 2504.25 | 2600.17 | 2585.86 | 2580.35 | 2554.46 |
| Pseudo $R^2$ | 0.066 | 0.066 | 0.105 | 0.071 | 0.076 | 0.079 | 0.09 |

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

on refugee shelters, by contrast, do not induce subsequent arson.

### Assault

Concerning the effects of local determinants, our estimation for assault exhibits the same dynamics as the arson model. In support of the competition hypothesis, rising numbers of asylum applicants increase the odds of violence against refugees. Indicators of socio-economic deprivation, in contrast, do not explain the observed regional variance in assault patterns. As before, a more diverse population reduces the odds of violence, while again regions with strong support for the right-wing extremist NPD exhibit significantly higher odds. A higher rate of political participation, in turn, reduces the odds of assault. The fact that Green Party vote shares are also a positive influence for more assault shows how ubiquitous assault against

***Table 3.5:*** *Logit estimations of assault*

| | Baseline | Deprivation | Competition I | Competition II | Contact | Preferences | Diffusion |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| log(Population) | 0.916*** | 0.968*** | 0.880*** | 0.989*** | 1.313*** | 1.658*** | 1.217*** |
| | (0.126) | (0.163) | (0.132) | (0.141) | (0.186) | (0.176) | (0.153) |
| LSE-Share | −0.073 | −0.071 | −0.077 | −0.086* | −0.071 | −0.101** | −0.061* |
| | (0.049) | (0.046) | (0.060) | (0.049) | (0.043) | (0.039) | (0.035) |
| East | 2.313*** | 2.139*** | 2.102*** | 2.262*** | 2.031*** | | 1.953*** |
| | (0.228) | (0.350) | (0.205) | (0.356) | (0.303) | | (0.293) |
| log(Disp. Income) | | −2.108 | −0.752 | −1.478 | | | |
| | | (2.171) | (1.746) | (1.502) | | | |
| Unemployment Rate | | −0.067 | | | | | |
| | | (0.090) | | | | | |
| Applicants per 100k Inhabitants | | | 0.025*** | | | | |
| | | | (0.002) | | | | |
| Applicants per Unemployed | | | | 0.425*** | 0.423*** | 0.378*** | 0.387*** |
| | | | | (0.089) | (0.094) | (0.106) | (0.086) |
| Foreigner Share | | | | | −0.105*** | −0.238*** | −0.109*** |
| | | | | | (0.036) | (0.080) | (0.035) |
| NPD Votes | | | | | | 0.348*** | |
| | | | | | | (0.115) | |
| Grüne Votes | | | | | | 0.131* | |
| | | | | | | (0.068) | |
| Turnout | | | | | | −0.050*** | |
| | | | | | | (0.016) | |
| Arson (10km) | | | | | | | 0.043 |
| | | | | | | | (0.524) |
| Assault (10km) | | | | | | | 0.699*** |
| | | | | | | | (0.150) |
| Demonstration (10km) | | | | | | | 0.195** |
| | | | | | | | (0.097) |
| Misc. Attack (10km) | | | | | | | 0.037 |
| | | | | | | | (0.066) |
| Constant | −18.352*** | 2.323 | −11.247 | −4.700 | −22.739*** | −23.489*** | −21.667*** |
| | (1.377) | (21.044) | (17.523) | (14.707) | (1.830) | (2.015) | (1.556) |
| N | 293460 | 293460 | 293460 | 293460 | 293460 | 293460 | 293058 |
| Log-likelihood | −1594.21 | −1592.63 | −1565.44 | −1586.63 | −1581.23 | −1596.83 | −1567.1 |
| AIC | 3196.43 | 3197.25 | 3142.87 | 3185.26 | 3174.46 | 3209.66 | 3154.2 |
| Pseudo $R^2$ | 0.143 | 0.144 | 0.159 | 0.147 | 0.15 | 0.142 | 0.158 |

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

refugees has been during the observation period. Nevertheless, the east dummy has an even higher estimated effect than in the arson model: It is between 8 and 15 times more likely to observe assault in East Germany.

The diffusion of events within a small radius of 10 kilometers is only significant for other instances of assault. Other types of events do not exert any influence on the odds of assault. Only if we expand the region of potential influence beyond about 50 kilometers will miscellaneous attacks on refugee shelters start to have a small but significant and positive effect (see figure 3.2 below).

### Miscellaneous Attacks

Miscellaneous attacks on refugee shelters (examples of which include rocks and firework thrown at the buildings, xenophobic graffiti etc.) can be predicted just

***Table 3.6:*** *Logit estimations of miscellaneous attacks on refugee shelters*

| | Baseline | Deprivation | Competition I | Competition II | Contact | Preferences | Diffusion |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| log(Population) | 1.040*** | 1.107*** | 1.010*** | 1.101*** | 1.372*** | 1.597*** | 1.237*** |
| | (0.034) | (0.046) | (0.047) | (0.047) | (0.075) | (0.104) | (0.076) |
| LSE-Share | 0.001 | −0.004 | −0.002 | −0.012 | −0.007 | −0.018 | −0.008 |
| | (0.015) | (0.015) | (0.025) | (0.015) | (0.014) | (0.013) | (0.013) |
| East | 1.502*** | 1.547*** | 1.495*** | 1.555*** | 1.181*** | | 0.997*** |
| | (0.112) | (0.183) | (0.326) | (0.173) | (0.135) | | (0.139) |
| log(Disp. Income) | | −1.051 | 0.223 | −0.213 | | | |
| | | (0.820) | (1.034) | (0.621) | | | |
| Unemployment Rate | | −0.082** | | | | | |
| | | (0.035) | | | | | |
| Applicants per 100k Inhabitants | | | 0.020*** | | | | |
| | | | (0.003) | | | | |
| Applicants per Unemployed | | | | 0.272*** | 0.277*** | 0.273*** | 0.239*** |
| | | | | (0.036) | (0.038) | (0.043) | (0.036) |
| Foreigner Share | | | | | −0.079*** | −0.082*** | −0.086*** |
| | | | | | (0.019) | (0.024) | (0.020) |
| NPD Votes | | | | | | 0.358*** | |
| | | | | | | (0.063) | |
| Grüne Votes | | | | | | −0.008 | |
| | | | | | | (0.026) | |
| Turnout | | | | | | −0.008 | |
| | | | | | | (0.009) | |
| Arson (10km) | | | | | | | 0.175 |
| | | | | | | | (0.221) |
| Assault (10km) | | | | | | | 0.369*** |
| | | | | | | | (0.120) |
| Demonstration (10km) | | | | | | | 0.358*** |
| | | | | | | | (0.114) |
| Misc. Attack (10km) | | | | | | | 0.244*** |
| | | | | | | | (0.054) |
| Constant | −19.159*** | −8.988 | −21.669** | −17.776*** | −22.645*** | −24.940*** | −20.881*** |
| | (0.497) | (7.999) | (10.248) | (6.035) | (0.815) | (1.254) | (0.837) |
| N | 293460 | 293460 | 293460 | 293460 | 293460 | 293460 | 293058 |
| Log-likelihood | −4880.73 | −4873.13 | −4818.07 | −4865.62 | −4846.29 | −4849.59 | −4791.3 |
| AIC | 9769.47 | 9758.25 | 9648.14 | 9743.25 | 9704.59 | 9715.18 | 9602.61 |
| Pseudo $R^2$ | 0.1 | 0.101 | 0.111 | 0.103 | 0.106 | 0.106 | 0.116 |

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

as well as arson and assault events using the same local determinants. One minor difference concerns the effect of a district's unemployment rate: While it had no significant influence on arson and assault, the odds of miscellaneous attacks seem to be slightly reduced in high-unemployment districts. This result is in contrast to the deprivation hypothesis, which predicts a positive effect.

As for the other event types, a rising number of first time asylum applicants (per state and per unemployed persons in the district) increases the odds of an event; East Germany (which is synonymous with regions where the right-wing extremist NPD receives a higher percentage of votes) again experiences higher chances of violence.

Our estimated diffusion effects show that the inhibition threshold for miscellaneous attacks is lower than for the other types of events: Previous incidences of assault, miscellaneous attacks and demonstrations increase the odds of miscellaneous attacks on shelters. Only arson does not seem to exert any influence – it seems likely that perpetrators tend to let the dust settle after arson attacks which gain relatively more attention by criminal investigators as well as the media.

**Summary**

This first step in our analysis to disentangle local determinants and diffusion effects of violence against refugees already produces a variety of results, confirming prior empirical research and adding new insights by being able to distinguish between different types of violence. The deprivation hypothesis does not receive much support in existing research (see e.g. Koopmans & Olzak, 2004) and our findings are no different for all types of violence. Contrary to theoretical expectations, a higher unemployment rate even reduces the odds of an event for miscellaneous attacks.

We find diffusion effects to pose a significant role, especially whithin the same category of violence (i.e. arson leads to more arson etc.). Assault has the broadest influence on violence as it affects all types of events. Miscellaneous attacks, on the other hand, are the most susceptible form of violence as prior events of assault, miscellaneous attacks as well as demonstrations against refugees increase their odds.

Our estimates of diffusion effects are based on influence regions of only 10 kilometers. In order to check the robustness of our findings, we have also run the diffusion models for larger radii ranging from 10 to 200 kilometers. The change in estimates for all types of prior events is depicted in figure 3.2. From the top left tile the tendency of arson to appear in clusters can be seen very clearly. Assault, in the second column, exerts a positive and significant influence on all types of events within a radius up to about 100 kilometers. As can be expected, diffusion effects generally vanish as the influence region is expanded.

Further checking the robustness of our findings, we also estimate the diffusion model while additionally controlling for other instances of crime within each district. Using regional data from federal crime statistics we can distinguish between 40 different types of criminal offences. Surprisingly, none of them have a positive and significant impact on the odds of any type of violence against refugees (see figure 3.3 in the appendix). Some exhibit a significant but small negative effect while the majority is simply insignificant. All previously observed effects remain unchanged. This suggests that the analyzed cases of anti-refugee attacks are not an expression of usual criminal activity.

As a last robustness check, we re-estimate the diffusion model using month-

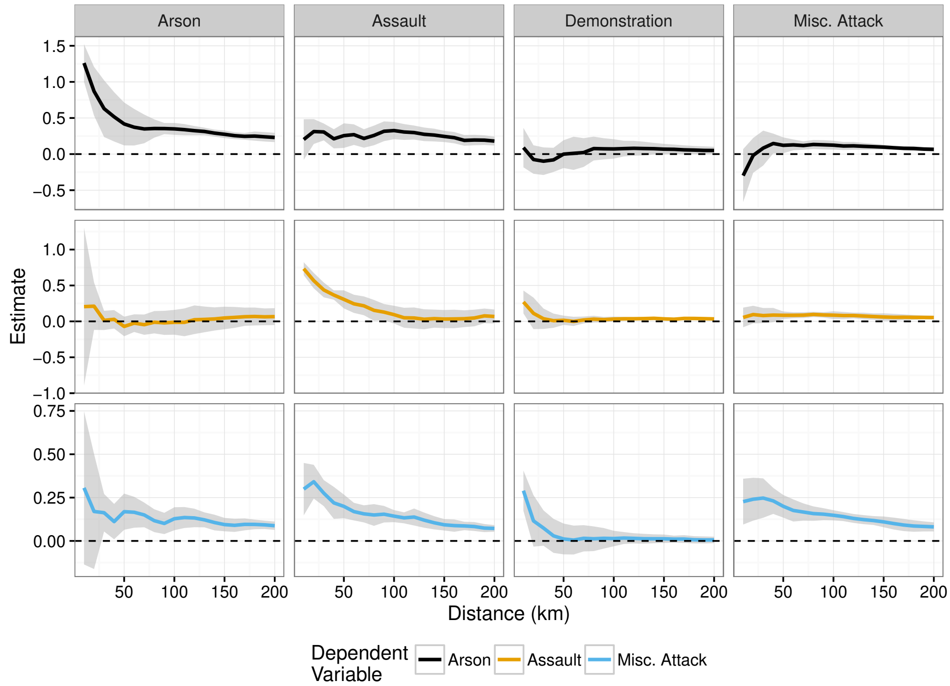


***Figure 3.2:*** *Estimated diffusion effect depending on the distance of included events (with 95% confidence interval)*

based time dummies to make sure not to bias the estimations with an underlying time trend in the data. Since the division into calender months is rather arbitrary, we use a rolling time window of 30 days and report average effects and standard errors in table 3.9. The most important difference here is the loss of significance in the asylum applications per unemployed person. This variable seems to have captured the time trend of rising violence against refugees accompanying the arrival of more and more asylum seekers rather than actual labor market competition.

So far, for analytical simplicity, we have not considered any temporal decay of diffusion but instead opted for treating all events within 14 days prior to any given date equally. In the following part of the analysis we therefore turn to a spatio-temporal regression model to better capture the diffusion of violence against refugees.

### 3.4.2 Spatio-Temporal Lag Model

Our econometric modelling has so far followed an intuitive approach combining widely-used local determinants of right-wing violence with simple, manual counts of prior events within a certain distance around the analyzed unit. As shown above, these diffusion variables help explain the patterns of different types of violence present in our data. In order to better capture the spatio-temporal dynamics of diffusion, however, we can apply more advanced methods that specifically incorporate a spatial and temporal lag of the dependent variable. During the past two decades a lot of research has explored the benefits of spatial-econometric models for the social sciences (see e.g. Goodchild, Anselin, Appelbaum, & Harthorn, 2000; Ward & Gleditsch, 2002; Anselin, 2003; Franzese & Hays, 2007; Beck, Gleditsch, & Beardsley, 2006).

We follow Franzese and Hays (2007) in formulating the model

$$\mathbf{y} = \rho\Omega\mathbf{y} + \mathbf{X}\beta + \epsilon, \tag{3.2}$$

where $\mathbf{X}$ holds the observations of previously determined significant local variables, the effect of which will be estimated by $\beta$. The binary dependent variable $\mathbf{y}$ is ordered by time periods and units: The $N$ first-period observations are stacked onto the $N$ second-period ones and so on. This way the spatio-temporal lag matrix $\Omega$ can be expressed as the Kronecker product $(\mathbf{D}_T \otimes \mathbf{W}_N)$ of a $T \times T$ temporal decay matrix $\mathbf{D}$ and an $N \times N$ spatial-weights matrix. We construct $\mathbf{W}_N$ as a binary contiguity matrix where $w_{ij} = 1$ if units $i$ and $j$ share at least one common border point and $w_{ij} = 0$ otherwise. Because we want to account for effects by prior events within the same district, units are also connected to themselves and diagonal entries $w_{ii} = 1$. We then additionally row-standardize $\mathbf{W}_N$ so each row sums to unity.

In the temporal decay matrix $\mathbf{D}_T$ entries $d_{ij}$ determine the discounted temporal influence of period $j$ on period $i$ according to some function $f(l)$ of the temporal lag $l = j - i$, with $f(l \geq 0) = 0$ and $\partial f(l)/\partial l > 0$. Same-period observations therefore do not exert any influence by assumption. We thus also omit problems of contemporaneous observations and biased estimates much like Beck et al. (2006). Although Franzese and Hays (2007) note that there are better ways to handle endogeneity concerns, due to our high level of temporal disaggregation, it is not only a modelling decision but theoretically more sensible for us to exclude same-period influence: In contrast to more frequently used annual data, daily observations can hardly exhibit diffusion effects within the same time period.

The spatio-temporal autoregressive coefficient $\rho$ to be estimated thus gives us the extent of diffusion between violence events against refugees. Since we want to distinguish between effects from different categories of violence $c$, we estimate the model

$$\mathbf{y}_\kappa = \sum_c \rho_c \Omega \mathbf{y}_c + \mathbf{X}\beta + \epsilon \tag{3.3}$$

for each $\kappa \in c$. In order to assess the temporal diffusion of violence, estimations were performed using three variants of the sigmoid temporal decay function

$$f(l) = \begin{cases} \frac{e^{l-d}}{1+e^{l-d}}, & \text{if } l < 0 \\ 0, & \text{otherwise} \end{cases} \tag{3.4}$$

setting the inflection point at $l = d$ to be at 7, 14 and 28 days and thus broadening the temporal window of diffusion from one to four weeks.

With regard to local determinants of violence, the results of the spatio-temporal lag model in table 3.7 generally match our estimations from above with two notable exceptions: (i) For the case of arson, systematic differences between East and West Germany have disappeared and the correspondent dummy variable is not significant. We interpret this result to show that arson is a nation-wide phenomenon and the spatio-temporal lag better explains its regional patterns. Assault and miscellaneous attacks on the other hand are still more prevalent in East Germany. (ii) The share of foreign nationals per district does not affect assault anymore and only significantly reduces the odds of arson and miscellaneous attacks on refugee shelters. This is likely the result of unit dummies at the state level, which significantly reduce the observed variance in foreign nationals – especially in East Germany, where a large share of the recorded assault occured. Despite the additional inclusion of monthly time dummies, the spatio-temporal lag model still shows a significant effect of the number of first time asylum applicants per unemployed person for all types of violence. Thus, even controlling for the joint time trend of asylum applications and violence against refugees, the competition hypothesis receives support in our model.

Based on the different temporal decay functions we can now capture the diffusion of violence more clearly: First of all, auto-diffusion between events of the same type is still strong and its effect decreases over time. Assault remains the most influential type of violence against refugees, increasing the odds of all event types (with the largest effects within the first week after an incidence). What we had not seen before, however, is the positive effect of demonstrations on the odds of arson. Right-wing demonstrations appear to induce arson attacks within the ensuing week. Demonstrations also have such a short-term effect on miscellaneous attacks. In both cases, we can imagine that demonstration participants, being reinforced in their beliefs, decide to turn their words into actions.

Unlike in our first specification, arson increases the odds not only of further arson. Miscellaneous attacks also become more likely, however not until at least one week has passed after an arson attack. This delayed effect supports our previous assessment that arson tends to induce (potential) perpetrators to seek cover.

***Table 3.7:*** *Spatio-temporal lag estimations*

| | arson | | | assault | | | miscellaneous attack | | |
|---|---|---|---|---|---|---|---|---|---|
| | $d = 7$ | $d = 14$ | $d = 28$ | $d = 7$ | $d = 14$ | $d = 28$ | $d = 7$ | $d = 14$ | $d = 28$ |
| log(Population) | $1.398^{***}$ | $1.386^{***}$ | $1.376^{***}$ | $1.269^{***}$ | $1.257^{***}$ | $1.235^{***}$ | $1.024^{***}$ | $1.014^{***}$ | $0.996^{***}$ |
| | (0.222) | (0.223) | (0.223) | (0.209) | (0.210) | (0.211) | (0.107) | (0.107) | (0.107) |
| LSE-Share | 0.006 | 0.008 | 0.009 | $-0.035$ | $-0.034$ | $-0.032$ | 0.018 | 0.019 | 0.020 |
| | (0.029) | (0.029) | (0.029) | (0.028) | (0.028) | (0.028) | (0.013) | (0.013) | (0.013) |
| East | 0.951 | 0.965 | 0.921 | $1.497^{**}$ | $1.506^{**}$ | $1.484^{**}$ | $1.316^{***}$ | $1.316^{***}$ | $1.320^{***}$ |
| | (0.651) | (0.651) | (0.651) | (0.682) | (0.682) | (0.682) | (0.346) | (0.346) | (0.347) |
| Applicants per Unemployed | $0.414^{***}$ | $0.410^{***}$ | $0.410^{***}$ | $0.332^{***}$ | $0.331^{***}$ | $0.330^{***}$ | $0.193^{***}$ | $0.191^{***}$ | $0.185^{***}$ |
| | (0.117) | (0.118) | (0.119) | (0.126) | (0.127) | (0.128) | (0.066) | (0.066) | (0.067) |
| Foreigner Share | $-0.083^{**}$ | $-0.083^{**}$ | $-0.084^{**}$ | $-0.018$ | $-0.016$ | $-0.015$ | $-0.063^{***}$ | $-0.063^{***}$ | $-0.062^{***}$ |
| | (0.035) | (0.035) | (0.035) | (0.037) | (0.037) | (0.037) | (0.016) | (0.016) | (0.016) |
| Arson (lag) | $3.254^{***}$ | $2.085^{***}$ | $1.786^{***}$ | $-1.889$ | $-0.184$ | 0.311 | 0.743 | $1.022^{**}$ | $0.713^{**}$ |
| | (0.871) | (0.691) | (0.505) | (1.313) | (0.717) | (0.469) | (0.637) | (0.402) | (0.293) |
| Assault (lag) | $2.184^{***}$ | $1.300^{**}$ | 0.566 | $2.314^{***}$ | $1.131^{***}$ | $0.797^{**}$ | $1.404^{***}$ | $0.719^{**}$ | $0.579^{***}$ |
| | (0.772) | (0.521) | (0.430) | (0.556) | (0.411) | (0.317) | (0.440) | (0.296) | (0.218) |
| Demonstration (lag) | $1.736^{***}$ | 0.524 | 0.472 | 0.638 | 0.184 | 0.216 | $0.987^{***}$ | $0.398^{*}$ | 0.090 |
| | (0.660) | (0.463) | (0.291) | (0.518) | (0.346) | (0.218) | (0.334) | (0.220) | (0.143) |
| Misc. Attack (lag) | 0.092 | 0.659 | 0.379 | $1.129^{**}$ | $0.801^{***}$ | 0.292 | $1.799^{***}$ | $1.164^{***}$ | $0.790^{***}$ |
| | (0.697) | (0.434) | (0.293) | (0.449) | (0.300) | (0.208) | (0.274) | (0.188) | (0.129) |
| Constant | $-24.907^{***}$ | $-24.812^{***}$ | $-24.664^{***}$ | $-23.336^{***}$ | $-23.234^{***}$ | $-22.929^{***}$ | $-19.381^{***}$ | $-19.284^{***}$ | $-19.071^{***}$ |
| | (2.805) | (2.811) | (2.821) | (2.621) | (2.626) | (2.631) | (1.354) | (1.356) | (1.359) |
| N | 293,460 | 293,460 | 293,460 | 293,460 | 293,460 | 293,460 | 293,460 | 293,460 | 293,460 |
| Log-likelihood | -1,234.008 | -1,232.902 | -1,230.966 | -1,535.497 | -1,538.715 | -1,539.655 | -4,710.104 | -4,706.359 | -4,701.990 |
| AIC | 2,538.016 | 2,535.803 | 2,531.932 | 3,140.993 | 3,147.429 | 3,149.310 | 9,490.209 | 9,482.717 | 9,473.979 |
| Pseudo $R^2$ | 0.886 | 0.886 | 0.884 | 0.825 | 0.827 | 0.828 | 0.869 | 0.868 | 0.867 |

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

All regressions include fixed time and unit effects (month and federal state). Their coefficient estimates are omitted here to conserve space.

### 3.4.3 Methodological Extension: Infectious Violence

While spatial-econometric methods have been receiving growing attention in the social sciences, we can still benefit from models and applications originally developed in other disciplines. For example, researchers from geophysics (Guo & Ogata, 1997; Ogata, 1999), criminology (e.g. Weisburd & Green, 1995; Ratcliffe, 2004; Johnson, Bowers, Birks, & Pease, 2009) or biostatistics (e.g. Neal & Roberts, 2004; Diggle, Kaimi, & Abellana, 2010) have already been more involved with geocoded data and spatio-temporal processes. Regardless of whether the research subject is earthquake patterns, residential burglaries or infectious disease outbreaks – the underlying statistical framework is the theory of point processes (for an overview cf. Daley & Vere-Jones, 2003). This framework is particularly useful for analyzing so-called epidemic phenomena, i.e. spatio-temporal processes that exhibit "self-exciting" behaviour. From this perspective, our event dataset containing individual occurrences of anti-refugee violence is not much different from data of a measles outbreak. So even though Meyer et al. (2012) explain observed patterns of invasive meningococcal disease, we can apply their "unifying regression framework [...] for the modelling, inference and simulation of spatio-temporal point processes" to our data and model the spread of different types of violence against refugees.

Meyer et al.'s (2012) two-component spatio-temporal intensity model (*twinstim*) is continuous in time and space which allows us to dispense with discrete units of observation for our dependent variable (i.e. days and districts). We can instead treat each event, identified in space by its geographical coordinates and in time by its occurence date, as realizations of a point process within the entirety of Germany during the two-year observation period. At the same time, we can still include independent and control variables that are necessarily based on some discretization of space and time. Furthermore, *twinstim* allows for a joint analysis of all events, irrespective of their category. Unlike in the previous models, it is therefore not necessary to perform separate estimations for the different types of violence in the dataset.

Using an epidemic perspective to describe patterns of anti-refugee violence lets us approach the topic in a slightly different manner than before and thus gain additional insights: So far we have been looking for evidence that these events are not solely based on local determinants and also interact and promote one another. Therefore, we have not only considered the spatial clustering of our observations but also included their temporal structure which combination has allowed us to trace their diffusion processes.[3] Having thus established the mechanisms and directions of influence among the different types of violence, we can now go one step further and use the epidemic perspective in order to assess how "infectious" different types of events really are. For this purpose, the *twinstim* uses a conditional intensity function that estimates the hazard for events from category $k$ at time $t$ and location **s**:

$$\lambda(\mathbf{s}, t, k) = \nu_{[s][t]} + \sum_{j \in I(\mathbf{s},t,k)} \eta_j f(\|\mathbf{s} - \mathbf{s_j}\| \mid k_j) g(t - t_j \mid k_j) \tag{3.5}$$

The first part of the model, which represents the endemic component, reflects the occurence of new events caused by local determinants that affect the risk of an observation – in our case variables such as population, the share of foreigners or the number of first time asylum applicants. These make up the log-linear predictor $\nu_{[s][t]}$ covering the entire spatio-temporal grid indexed by $[s][t]$.

The second part of the model is the epidemic component which accounts for the "infection pressure" from past events that occurred within the maximum spatial and temporal ranges $\delta$ and $\tau$, respectively. Their set is defined as

$$I(\mathbf{s}, t, k) = \{j : t_j < t \wedge t - t_j \leq \tau \wedge \|\mathbf{s} - \mathbf{s}_j\| \leq \delta \wedge q_{k_j,k} = 1\}. \tag{3.6}$$

In order to model spatio-temporal interaction, Meyer et al. (2012) follow an approach by Lawson and Leimich (2000) and use parametric interaction functions $f(\cdot)$ and $g(\cdot)$, which can be specified depending on the respective application.

Since we distinguish between $K = 4$ different event types that belong to the set $\mathcal{K} = \{1, \ldots, K\}$, we also need an indicator matrix $\mathbf{Q} = (q_{k,l})_{k,l \in \mathcal{K}}$, where elements $q_{k,l} \in \{0, 1\}$ denote possible transmissions between types. For example, assuming that all four types of events (arson, assault, demonstration, miscellaneous attack) can influence one another, **Q** would be a $4 \times 4$ matrix of ones. In contrast to infectious diseases, we cannot know with certainty which type of event causes which others to occur. Infectivity in the social sciences is unfortunately a more ambiguous concept compared to epidemiology. However, we can still make an informed decision based on theory as well as our empirical results from the models above:

[3]Diffusion necessarily requires the temporal alongside the spatial dimensions. This is why a statistic like Moran's $I$ is not sufficient to assess the existence and scope of diffusion, as it only considers spatial correlations. It does, however, serve as a first indicator: Within each event category, Moran's $I$ is 0.12, 0.31, 0.18 and 0.20 for arson, assault, demonstrations and miscellaneous attacks, respectively (with an expected value $E(I) = -0.0025$ for all of them and highly significant p-values).

For one, we do not try to describe the occurence of demonstrations and it would not make any sense to claim that an arson attack causes subsequent anti-refugee demonstrations. So demonstrations should merely be based on local determinants, the effects of which are modelled by the endemic component. Miscellaneous attacks on the other hand turn out to be strongly influenced by previous events of all categories (with arson having a delayed positive effect). Analogously, assault is only affected by prior assault (potentially miscellaneous attacks) and arson is influenced by previous arson, assault and possibly within the short term also by demonstrations.

The model is applied to our right-wing violence event data using the R package "surveillance" (Höhle, Meyer, & Paul, 2016). In order to select an appropriate model, we use AIC to compare permutations of the following specifications: As part of the **endemic component** we include local variables which were found to have a significant impact in the estimations above. In addition, we test a common and a violence type-specific intercept as well as a linear time trend that could account for a baseline increase in violence during the observation period. The **epidemic component** considers only the type of violence for each event. If we had more information to characterize individual events (e.g. some kind of measure of severity or the number of perpetrators), we could include it here as well to draw even more subtle inferences about their infectivity.

As the *twinstim* is computationally intensive, we restrict a first set of estimations to a constant spatial interaction function $f$ and only assume a step-wise temporal interaction function with one knot. Afterwards, the AIC-wise best specification is additionally estimated using two versions of a Gaussian distance-decay $f(x) = \exp(-x^2/2\sigma^2)$, one with a fixed variance parameter at 40 km and one at 80 km.

Table 3.8 shows the parameter estimates of the resulting best-fit model. The superiority of a type-specific intercept in the endemic component reflects the high variance of observation numbers across event types (as shown in table 3.1 above). As in all models above, the dummy variable for East Germany has a strong and positive effect on the chances of right-wing extremist events. Despite the significance of an upward linear time trend, rising labor market competition from increasing asylum applicants numbers per unemployed still increases the odds of an event. In this respect, the *twinstim* and the spatio-temporal lag model seem to be better suited to disentangle both effects in comparison with the simple spill-over logit model.

Different from our prior models, the share of foreign nationals actually increases chances of an event. The most likely cause for this result is the fact that we now include demonstrations as a type of event to be explained – which have taken place

***Table 3.8:*** *Twinstim parameter estimates*

| | Estimate | Std. Error | $z$ value | $P(\|Z\| > \|z\|)$ |
|---|---|---|---|---|
| Intercept (Arson) | −25.762 | 0.590 | −43.686 | $< 1 \cdot 10^{-04}$ |
| Intercept (Assault) | −25.631 | 0.583 | −43.963 | $< 1 \cdot 10^{-04}$ |
| Intercept (Demonstration) | −24.179 | 0.561 | −43.108 | $< 1 \cdot 10^{-04}$ |
| Intercept (Misc. Attack) | −24.040 | 0.575 | −41.813 | $< 1 \cdot 10^{-04}$ |
| log(Population) | 0.727 | 0.048 | 15.013 | $< 1 \cdot 10^{-04}$ |
| Applicants per Unemployed | 0.151 | 0.058 | 2.629 | 0.00857 |
| Foreigner Share | 0.154 | 0.012 | 13.200 | $< 1 \cdot 10^{-04}$ |
| East | 2.170 | 0.110 | 19.783 | $< 1 \cdot 10^{-04}$ |
| LSE-Share | −0.048 | 0.010 | −5.044 | $< 1 \cdot 10^{-04}$ |
| Time Trend | 1.355 | 0.121 | 11.186 | $< 1 \cdot 10^{-04}$ |
| (Intercept) | −12.947 | 0.179 | −72.332 | $< 1 \cdot 10^{-04}$ |
| Assault | −1.281 | 0.374 | −3.429 | 0.000606 |
| Demonstration | −3.020 | 0.941 | −3.209 | 0.001330 |
| Misc. Attack | −0.476 | 0.190 | −2.510 | 0.012089 |
| $\log \sigma$ | 3.690 | 0.065 | | |
| $\alpha_1$ | −1.290 | 0.235 | | |
| N | 1683 | | | |
| AIC | 44469 | | | |
| Log-likelihood | -22219 | | | |

*Note:* Estimates are shown for the endemic (top) and epidemic (middle) components of the model with Gaussian spatial interaction function and a temporal step function.

mostly in Berlin and other large cities with significantly higher shares of foreigners among their population.

Adding an epidemic intercept improves the fit compared to an endemic-only model: Therefore the point process seems to be self-exciting, i.e. violence against refugees is infectious. As arson serves as the reference category in the epidemic component, we can see that all other types of events are less infectious. Since we assume assault to be a potential source of arson, miscellaneous attacks and other assault, the number of potential offspring events is larger than for the other types. As a consequence, its infectivity is estimated to be 30% relative to arson. Miscelleaneous attacks are about twice as infectious as assault. Demonstrations are the least infectious types of events. As we have seen in the spatio-temporal lag model above, their influence on subsequent events is weak and short-lived. But since their absolute number is relatively high, their effect on further acts against refugees must not be overlooked.

In addition to these estimates, the model allows for calculating event-specific reproduction numbers, which tell us the mean number of secondary events for each type of anti-refugee event. Arson shows the highest number of secondary infections with $\mu_{\text{ar}} = 0.6$, followed by miscellaneous attacks ($\mu_{\text{ma}} = 0.38$), assault ($\mu_{\text{as}} = 0.27$) and demonstrations ($\mu_{\text{de}} = 0.03$). So while we have seen almost five times as many miscellaneous attacks in the observation period as arson attacks, the latter carry an enormous potential for further aggression – especially considering that we have shown the within-type diffusion effects of arson to be particularly strong.

## 3.5 Conclusion

This paper has analyzed potential determinants of different types of right-wing violence against refugees. Building on prior research, we have not only included local conditions as potential explanatory variables but focused particularly on spill-over effects between individual hate crime events. We have found support for the competition hypothesis, according to which a combination of high perceived immigration pressure and unfavorable economic conditions evoke violence. However, the most important local predictor of anti-refugee violence remains the dummy variable for East Germany. Even more than 25 year after the reunification of Germany, there still seem to exist fundamental differences between East and West with respect to social norms and political preferences.

Carefully and gradually constructing our econometric toolkit, the presented spatio-temporal models have shown strong evidence of diffusion among the different types of events. Assault exhibits the broadest influence on subsequent violence as it affects all types of events. Miscellaneous attacks, on the other hand, are the most susceptible form of violence as prior events of all types exert a positive influence.

This paper has also offered a methodological contribution to the analysis of event data in political science: Adopting a point process model from epidemiology, we could assess the contagiousness of the different types of events covered by the dataset. It has shown the danger of arson attacks as they evoke the highest number of secondary events. Generally, point process modelling is particularly well-suited for event data, which is increasingly being collected. The continuous space-time structure and the scalability of the model should provide further benefits in multiple applications. With more detailed and more current data, simulations of the spread of violence beyond the present may even serve as tools to assess the risk of future violence within well-defined geographical regions.

Our findings show that events of right-wing extremist violence do not constitute crime as any other, they also carry a message and represent “propaganda of the deed”. Thus stopping and prosecuting anti-refugee violence not only protects people locally but inhibits the spread of right-wing extremist behaviour throughout society.

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# Appendix

## 3.A Additional Material

***Table 3.9:*** *Diffusion model with rolling time fixed effects (by month)*

| | arson | assault | miscellaneous attack |
|---|---|---|---|
| log(Population) | 1.246*** | 1.201*** | 1.218*** |
| | (0.139) | (0.159) | (0.075) |
| LSE-Share | −0.011 | −0.054 | 0.003 |
| | (0.02) | (0.037) | (0.013) |
| East | 0.682*** | 1.9*** | 0.998*** |
| | (0.239) | (0.284) | (0.132) |
| Applicants per Unemployed | 0.005 | 0.186 | 0.059 |
| | (0.092) | (0.12) | (0.051) |
| Foreigner Share | −0.101*** | −0.104*** | −0.082*** |
| | (0.031) | (0.034) | (0.019) |
| Arson (10km) | 1.24*** | 0.08 | 0.219 |
| | (0.093) | (0.433) | (0.222) |
| Assault (10km) | 0.286 | 0.547*** | 0.217*** |
| | (0.269) | (0.157) | (0.084) |
| Demonstration (10km) | 0.142 | 0.082 | 0.335*** |
| | (0.207) | (0.12) | (0.072) |
| Misc. Attack (10km) | −0.296 | 0.055 | 0.219*** |
| | (0.214) | (0.069) | (0.029) |
| Constant | −23.917*** | −24.175*** | −22.786*** |
| | (1.55) | (1.879) | (0.949) |
| N | 293058 | 293058 | 293058 |
| Log-likelihood | -1191.242 | -1528.799 | -4613.826 |
| AIC | 2450.226 | 3125.341 | 9295.395 |

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

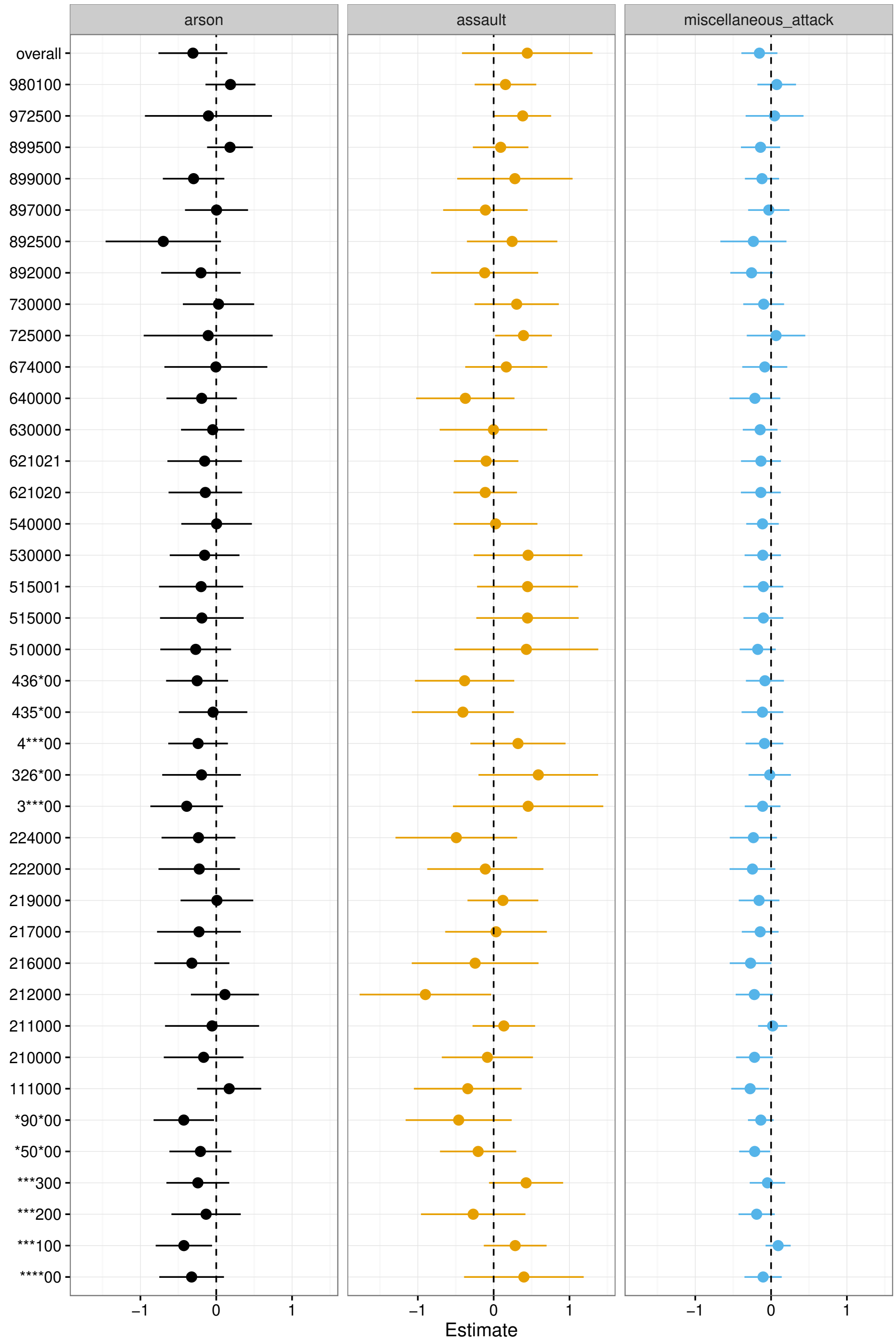


***Figure 3.3:*** *Estimated effect of criminal offences in a baseline model of local determinants. Offences were included individually, definition of crime IDs in table 3.10.*

***Table 3.10:*** *Definitions of crime identifiers*

| Crime ID | Description |
|---|---|
| overall | Straftaten insgesamt |
| 111000 | Vergewaltigung und sexuelle Nötigung §§ 177 Abs. 2, 3 und 4, 178 StGB |
| 210000 | Raub, räuberische Erpressung und räuberischer Angriff auf Kraftfahrer §§ 249-252, 255, 316a StGB |
| 211000 | Raub, räuberische Erpressung auf/gegen Geldinstitute, Postfilialen und -agenturen |
| 212000 | Raub, räuberische Erpressung auf/gegen sonstige Zahlstellen und Geschäfte |
| 216000 | Handtaschenraub |
| 217000 | Sonstige Raubüberfälle auf Straßen, Wegen oder Plätzen |
| 219000 | Raubüberfälle in Wohnungen |
| 222000 | Gefährliche und schwere Körperverletzung, Verstümmelung weiblicher Genitalien §§ 224, 226, 226a, 231 StGB |
| 224000 | Vorsätzliche einfache Körperverletzung § 223 StGB |
| 3***00 | Diebstahl ohne erschwerende Umstände §§ 242, 247, 248a-c StGB und zwar: |
| 326*00 | Einfacher Ladendiebstahl |
| 4***00 | Diebstahl unter erschwerenden Umständen §§ 243-244a StGB und zwar: |
| 435*00 | Wohnungseinbruchdiebstahl § 244 Abs. 1 Nr. 3 StGB darunter: |
| 436*00 | Tageswohnungseinbruch |
| ****00 | Diebstahl insgesamt und zwar: |
| ***100 | Diebstahl insgesamt von Kraftwagen einschl. unbefugte Ingebrauchnahme |
| ***200 | Diebstahl insgesamt von Mopeds und Krafträdern einschl. unbefugte Ingebrauchnahme |
| ***300 | Diebstahl insgesamt von Fahrrädern einschl. unbefugte Ingebrauchnahme |
| *50*00 | Diebstahl insgesamt an/aus Kraftfahrzeugen |
| *90*00 | Taschendiebstahl insgesamt |
| 510000 | Betrug §§ 263, 263a, 264, 264a, 265, 265a, 265b StGB |
| 515000 | Erschleichen von Leistungen § 265a StGB |
| 515001 | Beförderungserschleichung |
| 530000 | Unterschlagung §§ 246, 247, 248a StGB |
| 540000 | Urkundenfälschung §§ 267-271, 273-279, 281 StGB |
| 621020 | Widerstand gegen Vollstreckungsbeamte |
| 621021 | Widerstand gegen Polizeivollzugsbeamte |
| 630000 | Begünstigung, Strafvereitelung (ohne Strafvereitelung im Amt), Hehlerei und Geldwäsche §§ 257, 258, 259-261 StGB |
| 640000 | Brandstiftung und Herbeiführen einer Brandgefahr §§ 306-306d, 306f StGB |
| 674000 | Sachbeschädigung §§ 303-305a StGB |
| 725000 | Straftaten gegen das Aufenthalts-, das Asylverfahrens- und das Freizügigkeitsgesetz/EU |
| 730000 | Rauschgiftdelikte (soweit nicht bereits mit anderer Schlüsselzahl erfasst) |
| 892000 | Gewaltkriminalität |
| 892500 | Mord und Totschlag |
| 897000 | Computerkriminalität |
| 899000 | Straßenkriminalität |
| 899500 | Sachbeschädigung durch Graffiti insgesamt |
| 972500 | Unerlaubt eingereiste/aufhältige Personen (SZ: 725100, 725700) |
| 980100 | IuK-Kriminalität im engeren Sinne (SZ: 517500, 517900, 543000, 674200, 678000) |

# Part III

# Mobilization in the Digital Age

# Chapter 4

# Message Received: Analyzing Determinants of SMO Mobilization on Twitter

David Benček

## 4.1 Introduction

During recent years, online campaigns by social movements and non-state organizations have grown to be a firm pillar of their mobilization strategies. Just one example is the social media presence pursued by the "Islamic State" (IS), which has gained worldwide attention. Through an extensive and well-coordinated presence on various social media platforms, including Twitter, IS has managed to spread its propaganda effectively among followers and also seems to be successful in constantly mobilizing new members (Klausen, 2015). Of course, neither is the use of electronic communication in mobilization efforts limited to armed movements, nor is it an entirely new phenomenon and as such it has already fueled research in the past. However, most of it has focused either on the *opportunities* of online mobilization for social movement organizations (SMOs) (e.g. Diani, 2000; Ward, Gibson, & Lusoli, 2003; Stein, 2009) or the *identities* of online addressees (e.g. Krueger, 2006). So in spite of its steady proliferation, little is so far known about the precise *mechanisms* by which SMOs attract and mobilize followers via social media and whether or how they differ from traditional (offline) channels.

In order to address this gap in the literature, this paper develops an empirical approach to examine determinants of successful online mobilization efforts. This approach is demonstrated by analyzing the communication within extended Twitter networks of six SMOs across the *environmental* and *nuclear disarmament* movements. Methodologically, this paper advances previous research on SMO mobilization by combining different building blocks such as automated data collection, computational content analysis and instruments from social network analysis into a general regression framework. Future applications to other cases are facilitated by this modular framework, thereby also contributing to the growing field of computational social sciences.

The outlined approach allows for an empirical analysis of two distinct factors that determine success of mobilization: the message and the messenger. The former is rooted in research on traditional mobilization mechanisms in the social psychological literature that emphasizes the content of communication (e.g. Klandermans, 1984; Snow, Rochford, Worden, & Benford, 1986; Gamson & Meyer, 1996; Goodwin, 2004) as well as insights from modern communication theory (e.g. Stieglitz & Dang-Xuan, 2013; Hansen, Arvidsson, Nielsen, Colleoni, & Etter, 2011); the latter comes from a strand of the social movement literature that analyzes the role of networks and social ties in the way SMOs attract their members (e.g. McAdam, 1986; McAdam & Paulsen, 1993; Passy, 2003; Diani, 2013). Based on collected data, success of SMO mobilization in social media is operationalized in terms of two variables: (i) the popularity of messages and (ii) the distance of their dissemination throughout the extended networks.

The findings presented in this paper show that widespread *popularity* of messages is almost exclusively determined by their content. On the other hand, the *reach* of messages, measured by the distance of their dissemination throughout the network, barely depends on the message itself. Instead it is essential for a messenger to be highly visible and well connected in order to reach distant network members. A comprehensive online mobilization strategy therefore needs to balance these dimensions and spread messages among distinct and well-connected hubs throughout a communications network.

The remainder of this paper is structured as follows: Section two begins by briefly reviewing previous research on offline and online SMO mobilization strategies, laying out the framework for the subsequent analysis. Section three presents the case selection, the strategy for building the dataset and descriptive statistics. Section four describes the analysis and discusses its results. The final section concludes with outlining avenues for future research.

## 4.2 Literature and Framework

Mobilization processes have been researched extensively for several decades. A standard theoretical framework in the rational choice tradition is developed by Klandermans (1984) and Klandermans and Oegema (1987) who suggest that mobilization constitutes a progression of steps from becoming informed towards eventual active participation – each step in between depending on a cost-benefit rationale of the potential activist. The authors divide this chain of decisions into distinct sub-categories: First comes consensus mobilization, upon which subsequent action mobilization depends. As the basis of mobilization, consensus-spreading efforts require an effective and widespread dissemination of information in order to involve a large number of people with the SMO's cause. Only afterwards can action mobilization guide these individuals towards active participation, e.g. in demonstrations. Similarly, Snow et al. (1986) refer to the first stage of SMO mobilization activities as the process of *frame alignment* between an organization and individuals.

Within this general framework of the process, further research has sought more specific insights into successful mobilization: To this end, a broad literature emphasizes the relevance of social networks – their size and structure being an integral factor for the proximity and scope of interaction between individuals and an organization (see e.g. Rosenthal, Fingrutd, Ethier, Karant, & McDonald, 1985; Fernandez & McAdam, 1988; McAdam & Paulsen, 1993; Passy, 2003). Network centrality of actors in particular is found to be a strong predictor of inducing movement participation (Marwell & Oliver, 1993; Kim & Bearman, 1997). While the literature focused on traditional mobilization efforts examines only personal social networks in the real world, the network-centric view translates easily to the virtual realm and has thus been adopted by more recent studies to analyze information flow and collective action coordination online. Romero, Meeder, and Kleinberg (2011) find support for the sociological *complex contagion* hypothesis in the spread of information, according to which more controversial topics require multiple sources of contact before being adopted. González-Bailón, Borge-Holthoefer, Rivero, and Moreno (2011) evaluate the impact of social media platforms on the diffusion of social protest and show that central individuals are more likely to initiate larger waves of messages. Both studies rely on empirical data from Twitter as it has grown to be a central hub for widespread and targeted communication.

Apart from network effects, online communication has also been researched within the broader context of SMO mobilization. A number of studies have examined more specifically the way SMOs mobilize followers through new media. The majority of this line of research focuses on the *opportunities* that internet mobilization affords to SMOs. For example, comparing online and offline mobilization, Stein (2009) argues that the internet enables SMOs to mobilize followers "through a combination of greater speed, lesser expense, further geographical reach and relatively unlimited content capacity compared to older forms of print and electronic media". Similarly, Bimber (1998), Diani (2000) and Ward et al. (2003) suggest that electronic communication reduces the cost of information diffusion, thus facilitating mobilization and leading to a broader political participation of society. Postmes and Brunsting (2002) find that the internet's relative ease of reaching broad audiences empowers organizations and movements. And Van Aelst and Walgrave (2002) argue that the use of the internet furthermore levels the playing field between organizations with different resource endowments. Changing the focus from the *opportunities* of online mobilization to the *identities* of online followers, Krueger (2006) adds to the literature by pointing out differences between online and conventional offline mobilization of political parties and organizations. His findings suggest that many longstanding and robust predictors for conventional mobilization efforts (such as socio-economic traits of individuals) fail to predict who is actually mobilized online, whereas both political motivation and technical internet skills prove to be strong predictors. While these studies all identify online communication as an increasingly utilized channel for mobilization activities, they view it as just another medium in the communication portfolio of SMOs. But precisely because the virtual space levels the playing field and reduces costs and distances, it is not straightforward to assume that online mobilization is governed by the same mechanisms as traditional mobilization channels. An exhaustive analysis of underlying processes and effective determinants of successful online mobilization activities is still missing. In this sense the analysis of online social networks is still inadequately connected to the original theory of SMO growth and mobilization (Stein, 2009).

In order to address this gap, this paper develops a modular approach to examine the determinants and mechanisms of online SMO mobilization based on data sourced from Twitter. Theocharis, Lowe, Deth, and García-Albacete (2015) show that Twitter is a widespread tool for online mobilization efforts, which is, however, used primarily for discussions and the sharing of information – coordinated actions are not the focus of this mobilization channel. This is in line with Vissers, Hooghe, Stolle, and Mahéo (2012) who find clear medium-specific effects of mobilization: Online activities produce further information sharing, while face-to-face contact is more likely to result in active, real-world participation. Returning to the traditional framework by Klandermans (1984) and Klandermans and Oegema (1987), this suggests that online mobilization efforts should primarily be attributed to consensus mobilization. This stage in the overall process requires reaching and communicating with a large number of potential and new activists in order to disseminate information that can align them with an organization's cause.

Success of mobilization is consequently operationalized in this paper in two distinct ways: (i) The number of people reached with a message can be measured by its popularity. Messages that are retweeted more often are read and shared by more potential followers of an SMO. (ii) In order to reach beyond the set of existing activists, messages need to be read by people previously unconnected to an organization. Therefore the distance a message travels through the communication network helps assess its contribution to the mobilization efforts. Section 4.4.3 below offers a detailed explanation as to how these measures are constructed from the Twitter data.

In order to explain varying success of online mobilization activities, the early social psychology literature already indicates that the content of communication is essential. But for a more precise operationalization, this paper builds upon research in communication theory that determines which properties of online communication affect its dissemination: Stieglitz and Dang-Xuan (2013) find that the tendency to share information on Twitter is positively influenced by the level of emotions inherent in a message. Similarly, Hansen et al. (2011) study the link between the virality of messages and their capacity to evoke emotions. For messages that represent news they find that negative sentiments increase the likelihood of viral dissemination. In order to assess the effect of message sentiment in the context of SMO mobilization, one of the building blocks of the analysis below is therefore an evaluation of message sentiment. Subsequently, its effect on the mobilization success in terms of message popularity and reach can be estimated. Based on the cited online communication research, negative sentiments should be more likely to spread among a large number of people. While this obviously increases the chances of a negative message reaching more distant, previously unattached individuals, the actual effect depends on the network topology. For example, highly clustered communities might lead to messages cycling among the same set of closely connected people.

This conditional effect already shows the need to consider networks in more detail. As previous analyses of online communication such as González-Bailón et al. (2011) and Romero et al. (2011) have demonstrated, a network perspective provides valuable insights and data from Twitter furthermore offer necessary information to establish network structures. Since both analyses of online networks as well as traditional studies of personal ties emphasize the importance of centrality for the mobilization process, messages by central, well-connected individuals should reach a larger number and more distant people.

Taken together, this paper argues that in order to understand the mechanisms of online mobilization activities, two dimensions are important: First, emotional characteristics of the message spread via social media, and second, the network topology or characteristics of the individual messenger who spreads information. Both aspects are incorporated in a general framework in order to be able to estimate their concurrent effects within the mobilization process.

## 4.3 Data

The empirical approach presented in this paper is demonstrated by application to two movements: the *environmental* and the *nuclear disarmament* movement. Both are chosen to be sufficiently distinct, so as not to exhibit any overlap in their network members, while also representing large and well-established social movements that encompass multiple active organizations. In order to analyze the online mobilization efforts of specific SMOs, this paper selects six organizations from these movements. For the selection of the individual organizations, a first and more practice-driven requirement is that all organizations be active on Twitter, as this social media platform is widely-used by different kinds of organizations and thus a rich data source for the subsequent analysis. All organizations also need to be predominantly English-speaking in order to be able to conduct a computational content analysis of the collected communication data: The bulk of dictionaries used for this purpose is only available in English and comparisons across different languages are still not sufficiently researched. Apart from these requirements, the distinct SMOs are selected to represent a diverse array of organizations along several dimensions within each movement: First, they differ in their respective age. While long-standing organizations with several decades of experience would seem to be at an advantage regarding the dissemination of information and the expansion of their networks, it seems reasonable to assume that young and recently-founded SMOs may be more focused on the use of social media. Second, the organizational structure and method of operation differs among the selected cases. It ranges from organizations solely working on a national level to thoroughly international ones that in turn rely on local chapters. Third, the SMOs differ in their resource endowments – measured by the latest available data on net assets – as it determines the potential scope of mobilization efforts. Table 4.1 gives an overview of these properties for the selected SMOs.

Including an array of diverse organizations in each movement helps ensure the robustness of results derived from their online communication. The dataset thus provides insights that can be generalized within each movement. Additionally, by using multiple movements, the analysis gains a comparative dimension to furthermore point out general mechanisms that are valid irrespective of the movement or reveal fundamental differences between them.

***Table 4.1:*** *Properties of selected SMOs*

| Organization | Twitter Name | Founded | Net Assets | Structure |
|---|---|---|---|---|
| *Environmental Movement* | | | | |
| Environmental Defense Fund | @EnvDefenseFund | 1967 | $ 211 527 199 | US-based, international |
| Conservation International | @ConservationOrg | 1987 | $ 199 204 000 | US-based, international |
| Citizens Climate Lobby | @citizensclimate | 2007 | $ 44 457 | US-based, local chapters worldwide |
| *Nuclear Disarmament Movement* | | | | |
| Campaign for Nuclear Disarmament | @CNDuk | 1957 | £ 671 964 | UK-based, national and local |
| Nuclear Age Peace Foundation | @napf | 1982 | $ 4 368 849 | US-based, international |
| Global Zero | @globalzero | 2008 | $ 616 672 | International initiative, local chapters |

### 4.3.1 Creating the Dataset

This section describes the approach taken to create the dataset for the subsequent analysis. It is compiled using Twitter's freely accessible RESTful API, which allows for retrieving tweets (also called statuses) either from a specified user or simply based on search terms. In order to collect only those tweets that belong to an extended network of each selected SMO, it is necessary to apply a method that identifies and extracts them from the plethora of messages on Twitter. This can be accomplished by using the hashtags that each SMO has used to put their messages into a specific context, thus letting the organizations themselves define which tweets are relevant. From the set of tweets taken from each official SMO account a set $H$ of the 100 most frequently used hashtags is extracted and serves as a collection of search terms to find other tweets that have taken part in these conversations.[1] Those constitute the set of tweets $S$ belonging to the extended SMO network; each single tweet $s$ contains at least one hashtag $h_i \in H$.[2]

$$H = \{h_1, h_2, \ldots, h_{100}\} \tag{4.1}$$

$$S = \{s : \exists h_i \in s\} \quad i = 1, ..., 100 \tag{4.2}$$

In order to be able to construct an organizational communication network from the plain set of tweets, its elemental structure, i.e. the building blocks of the network, needs to be defined. Based on the information the dataset contains, it seems natural to think of users as the nodes of the network. The contents as well as the number of their tweets will then help define the role of each node. Some individuals might for example serve as distributory information hubs, while others generate original information or participate only in discussions on very specific topics.

Deciding on how to connect the nodes to one another requires slightly more attention. Even though Twitter users effectively constitute a network based on their friendship and follower relations, Huberman, Romero, and Wu (2008) demonstrate that links between individual users based these relationships tend to be superficial and do not necessarily reflect any type of joint interest or reciprocated communication. Following someone with a click of a button is cheap and does not lend the relationship any meaning yet (Cha, Haddadi, Benevenuto, & Gummadi, 2010). Therefore, such relationships would vastly overstate the extent and the density of the network. Previous studies, e.g. by Romero et al. (2011) and Tan et al. (2011), use a more suitable approach to work out the "hidden social network" (Huberman et al., 2008). Two users are only connected if they engage in active communication:

[1] Currently, the API returns up to 3200 tweets per search. Using all 100 key hashtags each SMO network could thus consist of a maximum of 320 000 tweets.

[2] A separate subscript denoting the SMO is omitted in this exposition in order to preserve legibility.

either a user includes someone else's name in a tweet, which is called a *mention* and requires adding "@username" to the body of a message; or a user *retweets* somebody else's message (which can be identified via the addition of "RT @username:" at the start of the tweet). In the former case, the link points from the tweeting user to the person being mentioned; in the latter, it points towards the retweeter. This way the directed relationships depict the flow of information across the network.

Another useful benefit gained from constructing links in the network based on *mentions* and *retweets* is a higher level of detailed information about the relationships: Every time two users engage in direct communication another link is added to the network, uniquely identified by the timestamp of the tweet and its key hashtag. So instead of only knowing whether or not two members of the network are connected, the network also provides insights on the frequency of their contact, the exact point in time and the topic over which this relationship was established.

Formally, the dataset of tweets and their respective authors is translated into a directed multigraph of the set of nodes $V$, representing all users of the network, and the multiset of ordered pairs of nodes $A$:

$$G := (V, A) \quad \text{with} \quad A = \{a_{mnt}\}, \tag{4.3}$$

where $m, n = 1, \ldots, M$ uniquely identifies the users as $M = \|V\|$ and $t = 0, ..., T$ denotes the discrete point in time at which a tweet has been created. Multiple arcs between two nodes are allowed as each communication between them establishes a new link. The adjacency matrix $A$ is therefore a three-dimensional array of size $M \times M \times T$.

### 4.3.2 Data & Network Description

The data for all six SMOs amount to a total of $867\,106$ tweets from $449\,169$ users and were collected on 24 and 25 June 2014. As table 4.2 shows, the number of tweets varies across the different SMO networks between $1.24 \times 10^5$ and $1.75 \times 10^5$ which translates into $1.79$ to $2.07$ tweets per user.

The size and structure of the resulting network graphs are outlined in table 4.3. All extended SMO networks have approximately the same size with respect to their diameter and the variance in their number of nodes and edges is proportional to the number of collected tweets. Generally, a similar number of tweets across the organizational networks could be attributed to the limits of the Twitter API; but as table 4.2 shows, the theoretical maximum of $320\,000$ tweets has not been encountered for any of the organizations. Therefore, the differences in the number of nodes and edges do suggest a larger set of active users in the networks of the *Nuclear Age Peace Foundation* and *Global Zero* (at least during the time period covered by the data). At the same time, their networks also show a slightly lower density than the others, coupled with a lower average tie strength. This suggests that while both organizations are part of larger extended networks, their users exhibit looser relationships. By contrast, the oldest organizations in both movements, *Environmental Defense Fund* and *Campaign for Nuclear Disarmament*, belong to networks with the highest density, so a larger share of all possible connections between users in these networks is being actively used to share and disseminate information. The network of *Conservation International* exhibits the highest average tie strength: Those members of the network that communicate with one another do so more often than members of the other networks.

Beyond information on the overall network structure, table 4.3 also points out differences between the organizations with respect to their own network integration. The degree of the SMO nodes is a measure for the sum of inward and outward links to other members of the network. Among the anti-nuclear SMOs it is the oldest one, *Campaign for Nuclear Disarmament*, that maintains by far the most direct connections; while *Global Zero*, who has only been founded in the year 2008, has the fewest. In the environmental movement, however, these roles are almost reversed: The oldest SMO, *Environmental Defense Fund*, exhibits the smallest degree, whereas the longer-established *Conservation International* as well as the young *Citizens Climate Lobby* are similarly well connected.

More generally, the data also show that within each movement the individual organizational networks strongly overlap. This does not come as a surprise since their purposes are closely aligned despite their different focuses. The networks constructed from the Twitter data are, however, also helpful in showing how closely different SMOs are connected within the broader network of their movement. In the environmental movement, at most two edges separate the SMOs from one another. In the nuclear disarmament movement, the SMOs are all just one edge apart and thus directly connected through active communication.

## 4.4 Analysis

The collected data provide detailed insight into the communication structure and flow of information within both social movements. As outlined in section 4.2 above,

***Table 4.2:*** *Data summary statistics per organization*

| Organization | #Tweets | #Users | min(#Tweets) | max(#Tweets) | var(#Tweets) |
|---|---|---|---|---|---|
| EnvDefenseFund | 123 921 | 59 955 | 1 | 750 | 59.86 |
| ConservationOrg | 143 266 | 72 002 | 1 | 1133 | 67.58 |
| citizensclimate | 131 270 | 65 291 | 1 | 750 | 56.26 |
| CNDuk | 123 593 | 63 437 | 1 | 467 | 31.99 |
| napf | 170 014 | 90 790 | 1 | 617 | 40.27 |
| globalzero | 175 042 | 97 694 | 1 | 1313 | 49.02 |

***Table 4.3:*** *Graph summary statistics*

| Organization | #Nodes | #Edges | Density | Tie Strength | Diameter | Degree (SMO) |
|---|---|---|---|---|---|---|
| EnvDefenseFund | 59 896 | 101 139 | $1.8\times10^{-5}$ | 3.38 | 25 | 1078 |
| ConservationOrg | 67 742 | 130 596 | $1.6\times10^{-5}$ | 3.86 | 24 | 3293 |
| citizensclimate | 66 419 | 123 069 | $1.6\times10^{-5}$ | 3.71 | 23 | 2835 |
| CNDuk | 62 042 | 110 893 | $1.8\times10^{-5}$ | 3.57 | 27 | 4120 |
| napf | 86 043 | 140 531 | $1.2\times10^{-5}$ | 3.27 | 27 | 3147 |
| globalzero | 92 711 | 140 263 | $1.0\times10^{-5}$ | 3.03 | 26 | 1892 |

*Note:* Density is the ratio of the number of observed edges and the number of possible edges. Tie Strength denotes the average weighted degree of nodes within each network.

two dimensions are important to comprehend the mechanisms of online mobilization activities by SMOs: the sentiment of messages spread via social media, as well as the network topology. In order to empirically examine this proposition, this paper combines two methodological approaches within a general framwork. First, to study the influence of message content on SMO mobilization, this section performs a sentiment analysis of all tweets. To study how network topology determines SMO mobilization, this section then calculates network metrics for each active user and maps them to the set of tweets. Finally, these results are used to disentangle the flow of information within the movements and explain its dissemination as a means of consensus mobilization.

### 4.4.1 Sentiment Analysis

The large size of the dataset lends itself to a computational approach for a sentiment analysis of each tweet. In that regard, Grimmer and Stewart (2013) provide an extensive account of the current methods, possibilities and limitations of modern text analysis. Furthermore, Schwartz and Ungar (2015) offer an up-to-date review of automated content analysis of social media. Since applying a machine learning method is beyond the scope of this paper, the analysis follows a lexicon-based approach to assess the sentiments of tweets.

There are a number of widely used dictionaries available for this purpose and each one has its preferred area of application. As the dataset of tweets represents a rather large body of text from a high number of different authors lacking a specific domain or unified terminology, an appropriate dictionary should (i) cover a broad set of words, (ii) offer a sentiment scaling beyond a dichotomous measure and (iii) preserve some of the variance by using a multi-dimensional concept of sentiments. Such a dictionary also helps preserve the "natural ambiguity" of language which lets individuals perceive words in different ways (Andreevskaia & Bergler, 2006).

This paper therefore uses an updated version of the ANEW dictionary provided by Warriner, Kuperman, and Brysbaert (2013) that heavily extends the original dictionary by Bradley and Lang (1999) to include almost $14\,000$ English words and their affective scores in the three dimensions "valence", "arousal" and "dominance". These are based on the theory of emotions put forth by Osgood, Suci, and Tannenbaum (1957). The extented ANEW dictionary (xANEW) was created using Amazon's Mechanical Turk platform and belongs to the category of *crowdsourced dictionaries*. While such a dictionary only encompasses a closed vocabulary and is not derived from the data it is applied to, it is less susceptible to bias and oversight (Schwartz & Ungar, 2015).
Furthermore, its scores reflect a reader's perception of words (Young & Soroka, 2012). This is beneficial to the purpose of the analysis, examining the way members of the networks perceive the flow of information. In each dimension the score is rated on a continuous scale from 1 to 9, low values of which correspond to unhappy/calm/submissive and high ones to happy/excited/in control. For an easier interpretation they are rescaled to the closed interval $[-1, 1]$.

The sentiment scores for all tweets are calculated as follows: Each entry in dictionary $\mathcal{D}$ is mapped to a tupel of affective scores $(v(\cdot), a(\cdot), d(\cdot))$. In order to determine the sentiment of a tweet $s_j$, only the intersection $\hat{s}_j = s_j \cap \mathcal{D}$ of all words found in the dictionary is relevant. Then their average affective scores are given by

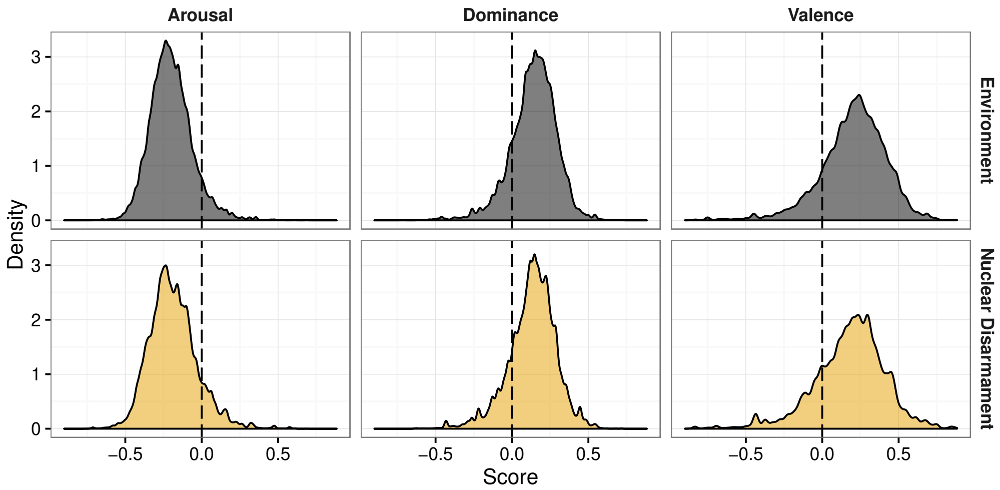


***Figure 4.1:*** *Distribution of affect scores across movements*

the vector

$$\phi(s_j) = \frac{1}{K} \sum_{k=1}^{K} \begin{pmatrix} v(\hat{s}_{jk}) \\ a(\hat{s}_{jk}) \\ d(\hat{s}_{jk}) \end{pmatrix}, \tag{4.4}$$

where $K = \|\hat{s}_j\|$ denotes the number of matched words in any given tweet.

The resulting distribution of affects identified in all tweets is shown in figure 4.1 for both movements. Except for minor kinks in the densities, both movements exhibit the same distribution of affects. This is not an unexpected finding: Due to the large number of messages used for the sentiment analysis, the set of words closely resembles the dictionary itself and the underlying affects approach the distribution of affects within the entire dictionary (see Warriner et al., 2013). While this plain distribution of affects does not show differences between both movements, it is not suited to evaluate the use and prevalence of affective language within the networks of communication. For this purpose the next section will include a measure of network structure.

But first, in order to ensure the validity of these affect values, a complementary sentiment analysis using other dictionaries should be performed. Employing the Syuzhet-package for the R environment by Jockers (2015), which incorporates three different dictionaries (Bing (Hu & Liu, 2004), AFINN (Nielsen, 2011) and NRC (Mohammad & Turney, 2013)), as well as using the Lexicoder Sentiment Dic-

***Table 4.4:*** *Correlation coefficients for valence scores across dictionaries*

| | xANEW | Bing | AFINN | NRC |
|---|---|---|---|---|
| Bing | 0.5383 | | | |
| AFINN | 0.5214 | 0.7016 | | |
| NRC | 0.5170 | 0.5201 | 0.4808 | |
| LSD | 0.5510 | 0.6767 | 0.6641 | 0.5310 |

*Note:* $N = 764\,194$ for the first column and $N = 867\,106$ otherwise. All correlations are significant at $p < 0.001$.

tionary (LSD) recently developed and tested by Young and Soroka (2012) provides sufficient data to validate the scores delivered by the xANEW. Since all of these supplementary dictionaries only include a measurement of valence in text, the comparison is confined to this dimension.

As Table 4.4 shows, all five dictionaries yield valence scores that are pairwise moderately or even strongly correlated. Since each dictionary is built to serve a slightly different purpose (e.g. being applied to a specific domain with a given terminology), absence of a perfect correlation is not suprising. Young and Soroka (2012) observe very similar values to those in table 4.4 in their comparison across automated dictionaries. More importantly, with its broad scope the xANEW exhibits similarities with measures from all other dictionaries, suggesting that it is a suitable option to quantify the sentiment of the large number of tweets from different authors.

### 4.4.2 Including Network Structure

The second module of the approach presented in this paper includes the topology of the communication network to examine the way it determines the effectiveness of SMO mobilization in social media. As with the role of individuals in traditional mobilization efforts, some users of a virtual network can be expected to be more influential or at least more vocal than others. Thus, their messages – and the sentiments they convey – would be more prevalent and dominate the overall network sentiment. In order to evaluate online mobilization, these diverse roles of users need to be accounted for and messages should be weighted according to the importance of their author in the network.

Differentiation between individual members of the network according to their potential prevalence and visibility requires some measure of centrality that reflects and characterizes their role. As this analysis focuses on the mechanisms of communication and information dissemination within directed SMO networks, centrality of users is expressed by their normalized betweenness centrality.[3] It measures how often a given node is exposed to a message traversing the network on the shortest possible path between two randomly chosen nodes. If the node of interest is located on a large number of shortest paths, it effectively serves as a distributory hub providing information to different parts and (possibly remote) user groups of the network.

To illustrate the effect of accounting for network centrality, figure 4.2 once more depicts the distribution of affects found in the tweets of each movement; this time, however, each tweet is weighted according to the betweenness centrality of its original author.[4] In contrast to the unweighted version, this results in a multimodal distribution with distinct spikes at the dominant levels in each affective dimension. The bimodal distribution of valence scores in the environmental movement makes this especially clear; but since the modes do not lie on opposite sides of the scale's midpoint at zero, they do not so much depict a split between conflictive sentiments but rather usage of either fairly neutral or very happy words.

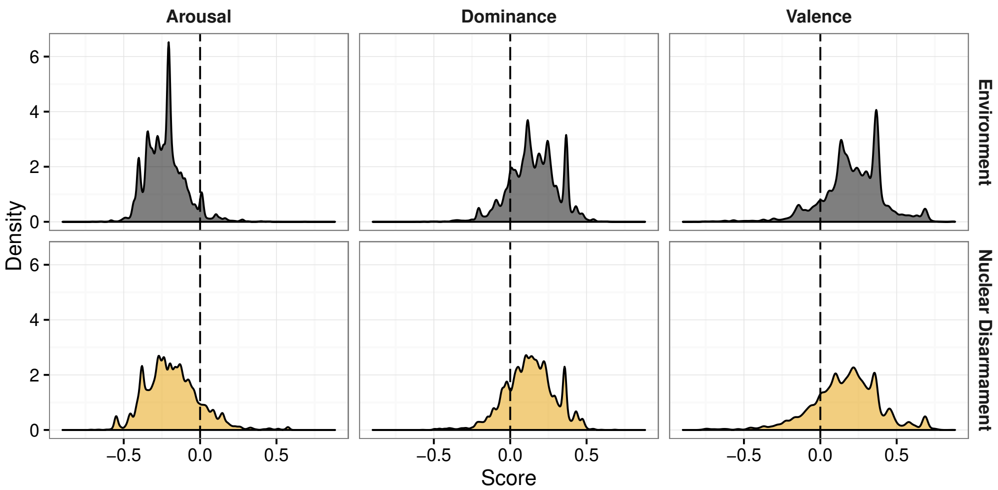


***Figure 4.2:** Distribution of betweenness-weighted affect scores across movements*

[3]All betweenness values of an SMO network are normalized according to $\tilde{b}_i = \frac{b_i - b^{\min}}{b^{\max} - b^{\min}}$.

[4]For ordinary tweets, the original author is the sender; for retweets the centrality of the person being retweeted is used.

### 4.4.3 Information Flow Models

Using the modules developed and outlined above, this section combines them in a general framework that estimates the impact of the message (the sentiment measures) as well as of the messenger (the network centrality) on the effectiveness of SMO social media mobilization. In general, mobilization efforts aim at reaching and communicating with as many potential and new activists as possible. This reflects two dimensions of mobilization that need to be taken into account: Information not only needs to be disseminated effectively among existing members but must also speak to individuals who are so far unconnected to an SMO. Consequently, this paper operationalizes mobilization success in two distinct ways as (i) the *popularity* of messages as well as (ii) their *reach*, i.e. the distance of dissemination throughout the networks.

#### Message Popularity

In order to explain the popularity of a message within the network, Twitter offers the unique possibility to track the number of times a single tweet is forwarded by other users. Thus the first operationalization of SMO social media mobilization is the number of retweets of a message. For each tweet $s_j$ the dataset contains information on how often it has been retweeted at the time of data retrieval. Unfortunately, the way the Twitter API returns search results poses a challenge to using this raw data as a dependent variable: Since the largest part of tweets in the dataset has been created within two days before the query, retweet counts are very likely right-censored. Not enough time had passed when the data was retrieved to confidently assume the given retweet count to be sufficiently close to its final value. As a result, the number of zero counts is highly inflated and any estimated effects of sentiment and network topology on popularity would be biased. In order to resolve this issue, the counts for all relevant tweets have been updated in an additional query to the Twitter API more than three months after the initial data collection. Due to tweets being generally short-lived messages, it seems reasonable to assume this updated count to persist.

Identifying the retweet count as $c(s_j) = c_j$, the stylized model to be estimated is

$$c_j = \alpha + \beta' \phi(s_j) + \gamma \tilde{b}(\omega_j) + \varepsilon_j, \tag{4.5}$$

where $\phi(s_j)$ is a vector of affect scores, $\omega_j$ is the original author of a given tweet $s_j$ and $\tilde{b}(\omega_j)$ is her normalized betweenness centrality in the network.

*Table 4.5: Descriptive statistics of variables*

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| *Environment* | | | | |
| Retweet Count | 35.95 | 927.94 | 0.00 | 123 494.00 |
| Valence | 0.18 | 0.24 | −0.90 | 0.88 |
| Arousal | −0.18 | 0.16 | −0.76 | 0.70 |
| Dominance | 0.14 | 0.16 | −0.83 | 0.72 |
| Betweenness | 0.03 | 0.16 | 0.00 | 1.00 |
| *Nuclear Disarmament* | | | | |
| Retweet Count | 53.35 | 1145.03 | 0.00 | 144 181.00 |
| Valence | 0.20 | 0.21 | −0.88 | 0.88 |
| Arousal | −0.20 | 0.14 | −0.71 | 0.70 |
| Dominance | 0.14 | 0.15 | −0.72 | 0.72 |
| Betweenness | 0.04 | 0.18 | 0.00 | 1.00 |

Descriptive statistics of the data are shown in table 4.5. A first glance at the mean and standard deviation of retweet counts in both movements already suggests that a simple Poisson model for estimating them is not appropriate as the data does not conform with its strict equidispersion requirement.[5] Using a negative binomial (NegBin) model presents an appropriate method to accomodate overdispersion (Zeileis, Kleiber, & Jackman, 2008). As the set of information criteria listed in table 4.6 clearly shows, the NegBin model improves the fit immensely, as it can handle the overdispersed counts. Additionally, however, the data still exhibit an inflated number of zero counts that would not be expected from a Poisson or NegBin model. In this case it is common to either specify a zero-inflated or a hurdle model, both of which are discussed in detail by Cameron and Trivedi (2013) and Zeileis et al. (2008). Both types of models consist of two components, one part to model zero counts and a count part for positive observations. Despite their similar approaches, the hurdle model is more appropriate based on the information criteria in table 4.6. The zero-inflated model assumes two sources of zeros whereas the hurdle model uses a truncated count component to strictly separate both kinds of realizations. Since all observations in the dataset of tweets underly the same pro-

[5]A more formal test is fitting a Quasi-Poisson model and estimating a dispersion parameter in the networks of both movements. This yields parameters of $1.65 \times 10^4$ and $2.39 \times 10^4$ and thus clearly shows the need to account for the overdispersed data.

***Table 4.6:*** *Retweet count models: Information criteria*

| | Pois | NegBin | Zinb | Hurdle |
|---|---|---|---|---|
| *Environment* | | | | |
| k | 5 | 6 | 11 | 11 |
| lnL | −18 074 367 | −229 230 | −229 231 | −214 383 |
| AIC | 36 148 743 | 458 474 | 458 484 | 428 789 |
| BIC | 36 148 790 | 458 530 | 458 586 | 428 891 |
| *Nuclear Disarmament* | | | | |
| k | 5 | 6 | 11 | 11 |
| lnL | −13 005 524 | −224 925 | −224 904 | −213 210 |
| AIC | 26 011 058 | 449 863 | 449 829 | 426 442 |
| BIC | 26 011 105 | 449 919 | 449 932 | 426 545 |

cess, there cannot be a second source for zero counts – messages are either passed on or not. Thus the hurdle model (using a negative binomial distribution) is chosen to estimate the determinants of a tweet's popularity.

Table 4.7 contains the regression results for both movements. The estimated coefficients in the zero model show the influence of affects and network centrality on the likelihood of a message receiving at least one retweet. Positive coefficients imply that higher values of the respective variable increase the likelihood of a retweet and thus of crossing the hurdle. The environmental and the anti-nuclear movement show entirely differential preferences governing the initial retweet of messages: In line with theory on traditional mobilization efforts, a central network position is beneficial in the environmental movement to being noticed at all. This is not the case, however, for the anti-nuclear movement, in which a high betweenness centrality decreases the likelihood of a retweet. It seems that among members of the anti-nuclear movement's network decentral users may stir up attention while central actors provide information that is only being absorbed. With regard to the affects conveyed in a message, the anti-nuclear movement only favours unhappy sentiments. In contrast, while the valence dimension shows no significant effect in the environmental movement, excited as well as submissive messages are more likely to be passed on.

Moving to the count part of the hurdle model, the factors contributing to a widespread popularity of a given message are the same for both movements: Contrary to

***Table 4.7:*** *Retweet counts: Negative binomial hurdle model*

| | Environment | Nuclear Disarmament |
|---|---|---|
| *Zero-Stage* | | |
| (Intercept) | 0.69 (0.01)*** | 0.54 (0.01)*** |
| Betweenness | 0.10 (0.04)** | −0.20 (0.04)*** |
| Valence | −0.05 (0.05) | −0.43 (0.05)*** |
| Arousal | 0.16 (0.05)** | 0.07 (0.05) |
| Dominance | −0.66 (0.07)*** | 0.00 (0.07) |
| *Count-Stage* | | |
| (Intercept) | −12.22 (33.43) | −11.68 (22.33) |
| Betweenness | −2.54 (0.05)*** | −3.25 (0.05)*** |
| Valence | 1.03 (0.05)*** | 2.42 (0.07)*** |
| Arousal | 0.87 (0.07)*** | 0.40 (0.08)*** |
| Dominance | −1.23 (0.08)*** | −1.47 (0.11)*** |
| Log(theta) | −18.40 (33.43) | −17.31 (22.33) |
| AIC | 428 789 | 426 442 |
| Log Likelihood | −214 383 | −213 210 |
| Num. obs. | 83 689 | 82 801 |

*p < .05; **p < .01; ***p < .001

expectations formed by research on traditional mobilization, the centrality of an author in the organizational network is not conducive to her message being noticed and passed on by many others. In both movements the estimated coefficient for the effect of centrality is highly significant and negative. Among the affects of messages, valence as well as dominance both have large and significant effects: High valence scores (i.e. words such as “honest”, “love” or “joy”) increase the expected retweet count, especially in the nuclear disarmament movement, where the effect is more pronounced. At the same time a low dominance score (from words like “earthquake”, “catastrophic” or “doom”) makes a message more popular. Arousal also exhibits a positive, though slightly smaller effect in both movements.

Taken together, the two stages of the model depict a consistent behaviour of the environmental network. A happy, excited and/or submissive message, possibly sent by a central member of the network, is more likely to pass the hurdle and receive a lot of attention. By contrast, the nuclear disarmament movement network seems slightly inconsistent: Only unhappy messages tend to have a higher chance of passing the hurdle and centrality is harmful. But in order to reach a large number of network members, the message content should be happy. In conclusion, only excited and/or submissive messages from non-central members are more likely to gain widespread attention – whether or not they pass the hurdle, however, seems to follow no clear mechanism.

Common to both movement networks is the lack of importance of the messenger; it is rather the content of a message that affects its widespread popularity. Happy, excited or submissive sentiments will generally reach a larger audience.

### Distance of Dissemination

Not only should SMOs be interested in crafting popular messages that reach a large number of potential activists; it should be similarly important whether a message has the capacity to extend their network and reach individuals who have not directly been in touch with them before. Therefore, the second operationalization of a successful social media mobilization strategy is the dissemination distance of tweets.

So instead of purely focusing on the bare number of readers, this approach considers their respective distances based on the network structure that results from the dataset. This effectively determines how far tweets travel across the network until they get adopted by another user. Unlike the retweet count there is no readily available measure for this purpose and it needs to be constructed. Two difficulties arise from this task: First, not every tweet can be used to measure distances since the majority of them may well be read, but without any kind of reaction or reference there is no way of knowing about it. This part of the analysis is therefore restricted to retweets as they are, by definition, a user's reaction to an original tweet and thus identify the two nodes involved. The set of retweets is a subset of all tweets, $R \subsetneq S$, and for each retweet $r_j \in R$ its original author and the user reacting to it are denoted by $\omega(r_j) = \omega_j$ and $\rho(r_j) = \rho_j$, respectively.

Focussing only on tweets in $R$ directly leads to the second difficulty: By construction the networks exhibit a link between two nodes if one of them retweets the other's message. Determining their distance would thus always result in the finding that they are in fact neighbours and thus only one edge apart. For this reason distances are not measured within a static network built from the entire dataset of tweets; instead information from the three-dimensional adjacency array is used in order to determine the distances between two nodes up to the point in time when the given retweet established a new edge. This is possible by constructing edge-induced subgraphs based on the time $\theta(r_j) = \theta_j$ of each retweet:

$$G_j(V, A_j) \quad \text{with } A_j = \{a_{mnt} : t < \theta_j\}, \quad \forall r_j \in R \tag{4.6}$$

In each subgraph the geodesic distance $\delta(\omega_j, \rho_j)$ between the two nodes involved describes the number of edges along the shortest path connecting them (Bouttier, Di Francesco, & Guitter, 2003). In order to find the shortest path, the Dijkstra algorithm is used (Dijkstra, 1959).[6] Defined in this way, however, the measure of mobilization success would end up being a zero-truncated variable since the number of edges between two distinct nodes must by definition at least be one. Without accounting for this circumstance, any parameter estimations would be inconsistent (Cameron & Trivedi, 2013; Gurmu, 1991). This is easily mitigated by slightly re-defining the distance to measure the number of edges beyond all direct neighbours, $\delta^1(\omega_j, \rho_j) = \delta(\omega_j, \rho_j) - 1$.

If two nodes are not connected, their distance is infinity by convention. Even though it would be of great interest to identify messages that are creating new links between previously unconnected nodes within the networks, these observations are excluded from the analysis because the dataset does not permit distinguishing between truly new connections and those that simply do not exist in the sample snapshot in time.[7]

A last thing to consider carefully are observations from an early point in time among the sample tweets. They require the overall graph to be reduced extensively since only a small fraction of all edges is established by then. In such a subgraph measures of centrality are much more polarized, resulting in outliers in the data and biased estimations. Furthermore distances between nodes are more likely to be overestimated on account of the limited amount of data. A burn-in period during which the network is constructed can handle these challanges appropriately. Therefore only observations that were made after the graph exhibits at least 25 percent of its maximum size enter the subsequent empirical analysis.[8]

[6] In spite of the graph's directedness, this calculation neglects the direction of edges to avoid inflating the distance due to the timewise limited sample.

[7] Using a broader sample of tweets by gathering data over the course of several months might mitigate this problem (see e.g. Romero et al. (2011) for applications of such large-scale datasets).

[8] The length of burn-in periods often seems to be determined haphazardly – usually some round number is chosen. In order to avoid this impression and to put the choice on a methodologically

The stylized model fitted to estimate the influence of affects $\phi(r_j)$ as well as network centrality measures $\zeta(\omega_j)$ on the maximum distance a message might travel through the network is as follows:

$$\delta^1(\omega_j, \rho_j) = \alpha + \beta^{'}\phi(r_j) + \gamma^{'}\zeta(\omega_j) + \varepsilon_j \tag{4.7}$$

As before, the data exhibit overdispersion and added zeros, so a negative binomial hurdle model as well as ZINB again seem appropriate. Both models lead to very similar estimated coefficients and the same qualitative results, however this time, the overall likelihood of the ZINB model is slightly higher. The interpretation of the ZINB with two concurrent sources of zeros is also more suited for the limited dataset used here: Part of the zero observations indicate that a given tweet has disseminated only within the confines of the author's neighbourhood. But some zero observations may stem from the fact that another user who passed on that message is just not part of the sample. The estimation results are presented in table 4.8 (table 4.9 in the appendix summarises the estimations of the hurdle model for completeness).

Two measures of centrality are included in the model: As before, a node's betweenness centrality measures its importance and influence in the network. But since each observation originates from its own edge-induced subgraph, it is also necessary to control for the varying network sizes. Therefore the relative degree is a version of the standard (in- and outward) degree centrality, normalized by the total number of edges present in the respective subgraph and thus confining the measure to the unit interval.

The zero stage of the model represents the publicity of a messenger and her message. In contrast to the hurdle model, the ZINB estimates the probability of observing a zero count. Thus the large and negative coefficient for a node's betweenness centrality indicates that a central actor is much more likely to reach other members of the network beyond her immediate neighbourhood. This is the case in both movements and clearly dominates the effects of message affects. As a counterbalance a high relative degree increases the probability of messages staying among direct neighbours. This is in line with expectations, since a higher relative degree means that the individual is directly connected to a larger set of other network

sound basis, the analysis was run with different levels of burn-in periods from 2% to 50%. The results revealed no common threshold below which outliers bias the results – the exact length of the burn-in does not matter. Therefore a value was chosen that ensures a reasonably large network while still maintaining a sufficiently large number of observations.

***Table 4.8:*** *Retweet distances: Zero-inflated negative binomial model*

| | Environment | Nuclear Disarmament |
|---|---|---|
| *Zero-Stage* | | |
| (Intercept) | −0.03 (0.03) | −0.08 (0.03)* |
| Betweenness | −30.37 (2.36)*** | −36.86 (3.95)*** |
| Relative Degree | 103.17 (8.20)*** | 136.43 (13.41)*** |
| Valence | 0.46 (0.11)*** | 1.54 (0.13)*** |
| Arousal | 0.30 (0.12)* | 0.31 (0.12)** |
| Dominance | 0.53 (0.15)*** | −0.77 (0.18)*** |
| *Count-Stage* | | |
| (Intercept) | 1.16 (0.01)*** | 1.15 (0.02)*** |
| Betweenness | −1.60 (0.19)*** | −2.28 (0.32)*** |
| Relative Degree | −8.96 (2.47)*** | −0.08 (2.98) |
| Valence | −0.05 (0.05) | −0.09 (0.07) |
| Arousal | 0.17 (0.06)** | −0.03 (0.06) |
| Dominance | 0.10 (0.07) | 0.13 (0.10) |
| Log(theta) | 2.47 (0.09)*** | 1.23 (0.05)*** |
| AIC | 59 571 | 54 703 |
| Log Likelihood | −29 772 | −27 338 |
| Num. obs. | 19 340 | 17 196 |

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

members. It should therefore become more unlikely to reach users beyond the direct neighbourhood. In both movements, unhappy messages are more likely to be disseminated further. The only difference shows up in the dominance dimension: While members of the anti-nuclear movement tend to respond to high dominance scores, the environmental movement prefers a submissive tone, which is in line with the results from the first model.

In the count stage of the model both centrality measures decrease the likelihood of reaching distant members of the network. However, with respect to content only the environmental movement appears to provide a systematic method to successful widespread dissemination, as more excited messages turn out to be read and passed on by more distant individuals. In the nuclear disarmament movement, none of the affect measures have any significant effect. Instead, potential members of nuclear-disarmament organizations rely entirely on the status of a messenger when deciding whether or not to connect. This may be a consequence of the slightly more complex and insular issue SMOs in this movement are concerned with in comparison to the broader environmental causes.

Overall, sentiments only seem to be helpful to lift message dissemination above the threshold of the direct neighbourhood. However, their effect is vastly dominated by a high betweenness centrality, which is in line with results from studies on traditional mobilization via personal networks (e.g. Snow, Zurcher, & Ekland-Olson, 1980; McAdam, 1986). So in order to mobilize previously unconnected members of an extended network, the messenger seems to be more important than the message. But status does not carry a message very far as the positive effect of centrality quickly vanishes beyond the immediate neighbourhood. A sound mobilization strategy would thus target other well-connected individuals that are scattered throughout the network and let them serve as dissemination hubs for a more distant reach.

## 4.5 Conclusion

This paper investigated the determinants of success of SMO social media mobilization strategies. Reviewing recent work on how SMOs operate online, it argued that while the internet is increasingly in the focus of social sciences research on SMOs, most studies have examined the new opportunities online campaigns offer, but few have actually investigated the precise *mechanisms* through which SMOs mobilize in social media. Building on previous research in social psychology and social network analysis, this paper argued that for SMOs to successfully mobilize in social media, characteristics of the *message* as well as of the *messenger* are both vital. This argument was empirically investigated in a novel dataset of 867 106 tweets of six SMO networks in the environmental and nuclear disarmament movement that were chosen to demonstrate the presented approach. The success of SMO mobilization in social media was operationalized with two variables – (i) the popularity of messages and (ii) the distance of their dissemination throughout the networks – while characteristics of the *message* and the *messenger* were studied by constructing measures of tweet sentiments and network topology.

Using a combination of sentiment analysis and graph theory, the empirical analysis showed that messenger characteristics are barely beneficial at all when operationalizing SMO mobilization via the popularity of messages – rather the sentiment of messages determines their popularity. On the other hand, measuring the success of mobilization as the dissemination distance of messages, messenger centrality is essential to reaching distant network members. These results suggest a more differentiated view on online mobilization efforts that distinguishes between specific targets and goals of a given campaign. In order to stir lots of attention for an issue, highly sentiment-laden messages are quite suitable and the messenger is only secondary. However, even in times of instant information and high connectedness, it is not straightforward to mobilize entirely new groups of people and the use of strategic hubs becomes more important than the message itself. In this respect, trust between existing and potential activists is still an essential part of the mobilization process and the transition from personal to virtual networks has not changed this condition.

This paper demonstrated a modular approach to harvest and utilize some of the vast amounts of information generated and disseminated within social networks. In this respect it also contributes to the growing field of computational social sciences. The approach also opens up avenues for future research to help overcome present limitations: For one, more sophisticated methods can be applied to analyze the content of messages. Instead of dictionary-based sentiment measures, machine learning techniques may be able to increase the explanatory power of content-related variables by assessing sentiments of complex phrases and distinguishing between different topics. Also, even though the introduced dataset is large in comparison to previous studies on social movements, the construction of exhaustive networks may require an even larger amount of information. Future efforts could improve on this by collecting data over longer time periods and by comparing a larger number of organizations and movements to one another. The presented modular approach allows for such methodological improvements and offers a general framework to further study the mechanisms of online mobilization.

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# Appendix

## 4.A Retweet Distances (Alternative Specification)

***Table 4.9:*** *Retweet distances: Negative binomial hurdle model*

| | Environment | Nuclear Disarmament |
|---|---|---|
| *Zero-Stage* | | |
| (Intercept) | $-0.07\ (0.03)^{*}$ | $-0.15\ (0.02)^{***}$ |
| Betweenness | $3.53\ (0.38)^{***}$ | $6.82\ (0.81)^{***}$ |
| Relative Degree | $-46.50\ (4.63)^{***}$ | $-54.27\ (6.53)^{***}$ |
| Valence | $-0.42\ (0.10)^{***}$ | $-1.41\ (0.11)^{***}$ |
| Arousal | $-0.24\ (0.11)^{*}$ | $-0.27\ (0.10)^{**}$ |
| Dominance | $-0.44\ (0.14)^{**}$ | $0.80\ (0.16)^{***}$ |
| *Count-Stage* | | |
| (Intercept) | $1.16\ (0.01)^{***}$ | $1.16\ (0.02)^{***}$ |
| Betweenness | $-0.85\ (0.21)^{***}$ | $-2.15\ (0.41)^{***}$ |
| Relative Degree | $-7.33\ (2.56)^{**}$ | $-0.69\ (3.51)$ |
| Valence | $-0.05\ (0.05)$ | $-0.09\ (0.07)$ |
| Arousal | $0.17\ (0.05)^{**}$ | $-0.04\ (0.06)$ |
| Dominance | $0.09\ (0.07)$ | $0.13\ (0.10)$ |
| Log(theta) | $2.54\ (0.09)^{***}$ | $1.24\ (0.05)^{***}$ |
| AIC | 59 777 | 54 887 |
| Log Likelihood | −29 875 | −27 430 |
| Num. obs. | 19 340 | 17 196 |

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

# Declaration to confirm that the dissertation has been produced independently

I hereby declare that I have produced my doctoral thesis "Essays on the Political Economy of Mobilization" independently and without external assistance, and that I have made a significant contribution as co-author to other scientific articles.

I have identified all word-for-word quotations fo other authors, as well as comments based closely on other authors' ideas, and I have cited the sources according to the guidelines I received.

Date

Signature